Online Appendix:
“What Do Cross-Country Surveys Tell Us About Social Capital?”

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Contents

1 Description of Variables

Generalized Trust Country-level average based on responses to the following question in the World Values Survey and European Values Study (WVS/EVS): "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" The variable is coded as (0) "Need to be very careful" and (1) "Most people can be trusted", so that higher values correspond to higher levels of trust. We average responses across all available waves for each country. The WVS consists of seven waves collected from 1981 to 2020. The EVS consists of five waves collected from 1981 to 2017. For Kenya, which is not included in the WVS or EVS, we use average responses to the same question from Wave 5 from the Afrobarometer. Responses are standardized at the country-level to have a mean of zero and standard deviation of one.

Trust (GPS) Country-level average based on responses to the following question from the Global Preference Survey (Falk et al. 2018): "I assume that people have only the best intentions" (from 0 "does not describe me at all" to 10 "describes me perfectly"). The GPS data were collected as part of the 2012 Gallup World Poll, a survey that includes representative samples in a large number of countries and which asks about social and economic issues on an annual basis. Responses are standardized at the country-level to have a mean of zero and standard deviation of one.

Generalized Morality Following Tabellini (2008), we compute the fraction of respondents in the WVS/EVS who select "tolerance and respect for other people" as one of their answers to the question "Here is a list of qualities that children can be encouraged to learn at home. Which, if any, do you consider to be especially important? Please choose up to five!" We average responses across all available waves for each country. The WVS consists of seven waves collected from 1981 to 2020. The EVS consists of five waves collected from 1981 to 2017. Responses are standardized at the country-level to have a mean of zero and standard deviation of one.

Universal Moral Values Following Enke (2019), we computed the difference between the strength of "universal" and "communal" moral values in the Moral Foundations Questionnaire (Graham et al. 2011). Universal moral values are measured as the sum of responses to all questions in the "fairness/reciprocity" and "harm/care" domains, while communal values are measured as the responses to questions in the "in-group/loyalty" and "authority/respect" domains. The MFQ data are from a sample of self-selected respondents who chose to complete the MFQ at www.yourmorals.org between 2008 and 2018. Responses are standardized at the country-level to have a mean of zero and standard deviation of one.

Norms of Civic Cooperation Following Guiso, Sapienza, and Zingales (2011), we computed the first principal component (extracted at the country-level) from the following questions in the WVS/EVS: "Please tell me for each of the following actions whether you think it can always be justified, never be justified, or something in between, using this card." (1) "Claiming government benefits to which you are not entitled", (2) "Avoiding a fare on public transport", and (3) "Someone accepting a bribe in the course of their duties" on a 10-point scale (from 0 “never justifiable” to 10 “always justifiable”). We average responses across all available waves for each country. The WVS consists of seven waves collected from 1981 to 2020. The EVS consists of five waves collected from 1981 to 2017. Responses are standardized at the country-level to have a mean of zero and standard deviation of one, and is coded so that higher values correspond to stronger disapproval.

Positive Reciprocity (GPS) Country-level average based on responses to the following questions from the Global Preference Survey (Falk et al. 2018): (1) “When someone does me a favor I am willing to return it” and (2) “Please think about what you would do in the following situation. You are in an area you are not familiar with, and you realize you lost your way. You ask a stranger for directions. The stranger offers to take you to your destination. Helping you costs the stranger about 20 Euro in total. However, the stranger says he or she does not want any money from you. You have six presents with you. The cheapest present costs 5 Euro, the most expensive one costs 30 Euro. Do you give one of the presents to the stranger as a ’thank-you’-gift? If so, which present do you give to the stranger?” Falk et al. (2018) aggregate these survey items by computing the z-scores of each question at the individual-level and weighing these z-scores using the weights (0.485 and 0.515, respectively) from the experimental validation procedure in Falk et al. (2016). The GPS data were collected as part of the 2012 Gallup World Poll, a survey that includes representative samples in a large number of countries and which asks about social and economic issues on an annual basis. To facilitate comprison with out other measures, responses are standardized at the country-level to have mean of zero and standard deviation of one.

Altruism (GPS) Country-level average based on responses to the following questions from the Global Preference Survey (Falk et al. 2018): (1) “How willing are you to give to good causes without expecting anything in return?” and (2) “Imagine the following situation: Today you unexpectedly received 1,000 Euro. How much of this amount would you donate to a good cause?” Falk et al. (2018) aggregate these survey items by computing the z-scores of each question at the individual-level and weighing these z-scores using the weights (0.365 and 0.635, respectively) from the experimental validation procedure in Falk et al. (2016). The GPS data were collected as part of the 2012 Gallup World Poll, a survey that includes representative samples in a large number of countries and which asks about social and economic issues on an annual basis. To facilitate comprison with out other measures, responses are standardized at the country-level to have mean of zero and standard deviation of one.

Return Lost Item Country-level average based on responses from the 2019 Lloyd’s Register Foundation World Risk Poll in which participants were asked to assess, “how likely a stranger would be to return a small bag of great financial value to you if found.” Responses were coded as 0 for “not at all likely”, 0.5 for “somewhat likely”, and 1.0 for “very likely.” Responses are standardized at the country-level to have a mean of zero and standard deviation of one, and is coded so that higher values correspond to stronger disapproval.

Index of Dishonest Behavior (United States) The first principal component from (1) the share of self-employed individuals in a city who reports an income in 2009 within U.S. $500 of the first Earned Income

Tax Credit (EITC) kink, as a percentage of individuals with non-zero self-employment income, as a measure of cheating on taxes (Chetty, Friedman, and Saez 2013), and (2) the number of federal court convictions for corrupt practices between 1976 and 2002 per 10,000 public officials in each U.S. state (Glaeser and Saks 2006). Following standard practice, we exclude Washington, D.C. from the analysis as the presence of the federal government makes a meaningful comparison with other states difficult (Saiz and Simonsohn 2013). The principal component has a mean of zero and standard deviation of one, and is coded so that higher values correspond to higher levels of dishonest behavior.

Index of Dishonest Behavior (Italy) The first principal component from (1) municipality-level rates of compliance or payment of a television licensing fee over the period 2004-2010 (Buonanno et al. 2019), (2) the difference between the cumulative amounts of public money allocated to capital expenditures and existing amounts of physical infrastructure in 1997 (Golden and Picci 2006), and (3) historical data (1948-1994) on prosecutors' requests to proceed with a criminal investigation against a member of parliament from the city's electoral district (Nannicini et al. 2013). The principal component has a mean of zero and standard deviation of one, and is coded so that higher values correspond to higher levels of dishonest behavior.

Log GDP per Capita The logarithm of a country's gross domestic product per capita in 2017. Based on the real gross domestic product at constant national prices (in mil. 2011 U.S. dollars) and the population (in mil.) from the Penn World Table 9.1.

Log Productivity (TFP) The logarithm of a country's total factor productivity at current purchasing power parities in 2017 from the Penn World Table 9.1. The variable measures the ratio of a country's economic outputs to its inputs (capital and labor), and this ratio is scaled relative to the United States (which takes a value of 1). For details of the construction, see Feenstra, Inklaar, and Timmer (2015).

Government Effectiveness The estimate of government effectiveness in 2017 from the World Bank (Kraay, Kaufmann, and Mastruzzi 2010). Government effectiveness measures the quality of public services, the quality and degree of independence from political pressures of the civil service, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Estimates are standardized to have a mean of zero and standard deviation of one.

