The Impact of Local Trust on Firm size

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Abstract

Firm size—measured by the number of employees— is an important object of interest in economics. This paper examines whether interpersonal trust, a key dimension of social capital, shapes firm size. I estimate the causal impact of local trust on the size of Spanish firms by exploiting latent patterns of mistrust across Spanish regions and using trigger variables as instruments for variation in trust levels across municipalities. Using balance sheet data from Spanish firms, I identify a positive causal relationship between trust and firm size, with effects that are significantly more pronounced among smaller firms. I document two mechanisms through which trust expands firm size: improvements in total factor productivity and greater access to credit. Overall, the results underscore the role of interpersonal trust as a fundamental driver of firm scale and economic performance.

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1 Introduction

Firm size—here, defined as the number of employees— is an important object of interest in economics. Larger firms are more likely to exploit economies of scale, adopt advanced technologies, engage in innovation, and provide stable employment, while smaller firms often face higher unit costs and tighter financial and organizational constraints (Acemoglu et al., 2018). Understanding the determinants of firm size is therefore essential for explaining why some economies sustain high-productivity, large-scale production, while others remain dominated by small firms. In this paper, I examine the role of an unexplored component, local interpersonal trust, and provide causal evidence that higher local levels of interpersonal trust lead to larger firms.

A large body of economic research emphasizes formal institutions—such as property rights, contract enforcement, and financial development—as primary determinants of firm size and scale (Beck et al., 2006; Kalkschmied, 2023). However, in many economic interactions, especially among small and medium-sized enterprises, transactions rely not only on formal rules but also on informal institutions, including social norms and interpersonal trust. Trust can reduce transaction costs and facilitate cooperation when contracts are incomplete or costly to enforce (Valentinov and Roth, 2024).

Recent empirical work highlights the importance of trust for economic outcomes, linking higher levels of social trust to increased trade, financial development, innovation, and economic growth (Algan and Cahuc, 2010; Guiso et al., 2004; Knack and Keefer, 1997). At the firm level, trust has been shown to affect organizational structure and access to finance (Guiso et al., 2016). Yet, despite its intuitive relevance, the causal impact of interpersonal trust on firm size remains underexplored, in part due to the difficulty of isolating exogenous variation in trust.

This paper studies the role of interpersonal trust as a determinant of firm size using balance sheet data from Spanish firms. I estimate the causal effect of local trust on firm size by exploiting persistent regional patterns of mistrust and using trigger variables as instruments for variation in trust across municipalities. Combining these measures with detailed balance sheet data, I find a positive causal relationship between trust and firm size. The effects are substantially stronger for smaller firms, suggesting that trust is particularly important where formal governance mechanisms and internal hierarchies are limited.

There are several reasons why Spain is an interesting setting to study the potential effect of trust on firm size. First, Spain exhibits substantial and well-documented variation in interpersonal trust across regions and municipalities, shaped by historical, cultural, and institutional factors, which provides rich within-country heterogeneity (Soto-Oñate, 2021). Second, the Spanish economy is characterized by a large share of small and medium-sized firms and a pronounced skew in the firm size distribution, making firm size a central economic issue and allowing meaningful variation in the outcome of interest (Moral-Benito, 2016). Third, detailed administrative balance sheet data at the firm level, combined with high-quality survey and municipal data on trust, enable a local empirical analysis of the relationship between trust and firm size. The availability of Spanish data allows me to follow Durante et al. (2025), who emphasize the importance of studying trust at the appropriate geographical level—namely, the local community—where most social interactions typically occur. Fourth, there is a significant and positive relationship between average firm size and interpersonal trust at the province level, suggesting a potential causal link between the two variables, as illustrated in Figure A.1 in the Appendix. Finally, Spain experienced a large decline in interpersonal trust following the 2008 economic crisis (see Figure A.2 in the Appendix); this provides an opportunity to make a causal statement about the effect of trust on firm size.

The primary challenge to identifying the causal effect of trust on firm size is endogeneity (due to potential measurement errors, reverse causality, and/or omitted variable biases); to deal with this, I adopt an instrumental variable approach to generate a well-defined local average treatment effect. My approach consists of instrumenting variations in trust levels with a combination of latent patterns of mistrust prevalent in Spain together with a trigger variable (Bellodi et al., 2024; Fouka and Voth, 2023). I posit that the 2008 financial crisis led to distrust among people, which is more likely to translate into a reduction in trust in municipalities where there is latent mistrust. As a proxy for the latter, I use municipality-level data on victims of the Spanish Civil War and the subsequent repression.

The instrument, similar to a shift-share IV, accurately predicts the variation in trust levels after the 2008 crisis. To justify the use of this instrument, I rely on the literature on shift-share IVs (Goldsmith-Pinkham et al., 2020); Borusyak et al. (2025), which clarifies the contexts in which these instruments can be used, outlines the identification assumptions, and recommends a series of tests to assess the validity of the identification assumption—all of which are satisfied in the case of my instrument.

I further investigate the mechanisms underlying this relationship. The results indicate that higher trust expands firm size through two main channels: improvements in firm total factor productivity and enhanced access to credit. These findings are consistent with theories in which trust lowers coordination costs, improves factor allocation, and relaxes financial constraints (Konte and Ndubuisi, 2021), thereby enabling firms to grow beyond otherwise binding organizational or financial limits.

This paper delivers several contributions to the literature. First, in relying on firm-level data, it provides novel evidence of the role of local trust as a determinant of firm size. While previous studies have documented correlations between organizational practices and firm outcomes, to the best of my knowledge this paper is the first to identify a causal link between trust and firm size. Another important contribution of my study is its empirical strategy, which leverages fine-grained, municipality-level trust data. By focusing on localized analyses of social capital, my approach directly responds to recent calls in the literature for more context-specific investigations (Durante et al., 2025). This allows me to overcome the well-documented limitations of cross-country studies that have dominated research and offer a more nuanced and precise understanding of social capital's role at the local level.

The remainder of the paper is structured as follows: Section 2 reviews the literature; Section 3 outlines the theoretical framework; Section 4 presents the data; Section 5 outlines the empirical model and the identification strategy; Section 6 reports the results and discusses the mechanisms; and Section 7 presents the conclusions.

2 Literature review

The microeconomic literature has identified a range of determinants that influence firm size. Classical industrial organization theory, particularly the traditional theory of the firm (Pindyck and Rubinfeld, 2009), emphasizes the role of cost structures in shaping production decisions and, consequently, firm size; a key result of this strand of literature is that in competitive markets, firms operate at the minimum efficient scale in the long-run equilibrium. Another fundamental determinant is the nature and structure of the market, particularly the degree of firm concentration. A substantial body of work has examined how the forces shaping competition among firms influence market concentration and, by extension, firm size (Tirole, 1988); this literature highlights factors such as sunk costs, industry characteristics, price competition, and advertising intensity as critical determinants (Sutton, 1991). Beyond these classical considerations, institutional factors such as regulations and corporate taxes also play a significant role, as discussed in **?**. In addition, antitrust laws may act as constraints on firm size (Caves, 2014). Financial constraints represent another important determinant: firms with better access to credit, often those located in regions with more developed financial systems, are more likely to grow in size (Gopalan and Rajan, 2018). Finally, international trade represents another critical determinant of firm size; it exerts substantial influence through the selection mechanism, by which only the most productive firms tend to enter and remain in international markets (Melitz, 2003), which ultimately evolve into larger firms potentially.

