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Affinity, Trust, and Information

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Abstract

Mutually beneficial trades often rely on both trust and trustworthiness. In exchanges where no history of behavior is observable, however, where does trust come from? Recent evidence suggests that the level of affinity parties in an exchange feel for each other positively affects trustworthiness and can, therefore, affect trust. We propose a simple model that predicts a positive relationship between trust beliefs, affinity, and trustworthiness and a negative relationship between the dispersion of trust beliefs and affinity level. Furthermore, the model suggests that trust should be slower to update after a shock to trustworthiness when affinity is high. We show that the model's predictions are supported by data from two unrelated datasets—a proprietary survey of Italian entrepreneurs and an extensive international survey (Eurobarometer). Finally, using data on international trade, we show that, in line with our model, adverse shocks to trustworthiness cause a reallocation of trade from low-affinity to high-affinity partners, and especially so in trust-intensive industries.

JEL: Z1, D8, D83, D9, F1

Keywords: Trust, Affinity, Trustworthiness, Information Acquisition

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1 Introduction

Pat meets Kelly for the first time. This meeting involves a potentially profitable exchange for both people. Kelly could cheat Pat, however, so the profitability of this exchange depends both on Pat's trust and on Kelly's trustworthiness. But Pat knows nothing about Kelly. In particular, Pat has no information stemming from previous interactions with Kelly. How does Pat infer Kelly's trustworthiness? If information about Kelly's reliability becomes available, how is Pat going to use it? And if this information is available at a cost, will Pat try to acquire it?

People face situations of this sort all the time: when taking a cab, when being introduced to a new person, when renting an apartment from an agent, or when meeting the owner of an apartment for sale. In all these cases, one has to figure out how reliable a stranger is before deciding whether to get in a cab, hire a particular agent, buy a house, and so on. We rely on this inferential process so routinely that sometimes we are not even aware of it.

Evidence has shown that in situations like these, people tend to trust more those who are (or appear to be) similar to themselves along some dimension, i.e., those toward whom they feel more affinity. In a remarkable study, DeBruine (2002) shows that manipulating the facial resemblance of one's partner in a two-person trust game enhances trust. On the other hand, randomly matching control subjects with these same (fictitious) partners did not enhance trust. On a larger scale, using a general survey on bilateral trust between nations, Guiso et al. (2009) find that trust in people from other countries is enhanced when both the genetic or the cultural distances between the two populations are small. Interestingly, this study implies that the channels through which affinity enhances trust are not limited to phenotype matching—as in DeBruine (2002)—but also apply to other dimensions of relatedness, such as cultural or religious affinity, that cut across genetic differences.[1]

But why does trust increase with affinity? And does affinity affect how people react to signals about the potential partner's reliability, either when they are freely observable or observable at a cost? In this paper, we propose a theoretical model to address these questions and obtain a number of predictions that we confront with data from two independent datasets.

In our model, when a person is matched and interacts with another person, predation can occur. Predation yields a benefit to the predator and inflicts a cost on the prey. However, the benefit from predation decreases with the affinity one feels with the (potential) prey. Individuals observe the

[1] Researchers also find that it is trust-enhancing to match partners on race, nationality, and ethnicity in the context of laboratory and field experiments (e.g., Glaeser et al., 2000; Fershtman and Gneezy, 2001). In cross-section data, trust is found to be lower in ethnically fragmented and income unequal societies (Alesina and La Ferrara, 2002; Tesei, 2015). Finally, studies document the prevalence of co-ethnic bias in highly trust-intensive industries, such as international trade (Rauch and Trindade, 2002) and finance (Hegde and Tumlinson, 2014; Hjort et al., 2019).

affinity their opponents feel toward them before they decide whether or not to trust. In addition, individuals also receive a signal about their opponents' reliability. Reliability is an individual trait that captures heterogeneity in trustworthiness across individuals of the same level of affinity and, thus, allows for variation in trust beliefs and behavior across individuals, holding affinity constant.

The assumption that affinity decreases benefits from predation gives rise to a positive relationship between trust and affinity, like that documented in DeBruine (2002) and Guiso et al. (2009). It also generates a positive correlation between affinity and trustworthiness, which has recently started to receive empirical support.[2] One may think of this assumption as due to a genetically acquired behavior dictated by the instinct of species preservation. In nature, animals of a given species rarely prey upon animals of the same species: dogs do not eat other dogs (*canis canem non est*). Hence, threats to survival often come from other groups rather than from members of the same group, and so, continuing with the proverb, a dog should place less "trust" in other animals and more in other dogs. Alternatively, it can be rationalized in terms of Hamilton's (1964) inclusive fitness hypothesis, according to which an organism may increase its evolutionary success by promoting the reproduction and survival of related or otherwise similar organisms.[3]

The baseline model generates two novel predictions. First, it suggests that the variability of trust beliefs decreases with affinity. That is, people paired with opponents who are deemed very similar tend not only to trust them *more* but to trust them *more surely*. Additionally, the model implies different reactions to information about an opponent's reliability depending on affinity: bad news about reliability lowers trust more the lower affinity is. High-affinity individuals have less scope to revise their trust beliefs downward when receiving negative information regarding the trustworthiness of the opponent.

Lastly, we extend our model to include endogenous costly information acquisition. We allow individuals to have perfect information about their partners' reliability at a fixed, positive cost. We show that the value of (perfect) information is hump-shaped in affinity, and that affinity eventually drives out information acquisition for any positive cost, no matter how low. With costly endogenous information acquisition, the cross-sectional dispersion in beliefs, besides decreasing in affinity, is

[2] Fisman et al. (2017) find evidence that affinity affects trustees' behaviors. They randomly pair loan officers and borrowers and find that pairing officers and borrowers of the same ethnic/cultural group affects both lenders' and borrowers' behavior. Loan officers extend more credit, and borrowers are more likely to repay. This suggests that affinity affects both sides of the trust relationship, rationalizing our model's mechanism.

[3] Under the inclusive fitness hypothesis, an opponent's incentive to act selfishly may be tempered by similarity with one's opponent. When the partner anticipates this incentive, it increases the partner's willingness to trust. Behavior consistent with the inclusive fitness hypothesis has been observed in animals. A classic example is Belding's squirrel, which gives an alarm call to warn its group of the presence of a predator (see Sherman, 1981). By emitting the alarm, the squirrel puts itself into increased danger as it reveals its location; in this way, however, the squirrel protects its relatives that live within the population.

also decreasing in the cost of information gathering. However, because affinity drives out information acquisition, the negative effect of the information cost is attenuated at higher affinity levels.

To test our model's predictions, we use two datasets: a proprietary survey of entrepreneurs and the Eurobarometer survey. The first dataset collects information on a sample of small Italian entrepreneurs interviewed in 2008–2009. An interesting feature of this dataset is that interviewers, who were randomly assigned to the entrepreneurs, were asked at the end of the interview to express their trust of the interviewed entrepreneurs and their perceived degree of affinity between them. The survey also collected a number of phenotype characteristics, such as eye color and height, as well as information on the place of birth, education, gender, and age for both the entrepreneur and the interviewers. We use these characteristics to construct measures of similarity between interviewers and entrepreneurs and validate the self-reported affinity measure. The Eurobarometer survey contains individual-level information on trust toward other people from their own country and a list of other countries. We combine these data with measures from Guiso et al. (2009) of the genetic and cultural distance across different nations.

In both surveys, the patterns are remarkably similar and consistent with our model's implications. First, we find support for the relationship between affinity and the first two moments of trust. In the entrepreneur survey, interviewers tend to trust entrepreneurs more when they report higher perceived affinity, and, further, the cross-sectional standard deviation of these trust beliefs is considerably lower for higher affinity levels. In the Eurobarometer sample, bilateral trust tends to be higher between genetically or culturally similar nations, as in Guiso et al. (2009). Most importantly, and so far undocumented, the standard deviation of trust beliefs of people in country i toward people in country j is smaller for countries that are closer either genetically or culturally.

To test whether affinity induces a differential response to information about opponents' trustworthiness, we exploit geographical variation in adverse economic shocks, leveraging recent findings that economic crises are detrimental for trust (e.g., Algan et al., 2017; Ananyev and Guriev, 2019; Graeber and Zimmermann, 2019). In both the entrepreneur survey and the Eurobarometer, we document that a negative economic shock suffered by the respondent's community lowers people's trust toward a given counterpart, but less so when affinity with the counterpart is high. Put differently, high affinity attenuates the mistrust consequences of negative news about others' trustworthiness. To test the model's implications when information entails an acquisition cost, we exploit cross-country variation in the cost of information-gathering in the Eurobarometer data. We find evidence consistent with the model's predictions: dispersion of trust beliefs is smaller when information is more costly to gather, but this effect is contained at higher affinity levels.

The effects are economically relevant: in the entrepreneur sample, a one-standard-deviation increase in affinity is associated with a 0.55-standard-deviation increase in people's trust in the entrepreneur sample, a 0.94-standard-deviation decline in the cross-sectional dispersion of beliefs, and a 12% attenuation of a negative news shock to people's reliability. Similar effects are observed in the Eurobarometer sample. In the latter, a one-standard-deviation-increase in the cost of gathering information is associated with a 0.16-standard-deviation decline in beliefs' dispersion.

Finally, we show that affinity matters for the success of economic interactions. Specifically, we find that, in the entrepreneur survey, interviewed entrepreneurs were more likely to disclose sensitive information when approached by high-affinity interviewers. This suggests that the survey completion rates could have been improved if one assigned interviewers based on affinity, proxied by the closeness of observable characteristics, as opposed to the random assignment.

Our findings are of interest for several reasons. First, from a general economic perspective, if trust is driven by affinity, at least in part, it is a natural force that would keep trade within close boundaries by acting as an impediment to geographically distant trade: it is simply easier to find similar people within a limited geographical radius. This helps explain why trade in goods and allocation of assets have a strong home bias (Lewis, 1999; Obstfeld and Rogoff, 2000). This tendency, in general, lowers the amount of trade because it limits the number of potential trade partners, a feature related to Dixit (2003). However, while in Dixit (2003) distance is a given, here we provide a rationale for what generates local bias.