Letter Grade Efficiency The fraction of correctly returned non-deliverable letters. Chong et al. (2014) mailed ten letters to non-existing business addresses in each country and measured whether they arrived back to a return address in the United States. Letters were mailed from Cambridge, MA between December of 2010 and February of 2011. Chong et al. (2014) recorded the fraction of return letters until February of 2012.

Trust in Strangers (online appendix only) Country-level average based on responses to the following question from the WVS/EVS: "Could you tell me for each whether you trust people from this group completely, somewhat, not very much or not at all? People you meet for the first time." The variable is recoded as (1) "Do not trust at all", (2) "Do not trust very much", (3) "Trust somewhat", (4) "Trust completely", so that higher values correspond to higher levels of trust. The WVS consists of seven waves collected from 1981 to 2020. The EVS consists of five waves collected from 1981 to 2017. Responses are standardized at the country-level to have a mean of zero and standard deviation of one.

2 Wallets

Our wallets were transparent business card cases (see Figure A1). We used transparent cases to ensure that recipients could inspect the wallet's contents without having to open it. Each wallet contained the same personal items: (i) three identical business cards, (ii) a grocery list, and (iii) a key. The business cards displayed the owner's name, email address, and job title. Their purpose was to identify the owner and provide contact details.

The business cards and shopping list serve to identify the owner as a local resident, signaling that it would be relatively easy to contact the owner and return the wallet. For the business cards, we typically created three fictitious male owners for each country using common local names. We used several sources to assemble lists of common first and last names, which we then checked to avoid names used as references for generic or unidentified persons (e.g., John Doe), were shared with celebrities, or led to a single user-profile on Facebook. The business cards provided the owner's email address, and identified him as a freelance software engineer (to avoid attempts by recipients to reach the owner through his place of employment).

There were some exceptions to how we generated business cards and shopping lists for our wallets. In Switzerland and the Czech Republic, we used the real name of research assistants so that we would be able to collect reported wallets for our internal validation check. For these two countries we also decided to use only two identities (rather than three) so that we could pick up a larger share of the wallets. In Canada and India, different names were used for some cities to accommodate the local language. Due to South Africa's history of race relations, we used two discernibly white and two discernibly black names, leading to a total of four names. We made occasional changes to the shopping lists to accommodate local customs, such as using rice instead of pasta or substituting milk with some other beverage where lactose intolerance was common.

Figure A1: Example lost wallet

Notes: Example of a wallet used in our field experiments. All wallets belonged to a male software developer with country-specific names. We placed the business cards in the wallets so that this information was visible to all recipients. The wallet dimensions were 93mm x 59mm x 5mm and it weighed approximately 24 grams in the NoMoney condition.

3 Robustness Checks on Lost Wallet Data

Legal Regulations for Lost Property One measurement concern is that wallet reporting rates reflect fear of punishment rather than social capital. According to this view, recipients who report a lost wallet are primarily motivated by the possibility of punishment for failing to report a wallet. We purposefully designed our experiment to minimize such concerns by telling recipients that the wallet was found around the corner and having our research assistants immediately leave upon handing over the wallet (thereby never receiving written confirmation for the lost item). We also note that legal sanctions for failing to return lost property are uncommon and rarely enforced (West 2003).

To examine whether wallet reporting rates can be explained by fear of punishment concerns, we exploit regional variation in lost property laws within the United States. The U.S. legal system is based on common law under which a person who finds lost property may keep the item until the original owner comes forward.[1] However, some states have enacted statutes that modify the law's treatment of lost property. For instance, the state of New York imposes a fine of up to one hundred dollars when a finder willfully fails to report lost property.[2] If reporting rates are driven by fear of legal sanctions, then we should expect wallet reporting rates to be higher in states with lost property laws.

About half of our lost wallet data in the United States originate from states that have adopted statutes explicitly requiring finders to return lost property to the rightful owner or to a relevant agency, such as the police. We regressed individual wallet reporting decisions (100 = wallet reported, 0 = wallet not reported) onto an indicator variable for whether the wallet drop-off took place in a U.S. state with an explicit lost property law (1 = yes, 0 = no). We also included our standard set of controls for treatment condition and recipient and situation characteristics, and clustered standard errors by city. Based on this specification, recipients in states with lost property laws were 3.7 percentage points *less* likely than recipients in states without lost property laws to return a lost wallet ($b = 3.66$, SE = 3.96, $p = 0.365$). This result, although not statistically significant, is opposite to what we would expect if recipients were motivated to return wallets to avoid legal sanctions.

As a second analysis, we examine how statistically adjusting for lost property laws affects the rank-order of wallet reporting rates across cities in the United States. We first calculated wallet reporting rates for each city, adjusting only for our standard set of control variables. We then calculated wallet reporting rates for each city, while also controlling for lost property laws (in addition to our standard set of controls). The rank-order correlation between city-level reporting rates with and without correction for lost property laws was 0.978. Thus, within the United States, using wallet reporting rates to compare city-level social capital does not meaningfully change when controlling for state lost property laws.

Cross-Country Variation in Legal Traditions Looking at the role of legal sanctions beyond the United States, we note that cross-national comparisons will have difficulty separating the effects of a single piece

1. Legal Information Institute, https://www.law.cornell.edu/wex/lost_property, accessed on September 18, 2016. Common law distinguishes between lost and mislaid property. Lost property is property that was unintentionally left behind by its owner. Mislaid property, on the other hand, is property that was intentionally set down in a location by its owner and then forgotten.

2. See N.Y. Personal Property Law § 252 (3).

of legislation from the numerous other differences among legal systems. While a detailed analysis of legal institutions in each country is beyond the scope of this paper, we can test the effect of different legal traditions more broadly. Following the classification by *JuriGlobe*,[3] we compare wallet reporting rates in common law versus civil law countries. The distinction between common and civil law is meaningful because civil law countries are more likely to have specific regulation that governs the rights and obligations concerning lost property.[4]

First, we examine if wallet reporting rates are higher in civil law countries. We regressed individual wallet reporting decisions (100 = wallet reported, 0 = wallet not reported) onto an indicator variable for whether the wallet drop-off took place in a country with an explicit lost property law (1 = yes, 0 = no). We also included our standard set of controls for treatment condition and recipient and situation characteristics, and clustered standard errors by country. Based on this specification, recipients in civil law countries were 5.1 percentage points more likely than recipients in common law countries to return a lost wallet ($b = 5.13$, SE = 4.63, $p = 0.275$). Although we fail to find a reliable association between broad legal traditions and wallet reporting decisions, we note that this result cannot separate the effects of specific legislation from other differences among legal systems.

Second, we examine how statistically adjusting for a country's legal tradition affects the rank-order of wallet reporting rates across countries. We first calculated wallet reporting rates for each country, adjusting only for our standard set of control variables. We then calculated wallet reporting rates for each country, while also controlling for legal tradition (in addition to our standard set of controls). The rank-order correlation between country-level reporting rates with and without correction for country legal tradition was 0.980. Thus, using wallet reporting rates to compare country-level social capital does not meaningfully change when controlling for whether the country has a common law or civil law legal tradition.

Fear of Detection: Security Cameras A related measurement concern is that wallet reporting rates reflect fear of possible detection by others — which may lead to formal or informal punishment — rather than social capital.

We first address this concern by examining how the presence of a security camera affects wallet reporting rates. Security cameras could serve as proof that the wallet was turned in to the recipient and therefore amplify concerns about detection if the wallet goes unreturned. After each drop-off, except in Poland and the United Kingdom, our research assistants took note of whether they observed a security camera. We regressed wallet reporting decisions on whether a security camera was present during the wallet drop-off (1 = yes, 0 = no), along with our standard set of controls. Since the presence of security cameras varied substantially by city, we also included city fixed-effects in the model and implemented robust standard errors. Based

3. World Legal Systems, JuriGlobe research group, University of Ottawa, accessed October 8, 2017, www.juriglobe.ca. The CIA Factbook provides an alternative classification that differs for two countries (Norway and UAE). Excluding these countries does not change the results.