From a macroeconomic perspective, firm size is typically modeled as a function of shocks and firm-level heterogeneity. Models commonly embed productivity shocks or demand shocks as primary mechanisms to generate variation in firm size. These shocks, together with ex ante (pre-entry) heterogeneity across firms (Sterk et al., 2021), play a central role in determining the amount of labor that firms require and thus their size. Pozzi and Schivardi (2016) and Dunne et al. (1988) consider multiple sources of unobserved heterogeneity, given the importance of disentangling demand and productivity heterogeneities (i.e., some firms grow due to demand shocks, while others grow because they become more productive). In a recent contribution using census microdata on US firms, Sterk et al. (2021) estimate that most size differences across firms are determined by pre-entry heterogeneity rather than persistent ex post shocks, like demand or productivity shocks.

Empirical studies taking an applied perspective aim to test the theoretical frameworks—both macro and micro—that seek to explain the determinants of firm size. An insightful example is Kumar et al. (1999), which examines the relationship between average firm size and factors such as market size, industry capital intensity, and the efficiency of the judicial system. More recent contributions include Laeven and Woodruff (2007) and Cingano and Pinotti (2016), who study how the quality of legal systems and organizational management, respectively, contribute positively to larger firm sizes. However, most of these studies focus on partial correlations. To the best of my knowledge, limited empirical research aims to establish causal relationships using firm-level data.

At the same time, the micro-literature on interpersonal trust is extensive and has primarily addressed agency problems within firms, which arise due to information asymmetry between employees and employers, with employees typically handling more information than their employers. Cingano and Pinotti (2016) show that the principal-agent problem is mitigated through interpersonal trust, which advances the delegation of decisions and tasks within firms, thereby allowing the expansion of more productive units. In a similar fashion, Chami and Fullenkamp (2002) propose trust between coworkers as a superior alternative to the standard tools used to mitigate agency problems (namely monitoring and incentive-based pay). They model trust as mutual, reciprocal altruism between pairs of coworkers, and they show how it induces employees to work harder relative to those at firms using the standard tools; they also show that employees in high-trust firms have higher job satisfaction and that these firms enjoy lower labor costs and higher profits. The study of La Porta et al. (1997) is also particularly noteworthy, as it underscores the role of trust, through the fostering of cooperation, as a fundamental determinant of organizational performance. Motivated by these findings, my paper provides causal evidence that firms operating in high-trust environment tend to grow more.

Finally, my paper also relates to literature on the persistence of historical events, since my instrumental variable exploits the presence of a latent mistrust in Spain that lasted for years as a consequence of the Spanish Civil War and the subsequent dictatorship. My empirical strategy builds on a growing body of literature showing that major historical events can exert lasting influences on present-day outcomes under specific conditions (Ochsner and Roesel, 2024; Rozenas et al., 2017). These findings indicate that collective memory and political legacies may shape contemporary behavior (Creutzig et al., 2022; Morelli et al., 2024; Tur-Prats and Valencia Caicedo, 2020; Voigtländer and Voth, 2012). For instance, Fouka and Voth (2023) provide evidence that regional variation in anti-German sentiment following the Greek debt crisis of 2009 is associated with the number of victims in massacres committed by German forces during World War II. Closely related to my paper,Tur-Prats and Valencia Caicedo (2020) demonstrate that the

Spanish Civil War had persistent effects on interpersonal trust, revealing a latent mistrust across Spanish municipalities through cross-sectional analysis. My paper builds on this finding; however, unlike Tur-Prats and Valencia Caicedo (2020), I exploit intra-municipality differences in trust that occur following the economic crisis/shock, taking advantage of the presence of latent mistrust and exploiting the fact that the variation in trust levels across municipalities after the shock is different depending on this latent mistrust. This allows me to obtain an exogenous source of variation in trust, which is helpful to isolate the causal effect.

3 Theoretical framework

To understand how interpersonal trust enhances organizational functioning, it is instructive to draw on task-based models (like that of Garicano and Wu (2010)), which conceptualize firms as systems for integrating dispersed knowledge and coordinating talent in production. These frameworks emphasize that the successful execution of tasks depends heavily on the communication and coordination structures that underpin organizational processes. Interpersonal trust directly reinforces these structures: trust among employees fosters smoother communication and more effective collaboration, thereby promoting growth in firm size.

To start, interpersonal trust enhances communication efficiency. In organizations where trust levels are high, employees are more likely to engage in exchanges of information (Kmieciak, 2021); this reduces misunderstandings and the need for extensive oversight or formalized communication protocols —factors that typically become more burdensome as firm size increases. Consequently, trusting interpersonal relationships can ease the internal complexities that accompany firm communication.

Second, trust fosters collaborative behavior across and within teams. As firms expand, maintaining cohesive interdepartmental cooperation becomes increasingly challenging. Trust mitigates this by encouraging knowledge-sharing and mutual assistance, thereby reducing the transaction costs associated with coordination in larger organizations. Employees who trust one another are more inclined to act in the collective interest rather than pursue narrowly-defined individual or departmental goals. In line with this, the study conducted by La Porta et al. (1997) is particularly relevant, as it underscores the role of trust, through the fostering of cooperation, as a fundamental determinant of organizational performance.

Finally, trust facilitates decentralized decision-making, which is a structural necessity as firms scale up. In the absence of trust, decisions tend to be centralized, which limits organizational agility and responsiveness; in contrast, when trust is prevalent, managers can delegate authority with confidence, knowing that employees are committed to shared objectives (Cingano and Pinotti, 2016).

Overall, interpersonal trust functions as a social lubricant, reducing frictions in workplace interactions and facilitating more cohesive organizational behavior. Therefore, trust is likely to contribute to firm size growth. This logic underpins the empirical analysis presented in the subsequent sections of this paper.

4 Data

This paper combines firm-level accounting information with interpersonal trust data and Civil War casualties data. The analysis relies on three microdatasets: (i) the **Balance sheet center (CBI)** from Bank of Spain, which provides annual accounting and balance-sheet information for Spanish non-financial corporations; the (ii) **CIS (Centro de Investigaciones Sociológias) surveys**, which provide annual data on interpersonal trust at the municipal level in Spain; and (iii) **Civil war casualties data**, which provide data on death tolls in the Spanish Civil War at the municipal level.