Second, our results also shed light on the patterns of exchanges over time. Because trust beliefs respond less to bad news about an opponent's reliability if affinity with him or her is high, when a pool of potential opponents is hit by negative news, such as during a global crisis, trust towards low-affinity members drops more relative to high-affinity members. Hence, following shocks to aggregate trustworthiness, exchanges are predicted to reallocate away from low-affinity to high-affinity pairs. We find supportive evidence for this prediction. Using international trade data in our cross-country panel, we show that, following the financial crisis and the resulting decline in trust, international trade growth falls overall but falls less vis-a-vis high-affinity partners, implying a flight in trade from low-affinity to high-affinity country-pairs. In turn, this differential decline is more pronounced in trade of differentiated and more trust-intensive products.[4]

Our paper is related to but is distinct from the literature on familiarity as a driver of trust (e.g., Gefen, 2000; Luhmann, 2000; Huberman, 2001). Familiarity—which arises when somebody is

[4]This finding is related to the literature on international trade and shocks to partners' trustworthiness, e.g., during armed conflict (Macchiavello and Morjaria, 2015; Korovkin and Makarin, 2019). Our results are also related to Nunn et al. (2018), who find that economic shocks lead to political turnover in countries with lower levels of trust. However, a closer test of our theory would be to see whether politicians who come to power as a result of this turnover tend to have higher affinity with the median voter.

known from long, close association—and affinity are obviously related. Members of a family share a high degree of affinity and are familiar with each other. In this case, it is blood affinity that causes familiarity. Familiarity is also about acquaintance with a person and may arise even among people that initially lack affinity. It may also be that the more acquainted one becomes with a person, the more one knows about his or her shortcomings, and the more easily he or she dislikes that person. Thus, while affinity breeds trust, familiarity may also breed contempt and mistrust (for evidence, see, e.g., Norton et al., 2007). Moreover, if familiarity is acquired through information, our model predicts that whenever information is costly to acquire, affinity may even lower familiarity: affinity acts as a substitute for information collection. Bernie Madoff's Jewish clients were unfamiliar with finance and did not become more familiar with the financial management of their investments when they entrusted their life savings to Madoff. They simply trusted Madoff because of their high affinity with him due to their shared religion and ethnicity (Gurun et al., 2018).[5]

Our paper is also related to the Gambetta and Hamill (2005) "signaling" theory of trust. In their book *Streetwise: How Taxi Drivers Establish Customer's Trustworthiness*, they argue that when lacking prior knowledge, a trustor (a taxi driver) infers the trustworthiness of a trustee (a client) from some observable signals.[6] However, an issue remains of whether and when a trustor trusts those signals, particularly when the trustee sends them, as they may be intentionally distorted to extract the trustor trust. In our model, affinity is the relevant feature that leads the trustor to trust the signals he or she receives about the trustee's reliability. Insofar as affinity is based on traits that are hard to mimic, such as somatic similarity, it helps filter the signals. In our model, we obtain testable implications of this role of affinity and provide supporting evidence.

The rest of the paper is organized as follows. Section 2 sets up a simple model and derives several potentially testable implications about affinity and trust. Section 3 describes the survey data. Section 4 shows the results of the estimates of the model implications. Section 5 puts the results in perspective. Section 6 concludes.

2 Theory

To understand the interplay between affinity, trust, and information, we construct a simple model. We assume a finite population of $2N$ individuals. The timing is as follows. First, each individual in the population is randomly paired with another individual to form N pairs. Upon being paired, both individuals discover the level of affinity they feel with each other. Each individual has

[5]As evident from the Madoff example, affinity may matter most in minority groups and groups of smaller size. However, to test this hypothesis, one would need more granular data than the two surveys analyzed in this paper.

[6]The authors describe the taxi market before the rise of Uber-like ride-hailing platforms, i.e., when information asymmetries were much more acute.

	P	$\neg P$
T	$(0, b_2(P))$	$(b_1(\neg P), b_2(\neg P))$
$\neg T$	$(\xi, 0)$	$(\xi, 0)$

Table 1: Monetary Payoffs

some inherent reliability, which is their private information. Each player does, however, obtain a noisy signal about their counterpart's reliability. Finally, each pair has an opportunity for a mutually beneficial trade, the outcome of which depends on the actions of both parties.

The stage game faced within each pair is represented by a sequential-moves game in which one member of the pair moves first and can create surplus, while the other member observes the action of the first-mover and decides whether to act as a predator. In other words, each pair engages in a trust game. Call the first-mover player 1, the second-mover player 2, and think of a predatory action as absconding with the entire created surplus.

Player 1 is endowed with a small starting fund, $\xi > 0$. Player 1's action set consists of two actions: $T(rust)$ or $\neg T(rust)$. If player 1 chooses $\neg T$, i.e., not to trust, the game ends, zero additional surplus is created, and neither player earns or loses any money. On the other hand, if player 1 chooses T, then positive surplus is created but player 2 controls how the surplus is distributed. Specifically, player 2's action set consists of two options: $P(redator)$ or $\neg P(redator)$. If player 2 chooses to act as a predator—i.e., chooses P—then player 2 absconds with the entire surplus. The payoffs for player 1 and player 2 in this case are 0 and $b_2(P) > 0$, respectively. On the other hand, if player 2 chooses $\neg P$, i.e., not to be a predator, then both player 1 and player 2 receive a positive amount of money, $b_1(\neg P)$ and $b_2(\neg P)$, respectively.

There are four possible outcomes. The strategic form of this game in terms of monetary payoffs appears in Table 1, where player 2 is the column player. To turn this into a situation that involves trust, we assume that $b_1(\neg P) > \xi$ and that $b_2(P) > b_2(\neg P)$.

Now that the game is in monetary terms, we must next translate monetary earnings into utility in a way that incorporates affinity. To do this in a straightforward manner, we assume that player 2's utility depends on two additional factors. First, preying on those with whom one feels more affinity is more odious: *canis canem non est*. Second, we allow for individual-specific heterogeneity in reliability. Being more reliable makes money earned from being a predator less satisfying. We can think of differences in reliability as stemming from individual-specific differences in adherence to shared cultural norms or in opportunities to take advantage of others.

First, we introduce the role of affinity. Denote by A_{21} the level of affinity that player 2 feels toward player 1. We assume symmetry in affinity, i.e., that $A_{21} = A_{12} = A$ and, as a result, A_{21}

	P	$\neg P$
T	$(0,(1-A)b_2(P)-R_2)$	$(b_1(\neg P), b_2(\neg P))$
$\neg T$	$(\xi,0)$	$(\xi,0)$

Table 2: The Game in Utility Terms

is known to player 1 as well.[7] We assume that A lies within the unit interval, $[0,1]$, for every pair of players. Higher values of A denote more affinity: a value of 0 denotes minimum affinity, while an affinity level of 1 denotes maximum affinity. Think of affinity as measuring genetic or cultural distance. Consistent with this interpretation, we assume that preying on individuals with whom one feels more affinity entails higher psychological costs than preying on an individual with whom one feels less affinity. Specifically, to get player 2's utility from choosing to be a predator, we scale down monetary earnings conditional on choosing P by a factor of $1-A$. That is, the marginal contribution of money to player 2's utility from acting in a predatory fashion is $1-A \leq 1$. Finally, since our interest is in comparing the distribution of trust across affinity levels, we rule out heterogeneity coming from the relative prevalence of some affinity levels in the population by supposing that there are M realized affinity classes, each containing the same number of pairings.

Next, we introduce the role of reliability, an individual-specific trait that captures heterogeneity in trustworthiness across individuals of the same level of affinity. This feature allows for variation in trust beliefs and behavior across individuals, holding affinity constant. We assume that each person in the role of player 2 has an idiosyncratic level of reliability, R_2, which is independently and identically distributed with a commonly known distribution, $F(\cdot)$. To put reliability and affinity on the same scale, we assume that the support of $F(\cdot)$ is the unit interval, $[0,1]$. We model the impact of reliability by subtracting R_2 from player 2's utility whenever he or she chooses to act as a predator. Incorporating these modifications yields the strategic form representation in terms of utility given in Table 2.

Player 2 strictly prefers to prey on player 1 whenever:

$$(1-A)b_2(P) - R_2 > b_2(\neg P) \ .$$

To allow for reliability and affinity to each play a part in player 2's decision, we assume that $b_2(\neg P) < b_2(P)$. In the absence of this assumption, player 2 always prefers not to be a predator. Rearranging terms, we can express the conditions under which player 2 prefers acting as a predator in terms of an upper bound on reliability. In the following equation, the left-hand side is the utility cost of acting as a predator, while the right-hand side can be thought of as the utility benefit from

[7] In Section 5.1, we present evidence that this symmetry holds in the data.

acting in a predatory manner:

$$R_2 \leq (1-A)b_2(P) - b_2(\neg P) \ .$$

Finally, player 1 obtains a noisy signal about their partner's reliability. In particular, the true distribution of reliability in the population is commonly known, and each player 1 receives a partially informative signal from this distribution before making their decision. We denote the common set of signals by $S = \{s_1, s_2, \dots, s_k\}$. We denote the posterior distribution invoked by signal s_j as $G(\cdot|s_j), \forall j \in \{1, \dots, k\}$. Since the prior distribution function over reliability levels, $F(\cdot)$, is the same across individuals, the posterior distribution function generated by any particular signal, $G(\cdot|s_j)$, will be identical across individuals as well and, in particular, will be independent of the match affinity A. Finally, to rule out trust heterogeneity across affinity levels coming strictly from differences in information, we assume that the conditional distributions of signals are identical across affinity.[8]

2.1 Trust in the Population

In the model, we define trust in a natural way: trust is player 1's belief about the probability that player 2 acts in a predatory fashion. Thus, trust is defined in terms of beliefs rather than observed actions.[9] To fix the notation, we denote as τ player 1's belief about how likely player 2 is to choose $\neg P$. Applying the posterior distribution introduced above, for a given signal, s_j, trust is then $\tau = 1 - G[(1-A)b_2(P) - b_2(\neg P)|s_j]$.

We can now examine how both the average level of trust and the dispersion of trust in such a population of players varies with affinity. First, we can show that the average level of trust increases with affinity. Second, under mild restrictions on the set S of realized signals and using the range of realized trust beliefs as our measure of dispersion, we show that the dispersion of trust beliefs in the population decreases with affinity.

Proposition 1. *The average level of trust in pairs with affinity level A is greater than the average level of trust in pairs with affinity level A' whenever $A > A'$.*

Proof. In the Appendix. □

Proposition 1 relies simply on the fact that cumulative distribution functions are increasing. To prove the next proposition, we introduce the following assumption:

[8]These are sufficient conditions that allow us to prove the results in this section. Some of them are not strictly necessary, as will be seen in the proofs, but they make the proofs straightforward.

[9]The latter definition is also common but is not the focus of this paper. The definition we use has the advantage that it provides an obvious measure of trust intensity on a scale of zero to one.

Assumption 1. *At the lowest affinity level, $A = 0$, there is at least one signal in the set S of realized signals about R_2 that creates full trust: $\tau = 1$.*

While this assumption may seem restrictive, it has a natural interpretation: some pieces of information, such as third-party guarantees or any other types of hard evidence, can induce full trust even if affinity is extremely low. Moreover, it is consistent with our survey data, which show that full trust is indeed reported at any level of affinity, no matter how low (see Figure 1). Given this assumption, the mapping from affinity to trust is essentially a contraction mapping, which immediately yields the following proposition:

Proposition 2. *Suppose Assumption 1 holds. Define the dispersion of trust beliefs as a range between the minimum and the maximum levels of trust for a given level of affinity. Then the dispersion of trust in pairs with affinity level A is smaller than the dispersion of trust in pairs with affinity level A' whenever $A > A'$.*

Proof. In the Appendix. □

An important corollary that follows from Proposition 2 is:

Corollary 1. *A negative signal to reliability has a signal impact that decreases with affinity.*

That is, take two pairs with the same trust τ but at different levels of affinity, $A_h > A_l$. Then, given the proof in Proposition 2, it is clear that a common shock leading to a certain decline in trust at A_l would lead to at most the same decline in trust at A_h.

The corollary implies that trustors with high levels of affinity will downplay negative signals about their trustees' trustworthiness. One important consequence is that relative trust toward high-affinity opponents increases when people's average reliability is hit by a negative shock. Thus, when aggregate trust falls, exchanges tend to fly away from low-affinity to high-affinity partners.

2.2 Endogenous Information

A natural extension of the setup above is to, within each pairing, allow player 1 to decide whether to acquire information about player 2's reliability. Specifically, we keep the setup above but make observing the signal about player 2's reliability costly. We now let player 1 decide whether to observe the signal at an associated fee, $c > 0$.

