Fund What You Trust?
Social Capital and Moral Hazard in Crowdfunding*

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Abstract

We study whether social capital mitigates moral hazard in crowdfunding. We construct a yearly index of social capital for all U.S. counties and combine it with a near-comprehensive sample of Kickstarter campaigns. Our results show a strong positive correlation between the social capital of the entrepreneur's home county and the campaign performance. For identification, we exploit a quasi-experiment based on a Kickstarter rule change that helps reduce the magnitude of moral hazard. We find that this rule change is associated with a significant reduction in the effect of social capital on campaign outcomes. In addition, the results are stronger for campaigns that are more vulnerable to moral hazard – as proxied by entrepreneur, regional, and campaign characteristics – and in times of high economic uncertainty and low sentiment. Overall, our findings suggest that crowdfunding campaigns benefit from social capital via the alleviation of moral hazard concerns.

JEL classification: D22, D81, G02, G23, L26

Keywords: crowdfunding, moral hazard, social capital, trust, kickstarter

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1 Introduction

"Our community is built on trust and communication." (Kickstarter rules)

Crowdfunding is an increasingly important source of financing for new ventures and one of the most successful segments of the fintech industry. By industry estimates, the global volume of crowdfunding surpassed that of angel investing in 2015, and crowdfunding may be on its way to surpass the venture capital industry.[1] Crowdfunding platforms enable entrepreneurs to raise funds directly from a large number of individuals (the "crowd"), removing the need for financial intermediaries. Some of the most successful platforms operate what are called *reward-based* schemes in which campaign backers commit funds in return for the promise of a *reward*. This reward is typically the product planned to be manufactured by the project being funded. Effectively, this type of funding means contracting to buy the product before the entrepreneur commits to invest in producing it. This new alternative for financing ventures offers obvious benefits. First, it allows the entrepreneur to learn about the demand for her product before having to invest in production. Second, at least in principle, it provides all entrepreneurs with equal access to financing by removing the potential barriers due to biased investment decisions.[2] Third, crowdfunding may provide a complementary source of financing alongside traditional forms of venture capital and angel investing and allow for more efficient capital allocation in the presence of product demand uncertainty.[3]

These benefits come with certain costs, of which one of the most important is moral hazard. Since customers commit funds before the entrepreneur invests in production, the entrepreneur may simply shirk or even embezzle the funds without investing and delivering the promised reward.[4] To understand the economics of reward-based crowdfunding, Strausz (2017) develops a theoretical model focusing on the implications of moral hazard. In addition to characterizing optimal mechanisms of crowdfunding schemes, his model provides a number of predictions related to the magnitude of moral hazard. In particular, the model predicts

[1]Source: CrowdFunder, statistics available at: http://www.forbes.com/sites/chancebarnett/2015/06/09/trends-show-crowdfunding-to-surpass-vc-in-2016/3/

[2]For example, current venture capital investments are highly concentrated in male-led startups. An estimated 4.9% of venture capital investments in 2016 were made in companies founded by women, and these investments accounted for only 2.2% of the dollar value of venture capital investment (PitchBook data, overview available at Fortune: http://fortune.com/2017/03/13/female-founders-venture-capital/)

[3]Several papers show that crowdfunding can help mitigate uncertainty over demand and therefore lead to more efficient investment (e.g. Strausz, 2017; Chemla and Tinn, 2016; Schwienbacher, 2015).

[4]As observed by Strausz (2017), instead of simply running away with the money, the entrepreneur could also provide the consumer with a product that "matches the formal description but is still worthless to the consumer" or claim that the project failed in a way that avoids any legal repercussions and allows her to not deliver the product and to keep the pledged funds.

that higher moral hazard risk results in a lower likelihood of campaign success.[5]

The main empirical challenge to test the implications of Strausz's (2017) model on the relationship between moral hazard and crowdfunding campaigns is the proper measurement of the magnitude of moral hazard at the entrepreneur level. The innovation of our paper is to exploit the tendency of regional social capital to generate trustworthy behavior through social norms, thereby mitigating the moral hazard in crowdfunding. In particular, we use the level of social capital in the county where the entrepreneur resides to measure the magnitude of moral hazard perceived by the potential campaign backers. There is growing recognition in finance and economics that networks of relationships and communities around individuals and organizations impact these actors' behavior through social norms and moral attitudes (e.g. Hirshleifer, 2015). Such forms of social organization generate trust and reciprocity and hence facilitate cooperation. This phenomenon is often called social capital, and it has spawned a large amount of literature in economics and other social science fields. People living in a community characterized by a high level of social capital are likely to trust each other more – partly because these communities provide better opportunities to punish those who do not abide with their norms and partly because of the moral attitudes imprinted by education (Guiso, Sapienza, and Zingales, 2004; Coleman, 1990).

The existing literature has shown that such social norms extend to company behavior. Hasan, Hoi, Wu, and Zhang (2017) find that firms located in high-social-capital counties are less prone to engage in corporate tax avoidance. In another paper (Hasan, Hoi, Wu, and Zhang, 2016), the same authors study bank loan data and find that high social capital is associated with lower bank loan spreads, looser other loan terms, and lower at-issue bond spreads. Their results suggest that social capital imposes behavioral norms on firms and hence mitigates the risk of opportunistic firm behavior against debtholders. Moreover, Jha and Chen (2015) find evidence that audit firms judge the trustworthiness of their clients based partly on where they are located, and firms headquartered in high-social-capital counties pay lower audit fees.

To measure regional social capital, we construct what we believe is the most comprehensive and consistent yearly measure of social capital available at the U.S. county level. We use a methodology similar to that of Rupasingha, Goetz, and Freshwater (2006), whose social capital index has been used in the studies mentioned above. Our index combines three components that aim to proxy the density of social networks and the strength of social norms. First, we use data from the *County Business Patterns (CBP)*, which is compiled by the Census Bureau, to measure the level of associational activity within each county.

[5]This prediction is consistent with two other papers that model the impact of moral hazard on reward-based crowdfunding campaigns: Chemla and Tinn (2016) and Chang (2015).

Second, we calculate the number of charitable non-profit organizations per capita using data obtained from the National Center for Charitable Statistics (NCCS). Third, we include the voter turnout rate from the most recent presidential election. As noted by Guiso et al. (2004), there are neither legal nor economic incentives to vote, so voting is driven by social pressure and internal norms. We then construct the index values using principal component analysis, aggregating the information in these three variables. As discussed in our Internet Appendix A, our index addresses several methodological issues present in the original index by Rupasingha et al. (2006).

For our analysis, we combine this social capital index with a near-comprehensive set of Kickstarter campaign data. We conjecture that trust and behavioral norms related to regional social capital mitigate moral hazard problems and therefore facilitate crowdfunding campaign performance. This means that a higher level of social capital should help entrepreneurs succeed in their crowdfunding campaigns. Our main hypothesis thus predicts that *entrepreneurs who reside in counties with high levels of social capital have higher campaign success rates.*

To test this hypothesis, we use a campaign success dummy and the ratio of funds pledged to the goal amount as dependent variables. On both measures, we find that social capital is significantly positively associated with campaign success. Controlling for a number of factors, including campaign and entrepreneur characteristics, prior experience, a county's size and level of wealth, state fixed effects, year-month joint fixed effects (101 months), and yearly product sub-category joint fixed effects (169 categories times 9 years), a one-standard-deviation increase in the social capital index leads to a 3.0 %-point increase in the expected likelihood of success and an 8.0% increase in the expected Pledged/Goal ratio.

To identify the causal effect of social capital, we exploit a quasi-experiment provided by a Kickstarter rule change that directly affected the magnitude of moral hazard. This change, which was announced in September 2014, clarified and strengthened entrepreneurs' obligation to deliver the promised reward to campaign backers and hence increased the expected cost of non-delivery. By definition, this increase in the expected cost of fraud reduces the magnitude of moral hazard and thus allows us to use difference-in-differences regressions around the rule change to identify the causal effect of social capital. We expect that the positive influence of social capital on campaign success will be mitigated after the rule change. We further strengthen this identification by observing that certain product categories are more vulnerable to entrepreneurs' failure to deliver. This heterogeneity allows us to add a third difference based on the differences in the change of the effect of social capital between the more risky and less risky categories.

The results provide strong support for our main hypothesis. We find that this rule change is associated with a significant reduction in social capital's effect on campaign success. The rule change also generally increases campaigns' likelihood to succeed, consistent with the interpretation that it mitigates moral hazard problems. Furthermore, the reduction in the effect of social capital is generally more pronounced in the product categories that are most likely to suffer from the failure to deliver rewards.

In our additional analysis, we also study the relationship between social capital and the likelihood of a campaign to be suspended by Kickstarter. The reasons for suspension are not disclosed, but there is anecdotal evidence suggesting that a number of these campaigns may have been identified by Kickstarter staff to be possibly fraudulent. Hence, they represent a noisy proxy for attempted fraud cases. We find that social capital is significantly negatively associated with the likelihood of campaign suspension. This finding provides additional support for our hypothesis, although we should note that our sample includes only 724 suspended campaigns, which limits the robustness of these results.

The key premise of our study is that social capital mitigates moral hazard, thus enabling us to test the effects of moral hazard indirectly by observing the effects of social capital on crowdfunding. However, different campaigns are likely to have different levels of moral hazard risk to begin with. Based on this intuition, we perform additional analyses on the differential impact of social capital. We identify a number of campaign attributes that are likely to indicate a higher risk of moral hazard and test their joint effects with social capital on campaign outcomes. Our results show that social capital's association with higher success rates is stronger (i) for individual entrepreneurs, (ii) for entrepreneurs who lack a track record, (iii) for small campaigns in which pursuing fraud cases via the legal system would be costly relative to potential proceeds for backers, (iv) for campaigns based in poor counties and in large cities, and (v) at times when economic policy uncertainty is high and investor sentiment is low. Conversely, being chosen as a "Staff pick" campaign by Kickstarter significantly reduces the positive effect of social capital. These differences are statistically and economically significant. For example, the estimated relationship between social capital and campaign success weakens in a monotonic fashion with the number of campaigns the entrepreneur has created. A one-standard-deviation increase in social capital increases the expected likelihood of success by 3.3 %-points in the first campaign but only by 0.1 %-points in the third campaign.

As an additional testable prediction, Strausz (2017) shows that the presence of moral hazard leads to higher goal amounts required by the entrepreneur because, to induce her to invest in the production, the entrepreneur must be compensated for the potential rewards from expropriating funds. Intuitively, this effect should be stronger when the risk of moral hazard is higher. We test this prediction by regressing campaign goal amounts on social capital and control variables. Consistent with the hypothesis, we find that campaigns based in higher-social-capital counties (which have a lower moral hazard risk) have significantly lower goal amounts. A one-standard-deviation increase in social capital is associated with a 2.2% decrease in the campaign goal amount.

We consider a number of alternative explanations for our empirical findings. First, prior literature suggests that social capital could facilitate information flows.[6] Strausz (2017) shows that the entrepreneur's private cost information can make moral hazard problems more severe in reward-based crowdfunding. However, he also argues that information asymmetry represents a second-order effect because misrepresenting cost information is profitable to the entrepreneur only in the presence of moral hazard. The expected effects of social capital on both the magnitude of moral hazard and information asymmetry are directionally similar for our results. Hence, it is difficult to quantify the relative contribution of information asymmetry. However, because information asymmetry alone should not cause the results, the potential reduction in information asymmetry represents merely a potential additional channel through which social capital can mitigate moral hazard; it does not qualitatively challenge our results. Furthermore, this reduction in information asymmetry due to social capital could only take place locally. Xu (2017) shows that on average, only 19% of campaign backers are from the same city as the entrepreneur. Because most backers are not from the same city as the entrepreneur, the concern that our findings are driven mainly by information asymmetry is mitigated. In Internet Appendix B, we include an analysis of the effect of another rule change that reduces information asymmetry for all campaigns due to Kickstarter's additional disclosure requirements. We find that it also reduces the effect of social capital, consistent with the interpretation that information asymmetry amplifies moral hazard.

Second, social capital might be correlated with access to alternative sources of financing linked to entrepreneurs' financial constraints. Schwienbacher (2015) models the effect of access to professional deep-pocket investors in the context of reward-based crowdfunding. He shows that the presence of such investors should lead to lower crowdfunding campaign goals and more campaigns being launched with less effort exerted by the entrepreneur, which ultimately reduces the average quality of the projects offered on the platform. While this prediction is in line with our results for goal amounts, it does not explain the results for campaign outcomes. Meanwhile, this prediction is inconsistent with our results that show that goal amounts are higher in wealthier counties, where access to alternative financing is likely to be better. Furthermore, any differences in financial constraints would be much more important between different states than between counties within a state because the legal

[6] See, e.g. ,Barr (2000); Tiepoh and Reimer (2004).

and regulatory frameworks are set at the state or federal level, while there are no intra-state differences in financial regulations or laws. Such differences between states are captured by the state fixed effects we include in our regression models. Our interaction results are also robust to including county fixed effects, which would also capture any intra-state differences.

Third, some of our findings might be consistent with differences in risk aversion. If high social capital is correlated with high risk aversion, that could result in entrepreneurs setting lower goal amounts and exhibiting higher success rates. However, this explanation seems inconsistent with both the intuitive impact of social capital and the empirical findings in the prior literature. Social capital provides a type of a financial safety net in that individuals can rely on others for help more than they could in the absence of social capital. A higher level of social capital should thus encourage risk taking rather than inhibit it. Consistent with this argument, Guiso et al. (2004) find that individuals in high-social-capital areas invest significantly more in stocks and hold less cash. As a robustness check, we also perform a regression analysis controlling for the cultural uncertainty aversion of the entrepreneur, proxied by Hofstede's (2001) Uncertainty Avoidance Index assigned based on the cultural origin of the entrepreneur's surname. We find that the positive relationship between social capital and campaign performance remains highly significant even when controlling for uncertainty aversion.

2 Literature review and hypothesis development

2.1 Social capital and trust

Social capital refers to communities and networks of relationships that affect individuals' behavior by imposing norms, creating reciprocity, and hence facilitating trust. Such norms, trust, and civic behavior can be viewed as resources for individuals and organizations (e.g. Coleman, 1990; Putnam, 1993) because they reduce transaction costs and facilitate economic activity, thereby arguably meriting the label "capital".[7]

Following the seminal works of Coleman (1988) and Putnam (1993), the concept of social capital has inspired a vast amount of literature in economics and other social sciences. Despite the proliferation of papers on the topic, there is no commonly accepted and precise definition of social capital. Durlauf and Fafchamps (2005) provide a review of the social capital literature and summarize the common elements of various authors' definitions as

[7]The term "social capital" has drawn criticism, with several authors arguing that the concept does not merit the label "capital" given that it lacks some of the usual attributes of capital, such as extension in time, deliberate sacrifice in the present for future benefit, alienability, non-negative payoff, and mechanisms for accumulation and depreciation (e.g. Solow, 1995, 2000; Arrow, 2000).

follows: i) social capital generates positive externalities for members of a group; ii) these externalities are achieved through shared trust, norms, values, and their consequent effects on expectations and behavior; and iii) shared trust, norms, and values arise from informal forms of organizations based on social networks and associations.

We focus on social capital's role in generating trust and trustworthy behavior. Social capital enhances trust partly because social networks in high-social-capital communities provide better opportunities to punish those who do not abide by the norms of the community (Guiso et al., 2004; Spagnolo, 1999; Coleman, 1990, 1988). In support of this argument, Guiso, Sapienza, and Zingales (2013) study individuals' willingness to strategically default on their mortgages and find that moral and social considerations are among the most important variables in predicting strategic default. Another mechanism by which high social capital communities may enhance trust is by imposing and strengthening moral attitudes by education (Guiso et al., 2004; Banfield, 1958). Many studies have found a positive relationship between social-capital-induced trust and regional economic performance and governance (e.g. Putnam, 1993; Knack and Keefer, 1997; Knack, 2002).

This idea that social capital generates trustworthy behavior and thus mitigates the agency costs caused by moral hazard in crowdfunding is consistent with prior findings in other contexts. The effectiveness of community governance in mitigating moral hazard is discussed by Bowles and Gintis (2002). Guiso et al. (2004) show that social capital is important for the spread of financial contracts and hence for the development of financial markets. They argue that this is because individuals' willingness to sign financial contracts depends "not only on the enforceability of contracts, but also on the extent to which they trust the counterpart." Millo and Pasini (2010) find evidence that social capital mitigates moral hazard in insurance markets.

There is also evidence of the effectiveness of social capital in imposing behavioral norms on firms. Hasan et al. (2017) find that firms located in high-social-capital counties are less prone to engage in corporate tax avoidance. In another paper, the same authors study bank loan data and find that high social capital is associated with lower bank loan spreads, looser other loan terms, and lower at-issue bond spreads (Hasan et al., 2016). Their results suggest that social capital imposes behavioral norms to firms and hence mitigates the risk of opportunistic firm behaviors against debtholders. Jha and Chen (2015) find evidence that audit firms judge the trustworthiness of their clients based partly on where they are located and that firms headquartered in high-social-capital areas pay lower audit fees.