Balance sheet data (CBI) The CBI is an annual administrative dataset covering Spanish non-financial corporations from 1995 onward. It includes over 115 numerical variables per firm and year and covers approximately 900000 firms annually. The information is sourced from mandatory annual account filings to the *Registros Mercantiles* and harmonized to a uniform reporting structure. Following the official classification, the CBI provides variables on production, value added (VAB), intermediate inputs, wages, operating costs, and profitability; balance sheet composition; financial position; and workforce indicators. The identifiers include a firm-level numeric ID, anonymized NIF, sector classification (CNAE-2009), and size categories.

Interpersonal trust data. The data on interpersonal trust are obtained from surveys conducted by the CIS (Centro de Investigaciones Sociológicas), a national statistical office. The CIS develops national surveys covering various sociological aspects—including political or socioeconomic attitudes, behaviors, and demographic trends—across different population groups. The data comes from stratified samples that are representative at the national level (for additional details on the sampling procedure, please refer to the Appendix). Since 2005, they have included in the surveys the following question in their surveys: "On a scale from 0 to 10, how much do you trust people?" With this information, I can obtain an indicator of interpersonal trust for each municipality[1] for each year in the period 2006–2017, along with other variables at the municipality level (e.g., the socioeconomic characteristics of the municipality). The total coverage is 1924 municipalities out of a total of 8132 municipalities in Spain (see Figure 3). To assess the representativeness of the final sample used for the final merge, refer to Table A.8 in the Appendix.

Civil War casualties data. As a proxy for latent mistrust, I use data on death tolls in the Spanish Civil War at the municipal level. To obtain this data, I use information recently released by the Spanish Ministry of Justice on mass graves related to the Civil War. The digital map of mass graves[2] was introduced after the passing of the Historical Memory Law (Law 52/2007), which recognized and extended the rights of individuals who suffered violence during the Civil War and the subsequent dictatorship. Regional governments and several civil entities contributed to the creation of this map by sending information to the central government;[3] I have complemented and updated this information using another local source called "Desaparición forzada andalucia.org", which gathers information collected by victim associations for Andalucía.

Final sample construction and merging procedure

I merge the three datasets using the municipality identifier. The final panel covers the period 2006-2017. The panel contains, for each firm and for each year, all the balance-sheet variables as well as a variable capturing the level of interpersonal trust prevailing in the municipality in which the firm operates. In

[1]This indicator is the average of all the surveyed individuals in the municipality.

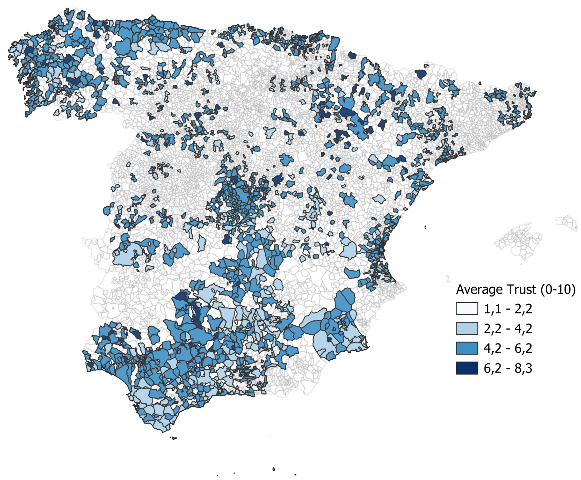
[2]See Figure A.3 in the Appendix.

[3]Article 12.2 of Law 52/2007 identifies that the administration is responsible for creating and making publicly available a map of the entire national territory, presenting the locations where the remains of individuals who disappeared under violent circumstances during the Civil War and the subsequent dictatorship have been discovered.

addition, there is also a variable that records the number of casualties at the municipal level, which serves as a proxy for latent mistrust. I restrict the sample to firms that appear in CBI for the whole period 2006-2017 and have non-missing production and employment data. The reason why I restrict the sample is because I want to have a balanced panel, to avoid all the potential biases associated with firms entry and exit. Specifically, firm survival may be correlated with local trust, which could confound the estimated relationship between trust and firm outcomes if firms selectively enter or exit the sample.[4] The final estimation sample consists of 69842 firms. Table 1 reports the size distribution of firms included in the final sample.

[4]For example, firms operating in low-trust municipalities may be more likely to exit due to higher transaction costs or weaker informal enforcement. If firm entry and exit are allowed, the sample composition may therefore change over time, with relatively weaker firms disproportionately dropping out in low-trust areas. This selective attrition would confound the estimated relationship between trust and firm outcomes, as observed performance would partly reflect survival effects rather than responses to changes in local trust. I show the results of estimating Equation (1) using the unbalanced panel in the Appendix.

Figure 3: Average trust by municipality, 2006-2017.



Mean is 4.8 .(Source: Author creation using CIS data.)

Table 1: Firm size distribution in the final sample, 2017

Category	**# Firms**	**Share**
Micro	62272	89.1%
Small	6927	9.9%
Medium	585	0.9%
Large	58	0.1%
Total	69842	100%

This table shows the size distribution of firms in the final sample for the year 2017. Size categories follow the size definition of the European Commission. Large firms have more than 250 employees; medium firms have up to 250 employees; small firms have up to 50 employees; and micro firms have up to 10 employees. (Source: Balance sheet Center, Bank of Spain).

5 Empirical strategy

I aim to identify whether interpersonal trust influences the number of employees of firms. My baseline specification can be expressed as:

$$\text{Ln(Employees)}_{i,m,p,t} = \alpha + \beta\,\text{Trust}_{m,p,t} + \gamma\,X_{m,p,t} + \theta_i + \eta_{p,t} + \epsilon_{i,m,p,t} \tag{1}$$

$Employees_{i,m,p,t}$ is the number of employees in firm i, located in municipality m, in province p, in year t. $Trust_{m,p,t}$ corresponds to trust in municipality m, in province p, and year t. $X_{m,p,t}$ is a set of control variables at the municipality level (e.g., socioeconomic controls such as share of educated individuals, employment share, or gender composition of the municipality). θ_i captures firm fixed effects and $\eta_{p,t}$ is a province-by-year fixed effect that captures province-specific time trends. Finally, $\epsilon_{i,,m,p,t}$ is the error term. This specification exploits within-municipality variation to estimate the impact of trust on the number of employees.