Information has positive value only when it changes actions. Consequently, without restricting the prior or posterior distribution functions, introducing a cost of information acquisition into our model immediately implies that affinity eventually drives out information acquisition. That is, there is always a level of affinity above which player 1 never acquires costly information about player 2.

Proposition 3. *Fix a signal observation cost, $c > 0$. Then there exists a level of affinity, A^*, such that whenever $A \geq A^*$, player 1 never chooses to buy a signal. If affinity is below A^*, player 1's choice to buy a signal depends on the cost $c > 0$. Let $\overline{A}(c) < A^*$ be the affinity threshold decreasing in c. If affinity is below $\overline{A}(c)$, player 1 acquires the costly signal; otherwise, no signal is obtained.*

Proof. In the Appendix. □

The proposition is very general. It implies that, in a model with endogenous information acquisition, dispersion in trust beliefs vanishes at a level of affinity strictly below unity. In fact, one can show a bit more. Consider a benchmark case in which perfect information is available at a fixed cost, $c > 0$. Then it is easy to show that the value of information is hump-shaped in affinity.

Proposition 4. *Suppose individuals in the role of player 1 can attain perfect information about their partners' reliability level, R_2. Then the signal's value is increasing in affinity for affinity levels below a threshold level of affinity, $\hat{A}$. Above this threshold, the signal's value always decreases with affinity. Furthermore, the threshold level of affinity, $\hat{A}$, is the level of affinity for which an uninformed player 1 is indifferent about his or her two actions, T and $\neg T$.*

Proof. In the Appendix. □

This last proposition implies that, with the possibility of endogenous, costly perfect information, we expect dispersion in trust beliefs to eventually vanish. This is the case because information is less valuable as affinity increases whenever affinity is so high as to make trust optimal, so the likelihood that the value of information exceeds a fixed cost of acquisition also decreases in affinity for sufficiently high levels of affinity. It also implies that the dispersion of trust beliefs decreases with the cost of information gathering. But because high affinity drives out information, the sensitivity of beliefs' dispersion to the cost of information gathering is attenuated at high affinity levels.

If individuals receive some signals exogenously and can also collect information at a cost, putting Propositions 2, 3, and 4 together suggests that dispersion in trust beliefs declines with affinity and information-gathering costs, and that when affinity is high, even a small cost induces people to avoid acquiring information about the opponent's reliability.[10]

[10] The relation between the dispersion of trust beliefs, $\sigma(c,A)$, and affinity A implied by the above propositions can be represented as $\sigma(c,A) = \alpha - \beta A$ if $A < A(c)$ and $\sigma(c,A) = 0$ otherwise. Here, $\alpha, \beta > 0$ are the coefficients on the linear approximation of the negative relationship between trust dispersion and affinity. Let $\pi(c)$ be the probability that $A < A(c)$, which is decreasing in c. Then the population relationship is $\sigma(c,A) = \pi(c)(\alpha - \beta A)$. It follows that $\sigma_c(c,A) = \pi_c(\alpha - \beta A) < 0$; $\sigma_A(c,A) = -\beta \pi(c) < 0$; $\sigma_{cA}(c,A) = -\beta \pi_c > 0$.

3 Data

To test the model's predictions, we use two data sources that contain information on trust and measures of affinity with the person receiving trust. The first is the ANIA Survey on Firms Insurance (SFI), and the second is Eurobarometer. We now briefly describe the two datasets.

3.1 SFI Data

The SFI dataset was collected in 2008–2009 under the sponsorship of Italy's National Association of Insurance Companies (ANIA). It surveyed 2,295 private Italian firms, randomly drawn from the population of firms with up to 250 employees.[11] The survey is unique in that, besides collecting various information on the firms, it also gathered information on the entrepreneurs managing the firms. Specifically, the person in charge of the firm, either its owner or CEO, was surveyed via a computer-assisted personal interview conducted by a professional interviewer, during which information on a broad set of characteristics of the entrepreneurs and their families was collected. These include risk preferences, beliefs, financial and insurance choices, as well as demographic characteristics. The interviewers worked repeatedly for the survey company; in a given region, they were randomly matched to the firms they would be interviewing. Overall, 248 interviewers were sent into the field. At the end of each interview, they were instructed to report two pieces of information on the entrepreneurs by answering the following two questions (in order):

"On the basis of your perception can you tell how much do you think the person interviewed is trustworthy? Report your answer on a scale 0-10 where lower values mean lower trustworthiness"

"Can you tell how much affinity do you have with the person interviewed? Report your answer on a scale 0-10 where lower values mean lower affinity."

The answers to the first question provide a measure of how much the interviewer trusts the entrepreneur; the answers to the second provide an index of affinity. In addition, the survey collected information on a number of phenotypic traits for both the entrepreneurs and the interviewers: eye color, hair color and type, height, gender, education, and age. We use these measures to obtain indicators of affinity based on observables by constructing indicator variables of whether the entrepreneur and the interviewer had the same eye color, same hair color, same hair type, same skin color, same gender, same education, and the measures of age distance (in years) and height distance (in centimeters), respectively. To get a summary measure of "sameness," we summarize these mea-

[11]While the survey was not designed to be representative at the region level, all regions were covered. In the sample, 59% of firms are from the North of Italy and 41% are from the Center or South. This distribution approximates the distribution of population across the two macro regions (60%, 40%).

sures of affinity by extracting their first principal component. Table 3 shows the summary statistics of these traits, as well as all other data we use in the ANIA survey.

To validate the measure of self-reported affinity, Table A1 in the Appendix reports regressions of affinity on various measures of sameness. Having the same eye color has no statistically significant effect, while having the same hair color and the same hair type has a positive effect, but the coefficients carry large standard errors. Being of the same sex and of the same region has a positive and significant effect on affinity: if the interviewer was matched with an entrepreneur of the same sex or region, his or her perceived affinity with the entrepreneur would be about 3/10 of a point higher. Sharing the same education level does not affect affinity; conversely, being not too different in terms of age and height increases affinity significantly. For instance, having the same age compared with being 20 years apart increases the affinity score by 1/5 of a point. Similarly, lowering the height difference from 20 centimeters to zero increases affinity by 1/3 of a point. These one-by-one effects validate the relationship between the self-reported and the objective measures of affinity. However, just sharing one trait may not contribute much if the other traits are dissimilar. To account for all traits simultaneously, we have extracted their first principal component, obtaining a summary index of similarity. We then regress the self-reported affinity index on the principal component and find that a positive and statistically significant relationship. The effect is also economically meaningful: a one-standard-deviation increase in the principal component of the observable common traits raises affinity by 8.2% of its standard deviation.

3.2 Eurobarometer Survey

The Eurobarometer, a survey sponsored by the European Commission and designed to measure public attitudes toward European Community institutions, has been interviewing representative samples of the adult E.U. population since 1970.[12] Respondents were asked to report how much they trust their fellow citizens and citizens of each of the other European Union countries. Specifically, they were asked the following: *"I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust or no trust at all."* In some of the surveys, this same question was also asked with reference to citizens of a number of non-E.U. countries, including the United States, Russia, Switzerland, China, Japan, Turkey, and some Eastern and Central European countries (Bulgaria, Slovakia, Romania, Hungary, Poland, Slovenia, and Czech Republic). From these individual-level data, we compute country-level means of trust from a given country (country of origin) toward each of the other countries in the sample (the country of destination), as well as the

[12]The set of countries sampled has grown as the European Union has expanded and as the number of countries-candidates for the E.U. membership has gone up. In the final year used here (1995), the sample covered 16 countries.

standard deviation of these trust beliefs toward countries of destination. We complement these data with standard measures of geographical and linguistic distance used in the trade literature. Following Guiso et al. (2009), we also calculate measures of genetic and cultural similarity between the populations of two countries, which we use as measures of affinity. Specifically, we use a measure of genetic similarity based on the genetic distance measures developed by Cavalli-Sforza et al. (1994)[13] and an index of religious similarity, measuring the probability that two random citizens of a country-pair share the same religion. Common ethnicity, captured by genetic similarity, and common religion are natural measures of affinity.[14] See Guiso et al. (2009) for more details about these data. To make interpretation easier, we standardize all the indices of genetic and cultural similarity to have a mean of zero and a standard deviation of one and use their first principal component as a summary measure of affinity. Table 4 displays the summary statistics for the Eurobarometer data.

4 Results

4.1 The Association between Average Trust and Affinity

We start by reporting results on the relationship between trust and affinity, as implied by Proposition 1. Columns 1 and 2 of Table 5 display the results using the SFI data. The first column reports an OLS regression with standard errors adjusted for interviewer-level clustering. Higher affinity between the interviewer and the entrepreneur is associated with higher levels of trust of the interviewer toward the entrepreneur, and the relationship is highly statistically significant. Roughly, a one-point increase in the affinity score is associated with a half-point increase in the trust score. Re-matching an interviewer whose affinity with a given entrepreneur is low (affinity equal to the 5th percentile of the sample distribution) with one whose affinity is high (at the 95th percentile) would increase the trust score by about 3.5 points. The second column adds the interviewer fixed effects to account for any systematic differences in interviewers' propensity to feel affinity toward others and to trust people in general. The association between affinity and trust is only slightly smaller.

One potential concern with these findings is that, in the entrepreneur survey, both trust and affinity are self-reported. Although the original questions intended to measure two separate underlying factors, it could be that interviewers viewed them as similar. Moreover, the answers could be correlated simply due to an order effect. We do not believe that this is a big concern, for two

[13] This measure is based on the existence of genetic or DNA polymorphism, a situation in which a gene or a DNA sequence exists in at least two different forms (alleles).

[14] The importance of religion as a measure of affinity is shown by the fact that perpetrators of Ponzi schemes often leverage common religion when targeting their victims. In a study of 367 Ponzi schemes, Deason et al. (2015) find that common religion is one of the most frequent affinity links cited by the SEC.

reasons. First, encouragingly, we discover the same relationship in the Eurobarometer dataset, in which we define affinity based on objective characteristics of genetic and cultural similarity between nations (more on this below). Second, we attempt to isolate the impact of affinity on trust by instrumenting reported affinity with a rich set of objective and predetermined measures of similarity between entrepreneurs and interviewers, such as whether they have the same sex or are of similar age. We combine this rich set of possible instruments and all their second-order interactions in an IV Lasso framework (Belloni et al., 2014; Drukker, 2019). Under the assumption that these similarity characteristics affect trust only through affinity, we obtain results qualitatively similar to the naive OLS—a one-point increase in the affinity score is associated with an increase of about 0.35 points in the trust score (Table A2).[15]

Columns 1 and 2 of Table 6 display the regressions based on the Eurobarometer sample. All specifications include fixed effects of the country expressing trust and the country receiving trust.[16] The estimates in Column 1 are essentially the same as those reported by Guiso et al. (2009): trust is higher when people are genetically close or when they are culturally close, as measured by the chances that the two populations share the same religion. The second column captures affinity with the principal component of genetic and religious similarity. A one-standard-deviation increase in this measure is associated with an increase in trust of 24% of its sample standard deviation.

