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Contents

To Eleftheria and Alessandro

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I dedicate this thesis to my family, Eleftheria and Alessandro. With you by my side, anything is possible.

Introduction

This thesis comprises three essays investigating the role of connections and personal experiences on firms' and individuals' decisions. In the first two chapters, I investigate how governance networks affect the transmission of information among competitors and their implications on product market outcomes. The third chapter contributes to the literature on the effects of personal experiences on individuals' patience and savings behavior.

In Chapter 1, I investigate the effects of board connections on coordination among U.S. legacy airlines. I focus on connections caused by the appointment of an airline director on the board of an intermediate firm. Such connections are unlikely to be related to the airline's current and future economic prospects. In my baseline specification, I find a reduction of 2.5% in offered seats when all legacy airlines in a market are board-connected. The effect materializes only in markets where all legacy airlines are connected. Finally, I show that board connections are associated with an average increase of 3.7% in ticket fares.

In Chapter 2, my co-authors and I investigate how common ownership between lenders affects the terms of syndicated loans. We provide a novel view on the role of common ownership in mitigating information asymmetries on the quality of borrowers and the resulting contractual distortions in the terms of the loan. Our empirical evidence shows that high common ownership decreases loan rates, lowers the share of the loan retained by the lead bank, and mitigates rationing at issuance. Further investigations lend support to the hypothesis that common ownership serves as a device for information transmission: common ownership especially affects the terms of loans for new borrowers when the lead arranger is likely to hold an informational advantage.

In Chapter 3, my co-authors and I examine the long-term effects of early-life exposure to food scarcity on individuals' patience and savings. We collect historical data on livestock availability during World War II at the province level in Italy and combined it with survey data on elicited patience and precautionary savings. Using a difference-in-differences approach, we find that individuals who experienced more scarcity during childhood showed higher levels of patience and savings. Thus, we show that early-life exposure to food scarcity can lead to a lasting increase in individuals' prudence.

Chapter 1

Board Connections and Competition in Airline Markets

Mattia Colombo

Abstract

I investigate the effects of board connections on coordination among U.S. legacy airlines. I focus on connections caused by airline directors' appointments to the board of third, non-competing firms. These connections do not arise from changes to airlines' boards, and are arguably unrelated to airlines' current and future economic prospects. In my baseline specification, I find a reduction of 2.5% in offered seats when all legacy airlines in a market are board-connected. Consistent with an anti-competitive effect, board connections are associated with an average increase of 3.7% in ticket fares. I provide evidence on director networks enabling tacit coordination among competing firms, even when direct interlocks are not allowed.

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1.1 Introduction

Antitrust scholars and authorities have since long recognized the anti-competitive effects of board connections (Dooley, 1969; Mizruchi, 1996). In the U.S., Section 8 of the Clayton Antitrust Act of 1914 (Clayton Act) forbids anyone from simultaneously working as an officer or director for competing corporations in the U.S. (board interlocks). However, past papers and authorities overlooked the possibility that directors of competing firms can meet on the board of other firms. Thus, it is still unclear how information flows across the entire network of directors and affects product market competition. The goal of this project is to fill this gap.

Directors often hold multiple directorships, and, most importantly, directors of competing firms often sit together on the board of another non-competing firm. In the airline industry, an outside director of American Airline sat together with Delta's CEO on the board of Bellsouth Corporation from 2001 to 2004.[1] In the same period, he also sat with two other outside directors of Delta on the board of General Motors. In the last two decades, these connections have become more common across all industrial sectors, Nili (2019). This phenomenon raises questions on the relation between board connections and competition. Under which conditions do board connections enable communication among competing firms? What are their effects on product market competition?

In this project, I investigate the impact of board connections among U.S. legacy airlines on product market competition. The focus on this industry has several advantages. First, the public availability of high-quality route-level seats and price data, with each route representing a separate market. Second, I focus on board connections generated by the appointment of airline directors on the board of third, non-competing firms, which are unlikely to be related to airlines' current and future economic activity. Third, I account for the unobserved confounding variation across markets and airlines over time, by including airline-market and airline-time dummies.

[1] https://www.sec.gov/Archives/edgar/data/732713/000095014404001649/g86981e10vk.htm

To measure board connections, I gather directors' data from BoardEx. The data contains extensive information on all U.S. airline directors (e.g., name, role, and education). Most importantly, it reports their entire employment history and their multiple appointments. Thus, I can track the entire employment network for each airline director in my sample at each point in time. I define two legacy airlines as connected if at least one director of each airline sits on the board of an intermediate firm. Next, to relate board connections to airlines' competitive behavior, I define a market as board-connected if all legacy airlines in that market share a board connection. The rationale is that all airlines in the market must be connected to tacitly coordinate and not have incentives to deviate.

I regress the log of seats offered by each airline in a market in a month on a dummy which equals one if the market is board-connected. In my baseline specification, I find that when all legacy carriers in a market are connected through their directors' network, the average number of seats offered declines by 2.5%. The effect monotonically increases with the number of legacy airlines in the market, ranging from 2.3% with two legacy carriers to 4.1% with four legacy carriers. Moreover, the effect is more pronounced in markets where legacy carriers compete against low-cost carriers (LCCs).

Connected directors of competing firms regularly meet and may easily exchange information. Recognizing this, the U.S. Department of Justice (DOJ) has recently started an investigation to tackle board connections. In his opening remarks at the 2022 Spring Enforcers Summit, Assistant Attorney General Johnatan Kanter stated the DOJ's intention to "*identify violations across the broader economy and bring Section 8 cases to break up interlocking directorates.*" In October 2022, seven directors of ten different companies resigned from their role.[2] However, there is still no clear evidence on the anti-competitive role of these indirect board connections.

I conduct a range of placebo tests to ensure that the established relationship is not driven by unobserved factors. For example, assume board connections reflect more skilled directors who are rewarded by the director labor market with multiple

[2] https://www.crn.com/news/managed-services/solarwinds-dynatrace-directors-resign-after-doj-crackdown

directorships. In that case, I should observe an effect also in markets where only a few legacy airlines are connected. However, I do not find such an effect. In markets where only one pair of legacy airlines are connected, board connections do not affect the number of offered seats. Similarly, when all but one legacy airline are connected, board connections do not impact seat availability. Taken together, these results highlight how board connections allow a firm to monitor its competitor's actions in connected markets and ensure tacit coordination.

Next, I address the endogeneity of market structure using a control function approach. If market structure is endogenous, then board connections will be endogenous as well. I instrument for market structure using the average distance between a market's origin and destination airport and the carrier's closest hub. This distance is a proxy for the fixed costs that a carrier faces to serve a market, Aryal et al. (2021); Ciliberto and Tamer (2009), and, consequently, determines its decision to enter that market. I find that legacy carriers reduce the number of offered seats by 2.5% in board-connected markets.

Finally, consistent with a reduction in competition among legacy airlines, I find that board connections are associated with a lower number of flights offered and an average increase in ticket fares by 3.7%. Even though I do not estimate a model of airline competition with board connections, the results highlight the potentially negative effects of board connections on consumers.

The paper is among the first to provide evidence of the anti-competitive effects of board connections. Closely related, Barone et al. (2022) show that the prohibition of interlocks among Italian banks resulted in lower loan interest rates and an increase in competition. Complementary to their result, I show that firms can still tacitly coordinate through their directors' network even when interlocks are formally banned. Thus, my results highlight the importance of going beyond direct interlocks and considering the entire network of director connections among competitors. Gopalan et al. (2022) conduct a cross-industry study of director connections among competing firms and provide evidence of higher profitability among connected firms. Similarly, Geng et al. (2022) show that the introduction of Corporate Opportunity Waivers in nine

U.S. states caused higher board overlap among firms in the same industry and higher profitability. Different from Gopalan et al. (2022) and Geng et al. (2022), I document a direct effect of board connections on product market outcomes (offered seats and ticket fares). Nili (2019, 2022) discusses the recent growth in director interlocks among firms in the same industry and the difficulties in enforcing Section 8 of the Clayton Act.

Moreover, I contribute to the large corporate governance literature on director networks and firms' outcomes (e.g., Renneboog and Zhao (2014); Dass et al. (2014); Coles et al. (2020); Duchin et al. (2010); Güner et al. (2008); Dittmann et al. (2010); Drobetz et al. (2018)). Part of the literature highlights the importance of directors' network in acquiring information and the resulting benefits for shareholders. For example, Cai and Sevilir (2012) find that board connections create a communication advantage and lead to higher value creation in M&A transactions. Fracassi (2017) shows that board-connected firms have similar investment policies and exhibit better economic performance. Coles et al. (2020) find that connected directors provide valuable advice to the management. By focusing on connections among competing airlines, I show the anti-competitive side of directors' networks. Thus, even if board connections may be valuable to airlines' shareholders, they may hurt consumers and reduce welfare.

Finally, I also contribute to the industrial organization literature on collusion in the airline market. Aryal et al. (2021) show that U.S. airlines coordinate via quarterly earnings calls with investors. Ciliberto and Williams (2014) find that multi-market contact, i.e., airlines repeated interaction in multiple markets, facilitates collusion among competing firms. Bet (2021) analyzes market power in the U.S. airline industry and the determinants of its growth in the past decade. Azar et al. (2018) demonstrate the anti-competitive effects of common ownership among U.S. airlines. I present a new important channel of communication among U.S. airlines, i.e., board connections, and its impact on product market outcomes.

The paper proceeds as follows. Section 2 discusses the main hypotheses. Section 3 contains a description of the data and construction of the sample. Section 4 reports the empirical analysis. Finally, Section 5 concludes by discussing the policy implications of the results.

1.2 Hypotheses Development

When coordinating, competing firms share monopolistic profits higher than those under oligopolistic competition. There exist several ways to coordinate among competitors. For example, firms may engage in price fixing by agreeing on product prices or production quotas. Alternatively, they may assign specific markets or clients to particular competitors in order to not compete with each other. In both cases, shareholders of the competing firms would enjoy a higher value, but consumer surplus and social welfare would be lower.

Successful coordination among competitors, however, is hard to achieve for several reasons. First, antitrust law forbids collusion, and competing firms may be restricted in the exchange of information with each other. For example, Section 1 of the Sherman Act forbids any exchange of information that may restrict trade. Second, monitoring the actions of all cartel members without direct communication is imperfect and difficult. Hence, a firm may find it optimal to deviate from the collusive agreement and increase its market share at the expense of its competitors. Consistently, Harrington Jr et al. (2006) and Marshall and Marx (2014) describe communication as one of the most important elements to sustain collusion.

Communication is crucial in the U.S. airline industry. Airline markets are characterized by stochastic demand and private and noisy monitoring, making it hard to collude without communication Aryal et al. (2021). Airlines cannot immediately observe their competitors' actions and cannot react quickly. Consequently, they may engage in several forms of inter-firm communication to tacitly coordinate. In the past decades, there have been accusations against airlines of communicating illegally. In 1992, the DOJ sued the U.S. largest airlines for fixing prices through the Airline Tariff Publishing Company's electronic fare system, Miller (2010). In 2015, consumers filed lawsuits in several U.S. courts accusing American, Delta, Southwest, and United of price fixing and reducing capacity despite the increased demand and lower fuel prices.

More recently, Aryal et al. (2021) show that U.S. airlines regularly communicate via quarterly earning calls to reduce capacity and raise prices on competitive routes.
In this setting, board connections represent an alternative communication channel to alleviate the above communication hurdles. Despite the Clayton Act, the DOJ has historically allowed directors and executives of competing firms to sit together on the board of a third non-competing firm. Due to their multiple appointments, connected directors meet and talk regularly. Hence, they may easily exchange information about their product market strategies and firm policies. Importantly, this does not require the direct exchange of a large amount of private information or agreeing on specific capacity levels in each market. For example, connected directors may regularly discuss capacity allocation policies in markets where they compete. Awaya and Krishna (2016) show that "cheap talk" in many cases is enough to achieve near-perfect collusion in environments where firms cannot observe each other actions. Finally, coordination among connected airlines may also happen implicitly. By hiring connected directors, airlines may signal to each other the intention to soften competition.
Thus, I should observe outcomes more consistent with a collusive equilibrium in markets where all airlines are connected via their directors' networks. I derive the two following hypotheses:

Hypothesis 1. *Board connections have a negative effect on the number of available seats*

Hypothesis 2. *Board connections have a positive effect on ticket fares*

In both cases, the null hypothesis is that board connections do not affect the number of available seats and ticket fares.

