The Role of Social Capital in Business Performance

An Empirical Analysis

Author Name:

Damanveer Singh Dhaliwal

Department of Economics

University of Toronto

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1 Executive Summary

When the COVID-19 pandemic struck in early 2020, businesses across the United States faced unprecedented challenges. Some of the businesses were able to adapt and survive, even thrive, but others were forced to close their doors permanently. This paper aims to understand whether the strength of community connections or social capital, helped determine which businesses survived. Using data available on nearly 14 million businesses and newly formed estimates of social capital across US counties using friendship data from Facebook, we use modern econometric and causal inference techniques to examine how social capital relate to business outcomes: cross-class economic connections, tight-knit community networks, and civic engagement.

Our findings indicate that social capital does not have a uniform effect on business survival and performance. Instead we find that, tight knit communities where residents have dense, overlapping social networks saw significantly higher business survival rates from 2019-2024. A one standard deviation increase in this social cohesion was associated with a nearly one percentage point increase in survival probability. This is meaningful given that roughly 24% of businesses failed during this period.

Cross-socioeconomic connections benefits top performing businesses but showed no benefits and possible negative effects for struggling business. Access to wealthy networks provided advantages for high-growth firms. The results also suggest that sectors that rely heavily on information flow, transportation, finance benefitted from social capital the most. Surprisingly, healthcare businesses in high social capital areas had lower survival rates, possibly due to the unique challenges faced during the pandemic.

For policymakers and business leaders, these findings highlight that building community cohesion and not just economic connections can be crucial for economic resilience. Programs that strengthen local networks and civic engagement may help businesses better withstand future shocks. For investors and business leaders, the analysis in this paper suggests that location matters beyond traditional factors like labor costs and market access. The social structure of a community can meaningfully affect business outcomes.

However, the social capital measures used in this analysis are based on Facebook data from 2022 which may not perfectly reflect future or past social networks. Additionally, while we control for many confounders, unobserved factors may still bias the results. Despite these caveats, this paper provides the first large-scale empirical analysis linking social structure to business outcomes.

2 Introduction

Social Capital, the strength of an individual's social networks and the resources accessible through them, has been the subject of extensive research in economics and other social sciences such as sociology. Economic intuition and conventional research suggests that social capital is a productive asset that reduces transaction costs and smooths friction in economic exchanges Putnam (1994). However, this concept has been difficult to quantify empirically due to the lack of comprehensive data on social networks at scale.

Until recently, the primary data for studying social capital was the National Longitudinal Study of Adolescent to Adult Health (Add Health) dataset which covered around 20,000 participants in 132 schools in the United States. The limited data made it difficult for researchers to study how social capital plays a central role in shaping social phenomena like income equality and economic opportunity.

Recently, Chetty et al. (2022a) utilized a novel dataset from Facebook that included over 21 billion social connections to estimate social capital at the local level across the United States. This data allowed the authors to construct a social capital index and examine its relationship with the economic mobility of individuals across different regions. Their findings indicated a strong positive correlation between social capital and economic mobility, suggesting that individuals in areas with higher social capital tend to have better economic outcomes.

This paper aims to build upon the findings of Chetty et al. (2022a) by exploring the relationship between social capital and business performance, which has not been extensively studied in the existing literature. We will investigate two aspects of social capital's effect on business performance: (1) the likelihood of business survival given an exogenous shock (the COVID-19 pandemic), and (2) the revenue growth of businesses over time. By analyzing these dimensions, we aim to provide a comprehensive understanding of how social capital influences business outcomes.

The research question is motivated by two main questions: First, does social capital contribute to the prosperity of counties by enhancing the performance of local businesses? Second, can social capital act as a buffer for businesses during economic downturns or crises, such as the COVID-19 pandemic? The results of this study could have significant implications for policymakers and business leaders, as they highlight the importance of fostering social capital within communities to support economic growth and resilience as well as inform strategies for capital allocation. The study may also motivate individuals and businesses to invest in building and maintaining strong social networks.

The paper is structured as follows: Section 2 reviews related literature in depth and defines the scope of the study in the context of existing research. Section 3 describes the data sources, including the social capital index, in depth and outlines the empirical model and identification strategy. Section 4 presents the main results and robustness checks. Finally, Section 5 concludes with a summary of findings and discusses potential avenues for future research.

3 Literature Review

Social capital has been a topic of interest in various fields, including sociology, economics, and political science. The origins of social capital theory can be traced back to Bourdieu (1986) who defined social capital as the aggregate of actual or potential resources linked to a durable network of institutionalized relationships. Importantly, the author posits that social capital requires extensive investment of time and energy to create and maintain. This signals that social capital might not be evenly distributed across individuals or communities, leading to disparities in access to resources and opportunities. It also suggests that social capital might not be easily transferable or liquidated, however, it is unsure if social capital is transferred intergenerationally.