4.2 Affinity and the Dispersion of Trust Beliefs

We now test the second and novel implication of the model in Section 2, i.e., the negative relation between the cross-sectional dispersion of trust beliefs and affinity (Proposition 2). Columns 3 and 4 of Table 5 report the results for the SFI data. The third column regresses the standard deviation of the interviewers' beliefs on affinity, weighting the observations by the number of pairs used to calculate the standard-deviation estimate at a given affinity level and clustering standard errors accordingly. It shows a clear negative correlation consistent with the model's predictions. Since, at affinity equal to 0, the standard deviation of trust is 2.87, if one raises affinity to 10, the standard deviation of trust drops to only 0.6. The fourth column shows how the interquartile range of trust evolves conditional on affinity. Using this measure of dispersion, which is closer to the one in Proposition 2, leaves the conclusion unchanged: at higher levels of affinity, people's beliefs tend to be more concentrated around a higher level of trust.

[15] One may argue that some of our similarity variables have a direct effect on trust. For instance, if an interviewer and an entrepreneur live in the same region, it may mean that they have common friends and are not far from each other in the social network. We note, however, that our results are robust to removing non-phenotypic-similarity variables, such as coming from the same region or sharing the same education level, from the set of instruments.

[16] The results are also robust to the inclusion of various country-pair-level control variables, such as geographic distance and commonality of borders.

Figure 1 shows the scatterplot of trust and affinity in the SFI sample and depicts both the relationship between mean trust and affinity and that between dispersion of trust and affinity. At zero affinity, average trust is around 5 with high dispersion, consistent with the idea that when affinity is low, people tend to rely more on available noisy signals, and when affinity is high, they disregard them. Figure 2 shows even more clearly that, in addition to the strong positive association between affinity and average trust, there is a remarkable negative relationship between affinity and the cross-sectional standard deviation of trust.

Columns 3 and 4 of Table 6 report similar estimates for the Eurobarometer sample. All regressions include fixed effects for the country of origin and the country of destination to capture systematic differences across countries in the average dispersion of trust. Holding these differences constant, trust beliefs are less dispersed when they refer to nations that are genetically closer or to nations that are culturally more similar because they share the same religion (column 3). Simultaneously increasing genetic and religious similarity by one standard deviation lowers the standard deviation of trust beliefs by 63% of the sample standard deviation. Column 4 replaces the two measures of similarity with their principal component. The effect is negative and precisely estimated; repeating the previous exercise, increasing the summary measure of affinity by one standard deviation lowers the dispersion of trust by 25% of its dispersion in the sample, validating the prediction of the model.

4.3 Affinity, Trust, and Information

Our model has distinct implications for (*i*) how affinity affects the updating of trust beliefs when new trust-relevant information becomes available, and (*ii*) how affinity affects information collection when signals are costly to obtain. On the first point, higher levels of affinity lead to softer updating of trust beliefs to new information (Corollary 1). Regarding the second point, if information can be collected only at some cost, high affinity entails lower benefits from information acquisition and thus a decreasing cross-sectional variance of beliefs as the cost of information increases and affinity increases (Propositions 3 and 4). Furthermore, the cross-sectional dispersion of trust beliefs decreases more slowly with affinity when the cost of information gathering is higher.

To test the first prediction, we use sudden economic crises as events detrimental to trustworthiness and, ultimately, to trust. Economic crises present a shock to trustworthiness because, during these periods, people are more likely to undertake selfish actions that may hurt others. In using economic crises as shocks to reliability, we rely on the recent empirical evidence showing that recessions cause distrust (e.g., Algan et al., 2017; Ananyev and Guriev, 2019; Graeber and Zimmermann, 2019).[17] In both of our datasets, we find evidence of differential updating of trust beliefs

[17] Alternatively, crises cause information revelation about wrongdoing that started in normal times. The Madoff

by the initial levels of affinity in response to economic hardship.

To test the second implication, we rely on variation in a trustor's cost to acquire information about a trustee, using data on press coverage about a given country in the country that expresses the trust. This variation is available only in the Eurobarometer. The evidence below also lends support to this prediction of the model. We start by showing evidence on the first prediction then continue with evidence on the second.

4.3.1 Affinity and the Trust Response to Information Accrual

Enterepreneur Survey. Here, we test for the differential updating of trust by affinity using the SFI survey of entrepreneurs. This survey is close to ideal for testing this particular hypothesis. First, accidentally, the survey was fielded precisely during the financial crisis, between October 2008, when the effects of the crisis were still mild, through June 2009, when they were fully felt. Second, the sample spans multiple Italian regions, which allows us to exploit regional variation in the exposure to the financial crisis. Finally, by design, the survey elicits trust toward businessmen, whose trustworthiness was likely to fall harder during the financial crisis.

We start by documenting the basic dynamics of trust during the financial crisis. Figure 3 illustrates that, consistent with the existing evidence that economic crises hurt trust (Ananyev and Guriev, 2019; Graeber and Zimmermann, 2019), average trust toward entrepreneurs fell over time as the crisis unfolded and deepened. The magnitude of the decline is meaningful—average trust dropped by 0.35 points, or 0.23 standard deviations, over three fiscal quarters. However, as Figure 4 shows, this decline was driven primarily by the interviewer-entrepreneur pairs with the lowest affinity.[18] These findings back the hypothesis that high-affinity pairs are less inclined to update their trust beliefs based on the new information.

To further test the differential-updating hypothesis, we exploit variation in the exposure of different Italian regions to the financial crisis. Using a quarterly panel of regional employment rates from 2004 through 2010, we calculate the region-specific drop in employment after the third quarter of 2008 relative to their precrisis deseasoned levels.[19] Figure 5 displays the drop in employment on a map of Italian regions, suggesting that the variation captured by this variable goes beyond the traditional North-South divide. We then estimate a difference-in-differences specification of trust

Ponzi scheme came to light only after the collapse of Lehman Brothers, which shocked people's trustworthiness, particularly in financial markets (Guiso, 2010).

[18]One may wonder whether affinity also declined with the unfolding of the financial crisis, and this explains the heterogeneous response. However, as Table A3 shows, affinity stayed relatively stable over the three fiscal quarters.

[19]To be specific, we estimate the decline magnitudes as coefficients on the interaction between region FE and a post-2008Q3 indicator in a regression of regional quarterly employment from 2004Q1 through 2009Q4, controlling for the region and quarterly fixed effects. We use employment figures rather than GDP becasue regional GDP is available only at annual frequency.

on the drop in employment in a region where an interview took place and the interaction between the drop in employment and the reported affinity.[20] To account for the common time-specific shocks and interviewer-specific heterogeneity, we include the interviewer and quarter fixed effects. Specifically, we estimate the following equation:

$$\text{Trust}_{ijrt} = \alpha_i + \gamma_t + \beta(\Delta\text{empl}_{rt} \times \text{Affinity}_{ij}) + \theta\Delta\text{empl}_{rt} + \delta\text{Affinity}_{ij} + \varepsilon_{ijrt},$$

where we regress interviewer i's trust toward an entrepreneur j after an interview conducted in region r in quarter t on a set of interviewer fixed effects, α_i, quarter fixed effects, γ_t, interviewer i's affinity with an entrepreneur j, the drop in employment in region r in quarter t, and the interaction of the two latter variables. The key coefficient of interest for us in this specification is β, which would tell us by how much the effect of the financial crisis on trust varies based on affinity. The identifying assumption in this specification is that, conditional on the fixed effects and the two variables individually, the interaction between the economic shock and affinity is orthogonal to other unobserved determinants of trust between i and j.

Columns 1 and 2 of Table 7 present the baseline results. First, trust fell more in regions with a larger drop in employment. According to our preferred specification in Column 2, a one-percentage-point bigger decline in regional employment rate is associated with a 0.9-point decline in average trust, which is 10.8% of the sample mean. However, this effect depends on affinity: raising affinity from 0 to 10 mitigates the effect of a one-percentage-point drop in regional employment by more than 60%. Columns 3 and 4 of Table 7 run the regression splitting the sample between high-affinity and low-affinity pairs (i.e., above and below the median affinity value of 7). As these results illustrate, most of the trust updating is taking place at the bottom of the affinity distribution.

Overall, these results on the SFI sample strongly support the model's prediction: when faced with a negative public signal regarding trustworthiness, high-affinity pairs tend to be less responsive in updating their trust beliefs relative to their low-affinity counterparts.

Eurobarometer. To be sure that the results obtained from the entrepreneur survey are not confined to one particular dataset or crisis, we run analogous estimates using the Eurobarometer survey. To obtain significant variation in trustworthiness, we focus on the biggest recession in Europe during the period covered by the survey (1976–1996): the 1993 economic recession.

[20] To account for variation in the interview dates, for each interview, we used the drop in employment from the third quarter of 2008 until the quarter of that specific interview.

We estimate the following difference-in-differences specification:

$$\text{Trust}_{ijt} = \alpha_{ij} + \gamma_t + \beta \mathbb{1}[\text{Post} \geq 1993] \times \Delta\text{GDP}_{i,1992-93} \times \text{Affinity}_{ij} + \delta \mathbb{1}[\text{Post} \geq 1993] \times (\Delta\text{GDP}_{i,1992-93} + \kappa \text{Affinity}_{ij}) + \varepsilon_{ijt},$$

which regresses trust of citizens of country i toward citizens of country j in year t on the interaction between the measure of affinity between i and j and the 1993 GDP percentage decline in country i. To allow for medium-run effects of economic shocks on trust, we interact the 1993 GDP decline with a post-1993 indicator. This specification choice is motivated by a stylized fact that trust typically drops rapidly but recovers slowly in the aftermath of a recession.[21] Country-pair fixed effects, α_{ij}, account for any variables that are fixed at the country-pair level, such as physical or linguistic distance between countries. Finally, we also include yearly fixed effects, γ_t, to account for any time-specific shocks that similarly affect all countries. To account for serial correlation in country-pair shocks, standard errors are clustered at the country-pair level. The identifying assumption in this specification is that, absent the 1993 recession, trust of nation i toward nation j would have evolved along parallel trends independent of the interaction between a decline in GDP in nation i and i's affinity with j.

The estimation results are displayed in Table 8. Column 1 suggests that a one-standard-deviation larger decline in 1993 GDP in the country expressing trust leads to a 0.126-standard-deviation decline in their trust toward people in other countries. However, as suggested in Columns 2 and 3, this effect varies depending on genetic and cultural similarity. A one-standard-deviation increase in genetic or religious similarity would dampen 65%–81% of the negative effect of the recession on trust beliefs. To succinctly present our results, in the last column, we measure affinity between county pairs using the principal component of genetic and religious similarity. A one-standard-deviation increase in the principal component of affinity fully negates the negative effect of the 1993 recession on trust.

Figure 6 displays the results of estimating a year-by-year specification in which the GDP decline and affinity are interacted with year fixed effects, normalizing the coefficient for the wave just before the recession to 0. Consistent with the idea that differential negative shocks to trust are absorbed slowly, the coefficient becomes positive and statistically significant in 1993, is slightly smaller in 1994, and only starts fading in 1996. At the same time, absence of a clear pretrend lends credence to the identifying assumption of the difference-in-differences strategy.

[21] E.g., see Ananyev and Guriev (2019) for evidence of a sharp decline in trust after the financial crisis in Russia and Graeber and Zimmermann (2019) for the persistent effect of crises on trust. In addition, using a long trust series from Guiso et al. (2009), we can document that trust tends to fall sharply and recover slowly both after the Great Recession and after the savings-and-loan crisis.