4. For the purpose of this analysis, countries where classified as having a common law tradition whenever its legal system is built at least partially on common law elements and we do not account for subnational differences. However, the results are unchanged when we exclude countries and regions with legal systems that combine common and civil law elements (South Africa, Scotland, Quebec). Several countries have mixed legal systems that combine common or civil law with elements from customary or religious legal traditions.

on this specification, recipients in the presence of a security camera were *less* likely to report a lost wallet compared to when a security camera was absent ($b = -2.65$, SE = 0.96, $p = 0.005$). This result, though small in magnitude, is opposite to what we would expect if recipients were motivated to return wallets to avoid detection.

Next, we examine how statistically adjusting for the presence of security cameras (at the individual level) affects the rank-order of wallet reporting rates across countries. We first calculate wallet reporting rates for each country, adjusting only for our standard set of control variables. We then calculate wallet reporting rates for each country, while also controlling for whether a security camera was present during the wallet drop-off (in addition to our standard set of controls). The rank-order correlation between country-level reporting rates with and without correction was 0.997. When we perform a similar analysis at the city-level (rather than country-level), the rank-order correlation was 0.999. Thus, using wallet reporting rates to compare social capital across countries or cities does not meaningfully change when controlling for the presence of security cameras during the wallet drop-off exchange.

Fear of Detection: Other Witnesses We also address detection concerns by examining the presence of other individuals when performing a wallet drop-off. Recipients may have been worried about negative reactions from bystanders — an informal punishment — for failing to report a wallet. After performing the wallet drop-offs, our research assistants also noted whether coworkers and other individuals were present during the exchange. If worries about informal sanctions influenced recipient's behavior then recipients should be more likely to report a lost wallet when their behavior was witnessed by others.

We first regressed wallet reporting decisions on whether a co-worker was present (1 = yes, 0 = no) and whether other bystanders, such as a customer, were present (1 = yes, 0 = no). Similar to our previous analysis, we also included our standard set of controls and city fixed-effects, along with robust standard errors. Based on this specification, recipients in the presence of coworkers were more likely to report a lost wallet than when coworkers were absent ($b = 4.68$, SE = 0.76, $p < 0.001$). However, recipients in the presence of other bystanders were less likely to report a lost wallet than when other bystanders were not present ($b = -3.90$, SE = 1.42, $p < 0.001$). The first result is consistent with a fear of detection account, while the second result is not. However, both results may simply be proxies for how busy the recipient was during the wallet drop-off — recipients may be more likely to send an email to report a lost wallet when another co-worker is available to take customers, or when there are not other customers present who require the recipient's attention.

Next, we examine how statistically adjusting for the presence of others during the wallet drop-off affects the rank-order of wallet reporting rates across countries. We first calculate wallet reporting rates for each country, adjusting only for our standard set of control variables excluding indicators for presence of co-workers or other bystanders. We then calculate wallet reporting rates for each country, while also controlling for the presence of co-workers or other bystanders (in addition to our other controls). The rank-order correlation between country-level reporting rates with and without correction was 0.996. When we perform a similar analysis at the city-level (rather than country-level), the rank-order correlation was 0.999. Thus, using wallet reporting rates to compare social capital across countries or cities does not meaningfully change when controlling for the presence of potential witnesses during the wallet drop-off exchange.

Differences in Email Usage Another concern is that differences in exposure to email communication could be responsible for cross-country differences in wallet reporting rates. We tried to minimize this concern by focusing on drop-off locations in urban places and also included institutions where email communication is common. In particular, hotel staff should be able to communicate via email in all parts of the world. Consequently, if email experience rather than social capital is a key driver of differences in reporting rates, then the cross-country differences we observe in the full sample should not correspond to cross-country differences when restricting our analysis to drop-offs only performed at hotels.

To examine this, we first calculate wallet reporting rates for each country using our full sample, adjusting only for our standard set of control variables. We then calculate wallet reporting rates for each country using only drop-offs performed at hotels (also adjusting for our standard set of controls). The rank-order correlation between country-level reporting rates in the full versus restricted sample was 0.923. Thus, using wallet reporting rates to compare social capital across countries does not meaningfully change when we restrict our analysis to institutions where email usage is likely to not vary substantially across countries.

As a further robustness check, we statistically adjust for county-level differences in email penetration rates using data from the World Bank Global Enterprise Survey.[5] We first calculate wallet reporting rates for each country, adjusting only for our standard set of control variables. We then calculate wallet reporting rates for each country, while also controlling for country-level email penetration (in addition to our other controls). The rank-order correlation between country-level reporting rates with and without correction was 0.950. Thus, using wallet reporting rates to compare social capital across countries does not meaningfully change when controlling for country-level differences in email penetration rates.

Returning the Wallet but Pocketing the Money Another concern is whether wallet return rates are a valid measure of social capital because recipients in the Money treatments may have been more likely to return the wallet after first pocketing the money. We decided not to collect reported wallets to minimize the inconvenience to the recipients, so it is possible that some recipients contacted the owner to return the wallet without the money. First, the high correlation between country-level reporting rates in the NoMoney and Money treatments (Spearman's $\rho = 0.939$) suggests that this concern does not substantially drive response rates in the Money condition. Furthermore, we picked up all reported wallets in seven cities from the Czech Republic (82 wallets) and Switzerland (90 wallets). We selected these two countries because they differ markedly in their level of corruption and presumably also in dishonest behavior.[6] If some recipients reported the wallet after first pocketing the money, then we should observe wallets that are returned without any money (especially in the Czech Republic where corruption is more prevalent). We recovered 99% and 98% of the money from the wallets that we picked up in Switzerland and the Czech Republic, respectively, and observe no reliable difference between the two countries ($Z = 0.22$, $p = 0.823$ by a rank-sum test). This suggests that collecting emails was a valid method to measure whether people would return a wallet with all of its contents.

5. The World Bank Global Enterprise Survey measures the share of firms that use email to interact with their customers and suppliers in a country. The data set does not cover most Western European countries and North America, so we limit our analysis of email usage to the 27 countries that overlap with our data set.

6. In 2013, Transparency International ranked Switzerland 7th and the Czech Republic 57th out of 177 countries.

4 External Validation of Wallet Reporting Rates

We examine variation in wallet reporting rates within the United States and Italy. We focus on these two countries because we sampled a greater number of cities in these countries (e.g., 25 cities in the United States compared to 4-5 in most countries), and because established city-level behavior-based proxies of dishonesty/corruption are available.

United States Analysis We compared city-level wallet reporting rates to two measures of corruption. Our dishonesty index was constructed by extracting the first principal component from (1) the share of self-employed individuals in a city who reported an income in 2009 within U.S. $500 of the first Earned Income Tax Credit (EITC) kink relative to individuals with non-zero self-employment income, as a measure of cheating on taxes (Chetty, Friedman, and Saez 2013), and (2) the number of federal court convictions for corrupt practices between 1976 and 2002 per 10,000 public officials in the state that the city belongs to (Glaeser and Saks 2006). We use an identical regression specification to that in the main text, except that we restrict ourselves to U.S. data and cluster standard errors at the city-level.

Table A1 reports the relationship between wallet reporting rates and dishonest behavior. We find that a one standard deviation increase in our U.S. dishonesty index is associated with a 4.4 percentage point decrease in reporting a lost wallet ($p = 0.016$). Columns 2 and 3 illustrate that this pattern holds when examining each proxy measure of dishonest behavior separately (for these analyses we standardized each variable to have a mean of zero and SD of one, to facilitate comparison across models).