The idea was then studied extensively by other scholars such as Putnam (1994) who drew on a multi-decade study of regional governments in Italy to argue that regions with deep traditions of civic engagement possess a civic community that serves as a foundation for economic development and democratic governance. Putnam emphasized that social capital increases with use, in contrast to physical capital which depreciates with use. He further argues, based on survey data, that erosion of trust in the United States has led to urban decay, decline in education and loss of trust in the government. These claims are not rooted in strong empirical evidence and have necessitated further research.

Over the years, there have been numerous economic studies aiming to model and quantify social capital and its effects on various economic outcomes. Dasgupta (2003) provides a rigorous economic model of social capital. The central contribution of the paper is to show how social capital can be modeled into standard macroeconomic production functions. The author also argues that dense social networks can inhibit the flow of capital and labour and might lead to equilibria that are suboptimal for economic growth.

More recently, Chetty et al. (2022a) and Chetty et al. (2022b) utilized a novel dataset from

Facebook that included over 21 billion social connections and modern computational techniques to form a first of its kind social capital index at the college, county, high school, and zip code levels across the United States. The authors meaningful results that revitalized interest in social capital research. In particular, they found that children who grow up in areas where cross-class interactions are common tend to have significantly higher upward income mobility. They also found that social capital tends to be highly stratified by socioeconomic status and that differences in this economic connectedness accounts for the relationships between upward mobility and factors such as poverty and racial segregation.

There has also been research exploring the relationship between social capital and public health outcomes. Makridis and Wu (2021) investigate whether areas with higher social capital experienced better health outcomes during the COVID-19 pandemic. They found that moving from the 25th to the 75th percentile of social capital is associated with a 18% reduction in COVID-19 cases and a 5.7% reduction in COVID-19 deaths.

On similar lines exploring social capital's role during crisis, Lins et al. (2017) examine how social capital that is generated by Corporate Social Responsibility (CSR) initiatives can help firms weather economic downturns. Using data from the 2008-2009 financial crisis, they find that firms with high social capital, as measured by their CSR activities, experienced significantly better stock performance during the crisis compared to firms with low social capital. The authors argue that social capital built through CSR initiatives enhances trust and cooperation among stakeholders, which can be particularly valuable during times of economic uncertainty.

It can be observed that while there is rich literature on social capital, there are still gaps that need to be addressed. Most existing studies have focused on individual-level outcomes such as income mobility or public health, with limited research on firm-level outcomes like business performance. Additionally, while some studies have explored social capital's role during crises, there is a lack of comprehensive analysis on how social capital affects business survival and growth during economic shocks.

This paper aims to overcome these limitations and contribute to the literature by exploring the relationship between social capital and business performance. Specifically, this paper examines how different dimensions of social capital influence business survival and revenue growth during the COVID-19 pandemic. By leveraging the novel social capital index developed by Chetty et al. (2022b) and combining it with detailed business performance data, this study provides new insights into the role of social capital in shaping firm outcomes.

4 Empirical Model and Data

4.1 Data

There are two primary data sources for this study:

4.1.1 Social Capital Atlas

The Social Capital Atlas developed by Chetty et al. (2022b) provides a comprehensive measure of social capital at the college, county, high school and zip code level. The index is constructed using data from Facebook users with the following attributes: US residents aged between 25-44; active on Facebook at least once in the 30 days preceding data collection; have at least 100 friends on Facebook; non-missing ZIP Code. This paper relies only on the county level data from 3,000 counties so we will not discuss the other levels in detail.

The social capital index consists of three main components: (1) Economic Connectedness (EC), which measures the extent of cross-class interactions; (2) Social Cohesion, which captures the density and clustering of social networks within a community; and (3) Civic Engagement, which reflects participation in civic activities such as volunteering and voting.

Economic Connectedness was calculated by first defining the socioeconomic status (SES) of individuals based on different variables such as income, wealth, educational attainment, occupation, family background, neighborhood and consumption. These measures were combined into a SES index using a machine learning algorithm and subsequently each individual was assigned a SES percentile rank within their birth cohort. Economic Connectedness was then measured as the share of friends an individual has from the other half of the SES distribution.

Social Cohesion included measures such as clustering, which indicate the extent to which friends of friends are also friends, and support ratio, which measures the rate at which pairs of friends in a community have other friends in common. Civic Engagement was based on a proxy variable that measured the rate of volunteering in each area using membership in Facebook groups related to volunteering activities.

4.1.2 United States Historical Business Data

To complement the social capital data, we utilize the United States historical business data from Axle (2022). This dataset contains detailed information on business establishments across the

United States, including data on industry classification, employment, revenue, and survival status over time. The data spans multiple years, allowing for longitudinal analysis of business performance and is collected by Data Axle, a leading provider of business data and analytics.