A number of studies have documented the effect of social trust on financial decisions made by both individuals and firms. Guiso, Sapienza, and Zingales (2008) find evidence of the importance of trust for stock market participation. La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997) show that trust is important for the existence and operation of large organizations. Similarly, Bloom, Sadun, and Van Reenen (2012) find that trust increases aggregate productivity by affecting the organization of firms and allowing them to decentralize their operations. Levine, Lin, and Xie (2018) find that liquidity-dependent firms in high-trust countries obtain more trade credit and suffer smaller drops in profits and employment during banking crises than similar firms in low-trust economies. Ang, Cheng, and Wu (2015) find evidence that foreign high-tech companies investing in China prefer to invest in regions where local partners and employees are considered more trustworthy; they are also more likely to establish joint ventures and to make greater research and development investments. Bottazzi, Da Rin, and Hellmann (2016) study the role of trust in venture capital investments and find that trust among nations positively predicts venture capital firms' investment decisions but has a negative correlation with successful exits. They also find evidence that earlier-stage investments require higher trust.

2.2 Social capital and moral hazard in crowdfunding campaigns

Strausz (2017) develops a theoretical model of reward-based crowdfunding in the presence of moral hazard. While he focuses on optimal mechanism design, the model also yields a number of predictions for campaign parameters and outcomes. In his model, moral hazard leads to inefficiently high goal amounts that entrepreneurs set in order to compensate for the potential rewards of expropriating funds. This inefficiency results from the entrepreneur's ability to take the money and run due to systemic weakness. In other words, for the entrepreneur to be incentivized to actually invest in production, the proceeds must be high enough. Since overall demand is uncertain, setting a higher goal amount leads to a lower likelihood of success but higher proceeds if the campaign is successful.

Strausz (2017) models the magnitude of moral hazard risk by a parameter α, which is defined as the proportion of the campaign proceeds that the entrepreneur can appropriate. This possibility exists because of the imperfect ability of campaign backers to enforce the entrepreneur's commitment to deliver the promised goods, conditional on campaign success.[8] Denoting the total amount pledged by P, we can think of the entrepreneur running away with the full amount P and $(1-\alpha)P$ being the expected fine the entrepreneur would have to pay. Alternatively, by incurring a cost of $(1-\alpha)P$, the entrepreneur can credibly claim that the project failed without fear of legal repercussions. The parameter α thus represents

[8] As noted by Strausz, this parameter can be considered to capture several types of moral hazard problems. Instead of simply running away with the money, the entrepreneur could provide the consumer with a product that "matches the formal description but is still worthless to the consumer" or claim that the project failed in a way that avoids any legal repercussions and allows her to not deliver the product and to keep the pledged funds.

general institutional weakness.

The level of institutional weakness represented by α can be interpreted as a measure of how much the entrepreneur can rationally be trusted. As discussed by Carlin, Dorobantu, and Viswanathan (2009), the answer to this question depends on both formal institutions, such as courts and the legal and regulatory environment, as well as informal institutions, such as community governance and behavioral norms. The latter is where social capital becomes relevant. If high-social-capital communities enforce behavioral norms that condemn fraud more strongly, this action increases the effective cost of fraud for an entrepreneur and hence reduces α. By implication, the results that Strausz (2017) derives for α should be inversely related to the level of social capital, assuming everything else is equal.

Hence, our main innovation in this respect is to study the impact of moral hazard, which we cannot measure, *indirectly* by studying the relationship between crowdfunding dynamics and social capital.[9] Combining the predictions on the effects of moral hazard discussed above and the prediction that social capital mitigates moral hazard, we formulate our main hypothesis as follows:

Hypothesis: *A higher level of social capital is associated with higher success rates for crowdfunding campaigns.*

3 Data and methodology

3.1 Crowdfunding data

We use a near-comprehensive web-crawled dataset of Kickstarter campaigns for the period from April 2009 to August 2017, collected over multiple years. As summarized in Appendix A, the original raw data include the details of 315,017 campaigns globally. Comparing these data with the Kickstarter statistics on the website, which show 364,332 projects launched to date, our data capture approximately 86% of all Kickstarter campaigns.[10] To our knowledge, this is the largest and most comprehensive sample of crowdfunding campaign data used to date.

Our data include identifiers for each campaign and each campaign creator's name and location, as well as many other variables on campaign characteristics. We can calculate

[9] Of course, the measurement of social capital is not perfect, either, but the types of proxies we use for social capital are widely used in prior literature and have been shown to be associated with trustworthy behavior.

[10] Figures as of mid-August 2017, at the time of the last campaigns in our data, are available online at https://www.kickstarter.com/help/stats

the social capital index only for U.S. counties, so we include only campaigns based in the U.S. After excluding campaigns that are still active, we are left with 227,752 campaigns. Additional data limitations, such as the ability to match the entrepreneur's location to a county, bring our final sample down to 223,679 campaigns.

With a methodology similar to Lin and Pursiainen (2017), we use creators' names to identify their gender and race or ethnicity. To determine gender based on first names, we use the analysis conducted by Peter Organisciak, who estimates the name frequencies by gender in the U.S. as of 2014 by using birth name statistics and U.S. Census data on age distributions.[11] For our analysis, we require that the likelihood of assigning the correct gender to be at least 80%. This methodology gives us gender estimates for 65.6% of the sample, with the remainder classified as "No gender." This third category includes individuals whose gender we cannot reliably estimate from the first name, groups of multiple individuals, or companies.

To estimate creators' race or ethnicity, we use the dataset compiled by Word, Coleman, Nunziata, and Kominski (2008) based on the U.S. Census 2000 data. They provide estimated percentages by race/ethnicity for each surname that occurs at least 100 times in the Census data. Their classification breaks down names by race for Whites, Blacks, Asians, and Native Americans. We omit the last group from our categorization because there are very few names identified as Native American in our sample. In addition to these races, Word et al. (2008) identify names associated with the Hispanic ethnicity, which we include in our analysis. We include the estimated race/ethnicity for each surname for which the likelihood of a correct race/ethnicity is greater than 50%. This threshold is necessarily lower than the one we apply for gender, given that most names occur for several races or ethnicities. A 50% share for a given race is therefore relatively high in comparison to the corresponding likelihoods that other races/ethnicities have the same name. This situation inevitably adds some noise to the race/ethnicity estimates, but we see no reason why it would produce a systematic bias in the results. Hence, if anything, this noise in estimation should only weaken the significance of our results. This methodology gives us race/ethnicity estimates for 62.5% of the campaigns included in our sample. The remainder are classified as "No race" in our analysis.

Our data also include the location of each campaign, based on which we assign the social capital level and other county-level variables. We winsorize all continuous variables at the 1% level. As a robustness check, we also run all our analyses excluding canceled campaigns and campaigns with a goal amount below $1,000, similar to the adjustments made by Kuppuswamy and Mollick (2016). The results and conclusions remain essentially unchanged.

[11] At the time of this writing, the data are available online at https://github.com/organisciak/names

3.2 Measuring social capital

To measure social capital, we construct what is – to our knowledge – the most comprehensive and consistent annual proxy of social capital by U.S. county introduced to date. We leverage the methodology of Rupasingha et al. (2006), whose index data have been used in a number of prior studies (e.g. Hasan et al., 2016, 2017; Jha and Chen, 2015).[12]

Our index combines three components aiming to proxy the density of social networks and the strength of social norms. The first component is the association density based on data from the *County Business Patterns (CBP)* compiled by the Census Bureau, a metric advocated by, e.g., Putnam (1993), to measure social capital. The second component is the number of charitable non-profit organizations per capita, calculated using data obtained from the National Center for Charitable Statistics (NCCS). The third component is the voter turnout rate in the most recent presidential election. As noted by Guiso et al. (2004), there are neither legal nor economic incentives to vote, so the decision to do so is driven by social pressure and internal norms. We then construct the index value using principal component analysis, aggregating the information in these three variables. The social capital index value is defined as the first principal component.

As we discuss in our Social Capital Appendix, our index addresses several methodological problems of the original index by Rupasingha et al. (2006), some of which are discussed in Hasan et al. (2016), among others. First, the social capital index by Rupasingha et al. and its component data are available only for the years 1990, 1997, 2005 and 2009. Second, there are several inconsistencies in the availability and values of different variables across different years and different counties (e.g., the number of registered non-profit organizations is not comparable in the 1990 data vs. the other years, and the census response rate is missing for a large number of counties, especially in 1990). Third, there are also several obviously wrong values included, e.g., counties having voter turnout rates much higher than 100 percent, with these wrong outlier values significantly biasing the principal component analysis. Similarly, the large number of missing values for some variables and some years means that the resulting principal components are not comparable across different years. Finally, their methodology also mixes data from different years to calculate the social capital index. For example, their 1990 social capital estimate uses voter turnouts for 1988 and 1992, while the social capital estimate for 1997 uses census response rates in 2000 and voter turnout for 1996, and so on. This situation causes several obvious inconsistencies between time periods. Likely for these reasons, Jha and Chen (2015) use only data for the 1997-2009 period, where consistency is better, and Hasan et al. (2016, 2017) re-estimate all registered organization density values

[12] At the time of this writing, the Rupasingha et al. (2006) index data can be downloaded from http://aese.psu.edu/nercrd/community/social-capital-resources

for 1990 based on later average growth rates.

We therefore use the same idea and same methodology as Rupasingha et al. but significantly improve the robustness of the social capital index by i) using only variables that we can measure on a consistent basis across the time period for all counties and ii) calculating the index on an annual basis instead of using sporadic intervals of 3-8 years. Hence, due to the lack of data availability on a consistent and frequent basis, we do not use the census response rate as a determinant of social capital.

4 Main results

4.1 Description of the data

We analyze a near-comprehensive sample of Kickstarter campaigns based in the U.S. Panel A of Table 1 shows the number of campaigns by year in our data, categorized into *Successful*, *Unsuccessful*, and *Suspended*.

Panel B of Table 1 shows summary statistics for the sample. The average goal amount for a campaign is $17,445. The average success rate is 0.406, and the average Pledged/Goal ratio 0.792. The average amount pledged by a backer is $70, while 18.6% of the campaign creators are identified as female and 47.0% as male. The remaining creators are companies or include multiple individuals, or their gender cannot be reliably determined from their names. In terms of race and ethnicity, 55.0% are identified as ethnic Whites, 3.8% as Hispanics, 2.2% as Asians, and the remaining 37.5% as *No ethnicity*, for the same reasons as those listed above for gender.

4.2 Social capital and campaign outcomes

Our hypothesis predicts a positive relationship between social capital and crowdfunding campaign success. To test for the relationship between social capital and the likelihood of success, we perform the following logit regression:

$$Successful_i = \alpha_0 + \alpha_1 \times SK_i + \beta \times X_i + \epsilon_i \qquad (1)$$

where $Successful_i$ is a dummy taking the value one if campaign i is successful and zero otherwise[13], SK_i is the social capital index value for campaign location county, and X_i is a vector of control variables. We include dummies for creator gender and race/ethnicity

[13]Failed and canceled campaigns are both included as unsuccessful campaigns. Since the creator has the option to cancel the campaign, we cannot distinguish between a failed campaign and a campaign cancelled amid weak demand.

campaign goal amount, and campaign length; a dummy for staff pick campaigns[14]; year-month joint fixed effects (101 months); state fixed effects (50 states) to control for any state-specific factors; campaign number fixed effects, which refer to the number of campaigns the creator created before the current campaign and capture the effect of campaign experience; and sub-category-year joint fixed effects (169 sub-categories times 9 years), which allow for product-category-specific factors on a time-variant basis. We exclude suspended campaigns in these regressions.[15]

As another measure for campaign performance, we use the ratio of the amount pledged by backers divided by the goal amount. We estimate the impact of social capital on this ratio using OLS regressions of the following form:[16]

$$ln(1 + Pledged/Goal)_i = \alpha_0 + \alpha_1 \times SK_i + \beta \times X_i + \epsilon_i \quad (2)$$

where $ln(1 + Pledged/Goal)_i$ is the natural logarithm of one plus the amount pledged divided by the goal amount for campaign j. This variable measures the amount pledged relative to the goal amount. We take logarithms due to the highly skewed distribution of the ratio and add one so that we can include the campaigns with zero pledged amounts.

The results shown in Table 2 provide support for our hypothesis. A higher level of social capital is associated with a higher likelihood of success and higher Pledged/Goal ratios, and these results are highly statistically significant. In terms of control variables, larger and longer campaigns are less likely to succeed, while campaigns identified as "staff picks" are significantly more likely to succeed. The aggregate size of the home county's economy (proxied by the aggregate personal income in the county) significantly increases the likelihood of success. The county's wealth level has no significant impact the campaign's likelihood of success.

The results for the Pledged/Goal ratio for all control variables are qualitatively very similar to those reported for the likelihood of success. In contrast to success rates, county wealth level is significantly positively associated with Pledged/Goal ratios. These results are robust to virtually all combinations of including or excluding fixed effects, which are not shown here for brevity. For comparison, we also show an OLS version of the regression model for success rate. In our other analyses, including interactions with social capital, we

[14]Campaigns highlighted by the Kickstarter platform.

[15]We do not observe the specific reasons for each campaign suspension, but generally, campaigns are suspended after being found to be in violation of Kickstarter's rules. The number of suspended campaigns is very small relative to our sample, and including them in the regressions would not result in any significant changes in the results.

[16]As a robustness check, we also perform the analysis using tobit regressions and obtain qualitatively similar results.

use OLS specifications to allow additional fixed effects that we cannot estimate using logit regressions.

4.3 Quasi-experiment: Rule change affecting moral hazard

To identify the causal effect of social capital, we exploit a quasi-experiment provided by a Kickstarter rule change announced on September 20, 2014.[17] This rule change clarified and strengthened entrepreneurs' obligation to provide backers with the promised rewards, hence reducing the magnitude of moral hazard. Prior to this change, Kickstarter rules stated that "Project Creators agree to make a good faith attempt to fulfill each reward by its Estimated Delivery Date." The new rules included much stronger wording, e.g., stating that "when a project is successfully funded, the creator must complete the project and fulfill each reward and that "once a creator has done so, they've satisfied their obligation to their backers." The new rules also added a number of other terms strengthening entrepreneurs' obligations to finish the project and provide the best possible outcome for project backers and to communicate honestly with backers. They explicitly stated that entrepreneurs who are unable to stand by the promises they made in their projects may be subject to legal action by backers.

Taken together, the new rules significantly strengthen the project backers' contractual position if the entrepreneur fails to deliver the product. Therefore, the rule change directly reduces the magnitude of moral hazard. Illustrating this point, in its review of the new rules, TechCrunch writes, "Kickstarter also reminds creators that they need to be honest and not make material misrepresentations in their communication to backers. (In other words, scammers beware.)", while SlashGear titles its summary "Kickstarter changes rules so nobody runs off with your money".[18]

Given that this rule change reduced the magnitude of moral hazard in Kickstarter campaigns, our main hypothesis suggests that it should have reduced the benefits of social capital. To test this prediction, we use difference-in-differences regressions of the following form

$$\begin{aligned} Successful_i = &\alpha_0 + \alpha_1 \times Post_i \times SK_i + \alpha_2 \times Post_i \\ &+ \alpha_3 \times SK_i + \beta \times X_i + \epsilon_i \end{aligned} \tag{3}$$

[17] The rule came into effect on October 19. We conduct our analysis around the announcement date on the basis that the rule change was widely discussed in both mainstream and specialized media and many of the articles discussing it do not mention the effective date. It is therefore likely that some of the fraud-deterring effect occurred before the effective date. As a robustness check, we also perform this analysis around the effective date and obtain qualitatively similar results.

[18] The TechCrunch article is available online at https://techcrunch.com/2014/09/19/kickstarter-updates-terms-of-use-section-related-to-failed-projects/. The SlashGear article is available online at https://www.slashgear.com/kickstarter-changes-rules-so-nobody-runs-off-with-your-money-19347238/

for the likelihood of success and

$$
\begin{aligned}
ln(1 + Pledged/Goal)_i = &\alpha_0 + \alpha_1 \times Post_i \times SK_i + \alpha_2 \times Post_i \\
&+ \alpha_3 \times SK_i + \beta \times X_i + \epsilon_i
\end{aligned}
\tag{4}
$$

for the Pledged/Goal ratio.

The results shown in Panels A and B of Table 3 provide strong support for our hypothesis. The first model excludes year-month joint fixed effects, showing that expected Pledged/Goal ratios and success rates are significantly higher following the rule change, consistent with the interpretation that it reduces the moral hazard risk. Adding year-month fixed effects in the second column naturally removes this timing effect. We observe that the effect of social capital significantly decreases after the rule change, as shown by the significantly negative coefficients on the $Post \times SK$ interaction term.