Italy Analysis We compared city-level wallet reporting rates to three measures of dishonesty. Our dishonesty index was constructed by extracting the first principal component from (1) municipality-level rates of compliance or payment of a television licensing fee (Buonanno et al. 2019), (2) the difference between the cumulative amounts of public money allocated to capital expenditures and existing amounts of physical infrastructure (Golden and Picci 2006), and (3) prosecutors' requests to proceed with a criminal investigation against members of Parliament (Nannicini et al. 2013). We use an identical regression specification to that in the main text, except that we restrict ourselves to data from Italy and cluster standard errors at the city-level.

Table A2 reports the relationship between wallet reporting rates and dishonest behavior. We find that a one standard deviation increase in our Italy dishonesty index is associated with a 7.0 percentage point decrease in reporting a lost wallet ($p = 0.001$). Columns 2-4 illustrate that this pattern holds when examining each proxy measure of dishonest behavior separately (for these analyses we standardized each variable to have a mean of zero and standard deviation of one, to facilitate comparison across models).

Table A1: Wallet Reporting Rates and Dishonesty (USA)

	(1)	(2)	(3)
Dishonesty Index	-4.403^{**}		
	(1.686)		
Cheating on Taxes		-3.446^{**}	
		(1.541)	
Corruption Convictions			-4.404^{**}
			(1.680)
Controls:			
Institution FE	yes	yes	yes
Recipient FE	yes	yes	yes
Situation FE	yes	yes	yes
Treatment FE	yes	yes	yes
Observations	970	1000	970
Cities	24	25	24

Notes: OLS estimates with city-clustered standard errors in parentheses. The dependent variable in all models takes a value of 100 if a wallet was reported and 0 otherwise. "Dishonesty index" is the first principal component from (1) "cheating on taxes": the share of self-employed individuals in a city who reports an income in 2009 within US $500 of the first Earned Income Tax Credit (EITC) kink, as a percentage of individuals with non-zero self-employment income, as a measure of cheating on taxes (Chetty, Friedman, and Saez 2013), and (2) "corruption convictions": the number of federal court convictions for corrupt practices between 1976 and 2002 per 10,000 public officials in each US state (Glaeser and Saks 2006). All explanatory variables are standardized to have a mean of zero and standard deviation of one. All models include controls for the type of institution the wallet drop-off was performed at, characteristics about the recipient of the lost wallet (gender, age), situational characteristics of the wallet drop-off (the presence of a computer, coworkers, or other bystanders), and treatment condition. For full details on control variables see Cohn et al. (2019). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Wallet Reporting Rates and Dishonesty (Italy)

	(1)	(2)	(3)	(4)
Dishonesty Index	-7.018^{***}			
	(1.593)			
TV Taxes		-3.663^{*}		
		(1.723)		
RAPs per Deputy			-7.171^{***}	
			(1.115)	
Golden-Picci score				-5.567^{**}
				(2.124)
Controls:				
Institution FE	yes	yes	yes	yes
Recipient FE	yes	yes	yes	yes
Situation FE	yes	yes	yes	yes
Treatment FE	yes	yes	yes	yes
Observations	400	400	400	400
Cities	16	16	16	16

Notes: OLS estimates with city-clustered standard errors in parentheses. The dependent variable in all models takes a value of 100 if a wallet was reported and 0 otherwise. "Dishonesty index" is the first principal component from (1) "tv taxes": municipality-level rates of failure to pay a television licensing fee (Buonanno et al. 2019), (2) "RAPs per deputy": historical data on prosecutors' requests to proceed with a criminal investigation against a member of parliament from the city's electoral district (Nannicini et al. 2013), and (3) "Golden-Picci score": the difference between the cumulative amounts of public money allocated to capital expenditures and existing amounts of physical infrastructure (Golden and Picci 2006). All explanatory variables are standardized to have a mean of zero and standard deviation of one. All models include controls for the type of institution the wallet drop-off was performed at, characteristics about the recipient of the lost wallet (gender, age), situational characteristics of the wallet drop-off (the presence of a computer, coworkers, or other bystanders), and treatment condition. For full details on control variables see Cohn et al. (2019). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Pairwise Correlations Between Survey Measures of Social Capital

Table A3: Country-level Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Generalized Trust	1.000						
(2) Trust (GPS)	0.666	1.000					
(3) Generalized Morality	0.513	0.232	1.000				
(4) Universal Moral Values	−0.006	−0.149	0.283	1.000			
(5) Norms of Civic Cooperation	0.461	0.360	0.327	0.244	1.000		
(6) Positive Reciprocity (GPS)	0.220	0.499	−0.111	0.230	0.290	1.000	
(7) Altruism (GPS)	0.207	0.536	−0.046	−0.133	0.449	0.716	1.000

6 Survey Measures and Wallet Reporting Rates

For all analyses in the main paper we regress wallet reporting rates on country-level variables of social capital using ordinary least squares (OLS) estimation. Observations are coded as 100 when a wallet was reported and 0 otherwise, and all survey measures are standardized at the country-level to have a mean of zero and standard deviation of one. With this coding scheme, regression coefficients can be interpreted as the percentage point difference in reporting rates associated with a one standard deviation change in the explanatory variable. For all models we also include fixed effects for treatment condition, institutional setting, and all recipient and situational characteristics recorded during the wallet drop-off. We adjust standard errors for clustering at the country-level, and also adjust *p*-values to control for the false discovery rate. Regression coefficients are provided in Table A4. Figure A2 illustrates that estimates based on the average marginal effects from a probit model are highly similar to those from our OLS model.

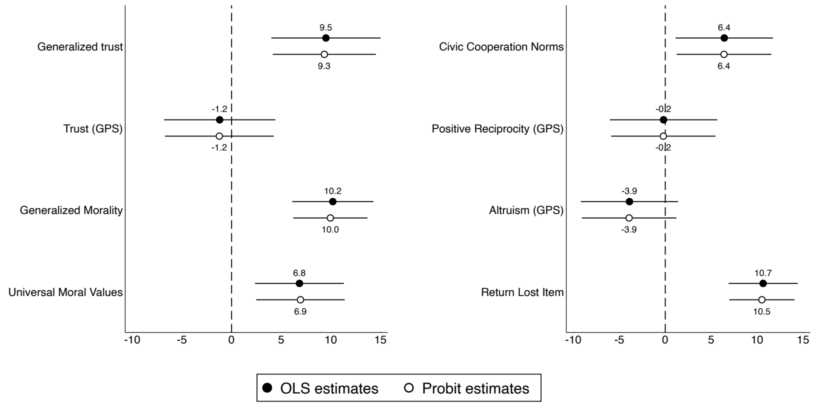
The OLS regressions in the main text also include an extensive number of controls, including controls for wallet recipient characteristics (e.g., gender, age), situational characteristics (e.g., the presence of a computer, coworkers, or other bystanders), institutional characteristics (e.g., whether the wallet was dropped off at a bank, cultural establishment, post office, hotel, or public office), and treatment condition (NoMoney vs Money). Figure A3 compares our estimates with controls to a baseline model that excludes these controls. As the figure illustrates, including controls in the model tends to modestly decrease coefficient estimates and does not change the rank-ordering of our social capital measures in predicting wallet reporting rates.