1.3 Data

1.3.1 Airline data

I collect data from several sources to construct two datasets. In order to establish the effect of board connections on capacity, I construct a panel of offered seats by airlines in each market. I download capacity data from the Bureau of Transportation Statistics (BTS) T-100 Domestic Segment. The T-100 reports monthly information on domestic non-stop segments (i.e., routes) reported by U.S. carriers. In particular, it contains information on the operating carrier, number of available seats, origin, and destination airport. The data, however, does not consider ownership or contracting relationships between national and regional carriers. For example, Piedmont is a fully owned subsidiary of American Airlines, but it is reported as an independent carrier in the T-100 data. To account for these relations between operating and ticketing carriers, I merge the T-100 data with that of Aryal et al. (2021). Aryal et al. (2021) collect information on airlines' subsidiaries and codeshare agreements from a private data provider to allocate capacity to the appropriate ticketing carriers from 2003Q1 to 2013Q3. The final sample contains seven legacy carriers, namely American Airlines (A.A.), Delta Airlines (DL), Continental Airlines (C.O.), United Airlines (U.A.), Northwest Airlines (N.W.), Alaska Airlines (AS), and U.S. Airways (U.S.), and four major low-cost carriers (LCCs), namely Southwest (W.N.), JetBlue (B6), AirTran Airways (F.L.), and Spirit Airlines (N.K.). Even though they directly compete, legacy carriers and LCCs offer different products. Legacy carriers are traditional airlines operating before deregulation.[3]. LCCs are airlines that entered the market in the post-regulation era. They display lower operational costs and offer lower-quality products compared to legacy carriers. Moreover, they maximize aircraft utilization rates by flying point-to-point. Legacy carriers utilize a hub-and-spoke network to operate among airport pairs, Bet (2021) I define a market m as a route between airport pairs. Thus, the unit of observation is denoted by jmt, namely capacity offered by airline j in market m in month t.

To estimate the effect of board connections on ticket fares, I gather price data from the BTS Airline Origin and Destination Survey (DB1B). The DB1B is a 10% sample of all domestic tickets sold each quarter and contains information on the complete itinerary (origin, destination, and connecting airports) and fare paid by all passengers

[3] In 1978, the Airline Deregulation Act removed federal controls over fares, routes, and market entry.

in the sample. Moreover, the data contains information on each itinerary segment's operating and ticketing carriers, the number of traveling passengers, and the distance flown. Following prior studies in the literature, I exclude fares greater than $2,500 or less than $25, as they most likely represent keypunch errors or frequent-fliers tickets, Ciliberto et al. (2019). Moreover, I drop carriers transporting fewer than ten passengers in the DB1B's sample of itineraries in a given year-quarter, Berry (1992). I follow Borenstein (1989), and Evans and Kessides (1994) and treat roundtrip tickets as two one-way tickets, dividing the fare by two. All fares are deflated using the 2008Q3 CPI index. Finally, I define a market as a unidirectional trip between airport pairs regardless of the number of connections between origin and destination. Noteworthy, markets in the capacity and the price panels do not always coincide. This is because airlines set capacity for each direct route, but ticket fares are determined based on the whole itinerary of each consumer. Hence, an itinerary may involve several connecting flights, and its price reflects the capacity of each of these routes.

1.3.2 Director data

I obtain data on directors and officers of U.S. airlines from BoardEx for the years 2003 to 2016. BoardEx mainly collects board and individual director characteristics from SEC filings and supplements them with additional publicly available information. It reports biographical information for each individual on current and past employment, education, and other activities. Hence, I can track all the appointments that an airline officer or director has on other boards during the sample period.

In my analysis, I focus on current employment connections, as directors serving on the same board regularly meet during the year. Hence, existing employment connections may better capture the information flow between connected airline directors. I consider two airline officers or directors to be connected if they sit together on the board of another firm. To avoid my connection measure capturing the transition between two jobs rather than the simultaneous employment for two firms, I exclude cases where an airline officer or director simultaneously serves on another board for less than a year.

Board connections among legacy carriers are pervasive in my sample. For example, from 2007 to 2011, one independent director of American Airlines (A.A.) and two independent directors of Delta Airlines (DL) served together on the board of Texas Instruments. American Airlines also shared board connections with United Airlines

Table I: **Board Connections Characteristics**

Panel A: Connection Duration (months)					
	Mean	SD	p10	p90	N
Connection Type					
Independent - Independent	36.0	32.0	3	77	23
Independent - Executive	24.1	19.4	4	48	14
Executive - Executive	18.9	16.2	5	44	10

Panel B: Airline-Year-Month characteristics					
	Mean	SD	p10	p90	N
# Connected Directors	1.3	1.5	0	4	507
AA	4.4	1.6	2	6	55
DL	1.9	1.6	0	4	55
CO	1.5	0.7	1	2	55
UA	1	0.9	0	2	55
NW	1.2	1.7	0	4	24
AS	0.2	0.4	0	1	55
US	1.1	0.7	0	2	44
WN	1.1	0.8	0	2	55
B6	0.7	0.7	0	2	55
FL	0.8	0.4	0	1	34
NK	0.2	0.4	0	1	44
# Connecting Boards	1.2	1.4	0	3	507
Legacy Carriers	1.5	1.6	0	4	319
LCCs	0.7	0.7	0	2	188

The table reports summary statistics on board connections. Panel A reports the distribution of board connections' duration (in months) for airline director pairs by connection type. "Independent - Independent" denotes connections established by two airline independent directors. "Independent - Executive" denotes connections established by one airline independent director and one airline executive. "Executive - Executive" denotes connections established by two airline executives. Panel B reports the distribution of the number of connected directors and connecting boards for each airline in a year-month.

(U.A.) and U.S. Airways (U.S.) in the same period. Hence, directors of the four largest

U.S. legacy airlines could have easily communicated through the board connections that American Airlines had in those years. From 2003 to 2016, U.S. legacy airlines had 47 board connections via 37 boards.

To better understand the board connections in my sample, Table I shows their main characteristics. Panel A reports the duration distribution of connections among connected airline directors by connection type. Around half of the connections in my sample are between airline independent directors ("Independent - Independent"), i.e., directors that do not hold any executive role in the airlines. In ten cases, I observe connections among airline executives ("Executive - Executive"). A priori, these connections are the most problematic in terms of antitrust concerns, as they directly involve airline executives. On average, connections among independent directors tend to last longer, three years, compared to connections involving airline executives, which last two years. Panel B of Table I shows that, on average, airlines have around one director connecting them to a competitor over a third non-competing board. However, there is considerable heterogeneity in the number of connections across airlines, with American having four connections on average, followed by Delta with two. Overall, legacy carriers are more connected compared to LCCs.

1.3.3 Variable Definitions

To estimate the effect of board connections on market outcomes, I identify those markets where carriers are board-connected. The idea is that to successfully coordinate, all legacy carriers must be connected. Consistent with the literature on communication in the U.S. airline industry (e.g.,Aryal et al. (2021)), I focus on board connections among legacy airlines. As discussed above, this choice is motivated by the fact that legacy carriers and LCCs traditionally have offered different products.

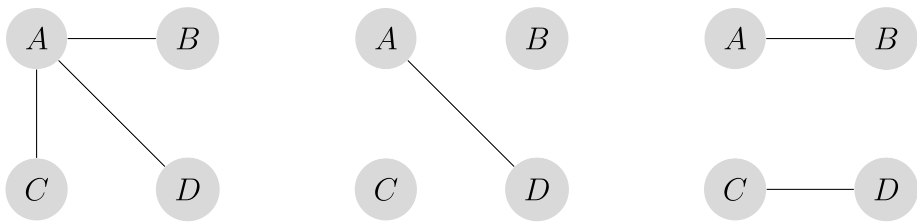
I define a market as connected if at least two legacy carriers serve it and all legacy carriers are connected through their boards. More specifically, I create the following dummy variable:

$$\text{Board Connection}_{m,t} =$$

$$\begin{cases} \mathbb{1} \quad \{\text{if } \exists i : \text{Board Connection}_{i,j,m,t} = 1 \; \forall j \in J_{m,t}^{Legacy}\} & , \quad |J_{m,t}^{Legacy}| \geq 2 \\ 0 & , \quad |J_{m,t}^{Legacy}| < 2 \end{cases}$$

where Board Connection$_{i,j,m,t}$ is a dummy equal to one if legacy carriers i and j have a board connection at time t, i.e. at least one director of i and a director of j sit together on the board of an intermediate firm. $J_{m,t}^{Legacy}$ represents the set of all legacy carriers serving market m at time t.

Figure 1.1: **Board Connection Examples**



(a) Board Connection = 1 **(b)** Board Connection = 0 **(c)** Board Connection = 0

The figure illustrates three possible board connections within a market. In sub-figure (a), legacy airline A has at least a board connection with B, C, and D. Hence, Board Connection = 1. In sub-figure (b), legacy airline A is board-connected to D, while C and D do not have any connection. Hence, Board Connection = 0. In sub-figure (c), legacy airline A is connected to B and C to D. However, A and B do not share any connection with C and D. Hence, Board Connection = 0.

Figure 1.1 provides a graphical interpretation of Board Connection$_{m,t}$. In Panel 1.1a, legacy carrier A has a board connection with all the other legacy carriers serving the market (B, C, and D) and, hence, Board Conn$_{m,t}$ is equal to 1. Conversely, in Panel 1.1b, legacy carrier A has only one board connection with D, while legacy carriers B and C do not have any board connection. In this case, Board Conn$_{m,t}$ equals 0. Finally, in Panel 1.1c, all legacy carriers have at least one board connection (A with B and C with D), but they are not all connected. Indeed, A and B can communicate but cannot exchange information with C and D, and vice versa. Hence, Board Conn$_{m,t}$ is equal to 0 also in this case. The idea is that, to successfully coordinate, all legacy carriers must be connected. Therefore, Board $\text{Conn}_{m,t}$ is equal to one if at least one legacy carrier has a board connection with all the other participants.[4]

Table II reports summary statistics at the carrier-market-month level for the capacity dataset. On average, legacy carriers offer 11,757.9 seats monthly and LCCs 11,255.1. The number of offered seats is higher in mixed markets (13,349.4), i.e., markets operated by both legacy and LCCs, compared to markets with only legacy carriers (9,915). Moreover, LCCs are less likely to participate in board-connected markets.

As in Aryal et al. (2021), I define the dummy variable $\text{Talk-Eligible}_{m,t}$ equal to 1 if there are at least two legacy carriers operating in market m in month t, and 0 otherwise. This variable controls for the fact that markets where legacy carriers could coordinate with each other, may function differently from markets where it is not possible. Similarly, I account for the differences between monopolistic and non-monopolistic markets by introducing the dummy Monopoly $\text{Market}_{m,t}$, equal to 1 if only on legacy airline servers market m in month t. In the sample, 24% of the observations have the potential for coordination, and 52% of the observations are monopolistic markets.

Table II: **Summary Statistics**

	Seats		Board Connection		Talk Eligible		Monopoly Market		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Carrier Type									
Legacy	11,757.894	12,264.478	0.104	0.305	0.311	0.463	0.546	0.498	562,469
LCC	11,255.056	10,467.260	0.034	0.180	0.106	0.307	0.471	0.499	279,522
Market Participants									
Mixed Market	13,349.373	12,749.700	0.061	0.240	0.197	0.398	0.321	0.467	410,888
Legacy Market	9,915.007	10,330.230	0.099	0.299	0.287	0.452	0.713	0.452	431,103
Total	11,590.963	11,700.888	0.081	0.272	0.243	0.429	0.521	0.500	841,991

The table reports the summary statistics for the key variables by carrier and market types. Observations are at the carrier-market-month level. Markets are defined at the airport-pair level.

[4]There exists cases in which all legacy carriers are connected in a market, but none of them has a direct board connection with all the others. For example, consider a market with legacy carriers A, B, C, and D. If A is connected with B, B is connected with C, and C is connected with D, all carriers are connected, but Board $\text{Conn}_{m,t}$ is equal to zero. When I include these cases in the definition of Board $\text{Conn}_{m,t}$, the results remain unchanged.