A potential concern related to our analysis is that we cannot perfectly control for the underlying quality of projects and entrepreneurs. It is possible that the underlying quality of projects is correlated with our measure of social capital and its interaction terms in a way that could yield some of our results. To mitigate this concern, we include an OLS version of all our interaction regressions in which we include county fixed effects. Given that our social capital index exhibits very high autocorrelation (ca. 99%, as shown in our Internet Appendix A), county fixed effects capture most of the effect of regional social capital. However, they also capture all other differences between areas related to entrepreneur and project quality. For example, large numbers of high-quality entrepreneurs may be concentrated in areas such as Silicon Valley. Such differences in entrepreneur quality will be captured by the county fixed effects. Our results remain highly significant after including county fixed effects.

To make sure our results are indeed driven by the rule change and not a time trend, we perform placebo tests of the same form but moving the timing of the rule change backward and forward by one year. The results are reported in columns 4 and 5 in Panels A and B of Table 3. We find no significant changes in the estimated effect of social capital in these placebo tests, supporting a causal interpretation of the rule change.

Intuitively, certain product categories are more likely to fail to deliver and hence are more prone to suffer from moral hazard. The product categories *Hardware* and *Product Design* are most obviously related to developing and manufacturing a product that does not yet exist, making them more likely to fail to deliver and hence arguably more prone to moral hazard. This interpretation is consistent with Kickstarter rules, which require projects in these categories to have a prototype and ban financing the development of such prototypes with Kickstarter campaigns. In our analysis, we label the campaigns in these two categories as *Risky*. This classification allows us to further strengthen our identification by adding a third difference into our regression models. The resulting Difference-in-Difference-in-Differences regression models are of the following form

$$\begin{aligned} Successful_i = & \alpha_0 + \alpha_1 \times Post_i \times Risky\ category_i \times SK_i \\ & + \alpha_2 \times Post_i \times SK_i + \alpha_3 \times Post_i \times Risky\ category_i \\ & + \alpha_4 \times Post_i + \alpha_5 \times Risky\ category_i \times SK_i \\ & + \alpha_6 \times SK_i + \beta \times X_i + \epsilon_i \end{aligned} \tag{5}$$

for the likelihood of success and

$$\begin{aligned} ln(1 + Pledged/Goal)_i = & \alpha_0 + \alpha_1 \times Post_i \times Risky\ category_i \times SK_i \\ & + \alpha_2 \times Post_i \times SK_i + \alpha_3 \times Post_i \times Risky\ category_i \\ & + \alpha_4 \times Post_i + \alpha_5 \times Risky\ category_i \times SK_i \\ & + \alpha_6 \times SK_i + \beta \times X_i + \epsilon_i \end{aligned} \tag{6}$$

for the Pledged/Goal ratio.

The results shown in Table 4 provide additional support for our hypothesis. In addition to the effect of social capital being reduced following the rule change, we see that this reduction in the effect of social capital is significantly larger in the categories we classify as *Risky*. This result is qualitatively similar across all model specifications and for both success rates and Pledged/Goal ratio, although the estimated coefficient for the $Post \times Riskycategory \times SK$ interaction term is not statistically significant for the success rates in column 3, when including county fixed effects. The corresponding coefficient for Pledged/Goal ratio, shown in column 6, is highly significant. Intuitively, it is not surprising that we find more refined difference results using the continuous outcome variable, Pledged/Goal ratio, rather than the binary variable Successful.

5 Additional results

5.1 Social capital and the likelihood of suspension

In our regression analysis, we exclude suspended campaigns. The reasons for suspension are not disclosed by Kickstarter. Anecdotal evidence suggests that a number of these campaigns have been identified by Kickstarter staff to be possibly fraudulent[19]. As such, they provide a

[19] For example, Cliqist.com reviews a sample of suspended video game campaigns, with a number of relatively clear cases of attempted fraud. At the time of writing, the analysis is available at

noisy proxy for attempted fraud cases and hence may provide relevant evidence for our moral hazard considerations. These campaigns are suspended before completion, and therefore, we cannot know if the entrepreneur would have delivered the promised rewards. These campaigns also exclude any possible fraud cases that have not been identified by Kickstarter ex ante. They are therefore by no means a perfect proxy for moral hazard risk. Nevertheless, we test for the determinants of the likelihood of campaign suspensions using logit regressions of the following form:

$$Suspended_i = \alpha_0 + \alpha_1 \times SK_i + \beta \times X_i + \epsilon_i \tag{7}$$

where $Suspended_i$ is a dummy taking the value one if the campaign is suspended and zero otherwise and X_i is the same vector of controls as used above. This analysis is weakened by the fact that we have only 724 suspended campaigns in our sample, limiting the number of right-hand variables we can include. We therefore include only a very slimmed-down version of fixed effects, including campaign number fixed effects as well as either state or year fixed effects.

Table 5 shows the results of these regressions. In models 1 through 4, excluding year fixed effects, social capital is significantly negatively associated with the likelihood of campaign suspension. Including year fixed effects makes this result statistically insignificant, possibly because of the small number of suspended campaigns in our data. These findings are qualitatively consistent with our hypothesis, although not very robust.

These findings and the small number of suspended campaigns are also consistent with an adjacent study by Mollick (2014), who examines a sample of Kickstarter campaigns and finds that the vast majority of founders seem to fulfill their obligations to funders, with 2.3% of his sample of 200 successfully funded projects showing indications of potential fraud. He also finds that over 75% deliver products later than expected, with the degree of delay predicted by the level and amount of funding a project receives. The main problem with the methodology of Mollick (2014) is that it is very difficult and labor-intensive to collect the data, and therefore, the potential sample size remains very small.

5.2 Differences in the importance of social capital

Our central argument is that social capital helps mitigate moral hazard. This enables us to test the effects of moral hazard indirectly by observing the effects of social capital. However, different campaigns may have different levels of moral hazard risk to begin with. As the severity of moral hazard increases, so should the benefits of high social capital for mitigating

cliqist.com/2016/04/07/suspended-kickstarter-video-game-campaign/.

moral hazard problems. Following this simple intuition, we propose a number of potential indicators of campaign sensitivity to moral hazard. We then perform the same multiple regression analyses as above but add interaction terms between social capital and proxies for sensitivity to moral hazard.

5.2.1 Social capital and entrepreneur characteristics

Individuals are plausibly perceived to be more prone to commit fraud than groups of individuals or companies. If a company is engaged in business prior to the campaign, it arguably has more to lose from the reputational damage caused by fraudulent activity than an individual might have. Companies may also be more likely to be pursued by campaign backers via the legal system. The mere act of establishing a company takes effort, and it does not seem obvious that a fraudulent entrepreneur would want to exert such effort. Similarly, it takes more effort to organize and coordinate a group of individuals and the proceeds of fraudulent campaigns would need to be shared. The benefits of having multiple entrepreneurs are also not obvious when entrepreneurs do not intend to fulfill their commitments to backers. It therefore seems that an entrepreneur would be less likely to choose to pursue a fraudulent campaign with partners than to do so alone. Intuitively, it also seems plausible that social capital will have a larger impact on individuals' campaigns than those launched by companies because the enforcement of norms in high-social-capital communities likely has a stronger effect on individuals. Panel A of Table 6 shows the results of regression analysis on the effect of social capital for individuals vs. groups or companies. Consistent with our prediction, we see that the effect of social capital is significantly larger for individual entrepreneurs. This result is statistically significant for both outcome variables and robust to including county fixed effects.

The entrepreneur's background is also likely to be relevant for the campaign backers. The first campaigns launched by an entrepreneur are likely to be perceived as riskier than campaigns launched by entrepreneurs with a good track record. An entrepreneur embezzling backers' funds obviously loses the option to return for another campaign, so serial campaign creators stand to lose more. This idea is consistent with the findings of Bottazzi et al. (2016), who show evidence that earlier-stage venture capital investments require greater trust. It is also consistent with the literature on reputation formation (see, e.g., Gorton, 1996). We hence expect that social capital has the largest effect during an entrepreneur's first campaign, and this effect decreases with the number of campaigns created by the same entrepreneur.

Panel B of Table 6 shows the regression results, including dummies for campaign number and their interaction terms with social capital. We exclude the dummy for the first campaign, so all campaign number coefficients are relative to the first campaign. Similarly, the table shows the results including interaction terms between social capital and prior campaign experience, with separate experience variables depending on the outcomes of prior campaigns. Consistent with our hypothesis, higher social capital is associated with a significantly higher likelihood of success and Pledged/Goal ratios in the first campaign, but its effect gradually decreases in subsequent campaigns. This decrease is near-linear in campaign number, providing strong support for the prediction that the importance of social capital depends on the campaign number. The results also show that average success rates and Pledged/Goal ratios improve in line with the campaign number. These findings are also highly statistically significant and robust to including county fixed effects.

5.2.2 Social capital and campaign characteristics

Campaign size might credibly impact the perceived level of the campaign's risk. However, the direction of this relationship is not obvious. Small campaigns may be more prone to fraud, as the cost for backers trying to reclaim their funds through litigation is high relative to the potential benefits, which would suggest that small campaigns should benefit the most from social capital. However, when the amounts involved are larger, the potential rewards of embezzling funds may also be larger. Hence, large campaigns would benefit more from social capital. Which one of these effects dominates is thus an empirical question. Table 7 shows the results including an interaction term for social capital and the dummy indicating that the campaign size is above our sample median. We observe that the effect of social capital on success rates and Pledged/Goal is significantly stronger for smaller campaigns, consistent with the interpretation that the relative cost of attempting to recover funds via the legal system is high for small campaigns, therefore weakening the ability to discipline fraudulent entrepreneurs.

Certain campaigns are highlighted by Kickstarter staff; until January 2016, these campaigns were called *Staff picks*. The Staff pick classification was subsequently replaced by the badge titled *Projects we love*. We refer to both classifications as Staff picks. While the process for being chosen is not transparent, the classification as a Staff pick is likely to be perceived as an endorsement by the platform and to create an additional level of trust in the campaign. The results shown in Table 7 support this prediction. We observe that the effect of social capital is significantly weaker for campaigns highlighted by the platform as a Staff pick. From the magnitudes of the coefficients for the Pledged/Goal ratio, it seems that social capital is virtually irrelevant for campaigns classified as Staff picks.

5.2.3 Social capital and regional characteristics

Residents of wealthier counties may be less likely to commit fraud for at least two reasons. First, by virtue of being wealthier, they may have more to lose from the possible legal and criminal proceedings of a fraudulent campaign. Second, a county's wealth level may be correlated with the more efficient enforcement of contracts and therefore lower potential profits from fraud. We therefore expect social capital to matter less in wealthier counties. The results shown in Table 8 are consistent with this prediction. Social capital seems to be significantly more important for campaign success rates and Pledged/Goal ratios in less-wealthy counties.

The size of the community in which the entrepreneur lives might also affect the benefits of social capital. The potential cost of fraudulent activity may be smaller in larger and more heterogeneous communities where residents may be less dependent on their neighbors. This situation would imply more severe issues caused by moral hazard in large cities. The results shown in Table 8 show that the effect of social capital is indeed stronger in large cities, which are defined as cities with a population of more than 100,000. In 2016, 304 cities in the U.S. had populations above 100,000, according to Census Bureau data. There are approximately 19,500 cities and towns in the U.S., so the cities classified as "Large" account for 1.6% of U.S. incorporated locations; 62.5% of the campaigns in our sample are located in a city classified as large.

5.2.4 Social capital and campaign timing

Perceived economic uncertainty likely has an impact on the perceived risk of fraud in crowdfunding. First, in unfavorable economic times, campaign backers may be more risk-averse and therefore more concerned about moral hazard. Second, entrepreneurs may have stronger financial incentives to commit fraud when their own economic situation is less certain. These arguments suggest that social capital should be more important in times of high uncertainty. We test this prediction using the Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016), which measures economic policy uncertainty based on i) newspaper coverage of policy-related economic uncertainty, ii) the number of federal tax code provisions set to expire in future years, and iii) disagreement among economic forecasters. A higher index value indicates a higher level of uncertainty. Similarly, the general sentiment might have a similar impact on the perceived risk of moral hazard. We use the Investor Sentiment index of Baker and Wurgler (2006) to measure the general market sentiment and test whether social capital matters less in times of high sentiment. This index is a composite measure of a number of proxies for investor sentiment, including the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.[20]

We note that campaign backers in reward-based crowdfunding are not making a financial "investment" in the traditional sense. Backing a campaign is more akin to pre-purchasing a product, albeit with a risk that the product may not be delivered and – in the case of moral hazard – with the risk of losing the purchase price. The relevance of either of these indices for campaign backing decisions is therefore also less obvious than it is in the case of a financial investment. However, we believe that these two indices remain likely to capture features of general feelings of uncertainty and optimism and therefore provide a useful context for assessing the importance of trust in crowdfunding.

Table 9 reports regression results on the effect of social capital on campaign outcomes, depending on the *EPU* index and *Sentiment* index at the time of campaign launch. We see that the effect of social capital is stronger when EPU is high and when sentiment is low. This difference is statistically significant in the specifications that control for county fixed effects. Apart from column 5, which shows the model for $ln(1 + Pledged/Goal)$ with an interaction term for social capital and EPU, the results excluding county fixed effects are not statistically significant, although directionally, they are all similar to the OLS results. These results provide support for our prediction that social capital is more important in adverse economic times.

5.3 Social capital and campaign goal amounts

As noted above, the main channel through which moral hazard affects the likelihood of campaign success in Strausz's (2017) model is through the higher-than-efficient goal amounts required to incentivize the entrepreneur to invest in production instead of appropriating the funds. In another recent paper focusing on moral hazard in reward-based crowdfunding, Chemla and Tinn (2016) predict a similar role of moral hazard in increasing the required goal amounts. If social capital mitigates moral hazard, it should thus have a negative relationship with goal amounts. We test this prediction using OLS regressions of the following form:

$$ln(Goal)_i = \alpha_0 + \alpha_1 \times SK_i + \beta \times X_i + \epsilon_i \qquad (8)$$

where $ln(Goal)_i$ is the natural logarithm of the goal amount set by the entrepreneur for campaign j. The vector of controls, X_i, excludes *Staff pick*, given that this status is not known at the time the goal amount is set, and the campaign length, which is set by the

[20] At the time of writing, the EPU index data is available online at www.policyuncertainty.com/index.html and investor sentiment data at people.stern.nyu.edu/jwurgler/

entrepreneur at the same time as the goal amount.

The results shown in Table 2 are consistent with the model predictions of Strausz (2017). Higher social capital is associated with lower goal amounts, and this result is significant at the 5% level when including all control variables. In terms of controls, the aggregate size of the county's economy is associated with higher goal amounts, as is the county's wealth level.

6 Discussion of alternative explanations

6.1 Information asymmetry

Higher levels of social capital may be associated with a better flow of information, consistent with prior evidence on social capital facilitating information flows, (e.g. Tiepoh and Reimer, 2004; Barr, 2000), and may result in reduced information asymmetry between the entrepreneur and campaign backers. Thus, we might ask to what extent the effect of social capital that we observe is driven by this reduction in information asymmetry rather than social norms for acceptable behavior.

As discussed by Strausz (2017), the entrepreneur's cost structure is likely not perfectly observable to the campaign backers. Such private cost information of the entrepreneur can intensify the problems caused by moral hazard, as the entrepreneur can falsely claim to be able to manufacture an attractive product at a low cost. However, such misrepresentation of the cost structure is profitable only in the presence of moral hazard and therefore represents only a second-order effect. We note that both effects should be in the same direction – i.e., a higher level of social capital should both mitigate moral hazard and potentially mitigate information asymmetry – and should result in similar implications for campaign performance. Furthermore, in the absence of moral hazard, neither impact should exist, so we should not find any effect of social capital. Information asymmetry is therefore not a qualitative problem for our analysis and results, although we cannot determine the extent to which information asymmetry contributes to our results.

By definition, any reduction in information asymmetry caused by higher social capital would have to occur among campaign backers who live in the same area as the entrepreneur. Xu (2017) studies Kickstarter data and reports that 19.5% of campaign backers are from the same city as the entrepreneur and 29.2% are from the same state, and these percentages are nearly the same for unsuccessful projects. It seems unlikely that a reduction in information asymmetry among such a small proportion of campaign backers would substantially contribute to campaign success.

In our Internet Appendix B, we include an analysis attempting to estimate the extent to which information asymmetry is a significant determinant of moral hazard problems. For identification, we exploit another quasi-experiment provided by a Kickstarter rule change. This rule change, announced on September 21, 2012, required entrepreneurs to discuss the risks and challenges related to their projects on the campaign page. We find evidence that this rule change also reduced the effect of social capital, consistent with information asymmetry contributing to moral hazard problems.

6.2 Financial constraints

It could be that some of our results are driven by the better access to alternative sources of financing among entrepreneurs in high-social-capital counties. Schwienbacher (2015) models the effect of access to professional deep-pocket investors in the context of reward-based crowdfunding. In his model, the presence of such investors leads to lower crowdfunding campaign goals and to more campaigns being launched with less effort exerted by the entrepreneur, ultimately reducing the average quality of the projects offered on the platform. While this effect could partly explain our results for goal amounts, it cannot explain the results on campaign outcomes. This explanation also appears inconsistent with our results reported in Table 10, which show that campaign goal amounts are higher in wealthier counties. It seems likely that entrepreneurs in wealthier counties would have better access to alternative sources of financing in general.