Table A4: Survey Measures and Wallet Reporting Rates

	Panel A			
	(1)	(2)	(3)	(4)
Generalized Trust	9.504***			
	(2.719)			
Trust (GPS)		−1.201		
		(2.766)		
Generalized Morality			10.199***	
			(2.019)	
Universal Moral Values				6.840***
				(2.202)
Controls:				
Institution FE	yes	yes	yes	yes
Recipient FE	yes	yes	yes	yes
Situation FE	yes	yes	yes	yes
Treatment FE	yes	yes	yes	yes
Observations	16,895	15,895	16,621	15,494
Countries	39	36	38	35
	Panel B			
	(5)	(6)	(7)	(8)
Civic Cooperation	6.426**			
	(2.615)			
Positive Reciprocity (GPS)		−0.187		
		(2.881)		
Altruism (GPS)			−3.895	
			(2.611)	
Return Lost Item				10.652***
				(1.859)
Controls:				
Institution FE	yes	yes	yes	yes
Recipient FE	yes	yes	yes	yes
Situation FE	yes	yes	yes	yes
Treatment FE	yes	yes	yes	yes
Observations	16,321	15,895	15,895	16,895
Countries	37	36	36	39

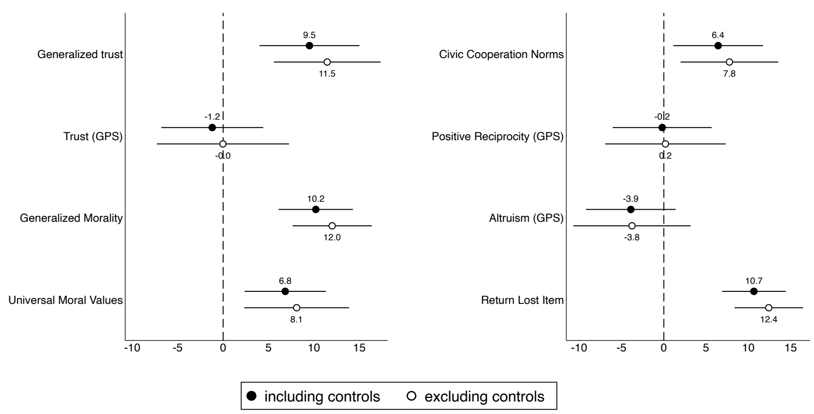
Notes: OLS estimates with standard errors clustered at the country-level. Observations represent whether an individual reported a lost wallet. The dependent variable in all models takes a value of 100 if a wallet was reported and 0 otherwise. All models include controls for the type of institution the wallet drop-off was performed at, characteristics about the recipient of the lost wallet (gender, age), situational characteristics of the wallet drop-off (the presence of a computer, coworkers, or other bystanders), and treatment condition. For full details on control variables see Cohn et al. (2019). Significance levels after correcting for the false discovery rate (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001): * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Figure A2: OLS vs. Probit Estimates



Notes: Regression estimates with 95% confidence intervals. Black circles represent coefficient estimates for a given explanatory variable when using OLS regression; white circles represent estimates based on the average marginal effect when using probit regression. Numbers next to each circle represent the coefficient value. The dependent variable in all models takes a value of 100 if the wallet was reported and 0 otherwise. To facilitate comparison, the marginal effects from the probit model are multiplied by 100 to match the scale of the OLS model. All models control for the type of institution the wallet drop-off was performed at, characteristics about the recipient of the lost wallet (gender, age), situational characteristics of the wallet drop-off (the presence of a computer, coworkers, or other bystanders), and treatment condition. For full details on control variables see Cohn et al. (2019).

Figure A3: OLS Estimates With Controls vs. Without Controls

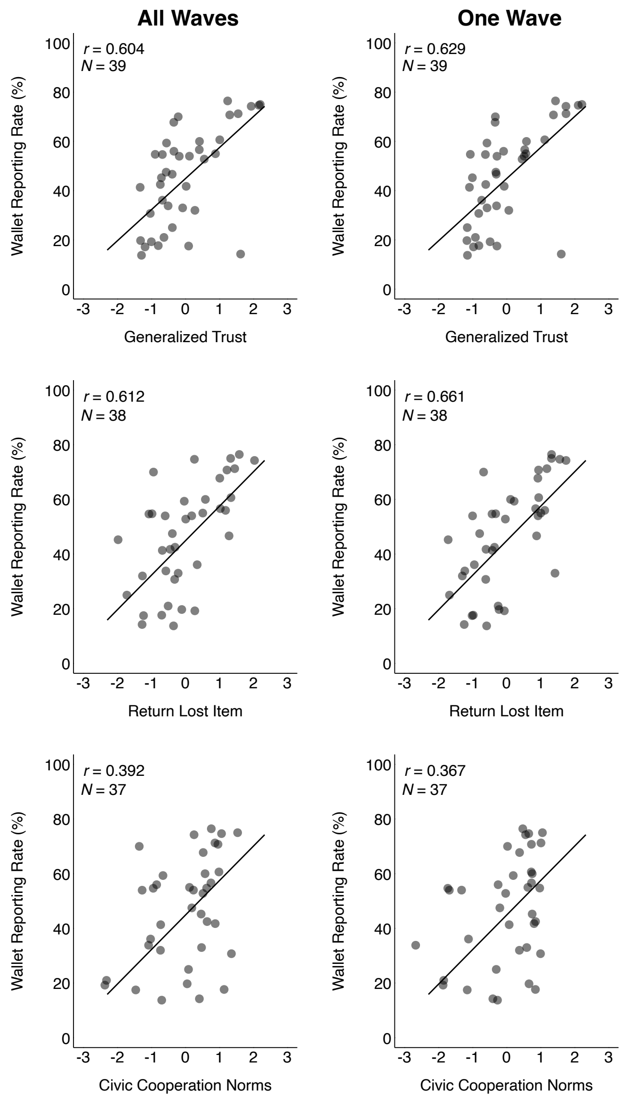


Notes: Regression estimates with 95% confidence intervals. Black circles represent OLS coefficient estimates for a given explanatory variable when additional controls are included in the model; white circles represent OLS estimates when additional controls are excluded from the model. Numbers next to each circle represent the coefficient value. The dependent variable in all models takes a value of 100 if the wallet was reported and 0 otherwise. All models control for the type of institution the wallet drop-off was performed at, characteristics about the recipient of the lost wallet (gender, age), situational characteristics of the wallet drop-off (the presence of a computer, coworkers, or other bystanders), and treatment condition. For full details on control variables see Cohn et al. (2019).

7 Robustness Test: Most Proximate EVS/WVS Wave For Each Country

For survey items from the WVS/EVS, we average responses across all available waves for each country. The WVS consists of seven waves collected from 1981 to 2020. The EVS consists of five waves collected from 1981 to 2017. Here we report results when only using WVS/EVS responses from the survey wave closest in time to when the lost wallet data was collected for each country. For countries where two survey wave are equally proximate, then we used the more recent dataset. For instance, if wallet data was collected in 2013 for a given country, and there is WVS data available for that country in 2011 and 2015, then we used the 2015 dataset. Figure A4 displays the country-level correlations when using all available waves from the EVS/WVS (as in our main analysis) to those same correlations when using only a single wave. Table A5 reproduces the same analysis from Table 2 in the main paper, for the three survey measures from the WVS/EVS.

Figure A4: Wallet Reporting Rates and Measures of Social Capital (All Waves vs One Wave)



Notes: Scatterplots display the country-level relationship between wallet reporting rates and (A) generalized trust from the World Values Survey (WVS) and European Values Study (EVS), (B) generalized morality ("respect and tolerance for others") from the WVS/EVS, and (C) index of norms of civic cooperation from the WVS/EVS (Guiso, Sapienza, and Zingales 2011). For each graph the y-axis represents wallet reporting rates in a given country (from 0-100%) and the x-axis represents the explanatory variable (standardized at the country-level to have a mean of 0 and standard deviation of 1). Lines represent the best fit to the data based on OLS estimation. The upper-left corner of each panel reports the country-level correlation between the outcome and predictor variable, as well as the number of countries in the analysis. The left panels display the correlation when averaging WVS/EVS responses over all available waves, whereas the right panels display the correlation using the survey wave closest in time to when lost wallet data was collected for each country.