1.4 Empirical Analysis

I investigate the relation between director connections among airlines and the number of seats offered, estimating the following fixed-effect model:

$$
\begin{aligned}
ln(seats)_{j,m,t} = {} & \beta_0 \times \text{Board Connection}_{m,t} + \beta_1 \times \text{Talk-Eligible}_{m,t} + \beta_2 \times \text{Monopoly}_{m,t} \\
& + \beta_4 \times X_{j,m,t} + \mu_{j,m} + \mu_{j,t} + \gamma_{origin,yr} + \gamma_{dest,yr} + \varepsilon_{j,m,t}
\end{aligned}
\tag{1.1}
$$

where the dependent variable, $ln(seats)_{j,m,t}$, represents the total number of seats offered by carrier j in market m and month t.

The main explanatory variable, Board Connection$_{m,t}$, is the dummy variable introduced in Section 1.3.3. It is equal to 1 if there are at least two legacy carriers in market m at month t and they are all connected via their directors' board seats, and 0 otherwise. Hence, Board Connection$_{m,t}$ captures the effect of having all airlines in a market sharing board connections on capacity allocation.

I control for unobserved confounding variation in the number of offered seats using a large set of fixed effects. First, I include carrier-year-quarter fixed effects, $\mu_{j,t}$, to control for any carrier-specific unobserved factor at time t (e.g., bankruptcy). Second, I use market-carrier fixed effects, $\mu_{j,m}$, to control for time-invariant differences in carrier behavior across markets. Third, I include origin- and destination-airport time trends, $\gamma_{origin,yr}$ and $\gamma_{dest,yr}$, to control for airport-specific unobserved factors that could influence the allocation of seats in a market in a given year. Fourth, there have been several mergers between U.S. carriers in the past two decades. Consequently, a carrier may change its behavior in specific markets following a merger. For example, following its merger with U.S. Airways, American Airlines reorganized its presence across several U.S. routes. Since these changes in conduct may bias my results, I follow Aryal et al. (2021) and introduce two separate fixed effects for the merged entity before and after the merger. Finally, I cluster standard errors by bi-directional market.

Given the fixed effects in equation (1.1), the coefficient of board connections is identified by the cross-sectional variation of Board Connection$_{m,t}$ across markets and over time, which in turn depends on the variation of airline directors' network and market structure.

1.4.1 Main results

Table III Column (1) reports the results from the estimation of equation (1.1). Markets in which all the legacy airlines share board connections are associated with an average statistically significant reduction in available seats by 2.5%.

Table III: **Board connections and capacity allocation**

	(1) Log seats	(2) Log seats	(3) Log seats	(4) Log seats
Board Connection	-0.025***			-0.030***
	(-2.821)			(-3.351)
Board Connection 2		-0.023**		
		(-2.384)		
Board Connection 3		-0.034*		
		(-1.736)		
Board Connection 4		-0.041*		
		(-1.838)		
Board Connection X Board Connection LCC			-0.054**	
			(-2.185)	
Legacy-Talk				-0.024***
				(-3.552)
Board Connection X Legacy-Talk				0.012
				(0.937)
Airline-market FE	Yes	Yes	Yes	Yes
Airline X Year-Quarter FE	Yes	Yes	Yes	Yes
Origin X Year FE	Yes	Yes	Yes	Yes
Destination X Year FE	Yes	Yes	Yes	Yes
Observations	841,804	841,804	840,632	841,804
Adjusted R-squared	0.891	0.891	0.903	0.891

The table reports the OLS regression parameter estimates and t-statistics of Equation 1.1. The dependent variable is the log of available seats offered by carrier j in market m and month t. The coefficient of interest is the one of Board Connection$_{m,t}$, a measure of board connections among legacy airlines as defined in equation 1.1. In column (2) the coefficients are interacted with the number of legacy airlines in the market. In column (3), they are interacted with market type (legacy only or mixed), and, within mixed markets, with carrier type (legacy or LCCs). Standard errors are clustered at the bi-directional market level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

To determine the economic significance of the main estimate, I follow Aryal et al. (2021) and compare it to the average change in capacity in non-connected comparable markets. In particular, I select all the talk-eligible markets where legacy airlines could have shared board connections but did not. The average change in the number of offered seats in these markets is 3.22%. Therefore, when legacy airlines share board connections, they reduce capacity by 63.6% of the average capacity change in comparable markets.

I then investigate how the above effect varies with market structure. As the number of legacy carriers in a market grows and competition increases, successful coordination becomes more difficult to achieve. Thus, if board connections allow successful coordination among competing airlines, their effect may increase with the number of market participants. I test this hypothesis by substituting Board Connection$_{m,t}$ with Board Connection k$_{m,t}$, where $k \in \{2, 3, 4\}$ represents the number of legacy carriers operating in market m in year-month t. Column (2) of Table III shows that the effect of board connections on capacity allocation is monotonically increasing. Board connections are associated with an average decrease of 2.3% in the number of available seats in markets with two legacy carriers. The reduction amounts to 4.1% when four legacy carriers are connected.

Next, I study how the effect of board connections varies with the presence of LCCs in the market. In particular, I create a dummy variable, Board Connection LLC$_{m,t}$, equal to one if at least one legacy carrier in market m shares a board connection with a low-cost carrier operating in market m. I then interact it with Board Connection$_{m,t}$ to capture the effect of having a board-connected low-cost carrier in a board-connected market. Column (3) reports the result. Having a board connection with an LCC in a board-connected market reduces seat capacity by 5.4%, on average.

Finally, I study the relation of Board Connection$_{m,t}$ with other measures of communications among legacy carriers previously documented in the literature. Aryal et al. (2021) provide evidence on legacy carriers communicating via quarterly earning calls. In particular, they document a reduction in capacity when all legacy carriers in the market communicate to investors their intention to reduce capacity in the future. In

Column (4), I include $Legacy{-}talk$, a dummy equal to one when all legacy carriers discuss capacity reductions in the market. The coefficient of Board Connection$_{m,t}$ remains unchanged. Interestingly, the interaction of Board Connection$_{m,t}$ and $Legacy - talk$ is not statistically different from zero. Hence, board connections appear to represent a substitute for other forms of communication among legacy airlines.

1.4.2 Endogeneity of board connections

Corporate governance literature has long studied directors' connections and firm outcomes. A very well-established fact is the endogeneity of board structure and firm policies. For example, anticipating future downturns and reductions in demand, an airline may appoint as a new director an industry expert who is also connected to other airlines. Moreover, more skilled directors may be rewarded by the labor market with more directorships and, hence, be more connected. Thus, board connections may only reflect similar policies of firms operating in the same markets. I address the potential endogeneity of board connections in several ways.

First, the airline-year-quarter fixed effects absorb airline-specific characteristics within the same quarter (e.g., board characteristics and bankruptcy period). Hence, the coefficient of Board Connection$_{m,t}$ is identified by the variation in airlines' behavior across markets within the same year-quarter.

Second, I exploit the timing of the connection between connected airlines and focus on board connections that are third-party initiated. Such connections do not stem from changes in the airlines' boards, but from the appointment of airline directors on the board of the connecting firms. Hence, conditional on the fixed-effects in Equation 1.1, they can be regarded as more exogenous to the airlines' current and future economic performance in each market.

I re-define Board Connection$_{m,t}$ as equal to 1 if at least one legacy airline in market m at month t shares at least one third-party initiated board connection with all the other legacy airlines in the market. Consistently, I exclude the market-months observations affected by connections that were, instead, initiated by the airlines. Column (1) of Table IV reports the estimate of Equation 1.1 using only third-party initiated board connections. The coefficient of Board Connection$_{m,t}$ remains negative and significant.

Table IV: **Board connections and capacity allocation: robustness tests**

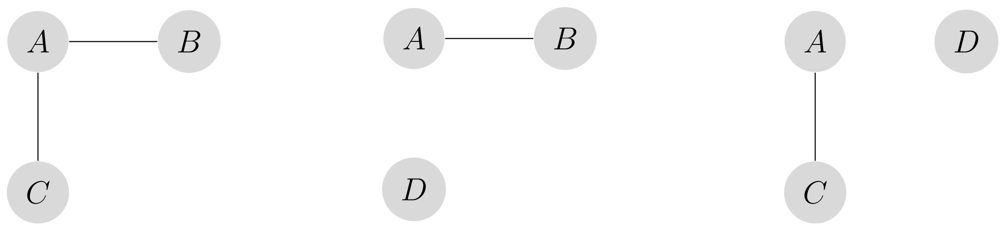
	(1) 3rd-Party	(2) Partial	(3) Partial	(4) Mkt Struct.	(5) CO	(6) MMC
Board Connection	-0.030**			-0.015**		
	(-2.109)			(-2.001)		
Only-One-Pair		0.002				
		(0.195)				
Board Connection (N-1)			0.001			
			(0.078)			
Log(MMC)					0.020**	
					(2.485)	
CO						-0.016
						(-1.283)
Airline-market FE	Yes	Yes	Yes		Yes	Yes
Airline-market-structure FE				Yes		
Airline X Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	777,007	841,804	841,804	840,632	399,851	841,804
Adjusted R-squared	0.891	0.891	0.891	0.903	0.891	0.891

The table reports the OLS regression parameter estimates and t-statistics of Equation 1.1. The dependent variable is the log of available seats offered by carrier j in market m and month t. Column (1) considers only third-party initiated board connections. In Column (2), the coefficient of interest is the one of Only-One-Pair$_{m,t}$, a dummy equal to 1 if only pair of legacy carriers has a board connection in market m and month t. In column (3), the coefficient of interest is the one of Board Connection (N-1)$_{m,t}$, a dummy equal to 1 if $(N-1)$ legacy carriers have a board connection in market m and month t. Column (4) includes the airline-market structure fixed-effect. Columns (5) and (6) respectively add common ownership and multi-market contact (MMC) to the set of controls. Standard errors are clustered at the bi-directional market level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Third, I conduct an additional test to rule out the possibility that the main result in table III is caused by unobserved characteristics of connected directors (e.g., managerial skills). Consider markets m_1, m_2, and m_3 depicted in Figure 1.2. The directors that determine the connections between legacy airlines A and B and legacy airlines A and C in market m_1 are the same that connect A and B in market m_2 and A and

C in market m_3. However, markets m_2 and m_3 are not board connected, as legacy airline D, which operates in both markets, does not share any connections. If the characteristics of the connecting directors spuriously determine the negative relation board connections and seat capacity, I should also observe a decline in the number of offered seats in partially connected markets, where both connected and non-connected legacy airlines compete.

Figure 1.2: **Fully vs partially connected markets**



(a) Fully connected market **(b)** Partially connected market **(c)** Partially connected market

The figure illustrates three possible board connections within a market. In sub-figure (a), legacy airline A has at least a board connection with both B and C. In sub-figure (b), legacy airline A is board-connected only to B and, does not share any director connections with D. In sub-figure (c), legacy airline A is board-connected only to C and, does not share any director connections with D.

Thus, I estimate the following variation of equation 1.1:

$$\begin{aligned} ln(seats)_{j,m,t} = & \beta_0 \times \text{Only-One-Pair}_{m,t} + \beta_1 \times \text{Talk-Eligible}_{m,t} + \beta_2 \times \text{Monopoly}_{m,t} \\ & + \beta_4 \times X_{j,m,t} + \mu_{j,m} + \mu_{j,t} + \gamma_{origin,yr} + \gamma_{dest,yr} + \varepsilon_{j,m,t} \end{aligned} \tag{1.2}$$

where the variable of interest $\text{Only-One-Pair}_{m,t}$ is defined as

$$\text{Only-One-Pair}_{m,t} = \begin{cases} \mathbb{1} \quad \{\text{if } \exists i, j \in J_{m,t}^{Legacy} : \text{Board Connection}_{i,j,m,t} = 1 & , |J_{m,t}^{Legacy}| \geq 3 \\ \quad \wedge \text{Board Connection}_{i,-j,m,t} = 0\} & \\ 0 & , |J_{m,t}^{Legacy}| < 3 \end{cases}$$

$\text{Only-One-Pair}_{m,t}$ is equal to one in markets where only one pair of legacy airlines i

and j is connected, conditional on having at least three legacy carriers in the market. If board connections reflect characteristics of the connected directors and not communication (e.g., directors' ability or industry knowledge), the coefficient of β_1 should be negative and statistically significant. I report the estimation results in Column (4) in Table IV. There is no evidence of capacity reductions when only one pair of legacy airlines is connected.