Furthermore, it is likely that any differences in financial constraints would be much more important between different states than between counties within a state because the legal and regulatory frameworks are set at the state level or federal level, while there are no intra-state differences in financial regulation or laws. Such differences between states are captured by the state fixed effects we include in our regression models. Therefore, it seems unlikely that the remaining intra-state differences drive our results.

Finally, we also include OLS specifications including county fixed effects in all analyses that involve interactions between social capital and other variables. These county fixed effects should also capture any intra-state differences in financial constraints. It thus seems very unlikely that our results would be caused by differences in financial constraints.

6.3 Differences in risk aversion

Some of our results could be explained by a higher risk aversion by entrepreneurs in high-social-capital counties. Such higher risk aversion could result in entrepreneurs setting lower goal amounts, pursuing lower-risk projects, and experiencing higher success rates. However, this explanation does not seem plausible for two reasons. First, social capital is likely to represent something of an economic safety net, as individuals in high-social-capital communities can rely on others to a larger extent than individuals in low-social-capital communities. Hence, high social capital should facilitate rather than inhibit individual risk taking. Second, the existing literature suggests that individuals in high-social-capital areas make more risky investments. For example, Guiso et al. (2004) show that high social capital is associated with significantly more investment in stocks and less in cash.

As a robustness check, we also perform an analysis controlling for the entrepreneur's cultural uncertainty aversion. We follow the methodology used by Pan, Siegel, and Wang (2017), exploiting the differences in risk attitudes between different cultures. We first estimate the entrepreneur's cultural background based on the surname. For this, we use the *Oxford Dictionary of American Family Names*. This dictionary is the product of a ten-year research project involving the work of 30 linguistic consultants led by Patrick Hanks. It contains more than 70,000 of the most commonly occurring surnames in the United States and provides information on their linguistic and historical background.[21] We use these estimates for cultural background to assign each entrepreneur a risk appetite value based on Hofstede's (2001) Uncertainty Avoidance Index (UAI). The UAI captures the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. For example, the family name "Schiemann" is of German origin. We thus assign entrepreneurs with the last name Schiemann an uncertainty aversion value of 65, based on the UAI for Germany. This methodology allows us to assign UAI value to 111,652 individual entrepreneurs. We then include the uncertainty avoidance index as a control variable in our regression analysis.

The results, shown in Table 11, are consistent with our arguments. The positive relationship between social capital and campaign performance remains highly significant when controlling for the entrepreneur's uncertainty aversion. We also see that uncertainty aversion is associated with significantly higher success rates and Pledged/Goal ratios. This is intuitive, as more risk-averse entrepreneurs are likely to pursue less risky projects that are more likely to succeed.

7 Conclusion

In this paper, we study the impact of moral hazard issues on crowdfunding campaigns. Because the magnitude of moral hazard for each campaign cannot be directly observed, the innovation of this study is the use of the well-documented tendency of social capital to generate trustworthy behavior and thereby mitigate moral hazard. We argue that the behavioral

[21] The dictionary is available online at:
http://www.oxfordreference.com/view/10.1093/acref/9780195081374.001.0001/acref-9780195081374.

norms that characterize high-social-capital regions act as a disincentive for entrepreneurs to commit fraud and hence help facilitate crowdfunding campaigns.

In support of this prediction, we find a strong positive relationship between social capital at the county level and crowdfunding success rates. We provide evidence of the causal effect of social capital by exploiting a Kickstarter rule change that reduced the scope of moral hazard. This rule change is associated with significant reduction in the effect of social capital. Furthermore, this reduction is most pronounced in the product categories most likely to suffer from the non-delivery of products, providing additional support for the causal interpretation.

In our additional analysis, we find evidence that social capital is negatively related to the likelihood of a campaign being suspended, a noisy proxy for possibly fraudulent campaigns. We also further explore whether the effect of social capital on crowdfunding differs among campaigns, arguing that campaigns that are more prone to suffer from moral hazard are likely to exhibit the strongest relationship between social capital and campaign performance. Consistent with our predictions, we find that the effect of social capital is stronger for individual entrepreneurs than for groups or companies, in cases where the entrepreneur lacks a prior track record, in small campaigns in which the cost of pursuing fraud cases via the legal system relative to potential proceeds is high, in poor counties, in large cities, and at times of high economic uncertainty and low sentiment. Conversely, being endorsed by the Kickstarter platform as a "Staff pick" significantly reduces the effect of social capital. Furthermore, we find a significant negative relationship between social capital and goal amounts. This last finding is consistent with the model prediction of Strausz (2017) that campaigns with higher moral hazard risk should have higher goal amounts.

Overall, our study is the most extensive analysis of moral hazard in crowdfunding campaigns to date and the first to link crowdfunding dynamics to social capital. Our findings are consistent with the notion that moral hazard is a significant determinant of crowdfunding dynamics and that social capital helps to mitigate the problem.

References

Ang, James S., Yingmei Cheng, and Chaopeng Wu, 2015, Trust, investment, and business contracting, *Journal of Financial and Quantitative Analysis* 50, 569–595.

Arrow, Kenneth, 2000, *Social Capital: A Multifaceted Perspective*, chapter Observations on social capital (The World Bank, Washington, DC).

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance* 61, 129–152.

Baker, Scott R., Nicholas Bloom, and Steven Davis, 2016, Measuring economic policy uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Banfield, Edward C., 1958, *The moral basis of a backward society* (Free Press, New York).

Barr, Abigail M., 2000, Social capital and technical information flows in the ghanaian manufacturing sector, *Oxford Economic Papers* 52, 539–559.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, 2012, The organization of firms across countries, *The Quarterly Journal of Economics* 127, 1663–1705.

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann, 2016, The importance of trust for investment: Evidence from venture capital, *The Review of Financial Studies* 29, 2283–2318.

Bowles, Samuel, and Herbert Gintis, 2002, Social capital and community governance, *The Economic Journal* 112, F419–F436.

Carlin, Bruce Ian, Florin Dorobantu, and S. Viswanathan, 2009, Public trust, the law, and financial investment, *Journal of Financial Economics* 92, 321–341.

Chang, Jen-Wen, 2015, The economics of crowdfunding, *Working paper* .

Chemla, Gilles, and Katrin Tinn, 2016, Learning through crowdfunding, *Working paper* .

Coleman, James S., 1988, Social capital in the creation of human capital, *The American Journal of Sociology* 94, S95–S120.

Coleman, James S., 1990, *Foundations of social theory* (Harvard University Press, Cambridge, MA).

Durlauf, Steven, and Marcel Fafchamps, 2005, *Handbook of Economic Growth*, chapter Social capital, 1637–99 (North Holland).

Gorton, Gary, 1996, Reputation formation in early bank note markets, *Journal of Political Economy* 104, 346–397.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *The Journal of Finance* 63, 2557–2600.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2013, The determinants of attitudes toward strategic default on mortgages, *The Journal of Finance* 68, 1473–1515.

Hasan, Iftekhar, Chun Keung (Stan) Hoi, Qiang Wu, and Hao Zhang, 2016, Social capital and debt contracting: Evidence from bank loans and public bonds, *Journal of Financial and Quantitative Analysis* Forthcoming.

Hasan, Iftekhar, Chun Keung (Stan) Hoi, Qiang Wu, and Hao Zhang, 2017, Does social capital matter in corporate decisions? evidence from corporate tax avoidance, *Journal of Accounting Research* Forthcoming.

Hirshleifer, David A., 2015, Behavioral finance, *Annual Review of Financial Economics* 7, 133–159.

Hofstede, Geert, 2001, *Cultures Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*, second edition edition.

Jha, Anand, and Yu Chen, 2015, Audit fees and social capital, *The Accounting Review* 90, 611–639.

Knack, Stephen, 2002, Social capital and the quality of government, *American Journal of Political Science* 46, 772–785.

Knack, Stephen, and Philip Keefer, 1997, Does social capital have an economic pay off? a cross-country investigation, *Quarterly Journal of Economics* 112, 1251–1288.

Kuppuswamy, Venkat, and Ethan Mollick, 2016, Second thoughts about second acts: Gender differences in serial founding rates, *[Revise and resubmit, Organization Science]* .

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny, 1997, Trust in large organizations, *American Economic Review* 87, 333–338.

Levine, Ross, Chen Lin, and Wensi Xie, 2018, Corporate resilience to banking crises: The roles of trust and trade credit, *Journal of Financial and Quantitative Analysis* Forthcoming.

Lin, Tse-Chun, and Vesa Pursiainen, 2017, Gender differences in crowdfunding - entrepreneur overconfidence and campaign outcomes, *Working paper* .

Millo, Giovanni, and Giacomo Pasini, 2010, Does social capital reduce moral hazard? a network model for non-life insurance demand, *Fiscal Studies* 31, 341–372.

Mollick, Ethan, 2014, The dynamics of crowdfunding: An exploratory study, *Journal of Business Venturing* 29, 1–16.

Pan, Yihui, Stephan Siegel, and Tracy Yue Wang, 2017, Corporate risk culture, *Journal of Financial and Quantitative Analysis* 52, 2327–2367.

Putnam, Robert D., 1993, *Making Democracy Work: Civic Traditions in Modern Italy* (Princeton University Press, Princeton, New Jersey.).

Rupasingha, Anil, Stephan J. Goetz, and David Freshwater, 2006, The production of social capital in us counties, *The Journal of Socio-Economics* 35, 83–101.

Schwienbacher, Armin, 2015, Entrepreneurial risk-taking in crowdfunding campaigns, *Working paper* .

Solow, Robert, 1995, Trust: The social virtues and the creation of prosperity (book review), *The New Republic* 213, 36–40.

Solow, Robert, 2000, *Social Capital: A Multifaceted Perspective*, chapter Notes on social capital and economic performance (The World Bank, Washington, DC).

Spagnolo, Giancarlo, 1999, Social relations and cooperation in organizations, *Journal of Economic Behavior & Organization* 38, 1–25.

Strausz, Roland, 2017, A theory of crowdfunding - a mechanism design approach with demand uncertainty and moral hazard, *American Economic Review* Forthcoming.

Tiepoh, M. Geepu Nah, and Bill Reimer, 2004, Social capital, information ows, and income creation in rural canada: a cross-community analysis, *Journal of Socio-Economics* 33, 427–448.

Word, David L., Charles D. Coleman, Robert Nunziata, and Robert Kominski, 2008, Demographic aspects of surnames from census 2000, *US Census Technical Documentation* .

Xu, Ting, 2017, Learning from the crowd: The feedback value of crowdfunding, *Job Market Paper* .

Appendix A: Summary of the sample

	# campaigns
Kickstarter total	364,332
Our raw data - all campaigns	315,017
Coverage	*86%*
Of which based in the US and location available	240,807
Of which completed	227,752
Of which all data available for	223,679

Appendix B: Definitions of variables

Variable	Definition
Social capital (SK)	Social capital index estimated yearly for each county.
Personal Income (PI)	County personal income, i.e. the income received by, or on behalf of, all persons from all sources: from participation as laborers in production, from owning a home or unincorporated business, from the ownership of financial assets, and from government and business in the form of transfer receipts. Includes income from domestic sources as well as from abroad.
PI per capita	County personal income divided by population.
Successful	Dummy taking the value 1 if the campaign is successful.
Failed	Dummy taking the value 1 if the campaign fails.
Canceled	Dummy taking the value 1 if the campaign is canceled.
Suspended	Dummy taking the value 1 if the campaign is suspended.
Unsuccessful	Dummy taking the value 1 if the campaign fails or is canceled or suspended.
Pledged/Goal	Amount pledged divided by the goal amount.
Sub-category	Kickstarter detailed category classification. Includes 169 categories.
Main category	Kickstarter main category classification. Includes 15 categories.
Amount pledged	Amount pledged by backers for a given campaign.
Goal amount	Campaign goal amount sought by the entrepreneur.
Campaign length	Campaign length set by the entrepreneur at the beginning of the campaign.
Staff pick	Dummy taking the value 1 if the campaign is chosen as a Staff pick.
Individual	Dummy taking the value 1 if the entrepreneur is identified as individual male or female
Female	Dummy taking the value 1 if the entrepreneur is female.
Male	Dummy taking the value 1 if the entrepreneur is male.
White	Dummy taking the value 1 if the race of the entrepreneur is white.
Black	Dummy taking the value 1 if the race of the entrepreneur black.
Asian	Dummy taking the value 1 if the race of the entrepreneur Asian.
Hispanic	Dummy taking the value 1 if the ethnicity of the entrepreneur is Hispanic.
No race	Dummy taking the value 1 if no race/ethnicity could be estimated based on last name.
N prior campaigns	Number of campaigns launched by the same entrepreneur before current campaign.
Uncertainty avoidance	Hofstede's Uncertainty Avoidance Index, assigned based on the cultural origin of the entrepreneur's last name.
EPU	Economic Policy Uncertainty Index by Baker et al. (2016).
Sentiment	Investor Sentiment index of Baker and Wurgler (2006).

Table 1
Summary statistics

Panel A shows the total number of campaigns by launch year, divided into *Successful*, *Unsuccessful*, and *Suspended* ones. The sample period is from April 2009 to August 2017. Panel B shows summary statistics for all campaigns in our sample. All continuous variables have been winsorized at the 1% level. Variables are defined in Appendix B.

Panel A: Number of campaigns by year

	Outcome			
	Successful	Unsuccessful	Suspended	Total
2009	386	463		849
2010	3,702	4,706	15	8,423
2011	10,859	12,938	42	23,839
2012	16,019	21,130	48	37,197
2013	16,361	20,058	45	36,464
2014	15,945	30,059	151	46,155
2015	13,309	23,269	287	36,865
2016	9,652	14,146	95	23,893
2017	4,587	5,366	41	9,994
Total	90,820	132,135	724	223,679

Panel B: Summary statistics - cross-sectional campaign data

	Mean	Std	p25	p50	p75
Campaign outcomes					
Successful	0.406	0.491	0.000	0.000	1.000
Failed	0.506	0.500	0.000	1.000	1.000
Canceled	0.085	0.279	0.000	0.000	0.000
Suspended	0.003	0.057	0.000	0.000	0.000
Pledged/Goal	0.792	1.467	0.008	0.205	1.091
Amount pledged ('000)	17.445	40.137	2.000	5.000	15.000
County variables					
Social capital (SK)	-0.488	0.661	-1.058	-0.430	-0.024
Personal income ('000)	112.120	143.750	18.189	51.414	147.538
PI per capita ('000)	55.511	26.681	41.025	47.986	55.881
Campaign variables					
Goal amount ('000)	17.445	40.137	2.000	5.000	15.000
Camp. length (days)	34.380	12.860	30.000	30.000	38.000
Staff pick	0.074	0.262	0.000	0.000	0.000
Entrepreneur variables					
Female	0.186	0.389	0.000	0.000	0.000
Male	0.470	0.499	0.000	0.000	1.000
No gender	0.344	0.475	0.000	0.000	1.000
White	0.550	0.497	0.000	1.000	1.000
Black	0.014	0.119	0.000	0.000	0.000
Asian	0.022	0.146	0.000	0.000	0.000
Hispanic	0.038	0.192	0.000	0.000	0.000
No race	0.375	0.484	0.000	0.000	1.000
N prior campaigns	0.416	2.371	0.000	0.000	0.000
Uncertainty avoidance	53.503	18.577	35.000	51.000	65.000
Timing variables					
EPU	124.595	36.149	93.501	114.654	157.496
Sentiment	-0.183	0.146	-0.305	-0.195	-0.082
N	223,679				

Table 2
Regressions on campaign outcomes vs. social capital

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful			ln(1+Pledged/Goal)	
	(1) Logit	(2) Logit	(3) OLS	(4) OLS	(5) OLS
Social capital (SK)	0.1620***	0.1688***	0.0291***	0.0218***	0.0206***
	(0.0269)	(0.0242)	(0.0044)	(0.0057)	(0.0046)
ln(Personal income)		0.0945***	0.0162***		0.0137***
		(0.0092)	(0.0017)		(0.0018)
ln(PI per capita)		0.0171	0.0035		0.0245*
		(0.0547)	(0.0095)		(0.0134)
ln(Goal amount)		−0.4205***	−0.0700***		−0.0888***
		(0.0146)	(0.0024)		(0.0036)
ln(Campaign length)		−0.4465***	−0.0833***		−0.0553***
		(0.0331)	(0.0070)		(0.0090)
Staff pick		2.6260***	0.4396***		0.4791***
		(0.1112)	(0.0133)		(0.0191)
Gender dummies	No	Yes	Yes	No	Yes
Race dummies	No	Yes	Yes	No	Yes
Year-month FE	No	Yes	Yes	No	Yes
State FE	No	Yes	Yes	No	Yes
Campaign N FE	No	Yes	Yes	No	Yes
Sub-category-Year FE	No	Yes	Yes	No	Yes
N	222,955	215,329	222,818	222,949	222,813
R^2			0.279	0.001	0.346
Pseudo R^2	0.002	0.211			