Table A5: Predictive Value of Wallet Reporting Rates (One Wave Per Country)

	Log GDP per capita		Log Productivity (TFP)		Government Effectiveness		Letter Grade Efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generalized trust	0.482***	0.239***	0.150***	0.049	0.624***	0.433***	0.073	−0.025
	(0.090)	(0.064)	(0.047)	(0.057)	(0.074)	(0.093)	(0.040)	(0.038)
Wallets		0.386***		0.166**		0.304***		0.156***
		(0.090)		(0.052)		(0.090)		(0.049)
N	39	39	38	38	39	39	39	39
R^2	0.462	0.641	0.238	0.418	0.644	0.736	0.071	0.267
Generalized morality	0.358***	0.077	0.174***	0.109	0.553***	0.327**	0.101**	0.012
	(0.092)	(0.125)	(0.038)	(0.060)	(0.084)	(0.116)	(0.041)	(0.067)
Wallets		0.433***		0.101		0.347**		0.137*
		(0.133)		(0.062)		(0.115)		(0.070)
N	38	38	37	37	38	38	38	38
R^2	0.318	0.572	0.379	0.444	0.518	0.629	0.134	0.268
Civic cooperation	0.167*	−0.012	0.102***	0.038	0.267**	0.070	0.072	0.021
	(0.076)	(0.088)	(0.032)	(0.047)	(0.098)	(0.099)	(0.049)	(0.064)
Wallets		0.490***		0.162***		0.542***		0.138**
		(0.083)		(0.049)		(0.076)		(0.056)
N	37	37	36	36	37	37	37	37
R^2	0.067	0.567	0.126	0.378	0.120	0.543	0.065	0.273

Note: OLS estimates with robust standard errors in parentheses. Outcome variables are log GDP per capita, log total factor productivity (relative to the United States), government effectiveness ratings from the World Bank, and the proportion of incorrectly addressed international mail from a country that is returned to sender (Chong et al. 2014). All explanatory variables are aggregated at the country-level and standardized to have a mean of zero and standard deviation of one. Significance levels after correcting for the false discovery rate (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001): * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

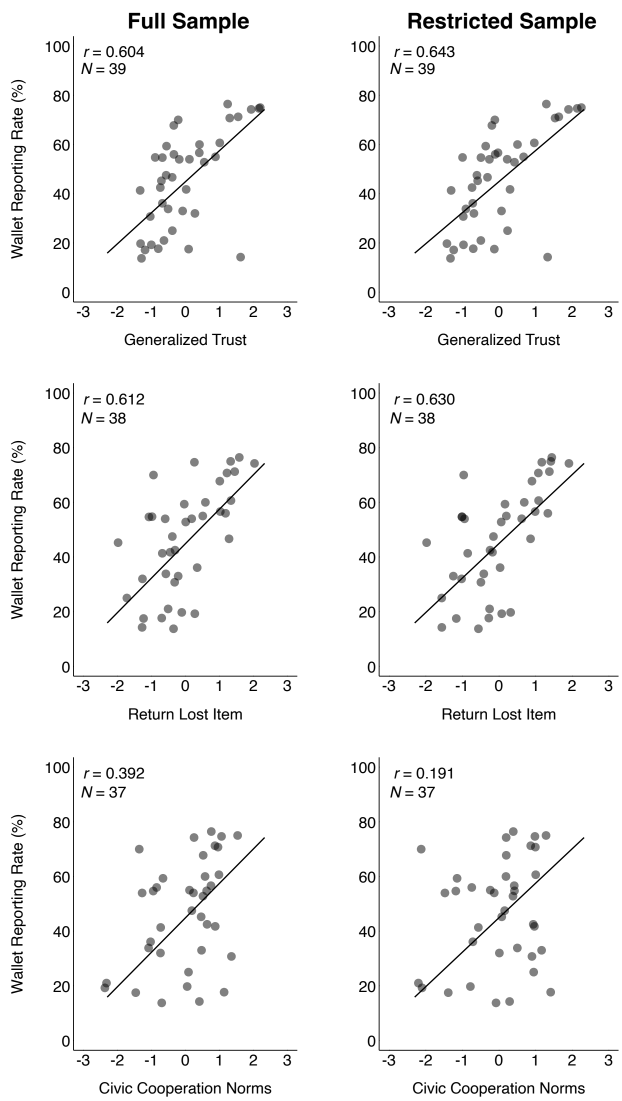
8 Robustness Test: Restricting EVS/WVS Respondents to More Closely Match Lost Wallet Data

Respondents in our lost wallet data were not representatively sampled from each country's population. Respondents were front-desk employees at public and private institutions, and we performed wallet drop-offs in larger cities (with populations of 100k or greater) within each country. By contrast, our survey measures come from data sets with nationally representative samples (with the exception of the Moral Foundations Questionnaire). Here we report results from a robustness test in which we compare coefficients for our WVS/EVS items with a restricted sample from the WVS/EVS that more closely resembles our front-desk workers based on demographic proxies available in the survey data. In particular, we restrict the sample to employed respondents who lived in a city population of 100k or greater.[7] These filters reduce the total sample of respondents by 84% (from 330,282 to 54,066 respondents).

We find qualitatively similar results when using a sample that more closely matches recipients in our lost wallet data: generalized trust and generalized morality remain our two strongest survey measures of wallet reporting rates, while norms of civic cooperation is a relatively weak predictor. Thus, differences in sample characteristics do not appear to meaningfully bias our results. Figure A5 displays the country-level correlations when using all available waves from the EVS/WVS (as in our main analysis) to those same correlations when using the restricted sample from the WVS/EVS. Table A6 reproduces the same analysis from Table 2 in the main paper, for the three survey measures from the WVS/EVS using the restricted sample.

7. For survey data from Kenya, which comes from the Afrobarometer, respondents were identified as living in an "urban" or "rural" environment. Since we do not have information on city size for these respondents, we use the urban designation as a replacement for living in a city with a population of 100k or greater. For survey data from Israel, information on city size was not available so we only screen on employment status for these respondents.

Figure A5: Wallet Reporting Rates and Measures of Social Capital (Full vs Restricted Sample)



Notes: Scatterplots display the country-level relationship between wallet reporting rates and (A) generalized trust from the World Values Survey (WVS) and European Values Study (EVS), (B) generalized morality ("respect and tolerance for others") from the WVS/EVS, and (C) index of norms of civic cooperation from the WVS/EVS (Guiso, Sapienza, and Zingales 2011). For each graph the y-axis represents wallet reporting rates in a given country (from 0-100%) and the x-axis represents the explanatory variable (standardized at the country-level to have a mean of 0 and standard deviation of 1). Lines represent the best fit to the data based on OLS estimation. The upper-left corner of each panel reports the country-level correlation between the outcome and predictor variable, as well as the number of countries in the analysis. The left panels display the correlation from the full sample of WVS/EVS respondents, whereas the right panels display the correlation from a restricted sample of respondents who are employed and live in a city of 100K or greater.