Similarly, I consider cases where all but one legacy carriers are connected in the market. I estimate equation 1.1 with the treatment variable Board Connection(N-1) equal to 1 if only one legacy carrier in the market does not have a board connection with any of the other market participants. Column (5) in Table IV reports the estimation results. The coefficient of interest, β_1, is not statistically different from zero. Overall, I find no significant effects of board connections on capacity allocations when only some legacy airlines in a market are connected.

1.4.3 Additional robustness tests

In Table IV, I conduct additional robustness tests. First, Board Connection$_{m,t}$ depends on the number of legacy airlines competing in the market and, hence, it may only capture the effect of market structure on capacity allocation rather than coordination through connected directors. For example, if American Airlines and Delta Airlines have a board connection, Board Connection will be equal to one in all markets where only American and Delta operate. The same connection, however, will result in Board Connection equal to 0 in markets with a third non-connected legacy carrier. It follows that Board Connection is mechanically correlated with the number of legacy carriers in the market. Therefore, I follow Aryal et al. (2021) and substitute the market-carrier fixed effect in equation (1.1) with the market structure-carrier fixed effect. The effect of board connections is now identified by the cross-sectional variation of Board Connection across markets with the same number of legacy carriers. Column (1) in Table IV shows that the inclusion of carrier-market-structure fixed effects does not affect the results. On average, board connections are associated with a capacity reduction of 3%.

Second, the literature has recently documented other important factors allowing market participants to coordinate. For example, Ciliberto and Williams (2014) provide evidence that multi-market contact facilitates tacit collusion among U.S. airlines. Moreover, Azar et al. (2018) show that common ownership reduces competition among U.S. airlines. In light of these previously documented effects, Board Connection may only represent a proxy for one of the above. For example, Azar (2022) provides evidence of a positive overlap between common owners and directors interlocks across U.S. public firms. Therefore, I re-estimate equation (1.1), including common ownership (C.O.) and multi-market contact (MMC) as additional controls. Columns (2) and (3) report the results. The coefficient of Board Connection remains statistically significant, and its magnitude is almost unchanged. Thus, the effect of *Board Connection* is not driven by multi-market contact or common ownership among U.S. legacy carriers.

1.4.4 Endogeneity of market structure

As previously discussed, Board Connection is the product of Talk-Eligible and whether all legacy carriers share director connections. Talk-Eligible is a function of market structure, i.e., the number of legacy airlines serving market m in month t. The airline's decision to serve market m depends on several unobserved factors (e.g., entry costs) that may not be entirely captured by the fixed effects in equation 1.1. Hence, both Talk-Eligible and Board Connection may be endogenous. In addition, the results in Table III could also be driven by reverse causality. Namely, the possibility that legacy airlines without board connections better anticipate reductions in future demand and exit, leaving only board-connected firms to compete in the market. Under this alternative hypothesis, I should also observe a negative correlation between Board Connection and the number of available seats.

I address the endogeneity of market structure by following the methodology outlined by Aryal et al. (2021). In particular, I instrument for market structure using the average distance between a market's origin and destination airport and the carrier's closest hub. This distance is a proxy for the fixed costs that a carrier faces to serve a market, Ciliberto and Tamer (2009), and, consequently, determines its decision to enter that market. Therefore, hub distance indirectly affects market structure [5]. I

Table V: **Control function: board connections and capacity allocation**

	(1) Log seats	(2) Log Seats
Board Connection	-0.025*** (-2.821)	-0.025*** (-2.811)
Residual		-0.277 (-1.563)
Airline-market FE	Yes	Yes
Airline X Year-Quarter FE	Yes	Yes
Origin X Year FE	Yes	Yes
Destination X Year FE	Yes	Yes
Observations	841,804	841,166
Adjusted R-squared	0.891	0.890

Column (1) reports the baseline estimation of equation 1.1. Column (2) reports the control function estimates. Standard errors are bootstrapped and clustered at the bi-directional market level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

estimate the effect of board connections on capacity using the hub-distances measure computed by Aryal et al. (2021) in a control function approach, Wooldridge (2007). In the first stage, I regress the endogenous market structure variable, Talk-Eligible, on the hubs-distances, $D_{j,m,t}$, for each carrier-market combination:

$$\text{Talk-Eligible}_{m,t} = \sum_{j \in J} \sigma_j D_{j,m,t} + \alpha_0 \times X_{j,m,t} + r_{m,t} \tag{1.3}$$

where, $X_{j,m,t}$ contains the same controls and fixed-effects as in equation 1.1. Next, in the second stage, I re-estimate equation 1.1, adding the residuals $\hat{r}_{m,t}$ as an addi-

[5]See Aryal et al. (2021) Appendix A for a detailed discussion on the use of hub distances as an instrument for market structure.

tional control. In Table V, I report the second stage estimates together with the baseline result from Table III[6]. Column (2) shows that the coefficient of Board Connection remains significant after controlling for the endogeneity of market structure. When all legacy carriers in a market are board-connected, they reduce their capacity by 2.5%.

1.4.5 Market-level changes, flights departure, and fares

After establishing the negative relationship between board connections and the number of offered seats, I now study the implications for other market outcomes and ticket fares.

First, I investigate if the firm-level reductions in seat availability documented in Table (II) imply a reduction in total market capacity and the number of scheduled flights. In Column (1) of Table VI, I re-estimate equation (1.1) at the market level. On average, board-connected markets are associated with a 2.2% decrease in market capacity. Hence, reductions in the number of available seats at the airline level in board-connected markets result in a decrease in the total offered seats.

Second, I investigate if the reduced number of offered seats observed in board-connected markets translates into a reduced number of offered flights. Hence, I follow Aryal et al. (2021) and assume that the number of flights in a market follows a Poisson distribution, with its mean depending on the explanatory regressors outlined in equation 1.3.3. I then estimate the coefficient of Board Connection using the conditional maximum likelihood method.

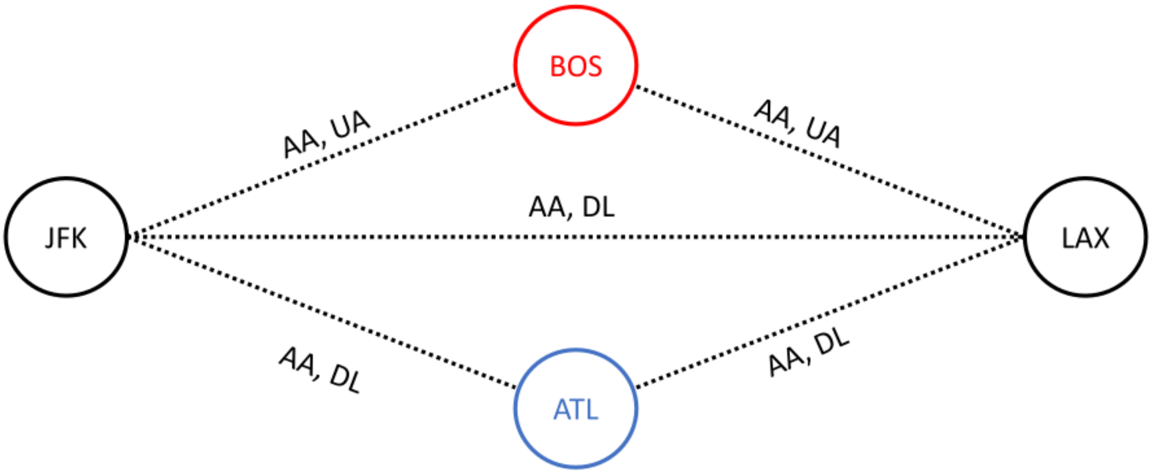
Column (2) of Table VI reports the estimation results. Board-connected markets are associated with a 1.2% average decline in the number of offered flights. Hence, all else equal, board connections in a market are associated with fewer available seats and flights.

Third, I estimate the relation between Board Connection and ticket fares. If board connections have anti-competitive effects, I should observe positive effects on ticket prices in markets where legacy carriers are board-connected.

[6] I do not report the first stage here, as it is the same as in Aryal et al. (2021) Appendix A

Differently from capacity, allocated at the nonstop segment level, tickets are sold for the origin and final destination airport pairs. Hence, the same airport pair may be served by airlines across different routes with different degrees of board connections. Figure 1.3 provides a graphical example. For the same market JFK-LAX, American Airlines (AA) offers three possible routes: a direct flight and two connecting flights over Boston and Atlanta, respectively. In these three routes, American Airlines competes with different airlines and different levels of board connections.

Figure 1.3: **Market definition for ticket fares**



The figure graphically illustrates the airport pairs market definition for ticket fares.

To account for the multiple routes within the same market, for each airline, I compute Perc. Board Connection$_{j,m,t}$ as the average percentage of board connections that legacy airline j has across all routes serving market m in quarter t. Then, I estimate the following equation:

$$\begin{aligned} ln(fare)_{j,m,t} = \beta_0 \times \text{Perc. Board Connection}_{j,m,t} + \beta_1 \times X_{j,m,t} \\ + \mu_{j,m} + \mu_{j,t} + \gamma_{origin,yr} + \gamma_{dest,yr} + \varepsilon_{j,m,t} \end{aligned} \tag{1.4}$$

where $X_{j,m,t}$ contains the same fixed effects and controls as in equation 1.1 with the addition of other standard controls in the literature. Namely, I add the share of connecting passengers, the distance between the origin and destination airport, and the number of legacy airlines operating in the market.

Columns (3)-(5) in Table VI report the estimation results. On average, board connections are associated with an increase of 3.7% in ticket fares. Moreover, the effect is not driven by common ownership or multi-market contact among legacy airlines.

Table VI: **Board Connections, market-level capacity, number of flights, and fares**

	(1) Log Market Seats	(2) Flights	(3) Price	(4) Price	(5) Price
Board Connection	-0.022**	-0.012*			
	(-2.016)	(-1.946)			
Perc. Board Connection			0.037***	0.042***	0.031***
			(4.700)	(5.291)	(3.822)
CO				0.029***	
				(5.853)	
Log(MMC)					0.058***
					(10.746)
Airline-market FE	Yes	Yes	Yes	Yes	Yes
Airline-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Origin X Year FE	Yes	Yes	Yes	Yes	Yes
Destination X Year FE	Yes	Yes	Yes	Yes	Yes
Observations	614,256	614,256	461,860	461,860	443,283
Adjusted R-squared	0.896		0.621	0.621	0.614

The table reports additional evidence on the effect of board connections. Column (1) reports a market-level estimation of equation 1.1. Hence, the dependent variable, number of available seats, is aggregated at the market level. Column (2) shows the estimate coefficient from the Poisson model on the number of flights. In columns (3)-(5), the dependent variable is the log of average fares charged by carrier j in market m and quarter t. The coefficient of interest is the one of $Board_conn_perc$, measuring the percentage of connections that a legacy airline has in market m in quarter t. Standard errors are clustered at the bi-directional market level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

1.5 Conclusion

In this article, I investigate the (anti)competitive effects of board connections among U.S. legacy airlines. Using detailed employment data for all U.S. airline directors, I find that when all legacy airlines in a market are connected via their directors' network, there is an average reduction of 2.5% in the number of offered seats.

Even though I do not estimate a structural model of competition featuring board connections among competing firms, the evidence is most consistent with board connections being harmful to consumers. Indeed, I find that board connections are, on average, associated with 3.7% higher ticket fares.

I address the endogeneity of board connections by focusing on third-party-initiated connections. Namely, I define two airlines as board connected if two airline directors sit together on the board of another firm. In my sample, most of these connections do not stem from airline board changes. Instead, airlines become connected because their current directors are appointed on the board of the connecting firms. Hence, they do not reflect changes in airline boards that may correlate with airlines' future performance. Furthermore, I conduct several placebo tests to rule out alternative hypotheses and employ a control function approach to rule out the possibility that the results are driven by endogenous market structure.

The results are especially relevant for policymakers. Even though competing firms may formally comply with antitrust regulations (e.g., section 8 of the Clayton Act), they can still communicate via their directors' network.

Finally, my findings unveil a new effect of board connections on product market outcomes. So far, the literature has primarily studied the impact of board connections on firm value and ignored potentially anticompetitive effects. I show that even if board connections may be valuable for shareholders, they may harm consumers.