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 3
Quasi-experiment: Rule change affecting moral hazard

The sample includes all campaigns during a two-year period (from one year before to one year after) around a Kickstarter rule change announced on September 20, 2014, which clarified and strengthened the obligation of entrepreneurs to provide backers with the promised reward. *Post* is a dummy taking the value 1 if the campaign was launched after the rule change, and 0 if before. *Controls* include the same control variables as in Table 2. Model 3 includes entrepreneur home county fixed effects. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

Panel A: Diff-in-Diff regressions on *Successful*

	Actual			Placebo tests (logit)	
	(1) Logit	(2) Logit	(3) OLS	(4) − 1 year	(5) + 1 year
Post x SK	−0.0608**	−0.0584**	−0.0112**	0.0309	−0.0250
	(0.0281)	(0.0283)	(0.0047)	(0.0259)	(0.0331)
Post change	0.3432***	−0.0727	−0.0119	−0.0291	0.3243***
	(0.1201)	(0.0962)	(0.0149)	(0.0756)	(0.1125)
Social capital (SK)	0.2198***	0.2140***	0.0268	0.1442***	0.1723***
	(0.0297)	(0.0284)	(0.0584)	(0.0308)	(0.0414)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No
N	83,552	83,552	83,135	78,165	64,652
R^2			0.295		
Pseudo R^2	0.228	0.237		0.193	0.335

Panel B: Diff-in-Diff regressions on *ln(1+Pledged/Goal)*

	Actual			Placebo tests	
	(1) OLS	(2) OLS	(3) OLS	(4) − 1 year	(5) + 1 year
Post x SK	−0.0144***	−0.0133***	−0.0127***	0.0027	−0.0052
	(0.0046)	(0.0048)	(0.0047)	(0.0043)	(0.0051)
Post change	0.0501***	−0.0002	0.0002	0.0010	0.0413**
	(0.0189)	(0.0130)	(0.0133)	(0.0164)	(0.0179)
Social capital (SK)	0.0277***	0.0258***	0.0412	0.0226***	0.0174***
	(0.0048)	(0.0047)	(0.0596)	(0.0061)	(0.0054)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No
N	83,609	83,609	83,133	78,192	64,751
R^2	0.322	0.330	0.350	0.265	0.440

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 4
Quasi-experiment: Rule change affecting moral hazard – by category

The sample includes all campaigns during a two-year period (from one year before to one year after) around a Kickstarter rule change announced on September 20, 2014, which clarified and strengthened the obligation of entrepreneurs to provide backers with the promised reward. *Post* is a dummy taking the value 1 if the campaign was launched after the rule change, and 0 if before. *Risky category* is a dummy taking the value 1 if the campaign is in the Hardware or Product Design categories. *Controls* include the same control variables as in Table 2. Models 3 and 6 include entrepreneur home county fixed effects. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful			ln(1+Pledged/Goal)		
	(1) Logit	(2) Logit	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Post x Risky cat. x SK	−0.0969***	−0.0855***	−0.0092	−0.0465***	−0.0460***	−0.0427***
	(0.0290)	(0.0305)	(0.0066)	(0.0054)	(0.0046)	(0.0074)
Post x SK	−0.0497*	−0.0473*	−0.0103**	−0.0110***	−0.0097**	−0.0097**
	(0.0277)	(0.0278)	(0.0049)	(0.0039)	(0.0041)	(0.0042)
Post x Risky cat.	0.9835*	1.1532*	0.2230**	0.1944	0.2208*	0.2226*
	(0.5686)	(0.6168)	(0.1053)	(0.1218)	(0.1247)	(0.1180)
Post change	0.2785***	−0.1765	−0.0287	0.0383***	−0.0165	−0.0166
	(0.1028)	(0.1348)	(0.0200)	(0.0146)	(0.0195)	(0.0198)
Risky cat. x SK	−0.0606	−0.0669	−0.0196***	0.0133	0.0133	0.0063
	(0.0398)	(0.0431)	(0.0053)	(0.0142)	(0.0150)	(0.0125)
Social capital (SK)	0.2198***	0.2143***	0.0217	0.0263***	0.0243***	0.0340
	(0.0303)	(0.0289)	(0.0569)	(0.0051)	(0.0050)	(0.0581)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	No	Yes	Yes
County FE	No	No	Yes	No	No	Yes
N	83,552	83,552	83,135	83,609	83,609	83,133
R^2			0.298	0.325	0.333	0.353
Pseudo R^2	0.230	0.240				

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 5
Logit regressions on suspension rate vs. social capital

The dependent variable, *Suspended*, is a dummy taking the value 1 if the Kickstarter campaign was suspended. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. We include *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *State fixed effects* based on the location of the campaign. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit
Social capital (SK)	−0.1227**	−0.2595***	−0.2687***	−0.4310***	−0.0173
	(0.0566)	(0.0899)	(0.0901)	(0.1537)	(0.0806)
ln(Personal income)		−0.0326	−0.0340	−0.0458	0.0752**
		(0.0393)	(0.0393)	(0.0461)	(0.0379)
ln(PI per capita)		0.4509**	0.4617**	1.0622***	−0.0856
		(0.1901)	(0.1903)	(0.2987)	(0.1885)
ln(Goal amount)		−0.1178**	−0.1285***	−0.1328***	−0.1461***
		(0.0470)	(0.0493)	(0.0481)	(0.0439)
ln(Campaign length)		0.2712**	0.2360*	0.2504**	0.4108***
		(0.1223)	(0.1235)	(0.1241)	(0.1310)
Gender dummies	No	Yes	Yes	Yes	Yes
Race dummies	No	Yes	Yes	Yes	Yes
Campaign N FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	No
Year FE	No	No	No	No	Yes
N	223,679	223,678	220,964	218,906	220,118
Pseudo R^2	0.000	0.009	0.010	0.017	0.044

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 6
Social capital vs. entrepreneur characteristics

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Individual* is a dummy taking the value 1 if the campaign creator is identified as male of female individual, i.e. not a company or a group of individuals. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. *County controls* include *ln(Personal Income)* and *ln(PI per capita)*. *Campaign controls* include *ln(Goal amount)*, *ln(Campaign length)*, and *Staff pick*. *Gender and race* controls include the same dummies for gender and race as in Table 2. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

Panel A: Individual entrepreneur vs. a group or a company

	Successful		ln(1+Pledged/Goal)	
	(1)	(2)	(3)	(4)
	Logit	OLS	OLS	OLS
Individual x SK	0.0557***	0.0071**	0.0137***	0.0116***
	(0.0200)	(0.0036)	(0.0044)	(0.0044)
Social capital (SK)	0.1333***	0.0021	0.0116*	0.0044
	(0.0298)	(0.0113)	(0.0063)	(0.0115)
Individual	−0.2901***	−0.0496***	−0.0546***	−0.0536***
	(0.0265)	(0.0048)	(0.0049)	(0.0050)
County controls	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes
Race controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Campaign N FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes
N	215,329	222,412	222,813	222,407
R^2		0.292	0.345	0.359
Pseudo R^2	0.208			

Significance levels: * 0.1, ** 0.05, * 0.01.**

Panel B: Prior track record

	Successful		ln(1+Pledged/Goal)	
	(1) Logit	(2) OLS	(3) OLS	(4) OLS
Social capital (SK)	0.1847***	0.0098	0.0252***	0.0166
	(0.0253)	(0.0110)	(0.0047)	(0.0107)
2nd campaign x SK	−0.0512*	−0.0073	−0.0142***	−0.0142***
	(0.0265)	(0.0046)	(0.0051)	(0.0052)
3rd campaign x SK	−0.1757***	−0.0309***	−0.0436***	−0.0448***
	(0.0505)	(0.0088)	(0.0091)	(0.0091)
4th or higher x SK	−0.2058***	−0.0413***	−0.0688***	−0.0736***
	(0.0779)	(0.0114)	(0.0193)	(0.0197)
2nd campaign	0.2569***	0.0503***	0.0669***	0.0657***
	(0.0433)	(0.0078)	(0.0107)	(0.0104)
3rd campaign	0.2720***	0.0526***	0.1066***	0.1030***
	(0.0648)	(0.0110)	(0.0154)	(0.0148)
4th or higher	0.6747***	0.1101***	0.2536***	0.2429***
	(0.1155)	(0.0167)	(0.0324)	(0.0314)
County controls	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes
Gender and race	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Sub-category-Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes
N	215,395	222,448	222,849	222,443
R^2		0.294	0.345	0.359
Pseudo R^2	0.210			

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 7
Social capital vs. campaign characteristics

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Large* is a dummy taking the value 1 if the campaign goal amount is above median in our sample. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. *County controls* include *ln(Personal Income)* and *ln(PI per capita)*. *Campaign controls* include *ln(Goal amount)*, *ln(Campaign length)*, and *Staff pick*. For models 1,2, 5, and 6, we also include the *Large* dummy in the controls. *Gender and race* controls include the same dummies for gender and race as in Table 2. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful				ln(1+Pledged/Goal)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit	OLS	Logit	OLS	OLS	OLS	OLS	OLS
Large x SK	−0.0337*	−0.0109***			−0.0056*	−0.0045		
	(0.0189)	(0.0035)			(0.0030)	(0.0032)		
Staff pick x SK			−0.1024***	−0.0026			−0.0283***	−0.0151**
			(0.0359)	(0.0056)			(0.0064)	(0.0068)
Social capital (SK)	0.1820***	0.0116	0.1737***	0.0069	0.0232***	0.0141	0.0226***	0.0131
	(0.0238)	(0.0111)	(0.0241)	(0.0109)	(0.0049)	(0.0109)	(0.0046)	(0.0108)
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender and race	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No	Yes	No	Yes	No
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes	No	Yes
N	215,329	222,412	215,329	222,412	222,813	222,407	222,813	222,407
R^2		0.294		0.294	0.346	0.360	0.346	0.360
Pseudo R^2	0.211		0.211					

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 8
Social capital vs. regional characteristics

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *High PI/Capita* is a dummy taking the value 1 if the entrepreneur home county PI/capita is above median in our sample. *Large city* is a dummy taking the value 1 if the entrepreneur home city has a population above 100,000. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. *County controls* include *ln(Personal Income)* and *ln(PI per capita)*. *Campaign controls* include *ln(Goal amount)*, *ln(Campaign length)*, and *Staff pick*. For models 1,2, 5, and 6, we also include the *High PI/Capita* dummy in the controls. *Gender and race* controls include the same dummies for gender and race as in Table 2. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful				ln(1+Pledged/Goal)			
	(1) Logit	(2) OLS	(3) Logit	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
High PI/Capita x SK	−0.0102	−0.0230***			−0.0035	−0.0251***		
	(0.0250)	(0.0087)			(0.0051)	(0.0083)		
Large city x SK			0.1417***	0.0090			0.0192***	0.0096*
			(0.0253)	(0.0054)			(0.0043)	(0.0054)
Large city			0.1826***	0.0314***			0.0286***	0.0322***
			(0.0204)	(0.0057)			(0.0039)	(0.0049)
Social capital (SK)	0.1746***	0.0152	0.0737***	0.0014	0.0220***	0.0212**	0.0067	0.0064
	(0.0246)	(0.0114)	(0.0266)	(0.0110)	(0.0049)	(0.0107)	(0.0051)	(0.0115)
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender and race	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No	Yes	No	Yes	No
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes	No	Yes
N	215,329	222,412	215,329	222,412	222,813	222,407	222,813	222,407
R^2		0.294		0.294	0.346	0.360	0.346	0.360
Pseudo R^2	0.211		0.211					

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 9
Social capital vs. campaign timing

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *High EPU* is a dummy taking the value 1 if the campaign was launched during a month that had EPU index value above median in our sample period. *High Sentiment* is a dummy taking the value 1 if the campaign was launched during a month that had Sentiment index value above median in our sample period.*Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. *County controls* include *ln(Personal Income)* and *ln(PI per capita)*. *Campaign controls* include *ln(Goal amount)*, *ln(Campaign length)*, and *Staff pick*. *Gender and race* controls include the same dummies for gender and race as in Table 2. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful				ln(1+Pledged/Goal)			
	(1) Logit	(2) OLS	(3) Logit	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
High EPU x SK	0.0083	0.0088***			0.0054*	0.0091***		
	(0.0180)	(0.0032)			(0.0030)	(0.0030)		
High sent. x SK			−0.0110	−0.0086**			−0.0024	−0.0056**
			(0.0175)	(0.0035)			(0.0027)	(0.0028)
Social capital (SK)	0.1652***	0.0024	0.1938***	0.0195	0.0184***	0.0076	0.0259***	0.0237**
	(0.0241)	(0.0110)	(0.0302)	(0.0141)	(0.0045)	(0.0106)	(0.0056)	(0.0111)
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender and race	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No	Yes	No	Yes	No
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes	No	Yes
N	215,329	222,412	178,842	182,062	222,813	222,407	182,490	182,059
R^2		0.294		0.272	0.346	0.360	0.303	0.320
Pseudo R^2	0.211		0.199					

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 10
Regressions on campaign goal amounts vs. social capital

The dependent variable is *ln(Goal)*. *Social capital* is the social capital index value of the entrepreneur home county. Other variables are as defined in Appendix B. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	(1) OLS	(2) OLS	(3) OLS
Social capital (SK)	−0.0942***	−0.0212**	−0.0224**
	(0.0142)	(0.0101)	(0.0101)
ln(Personal income)		0.0478***	0.0478***
		(0.0035)	(0.0035)
ln(PI per capita)		0.2050***	0.2056***
		(0.0188)	(0.0187)
Gender dummies	No	Yes	Yes
Race dummies	No	Yes	Yes
Year-month FE	No	Yes	Yes
State FE	No	Yes	Yes
Campaign N FE	No	Yes	Yes
Sub-category FE	No	Yes	No
Sub-category-Year FE	No	No	Yes
N	222,954	222,918	222,818
R^2	0.002	0.193	0.205

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 11
Robustness check: Social capital vs. uncertainty avoidance

The dependent variable is shown above each model. *Successful* is a dummy taking the value 1 if the Kickstarter campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Social capital* is the social capital index value of the entrepreneur home county. *Uncertainty avoidance* is Hofstede's Uncertainty Avoidance Index, assigned based on the cultural background of the entrepreneur's last name. Other variables are as defined in Appendix B. We include *Year-month fixed effects* based on the month the campaign was launched (101 months), *State fixed effects* based on the location of the campaign, *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign, and *Sub-category-Year fixed effects*, time-variant fixed effects based on Kickstarter category ID (169 different categories times 9 years). All continuous variables have been winsorized at the 1% level. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

	Successful			ln(1+Pledged/Goal)	
	(1) Logit	(2) Logit	(3) OLS	(4) OLS	(5) OLS
Social capital (SK)	0.1773***	0.2271***	0.0379***	0.0275***	0.0294***
	(0.0275)	(0.0322)	(0.0054)	(0.0063)	(0.0053)
Uncertainty avoidance	0.0008	0.0029***	0.0005***	0.0002	0.0004***
	(0.0005)	(0.0005)	(0.0001)	(0.0002)	(0.0001)
ln(Personal income)		0.1122***	0.0188***		0.0170***
		(0.0106)	(0.0019)		(0.0019)
ln(PI per capita)		−0.0623	−0.0093		0.0090
		(0.0656)	(0.0109)		(0.0134)
ln(Goal amount)		−0.4544***	−0.0736***		−0.0915***
		(0.0159)	(0.0026)		(0.0037)
ln(Campaign length)		−0.4642***	−0.0853***		−0.0580***
		(0.0348)	(0.0069)		(0.0071)
Staff pick		2.6762***	0.4408***		0.4742***
		(0.1162)	(0.0150)		(0.0182)
Gender dummies	No	Yes	Yes	No	Yes
Race dummies	No	Yes	Yes	No	Yes
Year-month FE	No	Yes	Yes	No	Yes
State FE	No	Yes	Yes	No	Yes
Campaign N FE	No	Yes	Yes	No	Yes
Sub-category-Year FE	No	Yes	Yes	No	Yes
N	111,652	108,030	111,515	111,652	111,515
R^2			0.282	0.001	0.350
Pseudo R^2	0.002	0.218			

Significance levels: * 0.1, ** 0.05, * 0.01.**

A Internet Appendix: Social Capital Index

This appendix provides additional details on the construction of the social capital index used in this paper. The methodology follows Rupasingha et al. (2006). However, we aim to improve the robustness of the metric, with the goal of creating a yearly social capital index on a consistent basis that includes no forward-looking data and limits the impact of erroneous values in the data. As we discuss above, the original Rupasingha et al. data have some shortcomings with regard to these points. To achieve this goal, we omit one of their four social capital components, census response rates, as it is only available at intervals of ten years, and the numbers available are not presented on a consistent basis even at those intervals.