Estimating the parameter of interest with ordinary least squares (OLS) would provide a partial correlation between trust and firm size; however, the lack of clear exogenous variation undermines any direct causal interpretation of the estimation. This is due to reverse causation problems, as other studies have shown that economic development could have a direct impact on trust levels (Brückner et al., 2021). In addition, despite the inclusion of a large number of fixed effects in the regression, the estimates may suffer from omitted variable bias. Finally, it may be the case that $Trust_{m,p,t}$ is not measured correctly and contains some measurement error. These concerns are likely to invalidate any causal interpretation of Eq. (1). To deal with such problems, I adopt an instrumental variable approach, using a combination of latent patterns of mistrust that are prevalent in Spain and trigger variables to instrument variations in trust levels. My empirical strategy builds on several studies that show how major past events can have a lasting impact on the present under certain circumstances (Ochsner and Roesel, 2024; Rozenas et al., 2017), implying that collective memory and political legacies can influence current behavior (Creutzig et al., 2022; Morelli et al., 2024; Tur-Prats and Valencia Caicedo, 2020; Voigtländer and Voth, 2012). For example, Fouka and Voth (2023) show that regional disparities in the backlash against Germany after the Greek debt crisis of 2009 were linked to the number of victims in massacres committed by German troops during World War II. In a closely related work to this paper, Tur-Prats and Valencia Caicedo (2020) show that the Spanish Civil War had a long-lasting effect on trust, identifying a latent mistrust in Spanish municipalities through a cross-section analysis. I build on this result by arguing—and showing—that this latent mistrust became salient in the aftermath of the economic crisis, driving variations in interpersonal trust. While the 2008 financial crisis led to an overall decline on interpersonal trust in Spain (see Figure A.2 in the Appendix), the drop was more severe in municipalities with pre-existing latent mistrust. As a proxy for this latent mistrust, I use the number of victims of the Spanish Civil War and subsequent repression. Hence, my instrumental variable approach involves a first-stage regression given as:

$$\text{Trust}_{m,p,t} = \lambda + \delta casualties_{m,p} \times 1_{t\geq 2009} + \rho\, X_{m,p,t} + \theta_i + \eta_{p,t} + \zeta_{i,m,p,t} \tag{2}$$

$Casualties_{m,p}$ is the ratio of the number of victims of the Spanish Civil War and subsequent repression over the population in 1930, and $1_{t\geq 2009}$ is a dummy variable equal to one in the post-2008 period (capturing the idea that latent mistrust came to the surface immediately after the 2008 economic shock). Province-by-year fixed effects are included in the regression. $X_{m,p,t}$ corresponds to municipality-level controls. The error term $\zeta_{i,m,p,t}$ captures unexplained variations in $Trust_{i,m,p,t}$.

The validity of the instrumental variable strategy rests on the assumption that Civil War casualties affect current municipal productivity only through their impact on interpersonal trust, and not through alternative channels, conditional on controls. A potential concern is that historical violence may have shaped long-run economic trajectories via demographic changes, land ownership patterns, political institutions, or other persistent local characteristics. However, note that the identifying variation does not come from cross-sectional differences in casualties per se, but from their interaction with the post-2009 economic crisis. Civil War casualties are time invariant, and firm fixed effects absorb all level differences in long-run development associated with historical violence. Identification therefore relies on differential changes in trust following a common macroeconomic shock, rather than on pre-existing productivity differences across municipalities.

As it is a combination of a time-invariant geographical component and a time-varying shock, my instrumental variable exhibits notable similarities to the shift-share instrumental variable (Borusyak et al., 2025; Goldsmith-Pinkham et al., 2020). First, the identifying assumption relies on the exogeneity of the casualties, in the sense that casualties are independent of current socioeconomic conditions in municipalities and do not account for outcome variations prior to the crisis conditional on the controls included; as demonstrated by Goldsmith-Pinkham et al. (2020), this exogeneity of the casualties serves as a sufficient condition for the instrument's validity. Second, the exogenous variation that I exploit is primarily driven by municipalities impacted by the war; consequently, the local exogenous variation is solely derived from municipalities affected by the casualties. One major concern is that the share component (i.e., the number of victims in the Spanish Civil War and subsequent repression) may influence the level of the dependent variable before the shock or through other channels than those implied by the financial crisis. To address this concern and to validate my research design, I follow Goldsmith-Pinkham et al. (2020) and perform two empirical tests to ensure the plausibility of the identifying assumption (see the Appendix).

Table 2 presents the results of the first-stage regressions. In the first column, I provide the baseline linear specification depicted in Eq. (2), but without controls at the municipality level. In the second column, I include controls. The instrument is a robust predictor of the variation in trust in the post-crisis period: the negative association between the instrument and interpersonal trust supports the hypothesis that in municipalities characterized by higher levels of latent mistrust, the decline in trust following the economic crisis was more pronounced. I conduct several placebo tests using years other than 2009 and show that the instrument loses validity, highlighting that it is only the inmediate posterior year of the economic crisis that are crucial for this shift in trust (see the Appendix for the placebo tests). The placebo tests reported show that the instrument does not predict trust in alternative periods, nor does it exhibit predictive power outside the immediate post-crisis window. This pattern is consistent with the interpretation that the crisis acted as a trigger that activated latent mistrust. Taken together, these tests support the interpretation of the instrument as isolating exogenous variation in interpersonal trust.

Table 2: First-stage results

	Trust	**Trust**
Casualties$_m \times 1_{t\geq 2009}$	**-0.28*****	**-0.51*****
	(0.02)	(0.01)
Controls	No	Yes
Firm FE	Yes	Yes
Prov-by-year FE	Yes	Yes
F-stat	92.1	85.9
Observations	581301	581301

Controls included are share of educated people at the municipal level, share of employment at the municipal level, and gender composition of the municipality. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

6 Results

I present the findings with an emphasis on the results of the second-stage regressions. Table 3 presents the results of the baseline specification depicted in Eq. (1), including both the IV estimation and the OLS estimation. The dependent variable across all the columns is the log of employees. The main conclusion to be drawn from this table is that the effect of interpersonal trust is positive and statistically significant according to 2SLS estimation. Controlling for several economic variables such as employment share, gender composition or share of educated people at the municipality level hardly affects the results. The interpretation of the magnitudes should be made in terms of semi-elasticities; for instance, the interpretation of the trust coefficient in column 3 is that a one-unit increase in the local trust is associated with an average increase of 75 per cent in firm size. [5] In other words, if a firm has for example 3 employees, a one-unit increase in trust would result in an increase of around 2 employees on average—a non-negligible number. The results are robust, and various robustness checks that ensure the reliability of the findings can be

[5]Note that 2SLS estimations correct downward biases of the OLS coefficients. One plausible explanation for the downward bias in the OLS estimates is measurement error in the interpersonal trust variable. Interpersonal trust is typically derived from survey data or perception-based indicators, which are subject to measurement error. If trust is measured imprecisely, OLS estimates could suffer from attenuation bias, thereby systematically biasing the estimated coefficient toward zero. A second potential source of bias comes from reverse causality, since firm size may itself influence the level of interpersonal trust; for example, larger firms may foster less interpersonal trust due to increased bureaucracy, hierarchical structures, or reduced interpersonal interaction, especially in vertically integrated or geographically dispersed firms. In such a case, OLS would be downward-biased as well.

found in the Appendix.