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Chapter 2

Credit Conditions when Lenders are Commonly Owned

Mattia Colombo, Laura Grigolon and Emanuele Tarantino

Abstract

We investigate how common ownership between lenders affects the terms of syndicated loans. We provide a novel view on the role of common ownership in mitigating information asymmetries on the quality of borrowers and the resulting contractual distortions in the terms of the loan. Our empirical evidence shows that high common ownership decreases loan rates, lowers the share of the loan retained by the lead bank, and mitigates rationing at issuance. Further investigations lend support to the hypothesis that common ownership serves as a device for information transmission: common ownership especially affects the terms of loans for new borrowers, when the lead arranger is likely to hold an informational advantage. As information flows from the lead arranger to syndicate members, we show that member-to-lead common ownership does not affect the terms of syndicated loans.

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2.1 Introduction

Over the last two decades, the banking sector has become increasingly interconnected due to the steady growth of shareholders owning equity in multiple banks: the literature refers to those shareholders as "common owners". In 2013, the four largest U.S. asset managers (Blackrock, Vanguard, State Street, and Fidelity) held a combined 20% of the shares of the four largest commercial banks (JP Morgan, Citigroup, Bank of America, and Wells Fargo).

Common ownership affects credit conditions and credit availability in a complex way. Recent empirical work mainly focuses on a potential downside of common ownership: an investor holding a controlling stake in several firms belonging to the same industry might influence their pricing with the purpose of softening competition (Azar et al., 2022, 2018; He and Huang, 2017). In this paper, we focus on a new potential upside of common ownership: reducing information asymmetries in syndicate relationships. We refer to the asymmetric information between lenders that characterizes the syndicated loan industry, where lead banks possess an informational advantage on the borrower's risk profile relative to other participants and are tasked with loan monitoring. We conjecture that a lender with superior information, such as the lead bank in a syndicated loan, can truthfully transmit such information to another lender when the two are interconnected via a common shareholder. As common ownership eases information asymmetries, the lead bank does not need to signal the quality of the borrower to potential investors. Thus, common ownership may have positive effects on risk-pricing and credit availability for borrowers.

Regulators explicitly acknowledge that common ownership between the lead bank and potential syndicate members can be conducive to the exchange of information between investors in syndicated loans (European Commission, 2019). This practice is not regarded as anticompetitive per se; however, lenders should not disclose sensitive information, collude, or otherwise harm the borrowers. The syndicated market has

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been subject to repeated investigations by the U.S., E.U., British, Dutch, and Spanish authorities to evaluate possibly harmful exchanges of information. High levels of common ownership would facilitate those exchanges: this direct effect of common ownership is supported by anecdotal evidence, with Shekita (2021) compiling 30 case studies of interventions by common owners on corporate governance.

To investigate how common ownership between lenders affects credit conditions and credit availability, we proceed in two steps. First, we use a stylized model to derive empirical predictions on the effects of common ownership in reducing information asymmetries, which, in turn, affect loan prices, the ownership structure within the loan, and the overall volume of lending. The lead bank represents a penniless borrower: the borrower and the lead bank privately observe the type of borrower, which can be either good or bad.[1] As the assets of the lead bank are insufficient to fund the borrower's project, the lead bank needs to form a syndicate. We distinguish between two scenarios: high and low common ownership. Only when common ownership is high can information on the borrower type be truthfully transmitted by the lead bank to the syndicate members. When common ownership is low, asymmetric information implies that, in equilibrium, the lead bank will have to promise higher returns to the syndicate members and commit its own funds to the loan. By doing so, the lead bank signals the quality of the borrower to other potential lenders. As only some lead banks possess sufficiently large funds to signal the quality of the loan in the capital market, low common ownership will determine rationing at issuance. If, instead, common ownership is high, lending can take place at the conditions that would prevail with symmetric information. In sum, at high levels of common ownership: (i) the interest rate paid to the syndicate members is lower; (ii) the lead bank retains lower funds; and (iii) we observe less rationing at the issuance. Our model also allows us to show that our empirical results are inconsistent with alternative recent theories of common ownership and syndicated lending markets. In particular, models in which common ownership is a mechanism for incentive alignment (as in Antón et al. 2023), or in which the lead

[1] The source of asymmetric information can be the probability of successful project completion, as we currently assume in the model, or the cost of monitoring the firm, as in Sufi (2007). The predictions of the model remain unchanged.

bank faces pipeline risk (as in Bruche et al. 2020) would yield different predictions.

In the second step, we empirically test these predictions using data on loans syndicated in the U.S. between 1990 and 2017. The syndicated lending market provides an ideal setting to test the three predictions of our theoretical framework. Although multiple banks can participate in a loan, only the lead bank conducts due diligence of the client: this creates a problem of information asymmetry between the lead bank and syndicate participants (Sufi, 2007; Ivashina, 2009). A syndicated loan typically consists of a number of tranches (facilities). After receiving the mandate, the lead bank announces to the market the non-price characteristics of the loan and its facilities, such as collateral and maturities. The price of each facility and the composition of the syndicate are set on the market, resulting in variations in price and composition of the syndicates across facilities of the same loan. In contrast, default risk and creditor rights are essentially constant across facilities of the same loan: lenders can force the borrower into bankruptcy if credit events occur, such as payment defaults or covenant violations.[2] Hence, in our most demanding specifications, we can credibly identify differences in lending conditions between facilities *within* a loan with varying degrees of common ownership, while keeping the default risk constant.

Before testing our theoretical predictions, we present two pieces of motivating evidence. The first shows that common ownership changes the intensity of lending relations between syndicate members and borrowers. We show that, after subscribing a loan featuring a high degree of common ownership with the lead bank, a syndicate member increases its lending relationship with the borrower. This result holds within the same member-borrower relation over time. The second empirically documents a positive relationship between common ownership and the degree of overlap between directors sitting on the board of lenders; this fact supports the plausibility of information transmission between lenders, for example, through common directors, when common ownership is sufficiently high.

We find support for all three predictions in the data. First, high levels of common

[2]Covenant-lite loans presenting a split structure are an exception, with different financial covenants between tranches; we remove them from the sample.

ownership between the lead bank and the syndicate participants are associated with lower prices. We identify the impact of common ownership on prices by leveraging variation in common ownership across facilities and loans. We obtain these results in specifications that account for other factors potentially affecting the loan spread, including an extensive set of controls and fixed effects related to: the loan and the facility; the borrower; and the lead bank. In panel regressions, coefficient estimates indicate that an increase of one standard deviation in common ownership is associated with a lower spread of 5 basis points, where the average spread is 170 basis points. Based on conversations with industry experts, we learned that, in the presence of ownership overlap, a lead bank might selectively transmit pre-bid information to investors in order to convince them to subscribe to the loan at the margin. This explains the relatively small size of our estimates when considering the average impact of common ownership, and the larger nonlinear magnitudes when considering the intra-quintile effects (see below).

To rule out the possibility that variations in common ownership and spread may reflect omitted characteristics that systematically correlate with prices and common ownership levels, we estimate the effect of common ownership on the pricing of facilities of the same type *within* a given loan. The within-loan estimates confirm the negative effect on prices: an increase of one standard deviation in common ownership implies a reduction in spread of 8 basis points.

We then discretize our common ownership measure into five indicator variables corresponding to the quintiles of its support. All our estimates show that reductions in spread are relevant only for high levels of common ownership (quintiles 3 to 5), and that those reductions are monotonically increasing in common ownership. Within a quintile, a change in common ownership from the minimum to the maximum level reduces the price by roughly 7 to 15 basis points, where the average loan spread is around 195 points for the upper quintiles.

Second, we find that an increase of one standard deviation in common ownership is associated with a statistically significant 0.75 percentage point decrease in the amount of the loan retained by the lead bank. As the lead arrangers retain on average 13% of the loan amount, the impact of common ownership is sizeable. In analyzing the share of loan retained by the lead arranger, we explicitly account for the presence of originate-to-distribute loans and sample selection in reported shares, as highlighted in the recent literature: Blickle et al. (2020). In practice, we exclude all term B and leveraged loans from the analysis; for those loans, the lead share at origination may not be a good measure for the lead arranger's exposure to the borrower over the loan's duration. We correct for sample selection bias by modeling the probability of missing information.

Third, we find that common ownership impacts credit supply. We empirically compare the intensity of lending relationships between two types of lead arrangers: arrangers that experience a prevalence of loans with high common ownership in their portfolio in a given quarter, and arrangers that do not. Lead arrangers with a prevalence of high common ownership have stronger lending relationships: they underwrite 17% more loans in a quarter with respect to lead arrangers with a low prevalence and 65% more in terms of the amount.

We are careful to rule out alternative explanations to our findings. First, we explicitly control for vertical relations, namely common ownership between lenders and borrowers. Second, we use a selection model to empirically address the fact that lenders' decisions to enter the syndicate may depend, among other factors, on the level of common ownership with the lead arranger and other unobservables collected in the error term. Our results are not qualitatively different when accounting for selection.

We provide two additional pieces of evidence consistent with common ownership as a mechanism of information transmission. First, we exploit borrower heterogeneity in our data to empirically show that common ownership has an impact only in the case of new borrowers, as the lead arranger is more likely to hold an informational advantage over the syndicate members. Second, we propose a falsification test of our theory. We conjecture that information flows from the lead bank to the syndicate members; thus, only common ownership between lead bank and syndicate members should have an impact on our outcome variables, not common ownership between syndicate members and lead bank. Our results confirm this intuition, thus providing an indirect confirmation that information transmission is effectively initiated by the lead bank.

These results offer practical guidance to policymakers. We provide novel empirical evidence consistent with a flow of information between the lead bank and the commonly owned syndicate member banks. As a result, the distortions caused by information asymmetry on the terms of credit contracts are mitigated through common ownership. Finally, we acknowledge that, on top of the beneficial effects on the conditions of credit documented in our analysis, common ownership may be detrimental for the borrower by, for example, preempting the entry of lenders outside the group of commonly owned banks. The study of these (potentially anticompetitive) effects will be of relevance for future research.

Related literature Common ownership has recently attracted significant attention from financial and industrial economists. The literature mainly focuses on the common ownership hypothesis, according to which an investor holding a controlling stake in several firms belonging to the same industry might influence their pricing with the purpose of softening competition (Azar et al., 2022, 2018; He and Huang, 2017).[3] We contribute to this literature by proposing a positive role of common ownership - so far overlooked in the literature - in reducing information asymmetries and distortions in credit conditions.

In related work, Saidi and Streitz (2021) look at the link between credit concentration and industry markups, where common lenders induce less aggressive behavior among their borrowers. Massa and Rehman (2008) study the relationship between mutual funds and banks in the same financial group, providing evidence of direct information flows within the financial conglomerates through informal channels, such as personal acquaintances. Jiang et al. (2010) investigate the simultaneous holding of both equity and debt claims of the same company by non-commercial banking institutions in syndicated loans; they show that syndicated loans with dual holders have lower spreads than those without. Finally, Cici et al. (2015), Ojeda (2019), and Wang

[3] Boller and Scott Morton (2020) use inclusion in a stock market index to identify the impact of an increase in the overlap among investors. Newham et al. (2022), Ruiz-Pérez (2019) and Gerakos and Xie (2019) analyze the effect of common ownership on entry. Antón et al. (2023) investigate how managerial incentives can link common ownership and competition. Aslan (2019) looks at the relationship between common ownership and costs. Backus et al. (2021a) use a test of conduct to reject that common ownership has a large effect on markups. Comprehensive reviews of this growing literature by Schmalz (2021) and Backus et al. (2020) provide a summary of the empirical evidence.

and Wang (2019) study the impact of common ownership between lenders and borrowers. Overall, they document lower loan spreads, larger loans, and more frequent lending activity in the presence of common ownership. In contrast to all these papers, we are the first to look at common ownership between lenders and its effect on credit terms. We find empirical evidence consistent with the results of a model in which, thanks to common ownership, the lead bank does not need to signal to other lenders in the syndicate the quality of the borrower by means of costly signals, such as the retention of a share of the loan. In all our specifications, we nevertheless account for relationships of common ownership between lenders and borrowers.