Overall, across two completely different datasets, we obtain support of the model's prediction on how affinity affects people's revision of trust beliefs. In response to sizable public shocks to trustworthiness, trust adjusts much more dramatically when affinity is low. One important consequence is that relative trust toward high-affinity partners increases when people's average trustworthiness is compromised.

4.3.2 Costly Information, Affinity, and Dispersion of Trust Beliefs

We test the final implication of the model using the Eurobarometer data complemented with Portes and Rey's (2005) measure of press coverage, which we use as a proxy for information-gathering costs. All else equal, coverage of country j on the front pages of newspapers in country i should be higher when the cost of information collection about country j is lower. Recall from footnote 10 in Section 3 that Proposition 3 and 4 imply the following relation between the cross-sectional dispersion of trust beliefs in country i toward people in country j: $\sigma_{ij}(c_{ij}, A_{ij}) = \pi(c_{ij})(\alpha - \beta A_{ij})$, where c_{ij} and A_{ij} are the cost in i of gathering information about j and the affinity between the two countries, respectively, while $\pi(c_{ij})$ is the probability that the level of affinity is below the threshold that makes it not worthwhile to acquire information, which is a decreasing function of c_{ij}. Taking a first-order approximation to $\pi(c_{ij})$, we estimate the following model:

$$\sigma_{ij}(c_{ij}, A_{ij}) = \gamma_0 + \gamma_1 A_{ij} + \gamma_2 c_{ij} + \gamma_3 A_{ij} \times c_{ij}.$$

Given the arguments laid out in Section 2, we expect to find $\gamma_1 < 0$, $\gamma_2 < 0$ and $\gamma_3 > 0$. That is, trust dispersion should decrease with affinity and the cost of information acquisition, but the reduction in acquisition costs should be less important the higher affinity is.

We report the estimates of this equation in the last column of Table 6. To make the interpretation easier, we recode press coverage so that it is increasing with the cost of information gathering. The estimates suggest that trust dispersion is negatively associated with both the cost of information and affinity, measured with the principal component of genetic and religious similarity (results are the same if we use each of these measures separately). Furthermore, the interaction between affinity and information cost is positive and statistically significant. This result lends support to the model's final prediction, suggesting that the existence of an investigation cost about the others' trustworthiness tends to amplify the role of affinity as a driver of trust beliefs.

5 Economic Implications of Affinity-based Trust.

The affinity-trust relationship rooted in our information framework has two important economic implications. First, matching on affinity should, *ceteris paribus*, foster exchange. Second, following an aggregate shock to trust, people should trade less overall, but at the same time they should reallocate trade away from low-affinity to high-affinity partners. This is a direct consequence of the fact that negative news about counterparts' trustworthiness lowers trust across the board, but more toward low-affinity counterparts, thus increasing relative trust toward high-affinity partners. It is the latter that is decisive for the allocation of a given volume of trade. Next, we offer evidence in favor of these two implications.

5.1 Gains from Matching on Affinity

To test the first implication that there may be gains from matching people on affinity, especially in trust-intensive exchanges, we use our entrepreneur survey. Face-to-face interviews require an interviewee to trust that the interviewer keeps the collected information confidential, particularly non-standard information that may touch on sensitive matters. In the last part of the survey, interviewers asked the entrepreneurs to participate in the measurement of their second and fourth digits (i.e., the length of their index and ring fingers) to obtain a measure of the entrepreneurs' digit ratio.[22] Despite being reassured that this measurement would be conducted exclusively for scientific purposes, about 40% of the entrepreneurs refused to participate. This was presumably due to entrepreneurs' skepticism regarding how this (unusual to collect) information could have been used. Our model predicts that affinity (as reported by the interviewer) should foster trust and curb skepticism, hence raising the entrepreneurs' willingness to let interviewers collect that piece of information.

The results in Table 9 are consistent with this implication, suggesting that one could have potentially increased the survey's success by matching interviewers and entrepreneurs based on affinity. Across various specifications, a one-point increase in reported affinity is associated with a four-percentage-point increase in participation rates.[23] Meanwhile, Columns 2 and 3 suggest that a sizeable share of this survey failure could have been avoided if interviewers and entrepreneurs were just matched based on gender, which, differently from the self-reported affinity, was observed by the survey designer.

5.2 Reallocation of Trade during Trust Crises

We test the second implication—that trust crises should induce a reallocation of trade toward pairs with high mutual affinity—in the context of the 2008 financial crisis, which entailed a substantial shock to people's trust (e.g., Guiso, 2010; Gurun et al., 2018; Ananyev and Guriev, 2019; Graeber and Zimmermann, 2019). Using data on intercountry trade flows from 2001 through 2014

[22] The digit ratio is often taken in the literature as a marker of exposure to prenatal testosterone, which is deemed to have a forming effect on several individual traits (Manning, 2002).

[23] Note that this is affinity reported by an interviewer, confirming one of our modeling assumptions that affinity tends to be symmetric.

coming from Fouquin et al. (2016), Figure 7 shows that trade flows exhibit a strong upward time trend, then stopped growing after the financial crisis. The hypothesis that we want to test is whether this break in the trend of trade flows was milder for country-pairs with stronger affinity, which would imply a rebalancing of trade patterns from low-affinity to high-affinity countries. To provide evidence for this, we estimate the following specification:

$$Trade_{ijt} = \alpha_{ij} + \beta \mathbb{1}[\text{Post} \geq 2009] \times T \times \text{Affinity}_{ij} + \delta \mathbb{1}[\text{Post} \geq 2009] \times (T + \kappa \text{Affinity}_{ij}) + \gamma T + \varepsilon_{ijt},$$

where Trade_{ijt} is the logarithm of trade flows from country i to country j in year t, T is the time trend, Affinity_{ij} is the level of affinity between i and j, and α_{ij} are the country-pair fixed effects.[24] In this specification, coefficient γ documents how much trade flows grow over time, on average; δ measures the change in this average time trend following the crisis; and the main coefficient β tells us by how much the time-trend change differs depending on the preexisting affinity between countries. Meanwhile, $\delta\kappa$ accounts for the change in trade *levels* after the crisis by affinity.

The main identification assumption behind this specification is that, after controlling for country-pair fixed effects, the interaction between the timing of the financial crisis, affinity, and time trend is uncorrelated with the error term. There are two potential issues with this assumption.

First, economic shocks following the global financial crisis may be correlated, and this correlation pattern could be such that high-affinity country pairs are, on average, *less* economically affected relative to pairs of countries with lower affinity. While we cannot fully test this concern, as country-pair-year fixed effects are collinear with our treatment, the results survive the inclusion of the origin-country-year and destination-country-year fixed effects, which account for any destination-country and origin-country shocks in a given year (see Column 4 of Table 10). Thus, individual country-specific shocks after the financial crisis are unlikely to drive our results.

Second, other changes contemporaneous with the financial crisis may have slowed trade between less affine country-pairs. First, nations that dislike each other may have changed their tariff structure to make trade with each other less favorable. Second, due to liquidity constraints, trade with more distant countries may have suffered disproportionately (Berman et al., 2013), and physical distance may correlate with cultural distance. To exclude these possibilities, we focus this analysis on the Eurobarometer sample of European countries. Because these countries belong to the European Union, there are no tariffs and no trade barriers. Hence, discretionary bilateral responses are banned. Additionally, countries in the Euro area share the same currency and payments system, and they show a high degree of financial integration, easing access to finance for trading

[24] We exclude year fixed effects for illustration purposes, so that to keep the coefficients δ and γ. Our estimates of β are practically identical if we include year fixed effects.

purposes with other countries in the Union. This approach also makes it easier to compare these results to other evidence we obtained earlier in the paper.[25]

Table 10 presents the estimation results. In line with the visual evidence in Figure 7, the financial crisis presents a structural break in the trade-flows time trend. Trade flows were growing roughly 8% a year before the crisis, then around only 0.1% a year afterwards. However, a one-standard-deviation increase in country-pair affinity significantly mitigates this change in time trend by about 14%–24%, depending on the measure of affinity. Thus, consistent with our theory, there is evidence of relative reallocation of trade during the crises toward pairs with higher affinity. Moreover, using UN Comtrade data disaggregated at the four-digit product-code level, and using the conservative classification of products into homogeneous and differentiated (Rauch, 1999), Columns (5) and (6) show the reallocation effect is more pronounced for differentiated than for homogenous products. Because the homogenous goods tend be traded in organized exchanges, they are less dependent on bilateral trust than differentiated goods. This heterogeneity pattern that we find confirms our hypothesis that the reallocation effect is driven by more trust-intensive industries and trade relationships.

6 Conclusion

This paper provides a rationale for the link between trust and affinity. It explores how affinity affects individual updating of trust beliefs when relevant information becomes available, either freely or at a cost. Affinity mediates how people react to news about counterparts' trustworthiness. High affinity induces people to attach less weight to information about partners' trustworthiness that becomes freely available and to collect less information when it is costly. This has two important consequences. First, the cross-sectional dispersion of trust beliefs decreases with affinity, implying that high-affinity partners not only trust more but trust more surely. Second, the revision of trust beliefs is stronger at low affinity levels than at high affinity levels. Hence, when a trust crisis hits, relative trust toward high-affinity partners increases, causing a reallocation of trade from low-affinity to high-affinity partners. We draw on firm-level and cross-country data to provide evidence on all these implications. We document that (*i*) trust increases with affinity, (*ii*) dispersion of trust beliefs decreases with affinity, (*iii*) costly information gathering lowers dispersion of trust beliefs, particularly at lower levels of affinity, (*iv*) matching on affinity fosters trade, and (*v*) trust crises induce a relative intensification of exchanges between high-affinity partners and a relative dilution of trade with low-affinity ones.

Our findings have far-reaching implications. If affinity matters for trade because it fosters trust,

[25]Note, however, that our results are generally robust to expanding the sample to the rest of the world.

then in some industries, exchanges could be promoted by matching participants based on affinity. This suggests that there could be substantial gains to be reaped by improving matching. This issue is likely to be particularly important in industries where trades are trust-intensive, such as finance (Guiso et al., 2004; Duarte et al., 2012; Pursiainen, 2019), and where matching may not be driven entirely by self-selection or endogenous matching. For instance, when assigning a portfolio manager to an investor, a bank may do so randomly. In this case, there are margins for improvement by allocating portfolio managers based on some measure of affinity with the investor if this induces investors to rationally invest more and managers to behave in a more trustworthy manner.

This is the bright side of matching on affinity. But there is also a dark side. When information about the opponent's reliability is costly to collect, high affinity drives out information gathering. Knowing this, trustees have incentives to manipulate their targets' perceptions of their affinity with one another, through, e.g., a shared identity. Endogenous matching on affinity can then expose people to financial fraud (Guiso, 2010; Deason et al., 2015; Gurun et al., 2018). Additionally, because at times of a general fall in trust, people tend to entrust high-affinity opponents, those in need of attracting people's trust have a strong incentive to dissimulate high affinity. This can rationalize why populist politicians—who emerge when skepticism of mainstream parties is high—stress nationalism in their narratives and why, according to recent evidence, they are more likely to match their supporters on observable characteristics (Dal Bó et al., 2018). Studying the implications of our theory for politicians' strategic behavior presents a promising avenue for future research.