Survival status is determined based on whether a business establishment present in 2019 is present in subsequent years, up to 2024. Revenue data is reported annually, allowing for the calculation of revenue growth over time. The dataset also includes industry classification codes based on the North American Industry Classification System (NAICS), enabling analysis of business performance across different sectors.

The two datasets are merged using county FIPS codes to create a comprehensive dataset that includes both social capital measures and business performance metrics at the county level. The social capital index was constructed in 2022, which limits the temporal scope of the analysis. Following Chetty et al. (2022b), we assume that social capital exhibits relative stable behaviour over the short to medium term, allowing for its application in analyzing business performance during the COVID-19 pandemic period (2020-2021). The Data Axle data was used for the years 2019-2024 to capture business performance before, during, and after the pandemic.

A summary of key variables is provided below. The summary table consists of all firms in 2019, including those that did not survive to 2024. Log sales change is estimated only for firms that survived.

Table 1: Summary Statistics

	N	Mean	SD	Min	Median	Max
Survived to 2024	13,821,668	0.76	0.43	0.00	1.00	1.00
Sales 2019 ($000s)	13,821,668	2,153	70,203	0	442	159,933,700
Employees 2019	13,821,668	11.22	106.07	1.00	3.00	88,000
Log Sales Change	8,916,298	-0.16	0.60	-9.71	0.00	9.65
Economic Connectedness	13,821,668	0.823	0.158	0.295	0.793	1.360
Social Cohesion	13,821,668	0.095	0.015	0.072	0.092	0.261
Civic Engagement	13,821,668	0.016	0.006	0.003	0.014	0.106

It can be observed that sales is highly right-skewed. Therefore, we use log sales in the empirical analysis to reduce the influence of outliers. The average survival rate from 2019 to 2024 is 76%, indicating that a significant portion of businesses were able to endure the economic challenges posed by the COVID-19 pandemic.

4.2 Identification Strategy

We are interested in two main outcomes related to business performance: (1) business survival during the COVID-19 pandemic, and (2) revenue growth over time.

We rely on the COVID-19 pandemic as a natural experiment to identify the causal impact of social capital on business resilience. The pandemic represents an exogenous shock that affect all US counties simultaneously, while they varied in their pre-existing levels of social capital. We hypothesize that if social capital provides economic resilience, high social capital counties should experience smaller declines in firm survival and higher revenue growth.

Our identification strategy involves a cross-sectional analysis of business performance with heterogeneous treatment intensity. We do acknowledge that social capital is not randomly assigned across counties, which raises concerns about omitted variable bias. To mitigate this, we include state fixed effects and industry fixed effects to control for unobserved heterogeneity at these levels. We further apply Double/Debiased Machine Learning to flexibly control for high-dimensional confounders.

Despite these controls, our estimates should be interpreted as conditional correlations that are suggestive of, but not definitive proof of, causal effects. The key contribution is documenting the heterogeneity in these associations across social capital dimensions, industries, and the firm performance distribution.

4.3 Key Variables

The primary outcome variables of interest are firm survival, a binary indicator equal to 1 if a firm present in 2019 remains in the Data Axle database in 2024, and sales growth, the log change in sales from 2019 to 2024, conditional on survival. We chose to study survival over the next five years to capture any lagged effects of the pandemic on business performance since some businesses may have initially survived but failed later due to prolonged economic challenges.

We examine all three components of the social capital index: Economic Connectedness (EC), Social Cohesion, and Civic Engagement. While Chetty et al. (2022a) found EC to be the strongest predictor of individual mobility, it is an empirical question whether the same holds for firm-level outcomes.

The control variables include log employees in 2019 (for survival specifications) or log sales in 2019 (for growth specifications), along with state fixed effects and two-digit NAICS industry fixed effects. We include only one size control to avoid multicollinearity between sales and employment

4.4 OLS Specification

We begin with a simple OLS specification to establish the average treatment effects. A linear probability model is preferred for the survival analysis due to its interpretability and ease of estimation with fixed effects. Furthermore, our goal is to estimate average treatment effects rather than predict individual survival probabilities, making the linear probability model a suitable choice. For the survival, we estimate the following:

$$Survival_{i,2024} = \alpha + \beta \cdot SC_c + \gamma \cdot ln(Emp_{i,2019}) + \theta_s + \mu_j + \epsilon_{ic} \tag{1}$$

where $Survival_{i,2024}$ is a binary indicator for whether firm i in county c survived until 2024, $SC \in \{EC_c, COH_c, CIV_c\}$ and EC_c, COH_c, and CIV_c are the Economic Connectedness, Social Cohesion, and Civic Engagement components of the social capital index for county c, respectively. $ln(Emp_{i,2019})$ is the log of employees for firm i in 2019, θ_s are state fixed effects, μ_j are two-digit NAICS industry fixed effects, and ϵ_{ic} is the error term. Here i indexes firm, c indexes county, s indexes state, and j indexes industry. Standard errors are clustered at the county level to account for potential correlation of errors within counties.