A potential threat to identification is the fact that firm size is significantly shaped by regulatory frameworks. For instance, firms exceeding 50 employees in Spain are legally required to establish a "work council", which entails additional costs; this may disincentivize firm size growth when firms approach this threshold. Nevertheless, this does not compromise the validity of the findings presented in this study, due to the identification strategy implemented; regulation-induced behavior around the 50-employee threshold may influence the distribution of firm sizes, but as long as the instrument is plausibly exogenous to this regulatory behavior, the identification remains valid. More specifically, the instrument does not exploit variation around the regulatory threshold, nor is it constructed in a way that is related to firm responses to regulations. It is also worth noting that latent mistrust may plausibly affect firm size through institutional channels. To account for this, I include firm fixed effects, which capture such potential influences. Additionally, although the 2008 financial crisis likely impacted regions differently, this should not pose a threat to my identification strategy, as I also control for province-by-year fixed effects.

Heterogeneity by sector. It is important to investigate wether the relationship between interpersonal trust and firm size varies across sectors. For this analysis, I begin with the primary sector (Table 4), then examine the manufacturing sector (Table 5) and finally the service sector (Table 6). The results indicate that trust plays a significant role only on services. The estimated coefficients for service sector are similar to those reported in the baseline results (Table 3). There are several potential explanations for this finding. First, sectors differ substantially in their organizational structures, coordination needs, and reliance on informal mechanisms of cooperation. For instance, knowledge-intensive services (e.g., information technology, consulting, or media) tend to require high levels of collaboration, autonomy, and tacit knowledge exchange, all of which may be facilitated by interpersonal trust; in contrast, sectors with more routinized processes (e.g., manufacturing) may rely more heavily on formal systems of control and less on interpersonal dynamics. Second, the cost and the feasibility of monitoring employee behavior and performance differ across industries. In sectors where tasks are difficult to codify or outcomes are hard to measure (e.g., professional services or RD), interpersonal trust can be a substitute for formal monitoring and reduce moral hazard problems. This may allow firms to scale more efficiently when trust is high.

Heterogeneity by size. Given that interpersonal trust has a strong social component, it is reasonable to expect its relevance to be greater in smaller firms, where interactions among workers are more frequent, direct, and less mediated by formal organizational structures. This hypothesis is examined in Table 7, which replicates the baseline specification while restricting the sample to firms that employed three or fewer workers in 2006. The estimated coefficients are notably larger in magnitude than those obtained using the full sample in Table 3. These findings suggest that interpersonal trust plays a more prominent role in small firms, where informal relationships and personal interactions are likely to be central to coordination, information sharing, and decision-making processes.

Table 3: Baseline results

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.01**	**0.009**	**0.75*****	**0.41*****
	(0.006)	(0.006)	(0.23)	(0.08)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	92.1	85.9
Number of firms	69842	69842	69842	69842
Observations	581301	581301	581301	581301

The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table 4: Results for primary sector

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.02**	**0.02**	**0.66**	**0.77**
	(0.03)	(0.03)	(0.34)	(0.37)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	28.1	27.3
Number of firms	1289	1289	1289	1289
Observations	11544	11544	11544	11544

The dependent variable of all regressions is the log of employees. Here are included all activities related to: Agriculture, livestock, forestry, and fishing. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table 5: Results for manufacturing sector

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.007**	**0.006**	**0.18**	**0.10**
	(0.01)	(0.01)	(0.28)	(0.17)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	8.3	7.9
Number of firms	4734	4734	4734	4734
Observations	40981	40981	40981	40981

The dependent variable of all regressions is the log of employees. Here are included all activities related to the manufacturing industry. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

Table 6: Results for services

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.002**	**0.001**	**0.56****	**0.3*****
	(0.007)	(0.007)	(0.22)	(0.09)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	60.1	55.9
Number of firms	46209	46209	46209	46209
Observations	459915	459915	459915	459915

The dependent variable of all regressions is the log of employees. Here are included all activities related to: wholesale and retail trade, repair of motor vehicles, transportation and storage, accommodation and food services, information and communication, financial and insurance activities, real estate activities, professional and technical services. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

Table 7: Results for small firms

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.01**	**0.009**	**0.82*****	**0.48*****
	(0.008)	(0.007)	(0.25)	(0.09)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	91.4	84.3
Number of firms	51549	51549	51549	51549
Observations	429040	429040	429040	429040

Small firms are firms with three or less workers in 2006. The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

6.1 Mechanisms: TFP improvements and greater access to credit

The heterogeneity analysis shows that the positive effect of interpersonal trust on firm size is concentrated in the services sector, while being negligible in the primary and manufacturing sectors. This pattern provides important guidance on the mechanisms through which trust operates. In particular, it suggests that trust matters most in environments where production relies heavily on human interaction and activities that are difficult to fully specify or monitor contractually. Building on this evidence, this section explores two mechanisms through which interpersonal trust can translate into larger firm size: higher total factor productivity and improved access to credit.

First, interpersonal trust can enhance firm size by increasing total factor productivity. As discussed in the heterogeneity analysis, many service-sector activities—especially knowledge-intensive services—depend on teamwork and information sharing. In such settings, trust reduces coordination frictions, facilitates the exchange of tacit knowledge, and allows employees greater autonomy without incurring large agency costs. By lowering the need for intensive monitoring and formal control, trust enables firms to operate more efficiently and to scale their workforce without proportional increases in managerial or organizational costs. This channel is less relevant in sectors with standardized production processes, such as manufacturing, where productivity depends more on capital intensity and formalized procedures than on interpersonal relationships. To examine the relationship between trust and total factor productivity (TFP), I estimate Equation (1) using TFP as the dependent variable. All other aspects of the specification remain unchanged, including the instrumental variable; however, the sample is restricted to firms in the service sector. This is a standard approach for testing the potential mechanisms that would rationalize the main result. I report the findings in the first two columns of Table 8 and show that there is a positive causal relationship between TFP and interpersonal trust. This finding is consistent with Moral-Benito (2016), who, using firm-level administrative data for Spain, find that productivity shocks are followed by significant increases in firm size defined by employment.

Second, interpersonal trust can also foster firm size growth by easing access to external finance. In environments characterized by higher levels of local trust, lenders face lower informational frictions and reduced concerns about opportunistic behavior, which in turn lowers the perceived risk of lending. Trust facilitates the formation of durable relationships between firms and financial intermediaries, improves the credibility of borrowers' commitments, and enhances contract enforcement beyond formal legal mechanisms. The results suggest that firms operating in high-trust municipalities are more likely to obtain credit, face fewer borrowing constraints, and access larger volumes of external finance at more favorable terms. This relaxation of financial constraints enables firms to expand operations, invest in physical and human capital, and scale up, thereby contributing to larger firm size. The effects are particularly salient for smaller firms, which are typically more dependent on relationship-based lending and more vulnerable to credit market imperfections. In columns 3 and 4 of Table 8, I show the results of estimating Equation (1) but using credit access as the dependent variable, again restricting the sample to firms in the service sector. I find that the relationship is also positive and significant, suggesting that this is another relevant mechanism. Taken together, Table 7 results suggest that trust operates through both productivity-enhancing and credit-relaxing channels.