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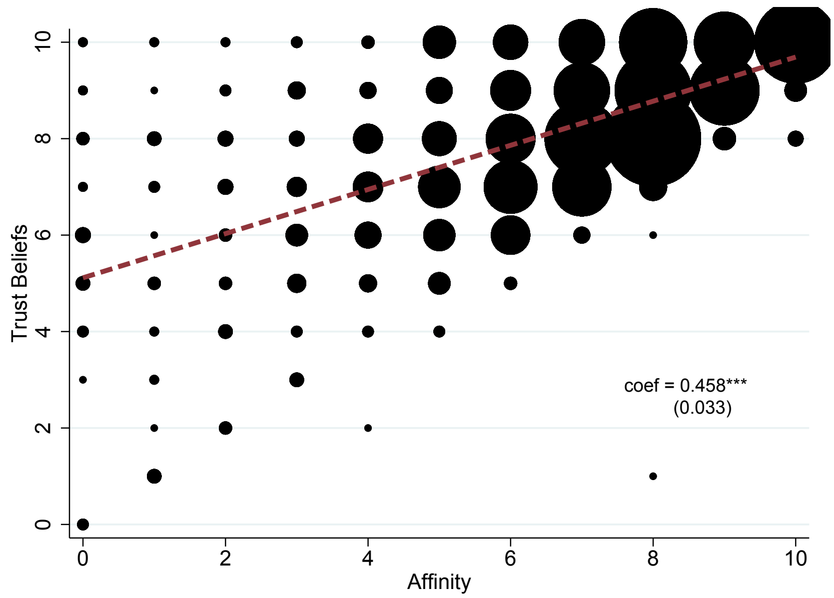
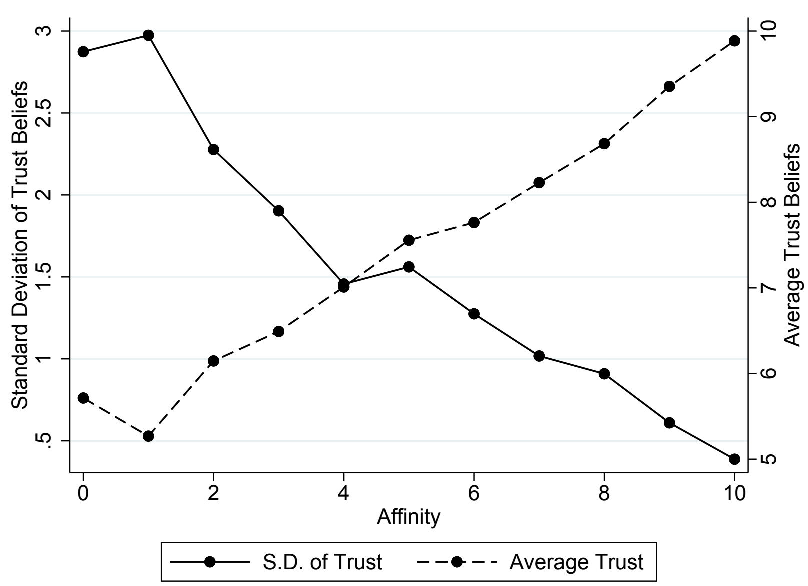
Figure 1: Trust vs. Affinity



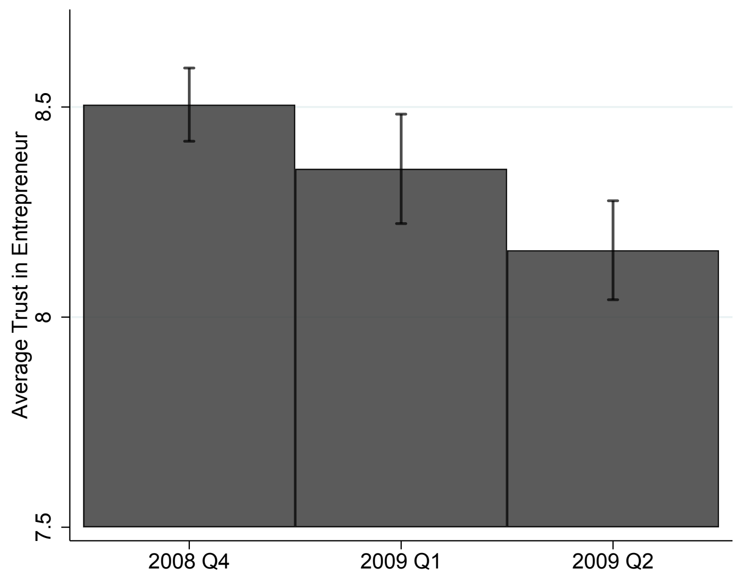
Notes: The figure displays the raw data for reported affinity and trust beliefs of an interviewer toward an entrepreneur. Data come from the ANIA survey of entrepreneurs. The size of the dots is proportional to the sample size in each affinity-trust value cell. The dashed line represents the linear fit, with the corresponding slope coefficient displayed in the bottom right corner.

Figure 2: Trust vs. Affinity (Mean and SD)



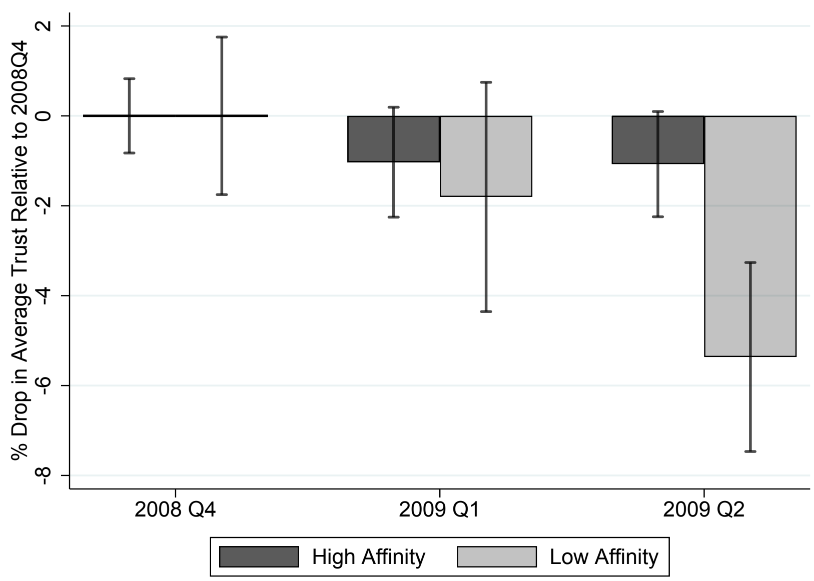
Notes: The figure displays the relationship between affinity and the mean and standard deviation of trust beliefs of an interviewer toward an entrepreneur. Data come from the ANIA survey of entrepreneurs.

Figure 3: Financial Crisis—Decline in Trust in the Entrepreneur Survey



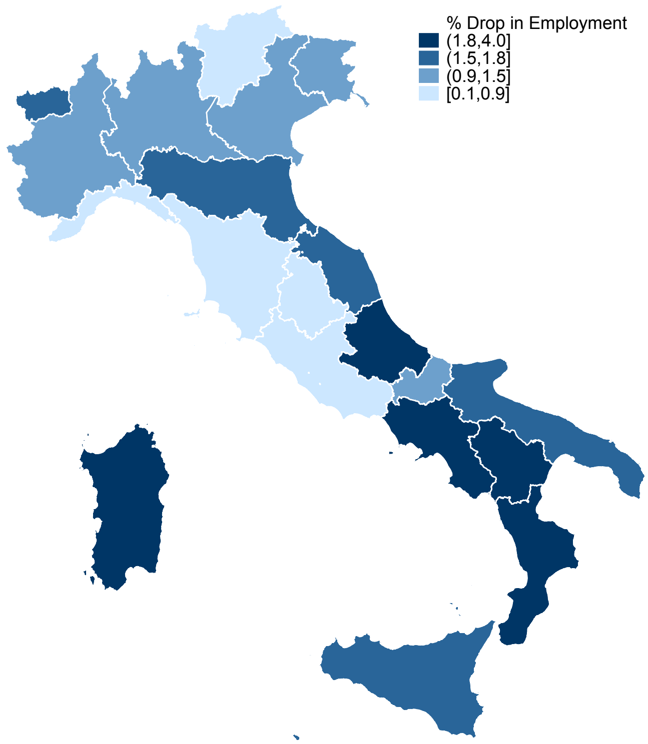
Notes: The figure displays the average trust beliefs of interviewers toward entrepreneurs in the ANIA survey grouped by the quarter of an interview. Black bars represent the 95% confidence intervals.

Figure 4: Decline in Trust in the Entrepreneur Survey by Affinity



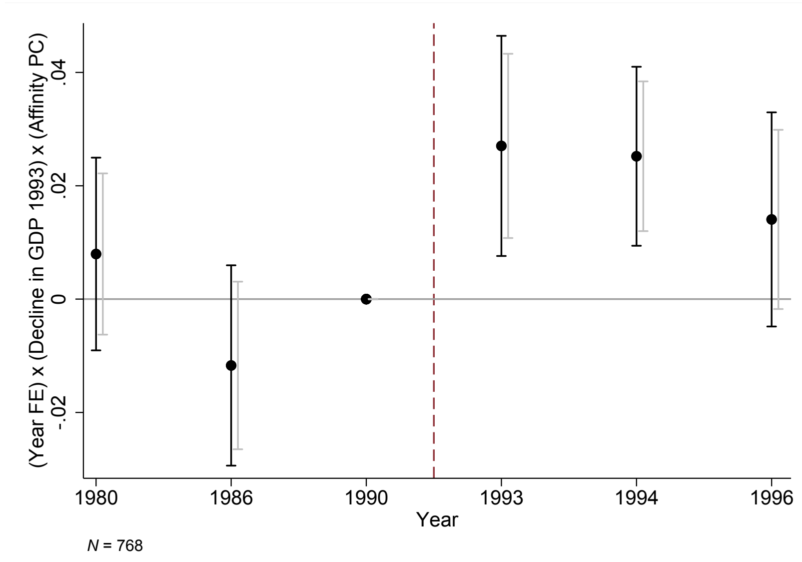
Notes: The figure displays the drop in trust of interviewers toward entrepreneurs in the ANIA survey relative to the fourth quarter of 2008, separately for pairs with affinity above and below the median. Black bars represent the 95% confidence intervals.

Figure 5: Drop in Employment across Italian Regions



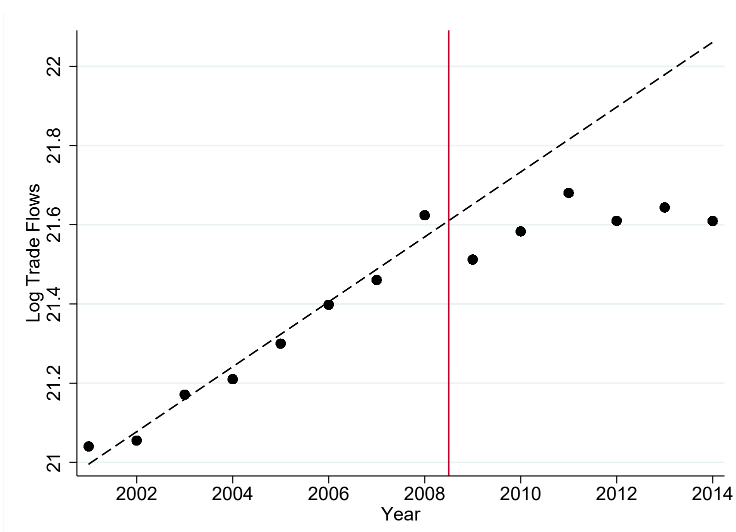
Notes: To account for seasonality, the estimates are obtained as coefficients on the interaction between the region fixed effects and a post-2008Q3 indicator in a regression of regional quarterly employment from 2004Q1 through 2009Q4, controlling for the region and quarter fixed effects.