We also contribute to the literature on syndicated lending. We are the first to show that common ownership reduces the distortions of risk pricing and credit rationing that the previous literature shows to be caused by information asymmetries. Early contributions in this body of work have documented that the lead bank, which conducts the due diligence and acts on behalf of the borrower, mitigates asymmetric information vis á vis syndicate members by retaining a larger share of the loan (Sufi, 2007; Focarelli et al., 2008; Ivashina, 2009). Analogously, as a larger portion of the loan retained by the lead bank signals a commitment by the lead arranger in monitoring and borrower quality, Lin et al. (2012) show that the fraction held by the lead bank increases in the divergence between control rights and cash-flow rights of the borrower's largest shareholder. Finally, Bruche et al. (2020) highlight that the presence of a pipeline risk taken by the lead arranger when originating a loan also plays a role in loan retention. Other aspects of syndicated lending examined in the literature include how the composition of the syndicate affects loan spreads (Lim et al., 2014), the propensity to syndicate a loan (Dennis et al., 2000), the relationship between final spreads and fees (Berg et al., 2016; Cai et al., 2018), and the role of covenants (Drucker and Puri, 2009; Becker and Ivashina, 2016).

2.2 Institutional Setting

2.2.1 Syndicated Credit: Asymmetric Information and Loan Structure

Syndicated lending is an important source of financing for U.S. corporations. Sufi (2007) and Ivashina (2009) report that more than 90% of the largest 500 non-financial Compustat firms in 2002 obtained a syndicated loan between 1994 and 2002. In 2006, syndicated loan issuance surpassed corporate bond issuance with a volume of $1.7 trillion. More recently, the Federal Reserve's Terms of Business Lending survey documented that 44% of all commercial loans in 2013 were syndicated loans.

The syndicated loan market operates over the counter. Transactions are the result of informal interactions between borrowers and lenders. The borrowers are firms that seek funding from the syndicate to leverage large capital investments. The syndicate is headed by the lead bank or arranger. Other syndicate members are banks or institutional investors.

The borrower solicits potential lead banks to submit a bid. These banks propose their syndication and pricing strategy to the borrower. The chosen lead bank then receives the mandate to issue a loan and performs the due diligence. Details of the mandate signed between the lead bank and the borrower remain confidential, including any potential rearrangement of the fees to the lead bank depending on the outcome of the syndication. Syndicated loans are not considered to be a "security" under federal or state laws, as recently confirmed by the Southern District of New York in the case Kirschner v. JPMorgan Chase Bank, and loan syndication is not a "security distribution". As a consequence, the due diligence standards are left to the criteria of the lead arranger, who also disclaims any responsibility for the accuracy of the information included in the memorandum provided to the potential investors (Ivashina, 2005).

Following Sufi (2007), most of the literature considers the presence of private information in the hands of the lead bank as a defining feature of the industry. In addition, lead arrangers are typically tasked with loan monitoring for the duration of the deal.

This industry is therefore characterized by the contemporaneous presence of adverse selection and moral hazard. More recent work has documented that the market has seen an increase in the originate-to-distribute loans, especially in the non-investment grade loan segment targeted toward institutional investors: Bord and Santos (2012) and Bruche et al. (2020). If the lead arranger syndicates a loan with the intention of selling it immediately, pipeline risk, that is the risk that the loan becomes a "hung" deal, may arise when the market is not willing to absorb the loan under the conditions arranged by the lead bank: Bruche et al. (2020). Pipeline risk adds a layer of complexity that intersects with asymmetric information because, for originate-to-distribute loans, loan retention may be the result of pipeline risk. In the empirical section of the paper, we propose a falsification test to show that pipeline risk is unlikely to explain our results (see Section 2.6.2). We will also take into consideration this feature of the market in our empirical strategy (see Section 2.5.3).

The loan issued by the lead bank is divided into tranches, or facilities, of different types (credit line, term loan), amount, and maturities. All non-price terms of the loan, such as type, amount, maturity, purpose, collateral, and covenants, are set before the marketing phase starts. Only type, amount, and maturity vary across facilities within a loan. Covenant-lite loans are an exception as they may present a split structure: term loan facilities lack financial covenants, while credit lines contain traditional financial covenants. Following Berlin et al. (2020), we identify the deals having split control rights and remove them from the sample (see Section 2.4).

The interest rate paid to syndicate members, calculated as the spread over LIBOR, and the composition of the syndicate are determined during the marketing phase. The lead bank proposes the price for each facility in the loan, and potential syndicate members decide whether they wish to buy at the specified spread. The deal is closed when the desired level of demand is met. The lead bank can subscribe part of the loan to close the deal, although it does not have an obligation to do so. If credit events occur, such as payment defaults or covenant violations, syndicate members can force the borrower into bankruptcy.

Finally, the syndicated lending market is highly concentrated. JP Morgan and the Bank of America arrange around 63% of the loans in the sample. We take care of concentration in our empirical analysis, by running our tests excluding the loans arranged by these two banks.

2.2.2 Common Ownership in the Syndicated Loan Market

Asset managers, such as Black Rock, Vanguard, State Street, and Fidelity are often shareholders in both the lead bank and the syndicate members, and their holdings have been growing substantially over the recent years, as documented in Table B.I. Recent literature has contributed to clearing the doubts regarding whether these investors exercise any influence on the firms they are invested in. Appel et al. (2016) and Brav et al. (2019) present evidence that institutional investors use their voting blocs to influence the governance of firms. In practice, asset managers may exert their control through "voice" (Edmans et al., 2019), by direct interventions, such as monitoring the managers, or by suggesting strategic changes. Matvos and Ostrovsky (2008) show that in mergers with negative acquirer announcement returns, mutual funds holding shares in both the acquirer and the target are more likely to vote for the merger. He et al. (2019) provide evidence that institutional investors play a more active monitoring role when common ownership is high. Appel et al. (2016) show that the presence of mutual funds has a direct impact on the composition of the board of directors, and in particular an increase in ownership by passive funds is associated with an increase in non-executive directors entrusted by the shareholders.

In our empirical framework, we study situations in which the lead bank and the members in the syndicate are commonly owned by large institutions, exploiting variations in the level of common ownership across loans and across facilities within a loan. Our conjecture is that common ownership facilitates the transmission of private information regarding the borrowing firms from the informed lead bank to the uninformed members of the syndicate. Regulators explicitly recognize the possibility of such influence: in a recent report on loan syndication and competition in credit markets, the European Commission acknowledges that information transmission may arise when the lead bank and syndicate members are commonly owned (European Commission, 2019). The syndicated market has been subject to repeated investigations by the U.S., European, British, Dutch, and Spanish authorities to evaluate possibly harmful exchanges of information: see the Jones Day Commentary. In 2006, the Antitrust Division of the U.S. Department of Justice (DOJ) investigated private equity syndicates ("club deals"), an industry that shares parallels with syndicated lending. The DOJ expressed concern that syndicate members may conspire to artificially reduce the acquisition price of the targets of those deals by allocating leveraged buyout opportunities among participants. In Section 2.4.4, we provide further evidence on the plausibility of information transmission through shared directors between lenders via the common owner.

Our conversations with industry experts confirm that the subscription process of syndicated loans involves close cooperation between market participants. On the one hand, in the presence of ownership overlap, a lead bank may selectively exchange pre-bid information during the formation of the syndicate in order to induce an investor to subscribe a loan. On the other hand, given the opaque and unregulated market setting, these exchanges may exacerbate conflicts of interest between the bloc of lead bank and syndicate members and the creditor.

2.3 Hypothesis Development

Consider a penniless borrower who owns a project but lacks the financial resources to carry it out.[4] The borrower delegates the lead bank (L) to form a syndicate for a loan of size 1; it then shares the returns of the investment with the lead bank. A continuum of potential members of the syndicate (M) operate in perfectly competitive financial markets and have the financial resources to fund the project. We denote by A, with $0 < A < 1$, the maximum amount of the loan that the lead bank can pledge. A then represents the lead bank's liquidity.

[4]This setting extends the model in Tirole (2006), Chapter 6, which in turn uses the mechanism approach in Maskin and Tirole (1992) to solve the contract's design problem. In this section, we describe the model we use to derive our empirical predictions. See the Theoretical Appendix for the derivation of the formal results.

The borrower's project can be one of two types: the good type (G) has a probability of success equal to p; the bad type (B) has a probability of success $q < p$.[5] Independent of the borrower type, the project yields R in the case of success and 0 in the case of failure. Throughout the scenarios we consider, the lead bank knows the type of the borrower's project. We use α and $(1 - \alpha)$ to denote the potential syndicate members' (M) prior probabilities that the borrower's project is of type G and type B, respectively.[6]

We assume that only the good borrower's project has a positive net present value (NPV) ($pR > 1$), and that the bad borrower's project has a negative NPV ($qR < 1 - A$). Moreover, we assume that the project return to the lead bank representing a bad type ($qR - A$) is positive, which makes it costly for the lead bank to signal the good type and achieve separation from the bad type. As a result of this assumption, a lead bank representing a good borrower would be strictly better off if it could truthfully disclose its information about the quality of borrowing.

We now describe the funding contracts. A sharing rule determines how the project returns are divided between the lead bank L representing a firm of a given type j ($R_{j,L}$) and the syndicate members M ($R_{j,M}$), with $j = G, B$ and $R_{j,L} + R_{j,M} = R$.[7] The sharing rule is complemented by two additional components. The first is a decision rule on whether the loan is extended by potential syndicate members to a firm of a given type $j = G, B$ ($x_j \in [0, 1]$). The second is the amount of cash that the lead bank L invests in the loan ($\mathcal{A}_j \leq A$).

The lead bank L holds all the bargaining power. It designs contracts that can be accepted or rejected by the syndicate members M. When indifferent, L will prefer not to commit any cash to the loan. This reflects, for example, the presence of alternative investment opportunities that are more remunerative than the borrower's project. We solve for the perfect Bayesian equilibrium of the contract design game. When solving

[5]The predictions of the model would not change if the lead bank had superior information on the cost of monitoring the borrower (see the discussion below).

[6]Parameter α can be interpreted as the fraction of good-type borrowers in the economy or the probability that a given borrower is of type G.

[7]The share of the lead bank is then split between the lead bank and the firm according to a bargaining game outside the model.

the model, we parameterize the level of common ownership between the lead bank and the syndicate member by κ, capturing the weight that the lead bank L places on the utility of the commonly owned syndicate members M. Finally, all agents in the economy are risk neutral, the lead bank is protected by limited liability, and the risk-free interest rate is nil.

We solve the model under two scenarios: the first is the case without common ownership ($\kappa = 0$); while the second considers the case with common ownership ($\kappa > 0$). The lead bank can use common ownership to truthfully channel its private information regarding the borrower's probability of success to the commonly owned syndicate members. In other words, in this model common ownership is equivalent to an information transmission technology.

Funding without common ownership We first consider the case without common ownership ($\kappa = 0$). We derive the *low-information-intensity* optimum of the contract design game (Rothschild and Stiglitz, 1976; Wilson, 1977). This corresponds to the separating allocation that maximizes the utility of the lead bank representing a good borrower subject to the constraint that the lead bank representing a bad borrower does not receive a rent. In practice, this separating contract is unappealing to a bad borrower and allows the potential members to break even.[8] In the discussion below, we describe the merits of this choice (including the condition such that the equilibrium we focus on is the unique equilibrium of the signaling game).

In equilibrium, if potential syndicate members subscribe the loan, the lead bank must choose between the contract targeting the bad borrower and the one targeting the good borrower. By construction, this choice is incentive compatible. The contract targeting a lead bank representing type B is such that this firm will not be funded. To achieve separation, the contract targeting a lead bank representing type G does two things. First, it requires the lead bank L to pledge all its funds as a signal that it

[8] Our assumptions guarantee that this optimum allocation exists across the cases we consider (with and without common ownership). The low-information-intensity optimum is the unique perfect Bayesian equilibrium of our game under a condition on the parameter α. If this condition is not satisfied, there may also exist pooling equilibria (see the discussion below).

is confident about the good borrower's future returns ($\mathcal{A}_G = A$). Second, the reward to the lead bank L is determined by the mimicking condition of the bad type: the lead bank picks the largest repayment that makes the lead bank representing a bad type indifferent between accepting the contract targeting the good type and remaining inactive ($R_{G,M} = R - A/q$). The good-type contract can be implemented by a debt contract featuring M transferring $1 - A$ upfront and receiving $R - A/q$ if the project succeeds.

Funding with common ownership Consider now the case in which the lead bank places a weight $\kappa > 0$ on the utility of the commonly owned potential syndicate members. Specifically, there is a fraction of commonly owned potential syndicate members (M_{Co}) and a complementary fraction that are not commonly owned with the lead bank (M_{NCo}). In line with our empirical application, any contract offered by the lead bank features the same reward to M_{Co} and M_{NCo} (so that $R_{j,M} = R_{j,M_{Co}} = R_{j,M_{NCo}}$, with $j = G, B$).