To assess which dimensions of social capital are most relevant for business survival, we also estimate a specification that includes all three components of the social capital index simultaneously:

$$Survival_{i,2024} = \alpha + \beta_1 \cdot EC_c + \beta_2 \cdot COH_c + \beta_3 \cdot CIV_c + \gamma \cdot ln(Emp_{i,2019}) + \theta_s + \mu_j + \epsilon_{ic} \tag{2}$$

For revenue growth, we estimate the following specification:

$$\Delta ln(Sales_{i,2019-2024}) = \alpha + \beta_1 \cdot EC_c + \beta_2 \cdot COH_c + \beta_3 \cdot CIV_c + \gamma \cdot ln(Emp_{i,2019}) + \theta_s + \mu_j + \epsilon_{ic} \tag{3}$$

where $\Delta ln(Sales_{i,2019-2024})$ is the change in log sales from 2019 to 2024 for firm i in county c. The other variables are defined as above.

We note that the growth specification conditions on firm survival. To the extent that social capital affects selection into survival, these coefficients capture effects among a non-random subsample of surviving firms

4.5 Double/Debiased Machine Learning (DML)

OLS with high-dimensional controls risks omitted variable bias if we exclude relevant confounders and regularization bias. Including many fixed effects and controls leads to biased estimates due to the model not being able to fully capture complex relationships. We believe that social capital's effects on business performance are likely confounded by many factors such as local economic conditions, demographics, and industry characteristics. Simply including fixed effects may not adequately control for these confounders, especially if their relationships with the outcome and treatment are non-linear or involve complex interactions.

Double/Debiased Machine Learning (DML) (Chernozhukov et al. (2024)) addresses both concerns by using machine learning to flexibly partial out confounders while preserving valid inference on treatment effects.

We use DML for two purposes:

1. to estimate the causal effect of social capital dimension with flexible controls, and
2. to explore heterogeneous treatment effects by industry.

We implement the Partially Linear Regression (PLR) DML estimator for social cohesion as follows:

$$Y_i = \theta \cdot SC_c + g(X_i) + \epsilon_i \tag{4}$$

$$SC_c = m(X_i) + \nu_i \tag{5}$$

where Y_i is the firm survival, $SC_c \in \{EC, COH, CIV\}$ is the social capital measure, X_i is a vector of control variables (log employees in 2019, state-fixed effects, two-digit NAICS industry fixed effects), and $g(\cdot)$ and $m(\cdot)$ are unknown functions estimated using machine learning methods.

We use XGBoost (Gradient Boosted Trees) to estimate $g(\cdot)$ and $m(\cdot)$ due to its strong performance in practice. Given our intent to estimate the heterogeneous effects by industry and sub-industry as well, XGBoost's sequential nature for training addresses any data imbalance issues and provides higher accuracy than other ensemble methods. The parameters for the XGBoost models are tuned using cross-validation to optimize predictive accuracy. Final parameters include a learning rate of 0.1, maximum tree depth of 3 and 200 estimators. The nuisance functions are estimated as:

- $\hat{g}(X_i) = \mathbb{E}[Y_i \mid X_i]$ is the outcome model
- $\hat{m}(X_i) = \mathbb{E}[SC_i \mid X_i]$ is the treatment model

Then we compute the residuals:

$$\tilde{Y}_i = Y_i - \hat{g}(X_i) \tag{6}$$

$$\tilde{SC}_{c,i} = SC_{c,i} - \hat{m}(X_i) \tag{7}$$

Finally, we estimate the treatment effect θ_{SC} by regressing the residualized outcome on the residualized treatment:

$$\tilde{Y}_i = \theta_{SC} \cdot \tilde{SC}_{c,i} + \tilde{\epsilon}_i \tag{8}$$

To avoid overfitting bias, we use 5-fold cross-fitting. For each fold, nuisance functions are estimated on the complement fold and used to compute residuals on the held-out fold. This ensures all predictions are out-of-sample.

A central contribution of this paper is to document the heterogeneity in treatment effects across industries. To do so, we extend the DML framework to by estimating separate DML models for each two-digit NAICS industry and each 4-digit NAICS sub-industry.