We hence use three components measuring different aspects of social capital:

- **Association density (available from 1986):** We use the annual County Business Patterns data collected by the Census Bureau to calculate the number of associations in each county, divided by population, including ten different association types:
  - Civic and social organizations
  - Bowling centers
  - Golf courses and country clubs
  - Fitness and recreational sports centers
  - Sports teams and clubs
  - Religious organizations
  - Political organizations
  - Labor unions and similar labor organizations
  - Business associations
  - Professional organizations
- **Registered organization density (available from 1995):** Total number of registered tax-exempt non-profit organizations based in the county, divided by population. We obtain the charitable organization data from National Center for Charitable Statistics (NCCS).
- **Voter turnout:** Total number of votes in the latest presidential election, divided by county voting age population.

We first winsorize each component at the 1% level each year to avoid a small number of very high observations having a large impact on the index (which is another problem with the original Rupasingha et al. index). We then perform a principal component analysis of these three components on a yearly basis. We use the first principal component as an index of social capital for each county in a given year. This methodology standardizes the average social capital index at zero, and the standard deviation at one for each year, so the differences in social capital that we use in our analysis can be interpreted as cross-sectional relative differences. They do not capture aggregate movements of average social capital levels across time.

Our social capital index is highly correlated (correlation coefficient of 0.96) with the Rupasingha et al. index for social capital for those years that their data is available, suggesting that by omitting census response rates we do not lose much valuable information. Table A.1 summarizes the correlations of the different components of social capital that we use.

Figure A.1 shows the estimated social capital levels for each U.S. county in 2014. For comparison, we also show the SK estimates for 1995, the first year for which we can calculate the index, in Figure A.2. As we see from these two charts, the distribution of social capital levels looks quite similar across time.

We also show charts below for the association density (Figure A.4), regulated organization density (Figure A.6), and voter turnout (Figure A.8), which we use as components of social capital. Whilst they do not look completely different, these charts still clearly illustrate that the different components capture quite different aspects of social capital, and the distribution of each component across counties differs significantly. Similarly, Figure A.3 shows a histogram of the distribution of the SK index in 1995 as well as in 2014. Figures A.5, A.7, and A.9 show histograms of the distributions of each of the components.

Figure A.1: Social capital index by county in 2014

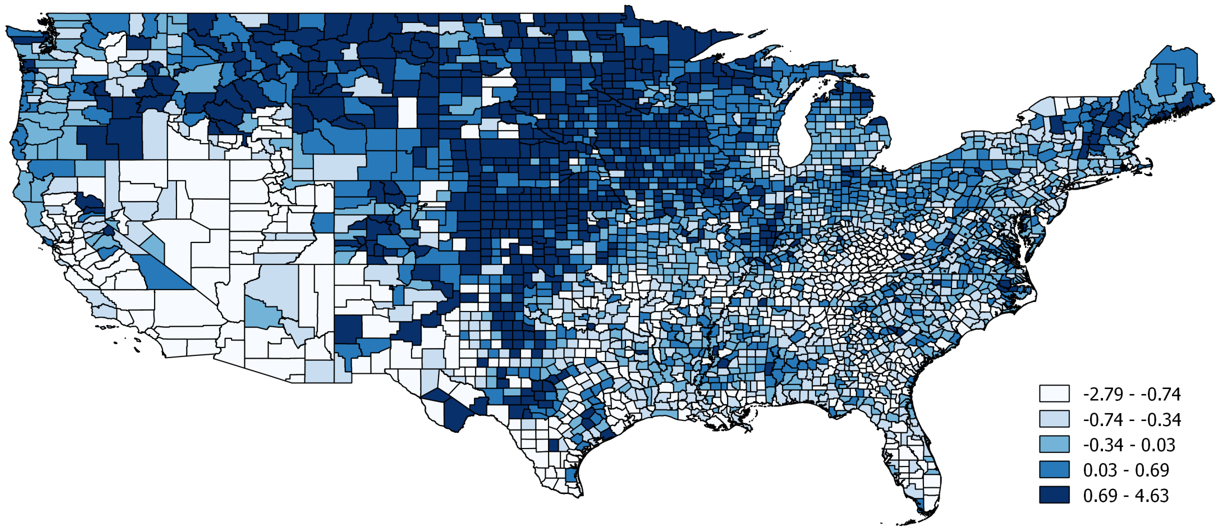

Figure A.2: Social capital index by county in 1995

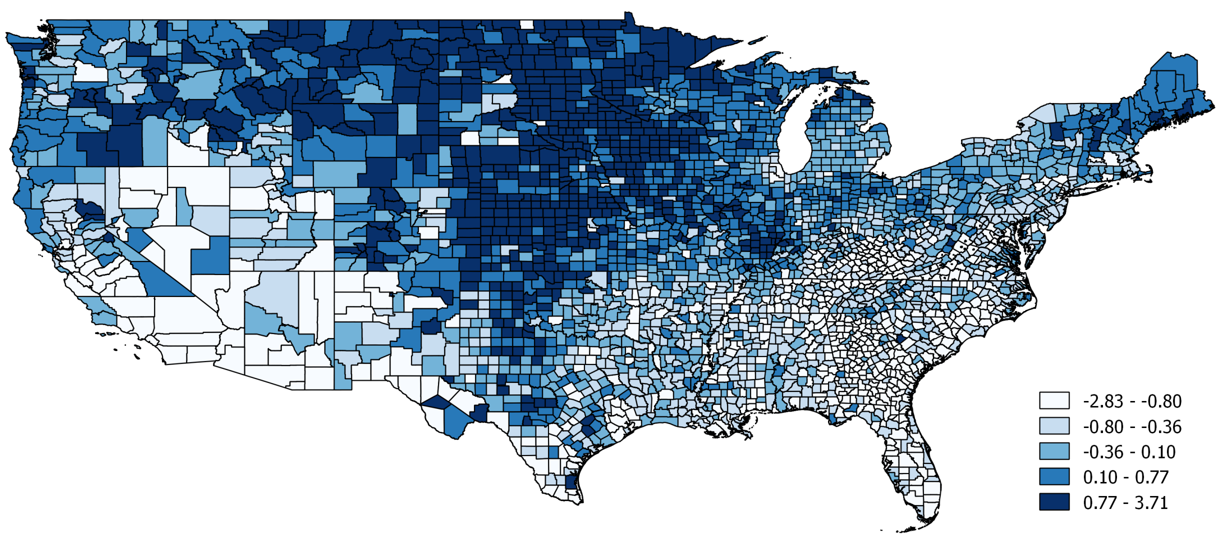

Figure A.3: Distribution of the social capital index in 1995 and 2014

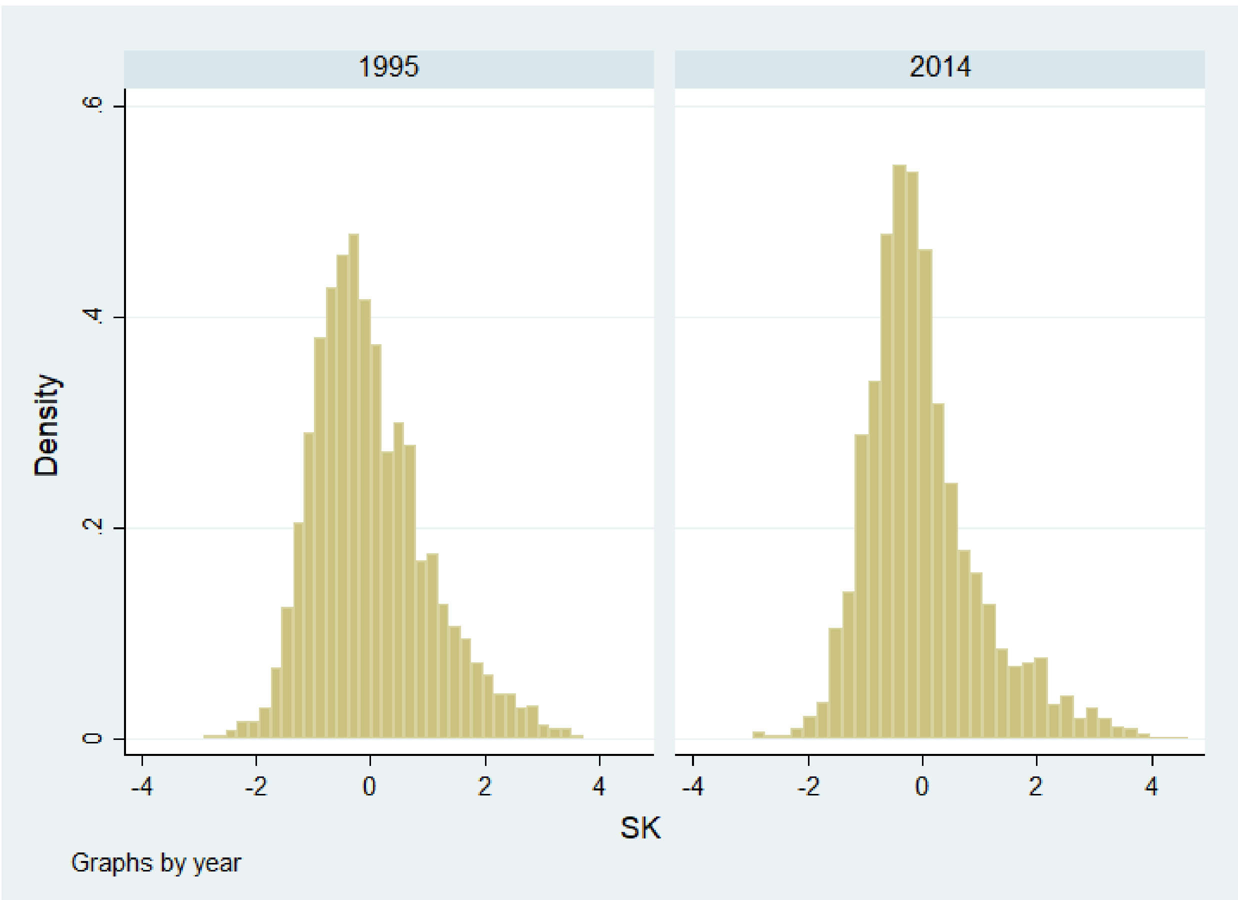

Figure A.4: Association density by county in 2014

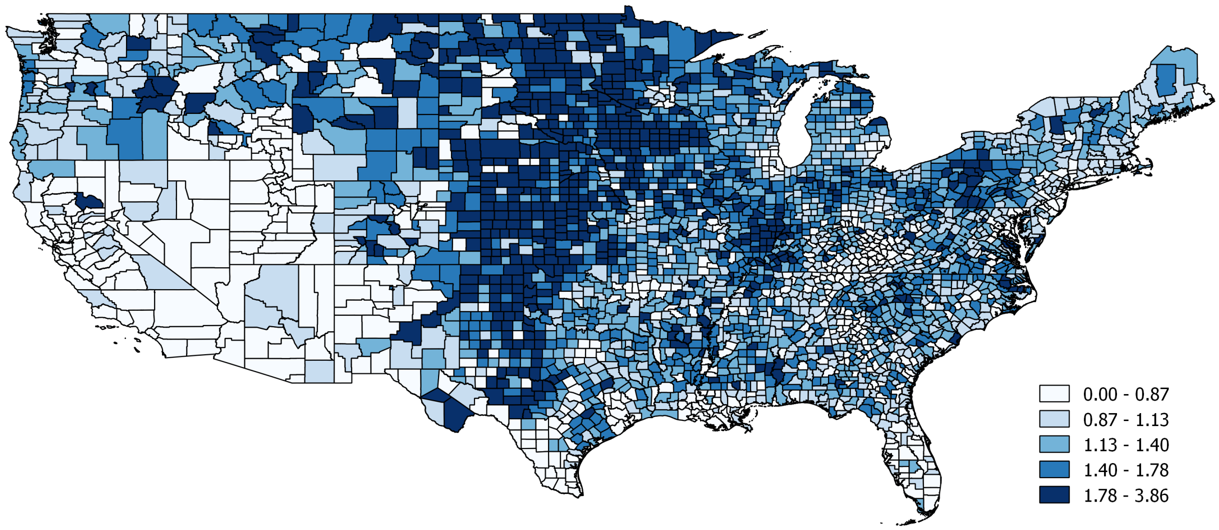

Figure A.5: Distribution of association density (winsorized at the 1% level)

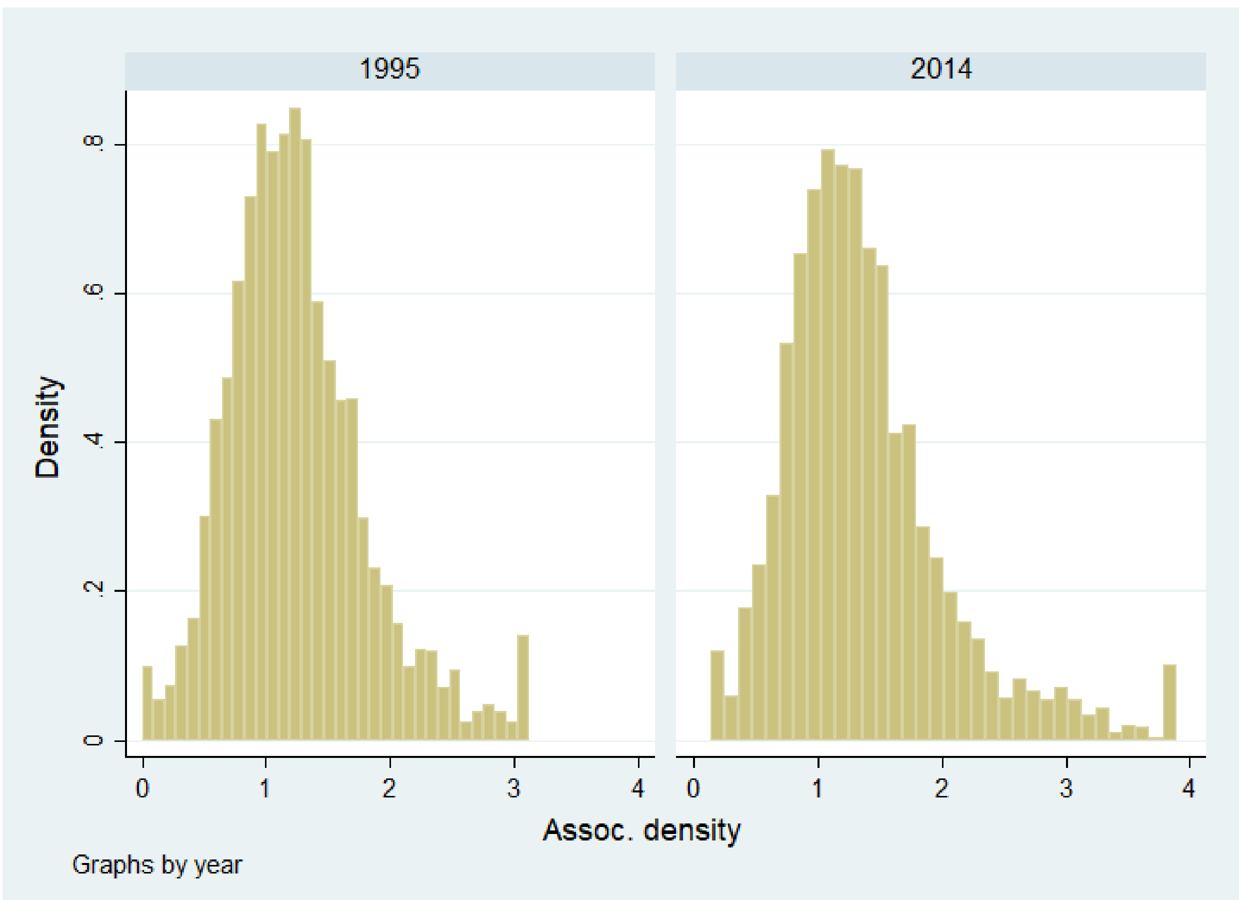

Figure A.6: Registered organization density by county in 2014

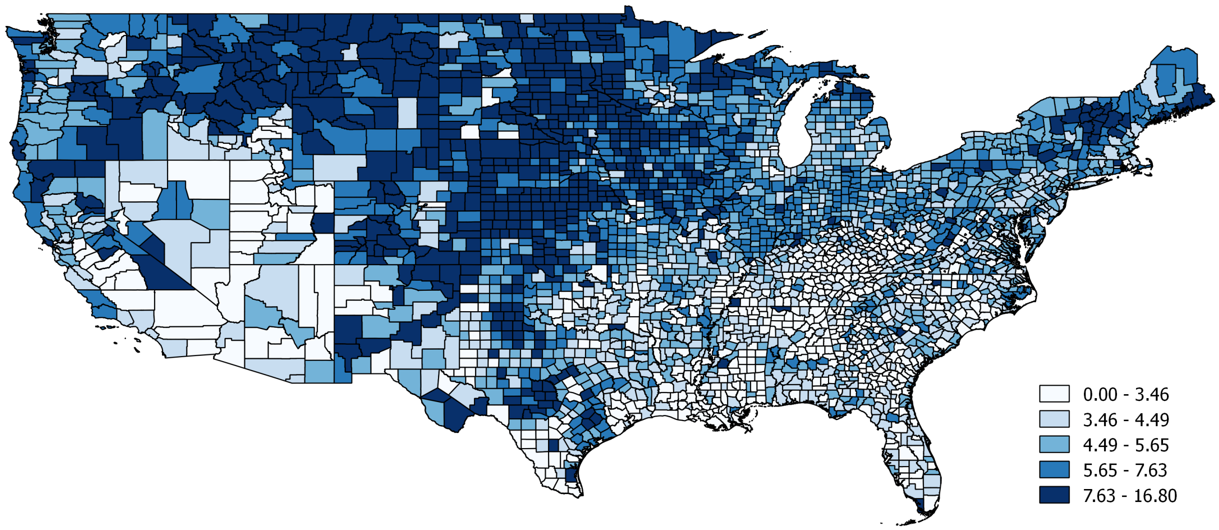

Figure A.7: Distribution of registered organization density (winsorized at the 1% level)