Table A6: Predictive Value of Wallet Reporting Rates (Restricted Sample)

	Log GDP per capita		Log Productivity (TFP)		Government Effectiveness		Letter Grade Efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generalized trust	0.471***	0.215***	0.142**	0.031	0.593***	0.380***	0.103**	0.022
	(0.086)	(0.070)	(0.044)	(0.054)	(0.064)	(0.085)	(0.039)	(0.048)
Wallets		0.399***		0.177***		0.333***		0.126**
		(0.088)		(0.059)		(0.086)		(0.056)
N	39	39	38	38	39	39	39	39
R^2	0.441	0.627	0.208	0.409	0.581	0.688	0.141	0.266
Generalized morality	0.407***	0.177*	0.213***	0.179***	0.595***	0.405***	0.098**	0.013
	(0.067)	(0.087)	(0.029)	(0.032)	(0.068)	(0.087)	(0.039)	(0.065)
Wallets		0.372***		0.054		0.307***		0.137*
		(0.109)		(0.037)		(0.095)		(0.071)
N	38	38	37	37	38	38	38	38
R^2	0.411	0.611	0.569	0.588	0.601	0.694	0.125	0.268
Civic cooperation	0.083	−0.009	0.056	0.028	0.209	0.104	0.078	0.052
	(0.100)	(0.082)	(0.039)	(0.046)	(0.115)	(0.090)	(0.050)	(0.052)
Wallets		0.487***		0.173***		0.547***		0.136***
		(0.073)		(0.041)		(0.071)		(0.043)
N	37	37	36	36	37	37	37	37
R^2	0.017	0.567	0.038	0.373	0.073	0.553	0.077	0.301

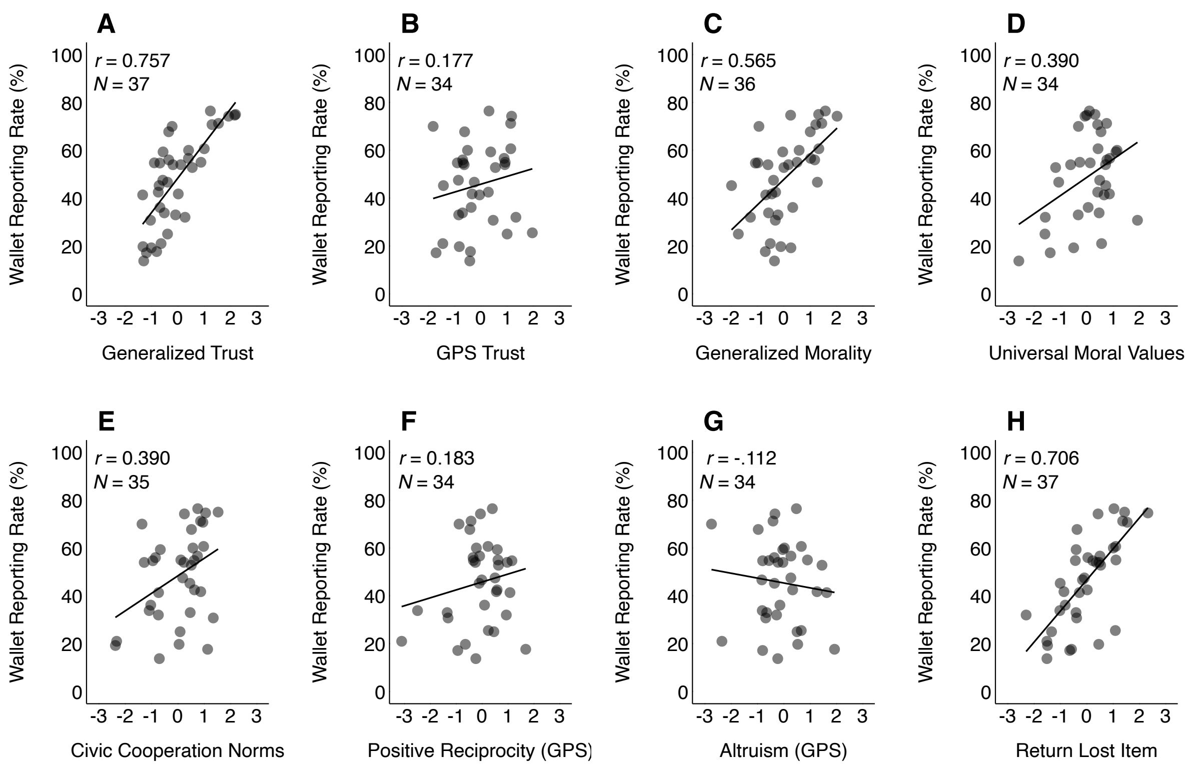
Note: OLS estimates with robust standard errors in parentheses. Outcome variables are log GDP per capita, log total factor productivity (relative to the United States), government effectiveness ratings from the World Bank, and the proportion of incorrectly addressed international mail from a country that is returned to sender (Chong et al. 2014). All explanatory variables are aggregated at the country-level and standardized to have a mean of zero and standard deviation of one. Significance levels after correcting for the false discovery rate (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001): * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

9 Robustness Test: Excluding China and Kazakhstan

Social capital researchers sometimes exclude China and Kazakhstan from cross-country comparisons, as the two countries appear to be outliers. Here we report results when these two countries are excluded from the data set. Figure A6 graphically displays correlations between survey measures of social capital and wallet reporting rates. Table A7 reproduces the same analysis from Table 2 in the main paper. As can be seen from the figure and table, we find qualitatively similar results when excluding the two countries.

To quantify the relative contribution of wallet reporting rates in explaining economic outputs, we also performed a series of dominance analyses (Azen and Budescu 2003; Budescu 1993) similar to that in the main paper. We conducted a dominance analysis for all 32 comparisons provided in Table A7 (eight multivariate models for each of our four outcome variables). We find that wallet reporting rates contribute the majority of variance explained in 28 of the 32 models. In 20 of the comparisons, wallet reporting rates outperform its survey counterpart by more than a factor of two. Thus, a country's propensity to report a lost wallet appears to contain considerable new information above existing survey measures in explaining cross-country differences in economic performance.

Figure A6: Wallet Reporting Rates and Measures of Social Capital (Excluding China and Kazakhstan)



Notes: Scatterplots display the country-level relationship between wallet reporting rates and (A) generalized trust from the World Values Survey (WVS) and European Values Study (EVS), (B) generalized trust from the Global Preferences Survey (Falk et al. 2018), (C) generalized morality ("respect and tolerance for others") from the WVS/EVS, (D) universal moral value scores from the Moral Foundations Questionnaire (Enke 2019; Graham et al. 2011), (E) an index of norms of civic cooperation from the WVS/EVS (Guiso, Sapienza, and Zingales 2011), (F & G) positive reciprocity and altruism scores from the Global Preferences Survey, and (H) expectations about having a lost item returned from the World Risk Poll. For each graph the y-axis represents wallet reporting rates in a given country (from 0-100%) and the x-axis represents the explanatory variable (standardized at the country-level to have a mean of 0 and standard deviation of 1). Lines represent the best fit to the data based on OLS estimation. The upper-left corner of each panel reports the country-level correlation between the outcome and predictor variable, as well as the number of countries in the analysis.