We model common ownership as an information transmission device. We say that information transmission can happen only if $\kappa \geq \underline{\kappa}$, and then empirically identify the threshold $\underline{\kappa}$ in the application. The lead bank can credibly channel its private information regarding the borrower's probability of success to the commonly owned syndicate members M_{Co}. As a consequence, M_{Co} are perfectly informed about the type of borrower. M_{NCo} observe the choice of the commonly owned syndicate members M_{Co}, and know that the lead bank shares its private information with M_{Co}, but do not observe the type of the firm represented by the lead bank L.

We construct an equilibrium in which the lead bank representing a bad borrower does not get access to funding. Instead, the lead bank representing a good borrower will get the equilibrium contract with symmetric information. In particular, the loan to the good firm is fully underwritten by the members of the syndicate ($\mathcal{A}_G = 0$) in exchange for the transfer for $R_{G,M_{Co}} = R_{G,M_{NCo}} = 1/p$.

Since they know that the lead bank L channels its private information to the commonly owned syndicate members M_{Co}, the non-commonly owned syndicate members

M_{NCo} are able to infer the type of borrower represented by L based on the contracts offered by L and M_{Co}'s decision to accept or reject the offer. As a consequence, they accept the symmetric-information contract if the commonly owned investors M_{Co} accept it. It is optimal for the lead bank to offer the symmetric-information contract because it yields the full NPV of the project. The lending contract can be interpreted as a debt contract in which the members of the syndicate lend 1 upfront and get $1/p$ in the case of the project's success, or else the borrower goes bankrupt.

Empirical predictions We now list the empirical predictions of the model (see the Theoretical Appendix for their formal derivation). Our null hypothesis is that sufficiently high levels of common ownership facilitate information transmission.

Proposition 1. *Comparing the lending conditions (interest rate and amount of the loan retained by the lead bank) with and without common ownership, we find that:*

1. *The interest rate charged by syndicate members is lower with high common ownership than without common ownership;*

2. *The lead bank commits more funds to the loan without common ownership than with high common ownership;*

3. *Without common ownership, we observe rationing at issuance. We do not observe rationing at issuance with high common ownership;*

Absent common ownership, the separation of types requires that the lead bank representing a good borrower is less greedy (compared with high common ownership) and promises higher rewards to the syndicate members. To achieve separation, the lead bank representing a borrower with a good project signals its type by committing A in the loan. The second implication in the proposition depends on the fact that, with low common ownership, the lead bank conveys the quality of the loan by means of a costly signal (loan retention). With high common ownership, instead, separation is achieved thanks to the channeling of the lead bank's private information to the commonly owned investors. Finally, for the third implication in the proposition, we assume heterogeneous lead banks with respect to the value of A that they can commit to the loan, so that only the lead banks with sufficiently large funds can offer the separating equilibrium contractual terms that avoid the breakdown of capital markets.

2.3.1 Discussion

Common ownership and interest alignment We now consider the situation in which common ownership purely serves as a mechanism to align interests across lenders (Antón et al., 2023), and there is no information transmission. We still expect common ownership to impact the design of the contract because, in contrast to the case without common ownership, the objective function of the lead bank features a weight $\kappa > 0$ attached to the utility of commonly owned syndicate members M_{Co}.

The key difference we expect is in the lead bank's decision to retain a share of the loan. With information transmission, the lead bank representing a good borrower does not need to engage in costly signaling to achieve type separation and, in equilibrium, $\mathcal{A}_G = 0$. If, instead, common ownership only has interest-alignment purposes, in the low-information-intensity optimum, the contract targeting the good borrower must signal the good type by committing all the liquidity of the lead bank to the loan ($\mathcal{A}_G = A$). Thus, if common ownership was mainly about interests' alignment, we should not find evidence consistent with Prediction 2 in Proposition 1 in our empirical application.

Common ownership and pipeline risk Bruche et al. (2020) study the situation in which the lead arranger syndicates a loan with the intention of selling it soon after under the risk that the loan becomes a "hung" deal (pipeline risk). The crucial difference with respect to our setting is the source of information asymmetry. In their model, potential investors (the market) hold private information on their loan valuation. Thus, the lead bank designs the contracts to maximize its profits under demand discovery. If common ownership allows the investors to transmit information to the lead bank credibly, the predictions would be similar to ours: it is unnecessary to retain a share of the loan or underprice the loan in the low-demand state.

The reversal of the source of asymmetric information results in a falsification test on the directionality of the information flow to study how common ownership interacts with pipeline risk. When looking at the weights that the syndicate members put on the profit of the lead arranger (from the investors to the lead arranger), we should find the same effects as in our primary empirical analysis. However, this is different from our setting; as we conjecture that the lead bank holds superior information and we focus on the heterogeneity of borrowers' creditworthiness, we use the weights that the lead bank puts on the profit of syndicate members (from the lead arranger to investors) as a proxy for common ownership. In Section 2.6.2, we find no statistically significant effect under the falsification test.

Model assumptions Although the predictions of our model are derived under the assumption that the lead bank holds private information on the expected return of the borrower, the qualitative results of the model would not change if the lead bank had superior information on the cost of monitoring the borrower (Sufi, 2007). If monitoring costs are unobservable to syndicate members, the lead bank needs to retain a share of the loan to signal that it has the incentive to exert the monitoring effort. Moreover, costly signaling would cause a lower reward to the lead bank and hence a larger reward to the syndicate members.

Tirole (2006) shows that, under a condition on the value of prior beliefs α, which we implicitly make, the separating equilibrium we consider is the unique equilibrium of the model. Otherwise, there may exist pooling equilibria in which both types are better off than in the separating allocation considered without common ownership. In such equilibria, the lead bank chooses between accepting a contract in which the borrower is rewarded only in the case of success and a contract with an upfront lump-sum payment A and no investment. In practice, the lead bank representing a bad borrower, which chooses the second option, is offered a bribe to go away. Our focus on the separating equilibrium in the analysis without common ownership is motivated by the fact that such pooling contracts are not offered in syndicated lending. Nonetheless, they still satisfy our prediction on the lead bank's commitment of A in the loan.

Finally, other costly signals could be used to achieve the separation of types without common ownership. For example, the borrower could accept shorter maturities or pledge collateral. However, the non-price dimensions of syndicated loans are set before the marketing stage; that is before syndicates form at the facility level. Moreover, except for maturity, the non-price attributes do not vary across facilities. Any correlation with common ownership would therefore be spurious or non-consequential.

2.4 Data

Our sample is constructed in two steps: in the first step, we assemble a sample of borrower-bank-loan-facility observations between 1990 and the first quarter of 2017; and in the second, we combine our data with information from Thomson Reuter S34 to determine the common investors of the lead bank and the syndicate members within a loan.

2.4.1 Sample Construction

Syndicated loans Our primary data source is the Loan Pricing Corporation's (LPC) DealScan database, which identifies bank-borrower relationships. DealScan contains detailed information on the loan, such as the interest rate paid to the lender group measured in basis points (the all-in drawn spread, which is the sum of the spread of the facility over LIBOR and any annual fees), loan size, loan type (credit line or term loan), purpose (mainly corporate, excluding leveraged buyout), and the presence of collaterals. We restrict the sample to loans issued by commercial banks incorporated in the U.S. to U.S. non-financial firms between 1990 and the first quarter of 2017. In addition, we remove from the sample all loans with split structure in terms of financial covenants; these are term loans tranches that lack financial covenants, while the credit line tranche contains traditional financial covenants. Following Berlin et al. (2020), we create an indicator for split control rights within a loan using the market segment data. If the term loan in a deal is identified as covenant-lite, we assume that the revolver has maintenance covenants and identify the deal as having split control rights. Following Ivashina and Sun (2011), we also exclude second-lien term-loan facilities so that our sample includes only senior facilities; differences in spread across facilities of the same type within a loan cannot arise from differences in their seniority.

We identify the participants in a syndicate at the loan-facility level. Following Ivashina (2009), we classify a bank as a lead bank if its Lender Role field in DealScan is one of the following: administrative agent, agent, arranger, book-runner, coordinating arranger, lead arranger, lead bank, lead manager, and mandated arranger.[9] We then use linking tables from Chava and Roberts (2008) and Schwert (2018) to merge the loan data with borrower and lender characteristics from Compustat, including borrower size, profitability and rating (investment-grade, high-yield, and unrated) and lender size and profitability. [10]

Common ownership To compute our common ownership measures, we use several sources. The primary one is the Thomson Reuters S34 database, which consolidates information from the mandatory 13F SEC filings that all institutions with at least \$100 million of assets under management have to report at quarterly frequency. We complement the Thomson Reuters S34 data with hand-collected 13F holdings from Backus et al. (2021b) and aggregate Blackrock holdings filed separately under different entities (Ben-David et al., 2021). We also use information on the 13D/G filings assembled by Schwartz-Ziv and Volkova (2020) for large (above 5%) shareholders; we, therefore, take 13D/G filings into account when 13F disclosures are not applicable, for example when the assets are owned by individuals. In addition, we conduct sample checks on other filings reporting information on insider holdings of executives and board members (Forms 3, 4, 5, and 144). These holdings are substantially lower than 5% and have a minor effect on our common ownership measure; we, therefore, ignore these individual stakes. Finally, we collect data on shares outstanding from the Center

[9] In the residual case in which no lead bank or multiple ones are identified, we attribute the role of lead bank to the banks for which the field "Lead Arranger Credit" is marked with "Yes".

[10] Schwert (2018) hand-matches DealScan lender names with Compustat GVKEYs for all lenders with at least 50 loans or at least \$10 billion in loan volume. The matching table takes into account bank subsidiaries and bank mergers during the sample period.

for Research in Securities Prices (CRSP), which we merge to historical CUSIP bank codes. The resulting sample allows us to determine which banks within a loan relationship have common institutional investors and the extent of overlapping ownership at syndicate member-facility-loan level.

2.4.2 Measures of Common Ownership

The literature proposes several measures of common ownership: see O'Brien and Salop (2000), Antón and Polk (2014), Newham et al. (2022), and Gilje et al. (2020). We adopt the profit weights approach based on the theory of partial ownership developed by Rotemberg (1984). This approach is closely linked to our model and to the theoretical literature on common ownership. In Appendix A.3, we replicate our main analysis using an alternative, model-free measure of common ownership and obtain similar results.

As in Rotemberg (1984), we assume that the lead bank maximizes a weighted average of shareholder portfolio profits. To construct the profit weights, we rely on O'Brien and Salop (2000). Each lead bank a places a weight κ_{ab_i} on the profit of each syndicate member bank in facility i (b_i) that is overlapping in ownership:

$$\kappa_{ab_i} = \frac{\sum_{s \in S} \gamma_{as}\beta_{b_i s}}{\sum_{s \in S} \gamma_{as}\beta_{as}}, \tag{2.1}$$

where S is the set of shareholders of lead bank a, and γ and β are, respectively, the voting and cash-flow rights of each investor s. These weights capture the importance to each lead bank of a dollar of profit generated by the syndicate members. We follow the vast majority of the literature and assume that one share corresponds to one vote (the proportionality of voting rights): $\gamma_{as} = \beta_{as}$ and $\gamma_{b_i s} = \beta_{b_i s}$.[11]

Given Equation (2.1), the average weight that the lead bank a places on the profit

[11] See Backus et al. (2021b) for a discussion on the importance of the one-share one-vote assumption and other measures of common ownership.

of other syndicate members in each facility i is:

$$CO_{ia} = \frac{1}{B_i} \sum_{b=1}^{B_i} \kappa_{ab_i}, \tag{2.2}$$

where $B_i \in [1, \overline{B}]$ is the number of syndicate members in each facility i. We consider other choices to aggregate profit weights between the lead bank and members at facility level, such as the median and mode, and find that estimation results remain unchanged. Finally, we repeat the same exercise to determine the degree of common ownership between: (i) borrowing firms and banks; (ii) syndicate member to lead arranger; and (iii) syndicate members within each loan relationship. Measure (i) will be an additional control to account for the presence of common and cross ownership between vertically related firms. Measures (ii) and (iii) will be useful to run falsification tests of our hypotheses.