Figure 6: Differential Decline in Trust by Affinity after the 1993 Recession, Eurobarometer (Year-to-Year Specification)



Notes: The outcome variable is the average trust from the respondents' country toward the country-counterpart. GDP decline in 1993 is measured as a negative value of a country's economic growth between 1992 and 1993 in the country of the respondents. The principal component of affinity is based on genetic and religious similarity indices and is standardized to have a mean of zero and standard deviation of one. Black bars represent the 95% confidence intervals; grey bars represent the 90% confidence intervals. Standard errors are clustered at the country-pair level.

Figure 7: Evolution of Average Trade Flows within the E.U., 2001–2014



Notes: The figure displays the evolution of average log trade flows between 15 European Union countries that are part of the Eurobarometer sample, namely: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, and Sweden. Dashed line represents a linear projection based on trade flows before the financial crisis.

Table 3: Summary Statistics, Entrepreneur Survey

Variable	Obs	Mean	Std.Dev.	Min	Max
Trust in an entrepreneur	2,191	8.346	1.506	0	10
Affinity with an entrepreneur	2,191	7.058	2.081	0	10
Decline in regional employment since 2008Q3, %	2,060	1.137	0.76	0.003	3.791
Entrepreneur Characteristics					
1 = Male	2,191	0.662	0.473	0	1
1 = Married	2,191	0.764	0.425	0	1
Age	2,191	47.37	10.33	19	89
Age at which started working	2,165	21.21	4.092	12	45
Height, cm	2,191	172.5	8.242	150	200
1 = Father was an entrepreneur	2,156	0.351	0.477	0	1
1 = First born	2,191	0.569	0.495	0	1
1 = Participated in finger measurement	2,191	0.591	0.492	0	1
Firm size (log employment)	2,191	2.927	1.012	1.099	5.517
Measures of Similarity between Entrepreneurs and Interviewers					
1 = Same eye color	2,086	0.412	0.492	0	1
1 = Same hair color	2,086	0.367	0.482	0	1
1 = Same hair type	2,013	0.462	0.499	0	1
1 = Same skin color	2,086	0.68	0.466	0	1
1 = Same sex	2,086	0.418	0.493	0	1
1 = Same education level	2,086	0.376	0.484	0	1
1 = Same region	2,191	0.807	0.395	0	1
Age distance	2,086	10.45	8.607	0	51
Height distance	2,086	10.06	7.459	0	41

Notes: The table displays the summary statistics of the ANIA survey of entrepreneurs. In addition, it presents the summary statistics of the estimated decline in employment during the financial crisis in an entrepreneur's region. To account for seasonality, these estimates are obtained as coefficients on the interaction between the region fixed effects and a post-2008Q3 indicator in a regression of regional quarterly employment from 2004Q1 through 2009Q4, controlling for the region and quarter fixed effects.

Table 4: Summary Statistics, Eurobarometer Survey and Trade Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Genetic similarity, standardized	978	0	1	-6.910	0.483
Religious similarity, standardized	978	0	1	-1.207	2.391
Average trust toward a nation	1,380	2.682	0.38	1.273	3.615
Standard deviation of trust toward a nation	1,380	0.814	0.114	0.525	1.194
Lack of press coverage, standardized	731	0	1	-6.311	0.769
GDP decline during the 1993 recession, %	1,380	-0.257	1.844	-4.031	2.086
Log (1 + Trade Flows), 2001–2014	2,912	21.485	1.659	16.59	25.41

Notes: Eurobarometer data include the surveys conducted in 1980, 1986, 1990, 1993, 1994, and 1996. The genetic similarity index is based on the genetic distance measures developed by Cavalli-Sforza et al. (1994). The religious similarity index measures the probability that two random citizens of a country pair share the same religion. Lack of press coverage is measured as minus the number of times another country appears in the headlines of major newspapers of a given country. GDP decline is measured as minus the % change in a country's GDP between 1992 and 1993.

Table 5: Association Between Trust, Trust Dispersion, and Affinity; Entrepreneur Survey

	Trust		S.D. of Trust	Interquartile Regression
	(1)	(2)	(3)	(4)
Interviewer-perceived affinity	0.458***	0.413***	-0.228***	-0.267***
	(0.033)	(0.028)	(0.015)	(0.059)
Interviewer FE	NO	YES	NO	NO
Observations	2,191	2,191	2,191	2,191
R-squared	0.400	0.653	0.959	

Notes: Columns (1) and (2) present the OLS estimates of regressing trust on affinity, with standard errors clustered at the interviewer level. Column (3) displays the OLS estimates of regressing the standard deviation of trust at a given affinity level on affinity, weighting the observations by the number of interviewer-entrepreneur pairs within each affinity class and clustering standard errors at the affinity-class level. Column (4) presents the estimates of an interquartile regression of trust on affinity. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Association between Trust and Affinity, Eurobarometer Survey

	Trust		S.D. of Trust		
	(1)	(2)	(3)	(4)	(5)
Genetic similarity	0.246***		-0.053**		
	(0.057)		(0.022)		
Religious similarity	0.048***		-0.017***		
	(0.012)		(0.004)		
Principal component		0.092***		-0.029***	-0.029***
		(0.018)		(0.006)	(0.006)
Lack of press coverage					-0.017***
					(0.004)
Principal component × Lack of press coverage					0.011*
					(0.006)
Country-respondent FE	YES	YES	YES	YES	YES
Country-counterpart FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	961	961	978	978	731
R-squared	0.682	0.672	0.594	0.592	0.588

Notes: The analysis is at the country-pair-year level. All similarity indices are standardized to have a mean of zero and a standard deviation of one. In columns (3)–(5), the standard deviation of trust is estimated within the pool of respondents using the micro-level survey data. Lack of press coverage is measured as minus the number of times another country appears in the headlines of major newspapers of a given country. Standard errors are clustered at the country-pair level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Heterogeneous Effect of Economic Crisis on Trust by Affinity, Entrepreneur Survey

	Trust			
	(1)	(2)	(3)	(4)
	Subsample			
	All	All	High Affinity	Low Affinity
Drop in regional employment	-0.579*	-0.897***	-0.360	-1.763***
	(0.301)	(0.332)	(0.292)	(0.487)
Affinity × Drop in regional employment	0.055*	0.056*	0.010	0.119**
	(0.033)	(0.032)	(0.030)	(0.052)
Affinity	0.351***	0.351***	0.413***	0.256**
	(0.049)	(0.048)	(0.049)	(0.100)
Interviewer FE	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES
Observations	2,031	2,031	1,377	592
R-squared	0.633	0.637	0.588	0.598

Notes: Columns (3) and (4) split the sample into interviewer-entrepreneur pairs with affinity higher and lower than the median. To account for seasonality, decline in regional employment is estimated for the entrepreneur's region as coefficients on the interaction between the region fixed effects and a post-2008Q3 indicator in a regression of regional quarterly employment from 2004Q1 through 2009Q4, controlling for the region and quarter fixed effects. Standard errors are clustered at the interviewer level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Heterogeneous Effect of Economic Crisis on Trust by Affinity, Eurobarometer

	Trust				
	(1)	(2)	(3)	(4)	(5)
Post-1993 × GDP decline in 1993	-0.026***	-0.019**	-0.021**	-0.020**	-0.020**
	(0.004)	(0.009)	(0.009)	(0.009)	(0.009)
Genetic similarity × Post-1993 × GDP decline in 1993		0.012**		0.007	
		(0.005)		(0.004)	
Religious similarity × Post-1993 × GDP decline in 1993			0.018***	0.018***	
			(0.007)	(0.007)	
Principal component × Post-1993 × GDP decline in 1993					0.021***
					(0.007)
Genetic similarity × Post-1993		0.005		-0.006	
		(0.012)		(0.009)	
Religious similarity × Post-1993			0.040***	0.040***	
			(0.010)	(0.011)	
Principal component × Post-1993					0.026*
					(0.014)
Country-Pair FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	1,380	854	854	854	854
R-squared	0.886	0.835	0.841	0.839	0.842

Notes: The analysis is at the country-pair-year level. Trust is an average trust from the respondents' country toward the country-counterpart. GDP decline in 1993 is measured as a negative value of a country's economic growth between 1992 and 1993 in the country of the respondents. All similarity indices (genetic, religious, and somatic) and standardized to have a mean of zero and a standard deviation of one. The principal component analysis is based on genetic and religious similarity indices. Standard errors are clustered at the country-pair level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Implications of Mismatch on Affinity, Entrepreneur Survey

	1 = Entrepreneur Agreed to Participate in Finger Measurement		
	(1)	(2)	(3)
Interviewer-perceived affinity	0.040***	0.039***	0.041***
	(0.007)	(0.006)	(0.006)
Male		-0.054**	
		(0.027)	
Same sex			0.053**
			(0.023)
Age		-0.000	-0.000
		(0.001)	(0.001)
Years of education		0.005	0.006
		(0.003)	(0.003)
Height		0.002	0.002*
		(0.001)	(0.001)
First born		0.025	0.021
		(0.020)	(0.020)
Firm size (log employment)		-0.007	-0.006
		(0.010)	(0.010)
Interviewer FE	YES	YES	YES
Region FE	NO	YES	YES
Observations	2,191	2,159	2,057
R-squared	0.464	0.463	0.469

Notes: The same-sex indicator is equal to one if an interviewer and an entrepreneur are of the same sex. Standard errors are clustered at the interviewer level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Reallocation of E.U. Trade after the Global Financial Crisis, 2001–2014

	Log Trade Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
					SUBSAMPLE	
					Homogeneous	*Differentiated*
Time trend	0.080***	0.080***	0.080***		0.100***	0.093***
	(0.003)	(0.003)	(0.003)		(0.003)	(0.002)
Post-2008 × Time trend	-0.079***	-0.079***	-0.079***		-0.088***	-0.094***
	(0.006)	(0.006)	(0.006)		(0.004)	(0.004)
Genetic similarity × Post-2008 × Time trend	0.019***					
	(0.005)					
Religious similarity × Post-2008 × Time trend		0.011**				
		(0.005)				
Principal component × Post-2008 × Time trend			0.016***	0.012**	0.009**	0.022***
			(0.004)	(0.006)	(0.004)	(0.004)
Genetic similarity × Post-2008	0.026					
	(0.017)					
Religious similarity × Post-2008		-0.005				
		(0.017)				
Principal component × Post-2008			0.011	0.020	0.022	0.022***
			(0.013)	(0.022)	(0.019)	(0.008)
Country-Pair FE	YES	YES	YES	YES	YES	YES
Origin-Country-Year FE	NO	NO	NO	YES	NO	NO
Destination-Country-Year FE	NO	NO	NO	YES	NO	NO
HS4 Product Code FE	NO	NO	NO	NO	YES	YES
Observations	2,912	2,912	2,912	2,912	580,292	1,021,811
R-squared	0.987	0.986	0.987	0.992	0.497	0.669

Notes: The table shows that the relative decline in the growth of international trade flows was more pronounced for low-affinity country pairs than for high-affinity country pairs. The sample is restricted to 2001–2014 and 15 European Union countries that are part of the Eurobarometer sample, namely: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, and Sweden. Columns (1) through (4) analyze the aggregate yearly trade flows between country-pairs. Columns (5) and (6) analyze the disaggregated trade flows at the four-digit product level. Columns (5) and (6) then split the results by whether trade flows are in homogeneous or differentiated products, according to the conservative classification in Rauch (1999). Standard errors are clustered at the country-pair level. *** p<0.01, ** p<0.05, * p<0.1.