For our industry heterogeneity analysis, we focus on social cohesion as the treatment variable, with economic connectedness and civic engagement included as controls in X_i. This choice reflects our baseline finding that cohesion is the dominant predictor of firm survival. These are specified as follows:

$$Y_{ij} = \theta_j \cdot COH_c + g_j(X_{ij}) + \epsilon_{ij} \tag{9}$$

where j indexes industry or sub-industry. This allows us to estimate industry-specific treatment effects θ_j while flexibly controlling for confounders within each industry.

The sub-industry level analysis is novel and is conducted to uncover whether granular findings are being masked at the broader industry or county level. This is particularly important for policy implications, as it can inform targeted interventions to foster social capital in specific sectors where it has the most significant impact on business performance.

4.6 Quantile Regression

Finally, to explore how the effect of social capital varies across the distribution of firm performance, we implement quantile regression. This approach allows us to estimate the impact of social capital on different points of the outcome distribution, such as the median or the 25th and 75th percentiles.

For firm performance, we estimate the following quantile regression model:

$$Q_\tau(Y_i \mid SC_c, X_i) = \alpha^\tau + \beta_1^\tau \cdot EC_c + \beta_2^\tau \cdot COH_c + \beta_3^\tau \cdot CIV_c + \gamma^\tau \cdot ln(Sales_{i,2019}) \tag{10}$$

where $Q_\tau(Y_i \mid SC_c, X_i)$ denotes the τ-th conditional quantile of the outcome variable Y_i given social capital measures and control variables.

Quantile regression allows us to test competing hypotheses about social capital's distributional effects. If social capital provides downside protection, we expect larger effects at lower quantiles. If social capital amplifies success, we expect larger effects at upper quantiles.

5 Empirical Results

5.1 OLS Results

Table 2: OLS Estimates of Social Capital Effects on Firm Survival and Growth

	Panel A: Survival (2019–2024)				Panel B: Sales Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Economic Connectedness	−0.0021*			−0.0016	0.0068***			0.0079***
	(0.001)			(0.001)	(0.001)			(0.001)
Cohesion		0.0079***		0.0080***		0.0031***		0.0051***
		(0.001)		(0.001)		(0.001)		(0.001)
Civic Engagement			0.0020	−0.0004			−0.0014	−0.0043***
			(0.001)	(0.001)			(0.001)	(0.001)
Log Employees	0.0317***	0.0321***	0.0318***	0.0321***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Log Sales 2019					−0.0952***	−0.0949***	−0.0952***	−0.0950***
					(0.001)	(0.001)	(0.001)	(0.001)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,821,668	13,821,668	13,821,668	13,821,668	8,894,396	8,894,396	8,894,396	8,894,396
R^2	0.012	0.012	0.012	0.012	0.181	0.181	0.181	0.181

Notes: Clustered standard errors at the county level in parentheses. Panel A reports linear probability model estimates where the dependent variable equals 1 if the firm survived to 2024. Panel B reports OLS estimates where the dependent variable is log sales change from 2019 to 2024, conditional on survival. All social capital measures are standardized. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The table above presents the OLS estimates of the effects of social capital components on firm survival and sales growth. In Panel A, we observe that social cohesion has a positive and statistically significant effect on firm survival, with a one standard deviation increase in cohesion associated with a 0.79 percentage point increase in survival probability (Column 2). Economic connectedness shows a negative effect on survival (Column 1), while civic engagement is not statistically significant (Column 3). When all three components are included simultaneously (Column 4), cohesion remains significant, while the effects of economic connectedness and civic engagement become insignificant.

In Panel B, we find that economic connectedness and social cohesion components of social capital positively influence sales growth while civic engagement is statistically insignificant. Economic connectedness has the largest effect, with a one standard deviation increase leading to a 0.68% increase in sales growth (Column 5). Cohesion also shows positive effects, though smaller in magnitude (Columns 6 and 7). When all components are included together (Column 8), economic connectedness and cohesion remain significant, while civic engagement becomes negative and significant.

5.2 DML Results

Table 3: Comparison of Estimates: OLS vs. Double Machine Learning (DML)

	Dependent Variable: Firm Survival (Indicator)	
Variable	(1) OLS Estimate	(2) DML Estimate
Economic Connectedness	−0.0021*	−0.0026***
	(0.001)	(0.000)
Cohesion (Clustering)	0.0079***	0.0099***
	(0.001)	(0.000)
Civic Engagement	0.0020	0.0028***
	(0.001)	(0.000)
Method	Linear Regression	Double ML
Controls	State + Ind. FE	High-Dim Controls
Inference	Clustered SE	Neyman Orthogonal

Notes: Column (1) reproduces Model (4) from Table 2. Column (2) reports results from the baseline DML specification. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The DML results refine the OLS findings by flexibly controlling for confounders. As shown in Table 3, the DML estimates (Column 2) indicate that all three components of social capital significantly affect firm survival, with cohesion having the largest effect (0.99 percentage points per standard deviation). Economic connectedness still shows a negative effect but it is more statistically significant while civic engagement now shows a positive and significant effect.