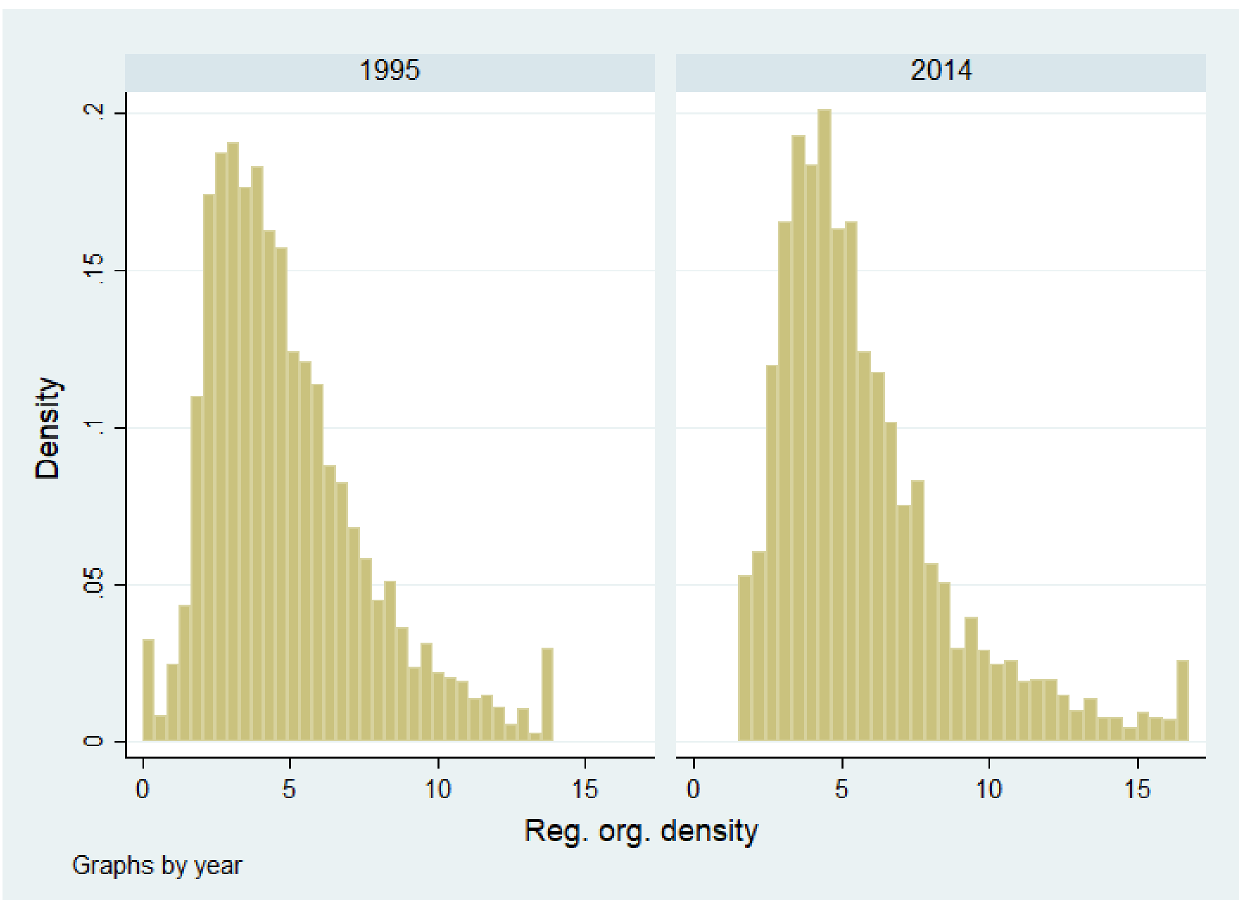

Figure A.8: Voter turnout by county in 2012 (latest available election for 2014)

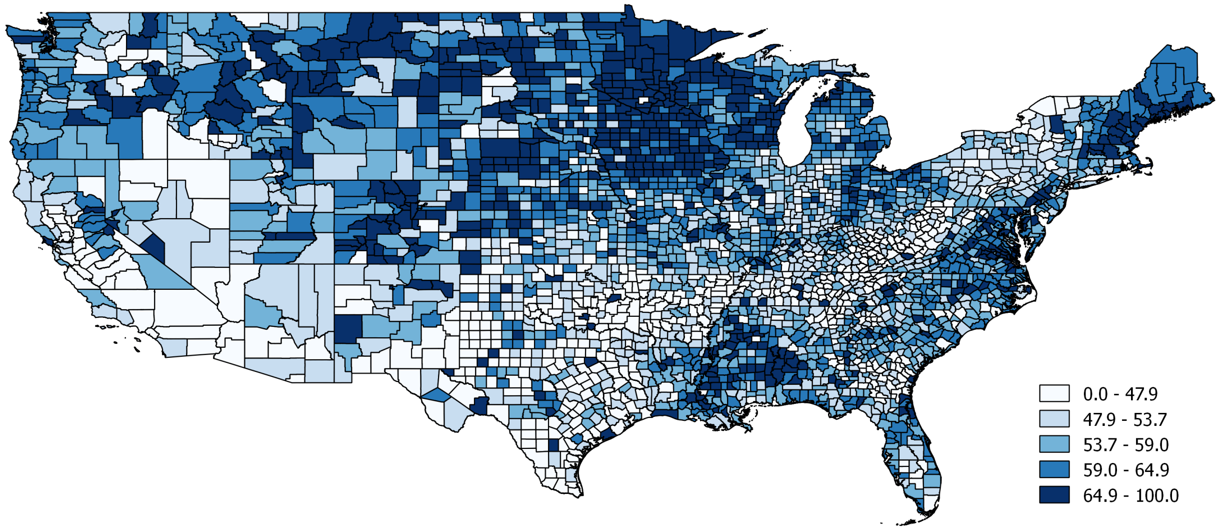

Figure A.9: Distribution of voter turnout (winsorized at the 1% level)

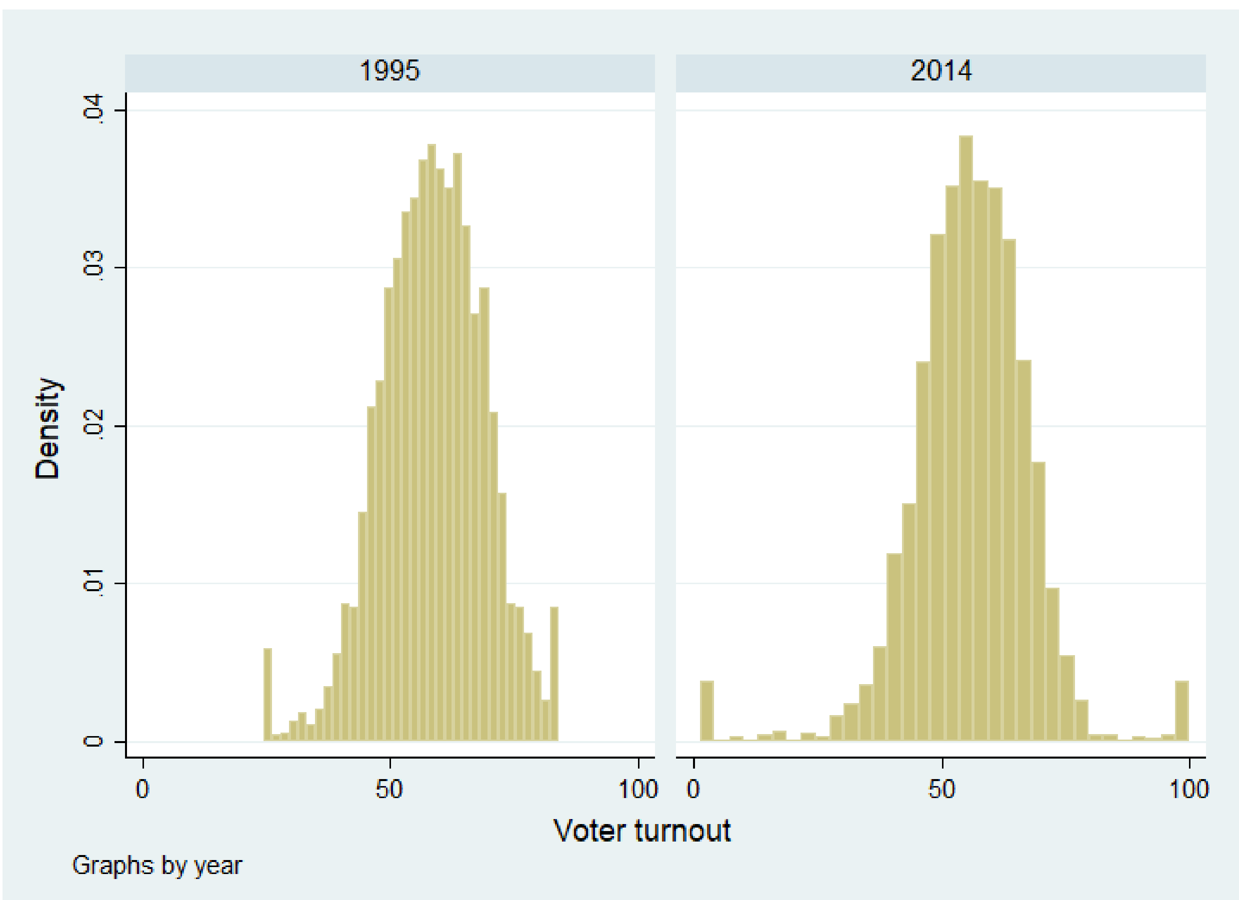

Table A.1
Correlations of social capital (SK) components

SK is our social capital index, defined as the first principal component from a principal component analysis using *Association density*, *Regulated organization density* and *Voter turnout*. *SK(t-1)* is one-year lagged SK index value. *SK (Rupasingha et al.)* is the social capital index calculated by Rupasingha et al. (2006), available for years 1997, 2005, and 2009.

	SK	SK(t-1)	Assoc. density	Reg. org. density	Voter turnout	SK (Rupa. et al.)
SK	1					
SK(t-1)	0.994	1				
Assoc. density	0.817	0.807	1			
Reg. org. density	0.878	0.874	0.635	1		
Voter turnout	0.682	0.682	0.339	0.519	1	
SK (Rupa. et al.)	0.956	0.952	0.766	0.839	0.668	1

B Internet Appendix: Additional Analysis

B.1 Another quasi-experiment: Rule change affecting information

In Section 4.3 of the main paper, we discuss analysis exploiting a rule change directly affecting the magnitude of moral hazard. Another rule change, announced on September 21, 2012, is also relevant for our analysis. It required entrepreneurs to discuss the risks and challenges of their project on the campaign website and also prohibited the use of product simulations and product renderings in the categories Hardware and Product Design, in order to avoid miscommunicating the stage of the project. This change is less likely to have directly changed the magnitude of moral hazard much. It did, however, change the amount of information available to campaign backers about the the project.

As we discuss in Section 6.1, information asymmetry affects crowdfunding campaigns by amplifying the effect of moral hazard. A shock reducing information asymmetry, in the presence of moral hazard, should therefore reduce the aggregate moral hazard problems. We test this prediction using similar difference-in-differences regression analysis as in Section 4.3. The results, shown in Table B.1 are consistent with the rule change mitigating moral hazard. The effect of social capital is reduced following the rule change. Furthermore, no such reduction in the effect is found in the placebo tests one year before and one year after the actual change.

B.2 Social capital and crowdfunding volumes

To study the relationship between social capital and crowdfunding volumes, we construct a data set with quarterly campaign volumes by county. We include all U.S. counties and all full quarters in our data, from Q3 2009 to Q2 2017. We winsorize all continuous variables at the 1% level. The full sample includes 97,402 county-quarter observations. We include three measures for campaign volume, *Campaigns/capita*, measuring the number of campaigns per capita in a given county during a given quarter, *Sought/capita*, measuring the aggregate amount sought by entrepreneurs per capita, and *Sought/PI*, measuring the aggregate amount sought divided by the size of the county economy, as proxied by the county *Personal Income* (PI). Panel A of Table B.2 shows summary statistics for this data set.

To test for the relationship between social capital and crowdfunding volumes, we use the following tobit regressions:

$$ln(1 + Sought/capita)_{i,t} = \alpha_0 + \alpha_1 \times SK_{i,t} + \beta \times X_{i,t} + \epsilon_{i,t} \quad (9)$$

where the dependent variable is either $Sought/capita_{i,t}$ or $Sought/PI_{i,t}$. *Sought* is the dollar amount sought by entrepreneurs for county i in quarter t. Due to the skewed distribution of these ratios, we take logarithms for the regression analysis. $X_{i,t}$ is a vector of control variables. We include the county population, county personal income (aggregate size of the county economy, abbreviated *PI* in our analysis) and county PI per capita, measuring county wealth level. We also include state-quarter joint fixed effects (50 states times 32 quarters), capturing any timing-related factors, as well as any state-specific factors. As is clear from Panel A of Table 1, there is a period of significant growth following the launch of the first campaigns in 2009, followed by more steady volumes from around 2011-2012 onwards. Such differences in the maturity of the platform are also captured by the state-quarter fixed effects. We cluster standard errors by county.

Panel B of Table B.2 shows the results of these regressions. We see that social capital is significantly positively associated with campaign volumes. This result is highly significant using all three metrics of campaign volume. We also see that larger counties, as measured by population, are associated with higher campaign volumes per capita. Similarly, the size of the county economy, as measured by the aggregate county *Personal income*, is associated with higher per capita campaign volumes. On the other hand, wealthier counties, as measured by *PI per capita*, appear to have lower campaign volumes per capita.

Table B.3 shows the results of the campaign volume analysis including interaction terms of social capital with the *EPU* and *Sentiment* variables, as well as with *PI per capita*. We exclude the Low EPU and Low Sentiment dummies from the models, so the coefficients are relative to the low bucket. The results show that the positive relationship between social capital and crowdfunding volumes is strongest in times of high uncertainty, as measured by EPU, and in times of low sentiment, as measured by the Investor Sentiment index. They also show that social capital increases crowdfunding volumes most significantly in the *Low PI/capita* bucket.

B.3 Economic uncertainty, sentiment, and crowdfunding dynamics

In the main section of the paper, we show how the impact of social capital on crowdfunding varies with the level of economic uncertainty, as measured by the EPU index of Baker et al. (2016), and sentiment, as measured by the Investor Sentiment index of Baker and Wurgler (2006). Since we focus on the interactions with social capital, the previous results do not show the impact of the *levels* of these indices themselves on campaign volumes and outcomes. Such time differences in EPU and sentiment are captured by the fixed effects we include, i.e. state-quarter joint fixed effects in the case of campaign volumes, and year-month joint fixed effects in the case of campaign outcomes and goal amounts. In this subsection, we explore how economic policy uncertainty and investor sentiment affect the campaign dynamics.

Panel A of Table B.4 shows the tobit regression analysis on quarterly campaign volumes, with the *EPU* and *Sentiment* variables explicitly in the models. We see that higher EPU is associated with significantly lower campaign volumes, while high sentiment is associated with high campaign volumes. These results are both intuitive and statistically highly significant.

In Panel B, we see that, somewhat counter-intuitively, campaign success rates and Pledged/Goal ratios are actually higher at times of high uncertainty and low sentiment. This finding is easier to understand looking at Figure B.3. This chart shows the number of successful and unsuccesful campaigns over time, as well as the corresponding EPU index values. We see visually that, as shown by the results in Table B.4, there is a clear negative relationship between EPU and campaign volumes, meaning that campaign volumes decline at times of high uncertainty. However, from the chart it is clear that the vast majority of the differences in campaign numbers come from unsuccessful campaigns, while the number of successful campaigns is actually relatively stable over time. This means that at times of high campaign volumes the average success rate decreases.

Table B.1
Another quasi-experiment: Rule change affecting information

The sample includes all campaigns during a two-year period (from one year before to one year after) around a Kickstarter rule change announced on September 21, 2012, which required entrepreneurs to discuss the risks and challenges of their project on the campaign website. It also prohibited the use of product simulations and product renderings in the categories Hardware and Product Design, in order to avoid miscommunicating the stage of the project. *Post* is a dummy taking the value 1 if the campaign was launched after the rule change, and 0 if before. Heteroscedasticity-consistent standard errors clustered at the sub-category level are shown in parentheses.