Table 8: Mechanisms

	TFP		**Credit access**	
	(1)	(2)	(3)	(4)
Trust	**0.04*****	**0.04*****	**0.13*****	**0.14*****
	(0.006)	(0.007)	(0.02)	(0.02)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-yearFE	Yes	Yes	Yes	Yes
F-stat	60.1	55.9	60.1	55.9
Number of firms	46209	46209	46209	46209
Observations	459915	459915	459915	459915

The dependent variable of regressions (1) and (2) is total factor productivity (TFP), which is estimated using ACF method (see Appendix for details). The dependent variable of regressions (3) and (4) is credit access which I proxy using debt ratio. Results are 2SLS results. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

7 Conclusion

This paper investigates whether interpersonal trust constitutes a meaningful determinant of firm size. Using detailed firm-level balance sheet data for Spanish firms and municipality-level measures of trust, I provide causal evidence that higher levels of local interpersonal trust lead to larger firms. Identification relies on an instrumental variable strategy that exploits the interaction between latent mistrust—proxied by the historical incidence of Civil War casualties—and the decline in trust following the 2008 financial crisis. This approach isolates exogenous variation in trust across municipalities and allows the estimation of a causal effect of social capital on firm growth.

The empirical findings reveal a robust and economically meaningful relationship between trust and firm size. Firms located in municipalities with higher levels of interpersonal trust employ significantly more workers, with effects that are particularly pronounced among small firms. This pattern is consistent with the idea that trust plays a more central role where formal governance structures and hierarchical controls are limited. In such environments, interpersonal relationships become an essential mechanism for coordination, information sharing, and collective problem solving.

The analysis also sheds light on the mechanisms through which trust affects firm growth. Two complementary channels appear to be particularly important. First, higher levels of trust increase total factor productivity, likely by reducing coordination frictions and facilitating knowledge sharing within firms. Second, trust improves firms' access to credit, suggesting that social capital may help alleviate informational frictions in financial markets and strengthen relationships between firms and lenders. Together, these mechanisms highlight how trust can shape both the internal efficiency of firms and their ability to mobilize external resources.

Beyond its academic contribution, the paper also has broader implications for economic development and policy. If interpersonal trust facilitates firm growth and productivity, then social capital should be considered an important component of the economic environment in which firms operate. Policies aimed at strengthening civic engagement, institutional credibility, and community cohesion may therefore generate economic benefits that extend beyond traditional policy tools focused solely on financial or regulatory reforms.

Several avenues for future research remain open. One promising direction would be to explore more directly the micro-level mechanisms linking trust to organizational behavior, potentially using matched employer–employee data to examine how trust affects delegation, teamwork, and workplace interactions. Another important extension would be to investigate how trust interacts with formal institutions—such as legal enforcement or financial regulation—in shaping firm growth. Understanding how formal and informal institutions complement each other could provide a more comprehensive view of the institutional foundations of firm development.

Overall, the results underscore the idea that economic performance is shaped not only by formal rules and market forces but also by the social fabric where economic activity takes place. Interpersonal trust, as a key component of this social fabric, appears to play a central role in enabling firms to grow, coordinate efficiently, and overcome financial constraints. Recognizing the economic value of trust may therefore help broaden our understanding of the institutional foundations of firm growth and economic development.

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Appendix

Robustness checks

I present a series of robustness checks that ensure the robustness of the baseline results. I show that the main results are robust to clustering at municipal level instead of at firm level (Table A.1), robust to dropping Madrid and Barcelona (Table A.2), robust to the introduction of firm profits as a control (Table A.3), robust to different controls (Table A.4) and finally robust to reduce the sample years (Table A.5). Besides this, I show some placebo tests where I take years 2007 and 2008 to build the instrumental variable instead of year 2009 (Tables A.6, A.7), finding that with these other years the instrument is not valid. Finally, I show the results of estimating Equation (1) but using an unbalanced panel, that is, considering all firms, including entries and exits (Table A.8).

Table A.1: Baseline results when clustering at municipal level

	OLS		**2SLS**	
	(1)	(2)	(3)	(4)
Trust	**0.01**	**0.009**	**0.76*****	**0.43*****
	(0.007)	(0.007)	(0.23)	(0.08)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	90.3	82.3
Number of firms	69842	69842	69842	69842
Observations	581301	581301	581301	581301

The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the municipal level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.2: Baseline results when dropping Madrid and Barcelona

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Trust	**0.001**	**0.007**	**0.52*****	**0.35****
	(0.006)	(0.006)	(0.20)	(0.18)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	72.2	77.6
Number of firms	57214	57214	57214	57214
Observations	476197	476197	476197	476197

The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.3: Baseline results controlling for profits

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Trust	**0.01**	**0.009**	**0.75*****	**0.41*****
	(0.006)	(0.006)	(0.23)	(0.08)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	92.1	85.9
Number of firms	69842	69842	69842	69842
Observations	581301	581301	581301	581301

The dependent variable of all regressions is the log of employees. Controls include firm profits. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.4: Baseline results when including different controls

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Trust	**0.01**	**0.01**	**0.75*****	**0.39*****
	(0.006)	(0.008)	(0.23)	(0.09)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	92.1	90.1
Number of firms	69842	69842	69842	69842
Observations	581301	581301	581301	581301

The dependent variable of all regressions is the log of employees. Controls include the share of Catholics, the share of individuals who identify as right-wing, and gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.5: Baseline results when dropping years 2014, 2015, 2016 and 2017

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Trust	**0.05**	**0.01**	**0.57***	**0.36*****
	(0.006)	(0.008)	(0.28)	(0.05)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	92.1	85.9
Number of firms	69842	69842	69842	69842
Observations	387534	387534	387534	387534

The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.6: First-stage results using year 2007 to build the IV

	Trust	**Trust**
$\text{Casualties}_m \times 1_{t \geq 2007}$	**-0.11**	**-0.21**
	(1.12)	(1.86)
Controls	No	Yes
Firm FE	Yes	Yes
Prov-by-year FE	Yes	Yes
F-stat	5.1	7.9
Observations	581301	581301

Controls included are share of educated people at the municipal level, share of employment at the municipal level, and gender composition of the municipality. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.7: First-stage results using year 2008 to build the IV

	Trust	**Trust**
$\text{Casualties}_m \times 1_{t \geq 2008}$	**-0.32***	**-0.29***
	(0.18)	(0.17)
Controls	No	Yes
Firm FE	Yes	Yes
Prov-by-year FE	Yes	Yes
F-stat	7.5	9.5
Observations	581301	581301

Controls included are share of educated people at the municipal level, share of employment at the municipal level, and gender composition of the municipality. Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%.