This suggests that OLS may have suffered from bias or was unable to capture the non-linearities, which DML helped to address. The DML approach provides more credible estimates of the causal effects of social capital on firm survival. Given that cohesion consistently shows the strongest positive effect, we focus on it for the subsequent heterogeneity analysis.

5.3 Heterogeneous Treatment Effects by Industry

Table 4: Heterogeneous Effects of Social Capital by Industry (Double Machine Learning)

NAICS	Industry Sector	Observations	Estimate	Sig.
49	Transportation & Warehousing	43,537	0.0322	***
51	Information	259,785	0.0319	***
55	Management of Companies	29,677	0.0181	***
52	Finance & Insurance	733,756	0.0174	***
71	Arts, Entertainment & Recreation	257,977	0.0131	***
54	Professional, Scientific & Tech. Svcs	1,289,754	0.0124	***
22	Utilities	24,357	0.0104	***
42	Wholesale Trade	409,814	0.0101	***
56	Admin., Support & Waste Mgmt	480,318	0.0101	***
44	Retail Trade (Store)	1,192,053	0.0101	***
99	Unclassified Establishments	88,362	0.0094	***
81	Other Services (excl. Public Admin)	1,562,354	0.0085	***
48	Transportation (Air, Rail, Truck)	225,369	0.0083	***
61	Educational Services	316,053	0.0083	***
72	Accommodation & Food Services	880,327	0.0083	***
33	Manufacturing (Durable Goods)	244,499	0.0078	***
92	Public Administration	357,384	0.0077	***
45	Retail Trade (Non-Store)	492,771	0.0066	***
53	Real Estate, Rental & Leasing	649,397	0.0060	***
32	Manufacturing (Non-Durable)	99,063	0.0054	**
31	Manufacturing (Food/Textiles)	79,944	0.0036	
23	Construction	958,139	0.0020	**
21	Mining, Oil & Gas	20,111	0.0002	
62	Health Care & Social Assistance	3,025,049	−0.0024	***
11	Agriculture, Forestry & Fishing	101,818	−0.0095	***

Notes: Estimates represent the Group Average Treatment Effects (GATEs) of standardized social capital on firm survival probability, estimated via Double Machine Learning. Industries are defined by 2-digit NAICS codes. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It can be observed from Table 4 that the effect of social cohesion on firm survival varies significantly across industries. The Transportation & Warehousing sector (NAICS 49) exhibits the largest positive effect, with a 3.22 percentage point increase in survival probability per standard deviation increase in social cohesion. This is followed closely by the Information sector (NAICS 51) and

Management of Companies (NAICS 55), both showing substantial positive effects.

It is very interesting to note that Health Care & Social Assistance (NAICS 62) shows a negative effect of social cohesion on firm survival, with a 2.4 percentage point decrease per standard deviation increase. This counterintuitive finding may reflect unique dynamics in the healthcare sector during the pandemic, such as increased regulatory pressures or shifts in demand that are not mitigated by social capital.

To probe this deeper, we conduct a sub-industry level analysis (results presented in Appendix A). It is found that the information sector's positive effect is driven primarily through wireless telecommunications carriers. Given the work from home mandate during the pandemic and the rise of digital communication, this finding aligns with expectations.

Another striking result was in the retail sector where essential retail exhibited strong positive effects while non-essential retail such as electronics stores showed negative effects. Furthermore, the negative effect in healthcare was concentrated in the independent physician offices while trust based sub-industries such as nursing care facilities, childcare facilities, and mental health services showed a positive effect.

Overall, the heterogeneity analysis underscores that the benefits of social cohesion are not uniform across industries. Sectors that rely heavily on information flow, coordination, and community engagement tend to benefit the most from social capital during crises. In contrast, sectors facing unique challenges during the pandemic may not experience the same protective effects.

5.4 Quantile Regression Results

The quantile regression results provide insights into how the effects of social capital vary across the distribution of firm performance. The plot below summarizes the estimated coefficients for each type of social capital at different quantiles of firm survival probability:

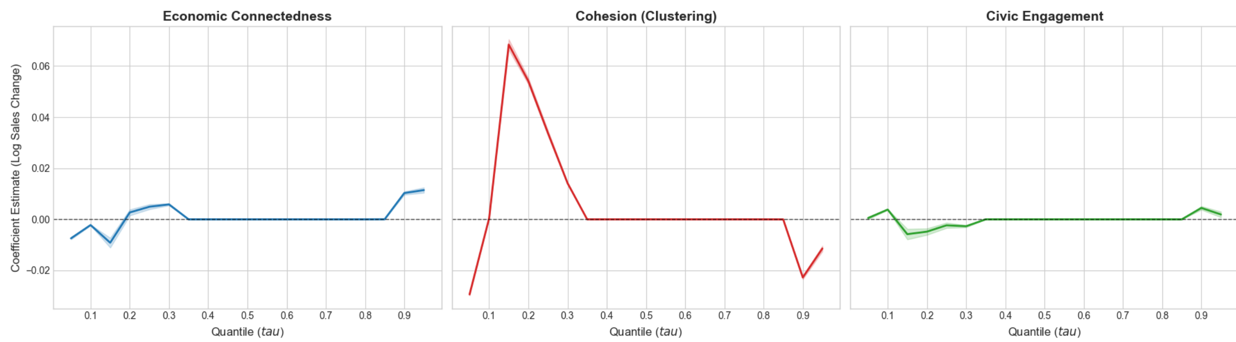

Figure 1: Quantile Regression Estimates of Social Capital Effects on Sales Growth

Economic connectness exhibits an inverted S shaped pattern where its effect is significantly negative for the bottom quantiles, flat in the middle and positive for the top quantiles. This implies that connection to high SES networks provide leverage for high performing firms but may impose costs on low performing firms.

Social cohesion shows a striking result where is provides a massive boost to the lower-middle distribution but has a negative effect at the extreme tails. This suggests that social cohesion acts as a safety net for struggling firms but may create conformity pressures that hinder the best and worst performers.

Civic engagement is negative for struggling firms but turns positive for high performing firms. This indicates that civic engagement may divert resources from survival efforts for weak firms but enhances reputation and networks for successful firms which is evidenced by literature as well.

5.5 Results Discussion

Our analysis yields a multi-faceted view of how social capital influences firm resilience during a crisis and firm growth. By using an OLS model, Double Machine Learning, and Quantile Regressions, we establish that social capital cannot be classified as good or bad across industries and firms but rather presents a set of distinct mechanisms with heterogeneous effects across firm performance distribution and industrial sectors.

For the analysis concerning firm performance during a crisis, it is clear that social cohesion emerges as the primary driver of survival. In our preferred DML specification, one standard deviation increase in cohesion increases survival probability by nearly one percentage point. They suggest that social capital creates a safety net and can prevent local businesses from bankruptcies during exogenous shocks.

Conversely, while economic connectedness was one of the key drivers of upward economic mobility for individuals, it had a small but significant negative effect on the survival of the firms during a crisis. It's also revealed that economic connectedness prefers to support businesses that are operating at a higher level and support the 90th quantile of the performance distribution.

It should also be noted that the predictive power of social capital was not uniform across the economy. Our heterogeneity analysis showed that the benefits of social capital were concentrated in the information and transportation sectors that rely on rapid information flow and coordination. There was also a surprising negative effect in the healthcare sector where higher social capital was associated with lower survival rates. This could be due to the exogenous shock being a healthcare crisis and thus there was higher stress in these industries.

6 Conclusion

This paper investigates the role of social capital in influencing business performance. Specifically, we leverage the exogenous economic shock of the 2020 COVID-19 pandemic to decompose the causal effects of social capital on firm resilience and to study whether social capital has a direct effect on firm performance over the years. By integrating high-dimensional business administrative data with novel measures on social structure and applying double machine learning quantile regressions and OLS frameworks, we challenged the view of social capital as a one-size-fits-all social surplus or a social negative. Instead, our results show that social capital is a complex landscape with different dimensions of social structure serving competing economic functions.

Our findings have important implications for policymakers and business leaders. First, fostering social cohesion within communities can enhance the resilience of local businesses during economic downturns. Second, strategies to build economic connectedness should be tailored to support high-performing firms, while recognizing that such connections may not benefit all businesses equally. Finally, the heterogeneous effects across industries highlight the need for sector-specific approaches to leveraging social capital for economic development.

Our central finding highlighted that in tight-knit communities, the ability to mobilize collective action and informal safety nets acts as a primary defense against exogenous shocks. This is what was labeled as social cohesion. Conversely, contrary to research about individual economic outcomes, economic connectedness served as an amplifier of business performance for the top-performing firms.

For the firms at the bottom end of the sales growth distribution, it was actually detrimental.

Methodologically, our results underscore the limitations of OLS in this sector of research. The application of double machine learning revealed that the estimates provided by the OLS suffered from bias regarding economic connectedness and civic engagement. By correcting for these non-linearities, we do learn that while economic connectedness does have a negative effect on firm survival, civic engagement acts as a strategic complement that confers survival benefits on average, though our quantile analysis suggests these benefits are concentrated among high-performing firms, potentially acting as a costly distraction for struggling entrants.