ONLINE APPENDIX

A Proofs

A.1 Proposition 1

The average level of trust in pairs with affinity level A is greater than the average level of trust in pairs with affinity level A' whenever $A > A'$.

Proof. Each signal $s_j \in S$ generates a particular level of trust in each affinity class. Slightly abusing notation, we denote these trust levels by $\tau(s_j|A), \tau(s_j|A')$. Since there are finitely many realized trust levels, we can choose the lowest trust level within affinity class A', and choose a signal s_j that yielded this trust level. Since distribution functions are weakly increasing, the image of the signal s_j will be a higher trust level in affinity class A: $\tau(s_j|A) = 1 - G[(1-A)b_2(P) - b_2(\neg P)|s_j] > 1 - G[(1-A')b_2(P) - b_2(\neg P)|s_j] = \tau(s_j|A')$. The same is true for the second-lowest trust level in A', as well as the third-lowest trust level, etc. The average level of trust in affinity class A can be written as $\overline{\tau}(A) = Pr(s_1) * \tau(s_1|A) + \ldots + Pr(s_k) * \tau(s_k|A)$ and within A' as $\overline{\tau}(A') = Pr(s_1) * \tau(s_1|A') + \ldots + Pr(s_k) * \tau(s_k|A')$, where $Pr(s_j)$ is an unconditional probability of receiving signal s_j. Since $\tau(s_j|A) \geq \tau(s_j|A')$ for every $s_j \in S$, the result follows. Clearly, the result holds for any probability distribution over the set of signals S that is identical for both affinity levels. □

A.2 Proposition 2

Suppose Assumption 1 holds. Define dispersion of trust beliefs as a range between the minimum and maximum levels of trust for a given level of affinity. Then the dispersion of trust in pairs with affinity level A is smaller than the dispersion of trust in pairs with affinity level A' whenever $A > A'$.

Proof. Assumption 1 posits that for the lowest affinity class, $A = 0$, there is some signal, s^*, in the set of realized signals S, such that $\tau(s^*|0) = 1$. Then, using the same logic as in the previous proof—in particular, the fact that distribution functions are increasing—this signal is associated with $\tau(s^*|A) = 1$ in any other affinity class A as well. Thus, maximum trust can be obtained at all affinity levels. Comparing the range of trust levels is therefore equivalent to comparing the minimum levels of trust between affinity classes. Since there are finitely many realized trust levels, these minima are well-defined.

Select the minimum level of trust in affinity class A. Call this level of trust τ^*. This level of trust is the image of some signal $s_j \in S$. Now, the image of s_j in affinity class A'—call this level of trust τ'—must be (weakly) less than τ^*, because the distribution functions are increasing. Clearly, the minimal level of trust in A' is (weakly) less than τ', since τ' is a trust level in this affinity class. Since $\tau' \leq \tau^*$, the proposition is established. □

The proof of Corollary 1 follows immediately from the proof of Proposition 2. Specifically, if one takes two signals, s_l and s_h, that generate the same level of trust, τ, for two affinity levels, A_l and A_h, and then compare them with another signal, s_j, that generates a certain drop in trust at A_l, the drop in trust at A_h will be at most as big, i.e., $\tau(s_l|A) - \tau(s_j|A_l) \geq \tau(s_h|A_h) - \tau(s_j|A_h)$.

A.3 Proposition 3

Fix a signal observation cost, $c > 0$. Then there exists a level of affinity, A^*, such that whenever $A \geq A^*$, player 1 never chooses to buy a signal. If affinity is below A^*, player 1's choice to buy a signal depends on the cost $c > 0$. Let $\overline{A}(c) < A^*$ be the affinity threshold decreasing in c. If affinity is below $\overline{A}(c)$, player 1 acquires the costly signal, otherwise no signal is obtained.

Proof. Notice that at affinity level 1, player 1 strictly prefers the action T. This is true because we assumed $\xi < b_1(\neg P)$, and when $A = 1$, player 2 always prefers action $\neg P$ in this case, because relevant inequality is always satisfied: $R_2 > (1-A)b_2(P) - b_2(\neg P) = -b_2(\neg P)$. Since this is true for any level of R_2, no matter how informative a costly signal is, it will never change player 1's preferred action and is hence worthless to player 1. Therefore, player 1 never buys a signal when affinity is maximal.

Next, choose an affinity level, $1 - \frac{b_2(\neg P)}{b_2(P)} \leq A' < 1$. This still satisfies $(1-A)b_2(P) - b_2(\neg P) \leq 0$. Conditional on affinity level A', player 1 is in the same situation as above: player 1 knows that for any possible partner reliability level, R_2, player 2 strictly prefers the action $\neg P$. Again, there is no signal about R_2 that can change player 1's beliefs about the probability player 2 acts as a predator. So, again, signals are worthless. Obviously, setting $A^* = A'$, the first part of the proposition follows.

We established that, whenever affinity lies in the interval $[A^*, 1]$, player 1 never buys a costly signal. Note, however, that if affinity is just below A^* by some ε, the benefits of purchasing the costly signal still do not exceed the cost $c > 0$ for a small enough ε. Moreover, naturally, there is a threshold $\overline{A}(c)$ at which player 1 is indifferent about acquiring and not acquiring the signal, and, as c goes up, this threshold moves closer to zero and further away from A^*. □

A.4 Proposition 4

Suppose individuals in the role of player 1 can attain perfect information about their partners' reliability level, R_2. Then the signal's value is increasing in affinity for affinity levels below a threshold level of affinity, $\hat{A}$. Above this threshold, the signal's value always decreases with affinity.

Furthermore, the threshold level of affinity, $\hat{A}$, is the level of affinity for which an uninformed player 1 is indifferent about his or her two actions, T and $\neg T$.

Proof. Case 1: Suppose that without a signal, player 1 prefers action T.

The expected earnings from playing T with no information are:

$$b_1(\neg P) * Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)].$$

The expected earnings when player 1 has perfect information are:

$$b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)] + \xi \times Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)].$$

The value of information for player 1 is the expected earnings with perfect information minus the expected earnings without perfect information. The value of the signal to player 1 is therefore $\xi \times Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)]$. Clearly this equation is decreasing in affinity. As affinity increases, $1-A$ decreases, reducing the probability that reliability is less than this threshold. Therefore, for those levels of affinity where an uninformed player 1 strictly prefers to play T, the value of perfect information is decreasing in affinity.

Case 2: Now, suppose that without a signal, player 1 prefers action $\neg T$.

The expected earnings from playing $\neg T$ are always ξ. Expected earnings when player 1 has perfect information are the same as noted above. The value of information for player 1 is the expected earnings with perfect information minus the expected earnings without perfect information:

$$b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)] + \xi \times Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)] - \xi.$$

Rearranging terms and simplifying yields the value of information:

$$Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)] \times (b_1(\neg P) - \xi).$$

Since $\xi < b_1(\neg P)$ by assumption, this expression is increasing in affinity. As affinity increases, $1-A$ decreases, which makes the probability that reliability exceeds this value increase. Thus, for those levels of affinity where player 1 strictly prefers to play $\neg T$, the value of perfect information is increasing in affinity.

Case 3: Now, suppose that without a signal, player 1 is indifferent about $\neg T$ and T. In this case, the value of information if an uninformed individual plays T is:

$$b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)] + \xi \times Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)] - \\ - b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)].$$

On the other hand, if an uninformed player 1 plays $\neg T$ the value of the signal is:

$$b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)] + \xi \times Prob[R_2 \leq (1-A)b_2(P) - b_2(\neg P)] - \xi.$$

Since player 1 is indifferent about his or her actions, it must be that the expected earnings from these two actions are the same: $\xi = b_1(\neg P)Prob[R_2 > (1-A)b_2(P) - b_2(\neg P)]$.

Consequently, whenever an uninformed player 1 is indifferent about his or her two available actions, the value of perfect information does not depend on the action the uninformed player plans to implement.

Wrapping up, the value of perfect information increases with affinity below the specific level of affinity (if any) for which an uninformed player 1 prefers to play $\neg T$, decreases above this threshold level of affinity, and the values of perfect information conditional on player 1's actions coincide at this threshold level of affinity. Therefore, the value of information follows a hump-shaped pattern in affinity whenever there exists a level of affinity that makes player 1 indifferent about his or her two actions. $\square$

Table A1: Determinants of Reported Affinity, Entrepreneur Survey

	Affinity									
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Same eye color	-0.055								-0.058	
	(0.096)								(0.100)	
Same hair color		0.130							0.144	
		(0.107)							(0.108)	
Same hair type			0.155						0.151	
			(0.100)						(0.099)	
Same sex				0.316***					0.262**	
				(0.098)					(0.112)	
Same education level					-0.057				-0.068	
					(0.109)				(0.113)	
Same region						0.296**			0.291**	
						(0.118)			(0.121)	
Age distance							-0.011*		-0.010	
							(0.006)		(0.006)	
Height distance								-0.015**	-0.004	
								(0.007)	(0.008)	
Principal component										0.171***
										(0.056)
Interview FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,086	2,086	2,013	2,086	2,086	2,191	2,086	2,086	2,013	2,013
R-squared	0.415	0.416	0.422	0.420	0.415	0.424	0.417	0.417	0.431	0.425

Notes: The principal component of similarity measures is standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the interviewer level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: Relationship Between Affinity and Trust, IV Lasso, Entrepreneur Survey

	Partialing-out LASSO IV with Cross-validation		Cross-fit Partialing-out LASSO IV with Cross-validation	
	(1)	(2)	(4)	(5)
Interviewer-perceived affinity	0.409***	0.411***	0.312***	0.654***
	(0.068)	(0.078)	(0.118)	(0.061)
Interviewer FE	NO	YES	NO	YES
Observations	2,013	2,013	2,013	2,013
Set of instruments	All	All	All	All
Number of selected instruments	15	16	23	25

Notes: The table presents the results of IV Lasso estimation in which affinity is instrumented with objective indicators of similarity between interviewers and entrepreneurs. As instruments, these specifications use the similarity variables from Table A1 (same eye color, same hair color, same hair type, same sex, same education level, same region, age distance, and height distance), all possible interactions between them, and their own square terms. Columns (1) and (2) estimate a partialing-out IV linear model. Columns (3) and (4) estimate a cross-fit partialing-out IV linear model with 10 folds in cross-fit. All specifications use cross-validation for selecting the penalty parameter on the model's complexity. For further reference, see Drukker (2019). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Dynamics of Trust and Affinity during the Financial Crisis, Entrepreneur Survey

	Trust	Affinity
	(1)	(2)
Quarter (1 = 2008Q4, 3 = 2009Q2)	-0.111**	-0.011
	(0.044)	(0.061)
Interviewer FE	YES	YES
Observations	2,160	2,160
R-squared	0.447	0.415

Notes: The table illustrates the change in average trust and affinity between an interviewer and an entrepreneur over the course of three quarters from 2008 Q4 until 2009 Q2. Standard errors are clustered at the interviewer level. *** p<0.01, ** p<0.05, * p<0.1.