Table A.8: Baseline results with entry and exit

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Trust	**0.0001**	**0.0001**	**0.0005**	**0.0006**
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Prov-by-year FE	Yes	Yes	Yes	Yes
Effective F-stat	-	-	92.1	85.9
Number of firms	517271	517271	517271	517271
Observations	2997439	2997439	2997439	2997439

The dependent variable of all regressions is the log of employees. Controls include the share of educated individuals, the employment rate, and the gender composition at the municipal level. Robust standard errors clustered at the firm level are in parentheses. Significance levels. Significance levels: *: 10%, **: 5%, ***: 1%.

Sampling procedure of CIS

Sampling procedure of CIS: Multistage, cluster-stratified, with selection of primary sampling units (municipalities) and of the secondary units (sections) in a random proportional manner, and of the ultimate units (individuals) by random routes and sex and age quotas. The strata have been formed by the crossing of the 17 autonomous communities with the size of habitat, divided into 7 categories: less than or equal to 2,000 inhabitants; from 2,001 to 10,000; from 10,001 to 50.000; from 50,001 to 100,000; from 100,001 to 400,000; from 400,001 to 1,000,000, and more than 1,000,000 inhabitants.

Table A.9: Population vs sample comparison

	Population (%)	**Sample (%)**
Males	0.493	0.498
Females	0.507	0.502
Highly educated	0.341	0.298
Low educated	0.659	0.702
Ideology (right-wing)	0.574	0.600
Catholics	0.783	0.778
Working	0.439	0.464
Self-employed	0.171	0.195

This table shows the shares of characteristics in my sample and in the Spanish population for the year 2006 (Source: INE, CIS).

Firm-Level TFP Estimation

This section describes how total factor productivity (TFP) is estimated. I assume that the production function is Cobb-Douglas. To estimate firm-level production functions, one needs to control for the simultaneity and selection bias which is inherently present. I follow the procedure developed by Ackerberg et al. (2015) who rely on an observable proxy variable being a function of the unobserved productivity level (aka control function approach) paired with a law of motion for productivity. This method builds on standard control function methods by taking into account the fact that the variable factor of production adjusts in response to a productivity shock, whereas the fixed factor does not react to contemporaneous shocks to productivity, but it is correlated with the persistent productivity term. The observable proxy variable that I use is expenditures on intermediates. The production function in logs is

$$y_{it} = \beta_l \ell_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}, \tag{3}$$

where y_{it} is real value added, ℓ_{it} is labor, k_{it} is the book value of tangible fixed assets and TFP is ω_{it}. The term ε_{it} is the measurement error, an i.i.d. unanticipated shock to production. The two-step estimation is as follows.

Stage One.

- Get expected output:

$$y_{it} = \phi_t(\ell_{it}, k_{it}, m_{it}) + \varepsilon_{it}, \tag{4}$$

$$y_{it} = \beta_l \ell_{it} + \beta_k k_{it} + h_t(m_{it}, k_{it}, \ell_{it}) \equiv \phi_t(\ell_{it}, k_{it}, m_{it}) + \varepsilon_{it}. \tag{5}$$

- Run OLS of y_{it} on a higher-order polynomial in $(\ell_{it}, k_{it}, m_{it})$ to obtain $\hat{\phi}_t(\ell_{it}, k_{it}, m_{it})$.
- I now have expected output $\hat{\phi}_{it}$ where ε_{it} is netted out.

Stage Two.

- Estimate the coefficients β_l and β_k using standard GMM techniques. Use block bootstrapping to get the standard errors.
- Guess the coefficients β_l and β_k. Get productivity:

$$\omega_{it}(\beta_k, \beta_l) = \hat{\phi}_{it} - \beta_k k_{it} - \beta_l \ell_{it}. \tag{6}$$

- Non-parametrically regress and take the innovations $\xi_{it}(\beta_k, \beta_l)$:

$$\omega_{it}(\beta_k, \beta_l) = E(\omega_{it}(\beta_k, \beta_l) \,|\, \omega_{it-1}(\beta_k, \beta_l)) = \omega_{it-1}(\beta_k, \beta_l) + \omega_{it-1}^2(\beta_k, \beta_l) + \omega_{it-1}^3(\beta_k, \beta_l) + \xi_{it}(\beta_k, \beta_l). \tag{7}$$

- There are two parameters and two moment conditions. Check if conditions are satisfied:

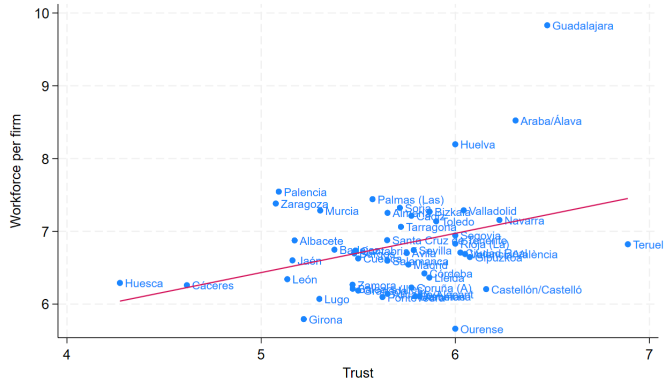
$$E\left[\xi_{it}(\beta_k, \beta_l) \begin{pmatrix} \ell_{it-1} \\ k_{it-1} \end{pmatrix}\right] = 0, \tag{8}$$

  i.e.

$$T^{-1} N^{-1} \sum_t \sum_i \xi_{it}(\beta_k, \beta_l) \begin{pmatrix} \ell_{it-1} \\ k_{it-1} \end{pmatrix} = 0. \tag{9}$$