Given that the social capital data was built in 2022, we do realize the limitation that we cannot generalize for the temporal component of this causal effect. Future research avenues include: 1. Building similar databases and indexes across different time periods, 2. Ensuring the robustness of findings across different economic shocks, 3. Exploring the institutional mechanisms that derive social capital formation and maintenance, and 4. Investigating the micro-level firm strategies that leverage social capital for resilience and growth.

As economies face global shocks from an increasingly volatile world, it is important to understand what factors contribute to economic resilience and success. Our analysis can inform investors, business leaders, and policymakers about the type of social capital that can positively affect a community as well as where to direct capital.

Appendix A: Sub-Industry Level Heterogeneity Results

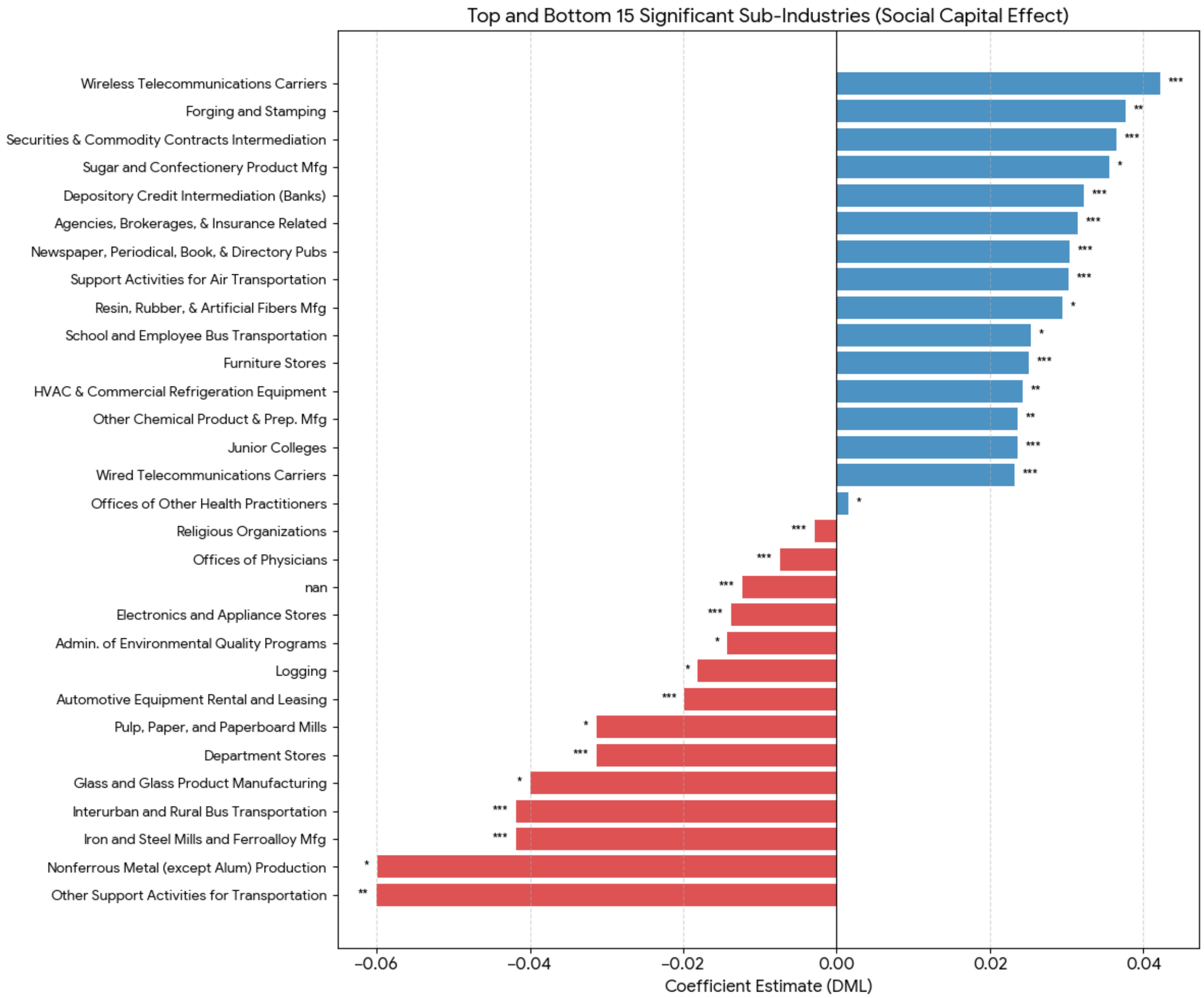

Figure 2: Sub-Industry Level Heterogeneous Effects of Social Cohesion on Firm Survival

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