Panel A: Diff-in-Diff regressions on *Successful*

	Actual			Placebo tests (logit)	
	(1) Logit	(2) Logit	(3) OLS	(4) − 1 year	(5) + 1 year
Post x SK	−0.0577**	−0.0617**	−0.0133**	0.0624**	0.0328
	(0.0276)	(0.0279)	(0.0056)	(0.0250)	(0.0256)
Post change	0.1677***	−0.0808	−0.0149	−0.0898	0.0712
	(0.0273)	(0.0787)	(0.0152)	(0.1117)	(0.0858)
Social capital (SK)	0.2278***	0.2394***	−0.0316	0.2491***	0.1399***
	(0.0456)	(0.0454)	(0.0291)	(0.0488)	(0.0309)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No
N	69,728	69,728	69,683	55,183	78,264
R^2			0.245		
Pseudo R^2	0.174	0.175		0.173	0.193

Panel B: Diff-in-Diff regressions on *ln(1+Pledged/Goal)*

	Actual			Placebo tests	
	(1) OLS	(2) OLS	(3) OLS	(4) − 1 year	(5) + 1 year
Post x SK	−0.0077	−0.0090*	−0.0113**	0.0076*	0.0025
	(0.0048)	(0.0048)	(0.0052)	(0.0045)	(0.0043)
Post change	0.0387***	−0.0085	−0.0095	−0.0184	0.0162
	(0.0060)	(0.0140)	(0.0131)	(0.0184)	(0.0173)
Social capital (SK)	0.0331***	0.0372***	−0.0301	0.0395***	0.0221***
	(0.0086)	(0.0085)	(0.0294)	(0.0090)	(0.0060)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	No	No
N	70,158	70,158	69,682	55,426	78,291
R^2	0.249	0.251	0.277	0.246	0.266

Significance levels: * 0.1, ** 0.05, * 0.01. p-values in parentheses.**

Table B.2
Campaign volumes vs. social capital

Panel A shows summary statistics for county-quarter observations, including all U.S. counties and quarters Q3 2009 - Q2 2017 (all full quarters in our sample). All continuous variables have been winsorized at the 1% level on a yearly basis. Panel B shows the results of tobit regressions on campaign volume. The dependent variable is shown above each model. The sample includes county-quarter observations for all U.S. counties and quarters Q3 2009 - Q2 2017 (all full quarters in our sample). *SK* is the social capital index value of the county. *PI* is the annual county Personal Income, as defined in Appendix B, measuring the aggregate size of the county economy. *PI/capita* is the county Personal Income per capita, measuring county wealth level. We include either *Year-Quarter fixed effects* (32 quarters) or *State-Quarter fixed effects* (50 states times 32 quarters). All continuous variables have been winsorized at the 1% level on a yearly basis. Heteroscedasticity-consistent standard errors clustered at the county level are shown in parentheses.

Panel A: Summary statistics - campaign volumes

	Mean	Std	p25	p50	p75
Campaign volumes					
Sought/capita	0.128	0.538	0.000	0.000	0.000
Sought/PI	3.088	12.672	0.000	0.000	0.000
County variables					
Social capital (SK)	-0.001	0.980	-0.644	-0.168	0.444
Population ('000)	88.730	189.061	11.026	25.770	67.234
Personal income ('000)	3.943	9.900	0.376	0.879	2.473
PI/capita ('000)	37.746	9.860	31.039	35.753	42.163
Timing variables					
EPU	131.802	31.940	107.566	125.683	155.159
Sentiment	-0.275	0.215	-0.349	-0.246	-0.174
N	97,402				

Panel B: Tobit regressions on campaign volumes

	ln(1+Campaigns/capita)		ln(1+Sought/capita)		ln(1+Sought/PI)	
	(1)	(2)	(3)	(4)	(5)	(6)
Social capital (SK)	0.0091***	0.0110***	0.0914***	0.1182***	0.3726***	0.4907***
	(0.0010)	(0.0001)	(0.0106)	(0.0012)	(0.0420)	(0.0049)
ln(Population)	0.0131	0.0165***	0.1180	0.1291***	0.6575	0.7366***
	(0.0185)	(0.0000)	(0.1867)	(0.0003)	(0.5911)	(0.0012)
ln(PI)	0.0098	0.0070***	0.1514	0.1619***	0.5543	0.5622***
	(0.0184)	(0.0000)	(0.1857)	(0.0004)	(0.5879)	(0.0017)
ln(PI/capita)	0.0070	−0.0042***	0.0899	−0.0734***	−0.0482	−0.7537***
	(0.0188)	(0.0000)	(0.1917)	(0.0003)	(0.6168)	(0.0013)
EPU	−0.0001***		−0.0013***		−0.0043***	
	(0.0000)		(0.0001)		(0.0003)	
Sentiment	0.0828***		0.9309***		4.0600***	
	(0.0017)		(0.0175)		(0.0617)	
State FE	Yes	No	Yes	No	Yes	No
State-Quarter FE	No	Yes	No	Yes	No	Yes
N	77,150	95,666	77,150	95,666	77,150	95,666
Pseudo R^2	-4.514	-3.711	0.333	0.372	0.217	0.245

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table B.3
Campaign volumes vs. SK by EPU, sentiment, and county wealth

The dependent variable for the tobit regressions is shown above each model. The sample includes county-quarter observations for all U.S. counties and quarters Q3 2009 - Q2 2017 (all full quarters in our sample). *SK* is the social capital index value of the county. *High EPU* is a dummy taking the value 1 if the Economic Policy Uncertainty index value in the quarter is above median of the quarters in our sample. *High sentiment* is a dummy taking the value 1 if the Investor Sentiment index value in the quarter is above median of the quarters in our sample. *High PI/capita* is a dummy taking the value 1 if the county PI/capita in the current year is above the median of all counties. *PI* is the annual county Personal Income, as defined in Appendix B, measuring the aggregate size of the county economy. *PI/capita* is the county Personal Income per capita, measuring county wealth level. We include *State-Quarter fixed effects* (50 states times 32 quarters). All continuous variables have been winsorized at the 1% level on a yearly basis. Heteroscedasticity-consistent standard errors clustered at the county level are shown in parentheses.

	ln(1+Sought/capita)			ln(1+Sought/PI)		
	(1)	(2)	(3)	(4)	(5)	(6)
High EPU x SK	0.0281***			0.1712***		
	(0.0022)			(0.0090)		
High sent. x SK		−0.0215***			−0.1320***	
		(0.0023)			(0.0091)	
High PI/Capita x SK			−0.0181***			−0.0801***
			(0.0023)			(0.0089)
Social capital (SK)	0.1065***	0.1360***	0.1303***	0.4181***	0.5856***	0.5433***
	(0.0016)	(0.0019)	(0.0021)	(0.0066)	(0.0074)	(0.0080)
ln(Population)	0.1269***	0.1027***	0.1263***	0.7234***	0.5686***	0.7258***
	(0.0003)	(0.0003)	(0.0003)	(0.0012)	(0.0013)	(0.0012)
ln(PI)	0.1641***	0.1830***	0.1641***	0.5750***	0.7042***	0.5701***
	(0.0004)	(0.0004)	(0.0004)	(0.0017)	(0.0017)	(0.0017)
ln(PI/capita)	−0.0764***	−0.0964***	−0.0831***	−0.7716***	−0.9050***	−0.7954***
	(0.0003)	(0.0003)	(0.0003)	(0.0013)	(0.0013)	(0.0013)
State-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	95,666	77,150	95,666	95,666	77,150	95,666
Pseudo R^2	0.372	0.381	0.372	0.245	0.251	0.245

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table B.4
Campaign volumes and outcomes vs. EPU and sentiment

The dependent variable is shown above each model. Variables are as defined in Appendix B. Panel A shows tobit regression analysis of campaign volumes including EPU and Sentiment variables. *County controls* are the same as in Table B.2. Panel B shows cross-sectional regression analysis on campaign outcomes and goal amounts including EPU and Sentiment variables. *County controls* include *ln(Personal Income)* and *ln(PI per capita)*. *Campaign controls* include *ln(Goal amount)*, *ln(Campaign length)*, and *Staff pick*. *Gender and race* controls include the same dummies for gender and race as in Table 2. Heteroscedasticity-consistent standard errors, clustered at the county level for campaign volume analysis and sub-category level for outcome analysis, are shown in parentheses.

Panel A: Tobit regressions on campaign volume

	ln(1+Sought/capita)		ln(1+Sought/PI)	
	(1)	(2)	(3)	(4)
EPU	−0.0032***		−0.0128***	
	(0.0001)		(0.0004)	
Sentiment		1.0514***		4.4477***
		(0.0196)		(0.0674)
Social capital (SK)	0.0695***	0.0866***	0.2767***	0.3565***
	(0.0100)	(0.0106)	(0.0400)	(0.0421)
County controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	95,666	77,150	95,666	77,150
Pseudo R^2	0.297	0.330	0.193	0.216

Panel B: Regressions on outcomes and goal amounts

	Successful (logit)		ln(1+Pledged/Goal) (OLS)	
	(1)	(2)	(3)	(4)
EPU	0.0007**		0.0002***	
	(0.0003)		(0.0001)	
Sentiment		−0.9828***		−0.1681***
		(0.1156)		(0.0217)
Social capital (SK)	0.1778***	0.1928***	0.0221***	0.0254***
	(0.0243)	(0.0252)	(0.0048)	(0.0050)
County controls	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes
Gender and race	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes
N	222,879	182,549	222,913	182,586
R^2			0.313	0.275
Pseudo R^2	0.209	0.192		

Significance levels: * 0.1, ** 0.05, * 0.01.**

Figure B.1: EPU, average success rate, and campaign volume

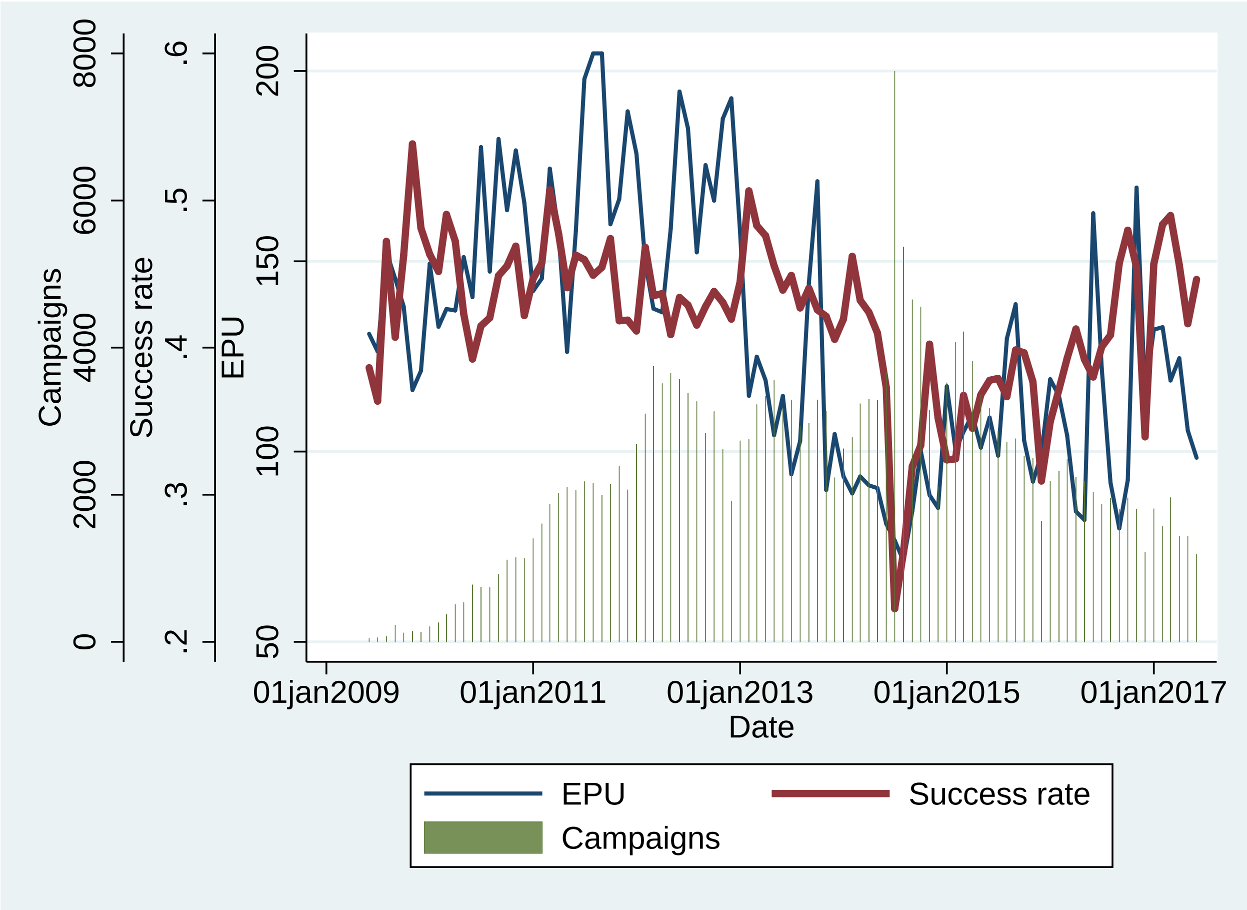

Figure B.2: Sentiment, average success rate, and campaign volume

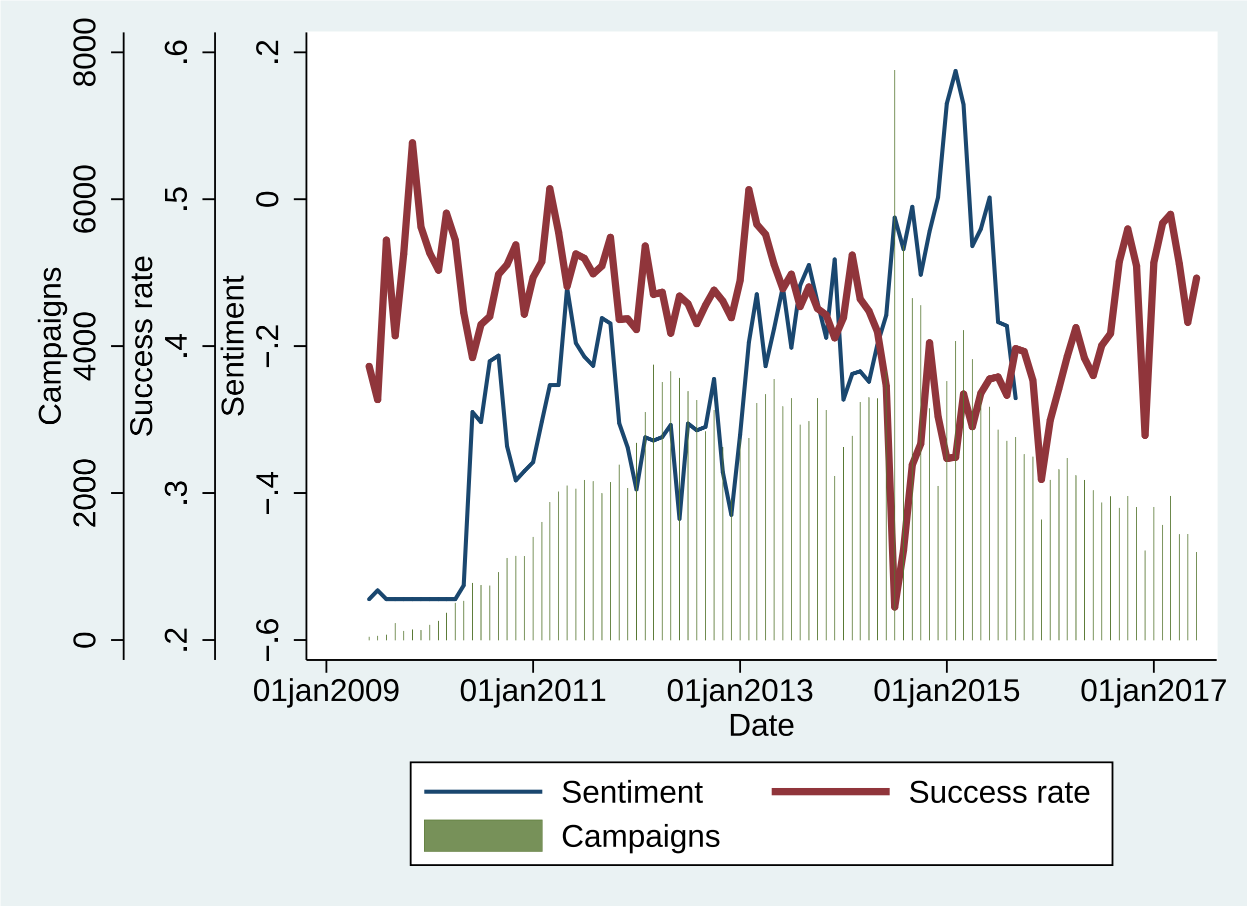

Figure B.3: EPU and campaign volume by outcome