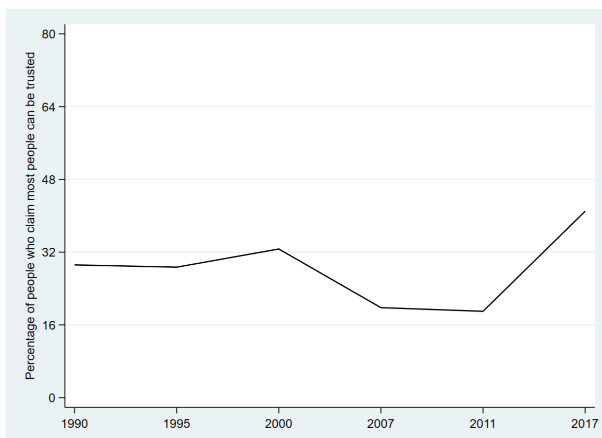
Additional figures

Figure A.1: Workforce per firm and trust (0-10 scale) in Spanish provinces, 2023



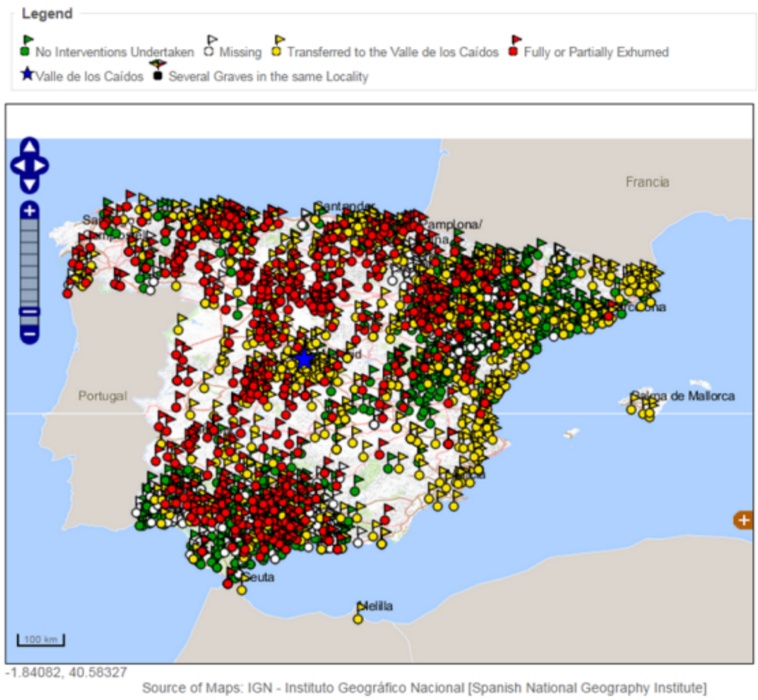
Workforce per firm is calculated as the total number of workers in a province divided by the total number of firms in the province. Source: Surveys from CIS (Centro de Investigaciones Sociológicas; Central Business Register (INE)

Figure A.2: Evolution of interpersonal trust in Spain, 1990–2017



Source: World Values Survey

Figure A.3: Map of Mass Graves



Source: Spanish Ministry of Justice

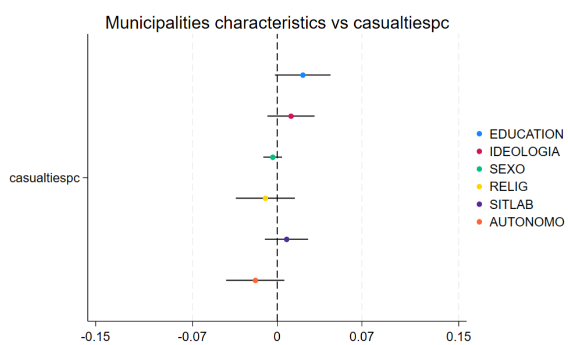
Tests for validity of identification assumption

First, in Figure A.4, I examine the relationship between various municipality-level characteristics in 2006 and the share of victims of the Spanish Civil War and subsequent repression. I present the main estimates along with their 95% confidence intervals. None of these partial correlations exhibit significant deviations from zero, indicating that the cross-sectional variation employed to construct the instrumental variable is unrelated to other sociodemographic and economic outcomes across municipalities. In addition, the R-squared of these regressions is very small, indicating a weak correlation between municipal characteristics at the beginning of the analysis period and the "share component" of the instrument (Goldsmith-Pinkham et al., 2020). This reassuring outcome suggests that the source of exogenous variation across municipalities is not correlated with other factors that could predict changes in firm size. The absence of correlations with a wide range of municipal characteristics at the start of my analysis period aligns with the identifying assumption concerning the exogeneity of the distribution of casualties. However, it is important to note that this condition is not sufficient for the validity of the identification strategy; what matters most (i.e., the sufficient condition for validity) is that the share of casualties, when considered independently, does not serve as a predictor of changes in firm size prior to the shock. To further explore this I implement an event study framework, shown in Figure A.5, to examine the potential dynamic treatment effects of my instrument and to assess the presence of any pre-trends associated with it. This specification can be interpreted as the reduced-form counterpart of my baseline equation (1), formalized through the following standard event study model (Miller, 2023):

$$\ln(\text{Employees})_{i,m,p,t} = \alpha + \sum_{t \neq 2007} \beta_t \,\text{Casualtiespc}_{m,p} \times \text{Year}_t + \gamma X_{m,p,t} + \theta_i + \eta_{p,t} + \epsilon_{i,m,p,t} \tag{10}$$

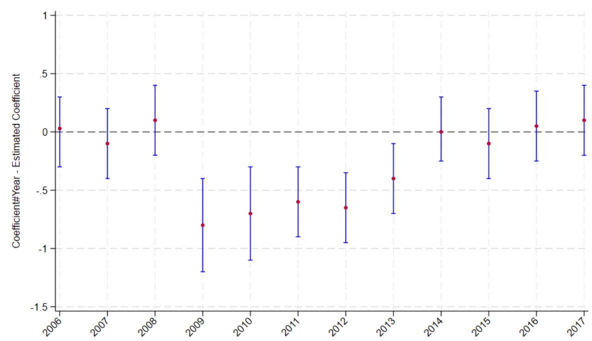
The time-varying parameters β_t capture the annual relationship between the share of casualties and firm size. Specification (10) includes the complete set of fixed effects and control variables from my baseline model (1), as well as the dependent variable, to ensure maximum comparability with the benchmark specification. My proxy for latent mistrust is expected to be relevant primarily after the crisis shock. Accordingly, I hypothesize: (i) no correlation between the share of victims and firm size before the crisis, and (ii) a negative correlation following the crisis shock. Evidence supporting (i) would confirm the absence of pre-trends, while evidence supporting (ii) would reinforce my hypothesis that latent mistrust became an influential factor on firm size after the 2008-09 crisis. Figure 10 presents the results of the event study analysis. Two main findings emerge. First, across all municipalities, the correlation between the proxy for latent mistrust and firm size is statistically indistinguishable before the crisis. This supports my assumption that such mistrust was not salient prior to the financial crisis, and only became relevant after. Second, after the crisis shock, we find a negative correlation between the share of victims and firm size. Overall, the event-study estimates indicate that the proxy for latent mistrust is a weaker predictor of firm size during the pre-crisis period but became relevant in the immediate post-crisis period (i.e., 2009, 2010, 2011, 2012 and 2013), suggesting that the identified LATE effect is primarily driven by pre- versus post-2009 variation. These set of findings provide additional support for the identifying assumption. In summary, the instrument performs well, explains changes in trust following the crisis, and passes the two important tests proposed in the literature that serve to validate the identification assumption.

Figure A.4: Initial conditions test (for the year 2006)



This figure reports the partial correlations between the share of victims (i.e. casualties per capita) and various municipality characteristics. It presents both the estimated coefficients and the 95% confidence intervals. The Municipality characteristics are: share of educated people at the municipal level, share of people who position themselves on the right of the political spectrum, gender composition, share of Catholics, share of employed people, and share of self-employed people.

Figure A.5: Event study



This figure reports the event study coefficients and confidence intervals at 95% level.