Table A7: Predictive Value of Wallet Reporting Rates (Excluding China and Kazakhstan)

	Log GDP per capita		Log Productivity (TFP)		Government Effectiveness		Letter Grade Efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Generalized trust	0.525***	0.217**	0.169**	0.060	0.654***	0.484***	0.105***	0.011
	(0.080)	(0.082)	(0.036)	(0.054)	(0.059)	(0.102)	(0.032)	(0.050)
Wallets		0.406***		0.148**		0.224*		0.124
		(0.111)		(0.061)		(0.101)		(0.067)
N	37	37	36	36	37	37	37	37
R^2	0.518	0.652	0.310	0.415	0.677	0.711	0.149	0.240
Trust (GPS)	0.410**	0.327**	0.121*	0.075	0.424***	0.340***	0.016	−0.006
	(0.132)	(0.115)	(0.062)	(0.054)	(0.113)	(0.081)	(0.052)	(0.043)
Wallets		0.479***		0.179***		0.483***		0.125**
		(0.097)		(0.052)		(0.075)		(0.049)
N	34	34	32	32	34	34	34	34
R^2	0.281	0.639	0.130	0.402	0.281	0.621	0.003	0.184
Generalized morality	0.398***	0.163**	0.191***	0.146***	0.603***	0.409***	0.069	−0.012
	(0.062)	(0.067)	(0.027)	(0.031)	(0.074)	(0.081)	(0.038)	(0.047)
Wallets		0.420***		0.082*		0.346***		0.145**
		(0.099)		(0.038)		(0.079)		(0.057)
N	36	36	35	35	36	36	36	36
R^2	0.366	0.639	0.478	0.530	0.582	0.710	0.062	0.244
Universal moral values	0.259*	0.053	0.164***	0.101	0.160	−0.091	0.100*	0.059
	(0.119)	(0.086)	(0.050)	(0.063)	(0.135)	(0.077)	(0.045)	(0.045)
Wallets		0.514***		0.158***		0.626***		0.102***
		(0.096)		(0.047)		(0.084)		(0.032)
N	34	34	34	34	34	34	34	34
R^2	0.130	0.591	0.268	0.491	0.037	0.546	0.151	0.291
Civic cooperation	0.213**	0.017	0.133***	0.081	0.292**	0.080	0.105*	0.061
	(0.088)	(0.091)	(0.038)	(0.054)	(0.117)	(0.107)	(0.046)	(0.057)
Wallets		0.507***		0.136**		0.550***		0.115*
		(0.083)		(0.049)		(0.070)		(0.054)
N	35	35	34	34	35	35	35	35
R^2	0.105	0.602	0.233	0.418	0.138	0.548	0.144	0.286
Positive reciprocity (GPS)	0.152	0.061	0.002	−0.031	0.141	0.047	0.031	0.010
	(0.120)	(0.093)	(0.051)	(0.044)	(0.110)	(0.072)	(0.039)	(0.049)
Wallets		0.526***		0.204***		0.535***		0.122**
		(0.113)		(0.046)		(0.091)		(0.049)
N	34	34	32	32	34	34	34	36
R^2	0.041	0.472	0.000	0.366	0.033	0.449	0.013	0.185
Altruism (GPS)	0.085	0.145	0.022	0.033	0.078	0.138	−0.011	0.003
	(0.132)	(0.102)	(0.049)	(0.050)	(0.139)	(0.093)	(0.035)	(0.040)
Wallets		0.555***		0.200***		0.560***		0.124**
		(0.115)		(0.049)		(0.079)		(0.047)
N	34	34	32	32	34	34	34	34
R^2	0.013	0.502	0.005	0.367	0.010	0.476	0.001	0.184
Return lost item	0.447***	0.174	0.182***	0.070	0.554***	0.336**	0.090**	−0.004
	(0.076)	(0.185)	(0.023)	(0.053)	(0.078)	(0.120)	(0.036)	(0.072)
Wallets		0.399		0.145		0.319**		0.137
		(0.214)		(0.075)		(0.126)		(0.074)
N	37	37	35	35	37	37	37	37
R^2	0.375	0.516	0.387	0.461	0.512	0.592	0.117	0.244

Note: OLS estimates with robust standard errors in parentheses. Outcome variables are log GDP per capita, log total factor productivity (relative to the United States), government effectiveness ratings from the World Bank, and the proportion of incorrectly addressed international mail from a country that is returned to sender (Chong et al. 2014). All explanatory variables are aggregated at the country-level and standardized to have a mean of zero and standard deviation of one. Significance levels after correcting for the false discovery rate (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001): * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

10 Correcting for Measurement Error

We use a technique suggested by Gillen, Snowberg, and Yariv (2019) to correct for the role of measurement error. This requires separate and near-identical measurement of the dependent variable (wallet reporting rates) and predictor variable (generalized trust). For each variable we conduct an "obviously related" instrumental variables regression (ORIV) with the original measurement instrumented by the replicant measurement. The resulting estimate corrects for measurement error. We then adjust the country-level correlation between wallet reporting rates and generalized trust based on these unbiased estimates.

We restrict our analysis to countries in which we had measures of both generalized trust and trust in strangers ($n = 37$). Generalized trust (our predictor variable) was highly correlated with trust in strangers ($r = 0.814$) so we instrumented one variable onto the other. For wallet reporting rates (our dependent variable), recipients in all countries were randomly assigned to either a wallet containing no money or some amount of money. Among the 37 countries in our retained data set the correlation between the No-Money and Money conditions is 0.943, so we instrumented reporting rates in one condition onto the other condition. As suggested by Gillen, Snowberg, and Yariv (2019), we perform a stacked regression in which each variable serves as both an instrument and an instrumented variable, and then split the difference between the two estimates. We then adjust the country-level correlation based on these estimates. Using this procedure, we find that the country-level correlation between generalized trust and wallet reporting rates increases from 0.584 (without correction) to 0.692 (with correction).

11 Dominance Analysis

Table A8 shows the results from dominance analyses for all multivariate models reported in Tables 2 of the manuscript. Dominance analysis (Azen and Budescu 2003; Budescu 1993) is an algorithmic approach to determining the relative contribution of predictors in explaining the variance captured by a regression model. For each multivariate model, the algorithm performs all comparisons with and without the inclusion of a predictor and calculates the average marginal improvement in the R-squared when that predictor is included in the model. This statistic is then normalized so that the sum of all predictors adds up to 1. For instance, Table 2 in the main text reports an R-squared of 0.634 when generalized trust and wallet reporting rates are used to predict GDP per capita. The results reported in Table A8 indicate that wallet reporting rates contribute 61.4% to that explained variation, and generalized trust contributes 38.6%.

Table A8: Dominance Analysis

	Log GDP (1)	Log TFP (2)	Government Effectiveness (3)	Letter Grade (4)
Wallets	61.4	77.3	48.2	84.9
Generalized Trust	38.6	22.7	51.8	15.1
Wallets	69.2	92.3	69.7	98.2
Trust (GPS)	30.8	07.7	30.3	1.8
Wallets	66.6	39.3	45.5	84.2
Generalized Morality	33.4	60.7	54.5	15.8
Wallets	86.9	61.0	94.1	61.4
Universal Moral Values	13.1	39.0	05.9	38.6
Wallets	92.1	75.0	85.0	77.7
Norms of Civic Cooperation	7.9	25.0	15.0	22.3
Wallets	95.1	98.3	97.2	99.7
Positive Reciprocity (GPS)	4.9	1.7	2.8	0.3
Wallets	94.6	98.9	95.5	96.4
Altruism (GPS)	5.4	1.1	4.5	3.6
Wallets	59.3	59.7	52.0	79.0
Return Lost Items	40.7	40.3	48.0	21.0

Notes: The table reports the results of a dominance analysis between each explanatory variable and wallet reporting rates for (1) log GDP per capita, and (2) log total factor productivity (relative to the United States), (3) government effectiveness ratings from the World Bank, and (4) letter grade efficiency scores from Chong et al. (2014). For each pair of explanatory variables, numbers represent the percentage contribution of that variable to the total R^2 (with pairs adding up to 100%). All variables are standardized at the country-level to have a mean of 0 and standard deviation of 1.

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