Following Backus et al. (2021b), we decompose the profit weights in Equation (2.1) to study the sources of common ownership variation at the facility level. Let $IHHI_a = \|\beta_a\|^2$ be the Herfindahl-Hirschman Index for the investors in company a. Define $\cos(\beta_a, \beta_{b_i})$ as the cosine similarity between vectors a and b_i, representing the cosine of the angle between the positions that investors hold in a and those that investors hold in b_i. Backus et al. (2021b) show that:

$$\kappa_{ab_i}(\beta) = \underbrace{\cos(\beta_a, \beta_{b_i})}_{\text{overlapping ownership}} \cdot \underbrace{\sqrt{\frac{IHHI_{b_i}}{IHHI_a}}}_{\text{relative IHHI}}. \tag{2.3}$$

The first term is the overlapping ownership, which captures the similarity in investor positions. For investors holding positions in both the lead bank a and a syndicate member bank b_i, a higher position will determine a smaller angle with cosine similarity approaching one. The second term captures the relative concentration of investors. Ceteris paribus, if the lead bank has fewer, larger investors, then the value of $IHHI_a$ is large, control rights are relatively expensive, and profit weights $\kappa_{ab_i}(\beta)$ are smaller. Conversely, if the lead bank has many small investors, the value of $IHHI_a$ is small, control rights are relatively cheaper, and profit weights $\kappa_{ab_i}(\beta)$ are larger. In the descriptive analysis below, we use the decomposition in Equation (2.3) to document the patterns of common ownership.

Finally, we define as common owners all institutions filing the mandatory 13F SEC filings (or, less frequently, 13D/G). In a limited number of cases, those institutions are asset management divisions of the lead bank itself: more precisely, direct investment of a lead bank in other lenders configures a situation of cross-ownership rather than common ownership. We identify those management divisions and create profit weights that exclude them as common shareholders while controlling for the presence of cross-ownership. As those divisions tend to hold very low equity in other lenders, the distribution of profit weights is practically unaffected by such exclusions. For simplicity, our main measure of common ownership, therefore, includes those institutions as shareholders, whereby separately controlling for cross ownership does not affect our results.

2.4.3 Summary Statistics

Table I provides the summary statistics. Our final sample consists of 27,868 borrower-bank-loan-facility observations. We observe 17,430 loans granted to 3,988 firms between 1990 and the first quarter of 2017. We identify 70 lead banks. The average syndicate size is 10 members. Syndicates extend loans of \$1,180 million on average. Every loan comprises a number of tranches called facilities, which are our unit of observation. On average, a syndicated loan consists of 1.8 facilities. The average facility spread is 170 basis points and the average amount \$685 million. 44% of loans are secured by collateral. Most facilities in our sample are credit lines (71%).[12] On average, lead banks retain 19.3% of the facility amount, and this variable is reported for around half of the observations in our sample.

[12] In the summary statistics, we present two aggregate types: credit lines and term loans. In the data, we observe more granularity, with different types of term loans (A, B, C, and higher designations). We account for these types in the empirical application. Following Lim et al. (2014), we consider all facilities with designation B or higher as term loan B and use the following three categories for facility types: (i) credit line; (ii) term loan A; and (iii) term loan B and higher.

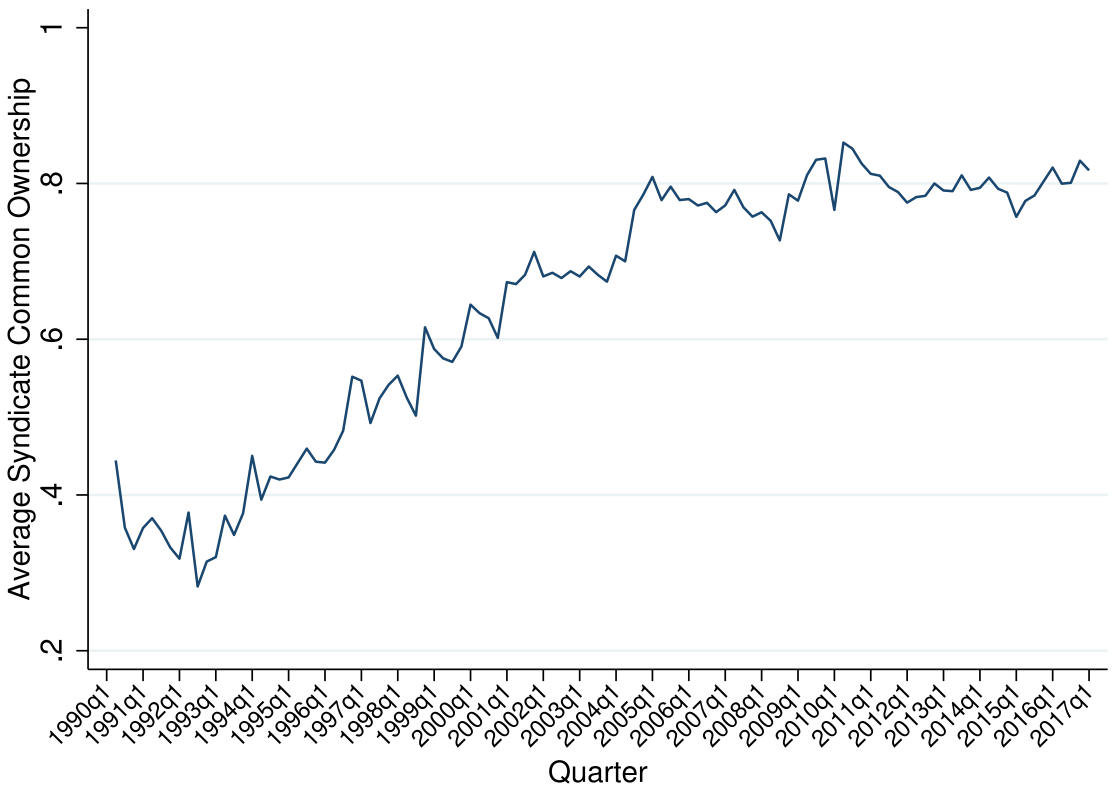
Table I: **Summary statistics**

	Mean	Std.Dev	p25	p50	p75	Obs.
			Loan Variables			
All-in-Drawn Spread	170	107	100	150	225	27,868
CO	0.720	0.180	0.630	0.760	0.840	27,868
CO Member-Borrower	0.480	0.350	0.070	0.550	0.770	27,868
Facility Amount $M	684.9	1,293.7	150.0	345.0	760.0	27,868
Loan Amount $M	1,180.4	2,187.3	250.0	600.0	1,350.0	27,868
Lead Amount	19.3%	15.1%	9.1%	14.0%	25.0%	12,165
# Facilities within Loan	1.840	1.090	1.000	2.000	2.000	27,868
Log Maturity	3.810	0.600	3.610	4.090	4.090	27,868
Secured Loan	0.440	0.500	0.000	0.000	1.000	27,868
Refinancing	0.720	0.450	0.000	1.000	1.000	27,868
Log Number of Members	2.170	0.700	1.790	2.200	2.640	27,868
Guarantor	0.110	0.310	0.000	0.000	0.000	27,868
Relationship Score	0.040	0.020	0.030	0.040	0.040	27,868
New Lending Relation	0.500	0.500	0.000	0.000	1.000	27,868
LIBOR 3M	0.020	0.020	0.000	0.010	0.050	27,868
Non-Bank Synd. Member	0.200	0.400	0.000	0.000	0.000	27,868
Prob. Default	0.030	0.120	0.000	0.000	0.000	27,868
Stock Volatility	0.380	0.180	0.260	0.340	0.450	27,868
Credit Line	0.710	0.460	0.000	1.000	1.000	27,868
Term Loan	0.290	0.460	0.000	0.000	1.000	27,868
			Borrower Variables			
Size	7.890	1.610	6.780	7.830	8.950	27,868
ROA	0.100	0.070	0.060	0.090	0.130	27,868
Book Leverage	0.330	0.200	0.200	0.310	0.440	27,868
Tangibilities	0.300	0.230	0.120	0.240	0.450	27,868
Tobin's Q	1.780	0.950	1.220	1.520	2.000	27,868
Log Int. Cov.	2.230	0.960	1.580	2.100	2.730	27,868
Liquidity Ratio	0.070	0.070	0.010	0.040	0.090	27,868
Unrated Borrower	0.340	0.470	0.000	0.000	1.000	27,868
High Yield	0.660	0.470	0.000	1.000	1.000	27,868
Investment Grade	0.340	0.470	0.000	0.000	1.000	27,868
			Bank Variables			
Lead Size	13.480	1.160	12.620	13.920	14.470	27,868
Lead Market Equity	0.120	0.060	0.080	0.110	0.150	27,868
Bank Book Equity	0.080	0.020	0.070	0.090	0.100	27,868
Lead Book Leverage	0.250	0.100	0.200	0.240	0.290	27,868
Lead ROA	0.010	0.000	0.010	0.010	0.010	27,868

The table reports summary statistics of the main variables in our sample related to (i) facilities and loans; (ii) borrowers; (iii) lead banks. CO denotes common ownership. All variables are defined in Table B.II in Appendix A.3.

Common ownership patterns In the U.S. banking sector, the four largest asset managers (Blackrock, Vanguard, State Street, and Fidelity) hold together around 20% of the four largest commercial banks' shares in 2017. Figure 2.1 documents the striking increase in common ownership during our sample period, confirming the findings of previous studies (Azar et al., 2018; Backus et al., 2021b). We calculate profit weights at the facility level and find that on average, lead arrangers have a weight of 0.72 on the profits of the other syndicate members, with an increase from 0.44 in 1990 to 0.82 in 2017.

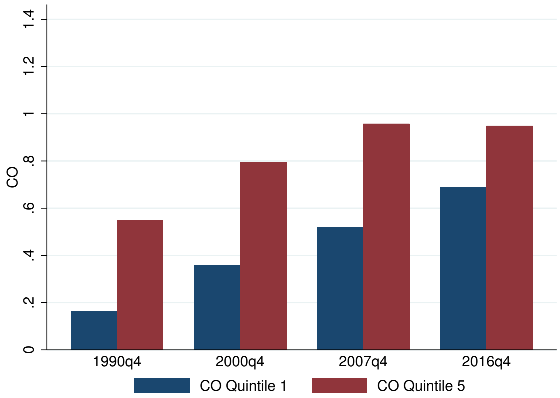
Figure 2.1: **Average common ownership in the syndicated loan industry over time**



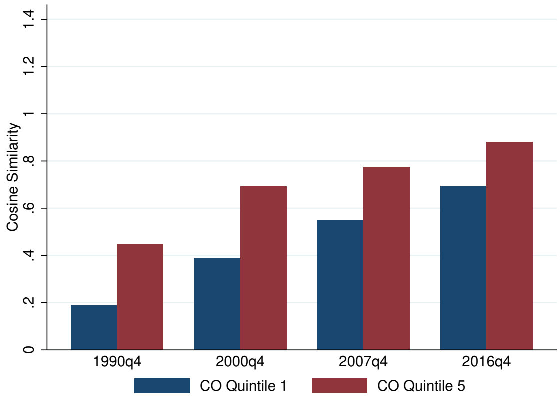
This figure reports the average common ownership among banks in the same syndicate between 1990 and 2017q1 at a quarterly frequency. Common Ownership is defined as the average profit weights between the syndicate lead-arranger(s) and the syndicate members.

To interpret these patterns, we decompose the profit weights into overlapping ownership and relative investor concentration, see Equation (2.3). Figure 2.2 shows the results of such decomposition between 1990 and 2016.

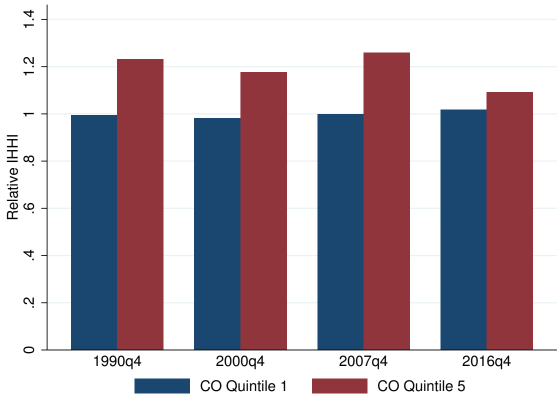
Figure 2.2: **Decomposition of lead-member common ownership measure**



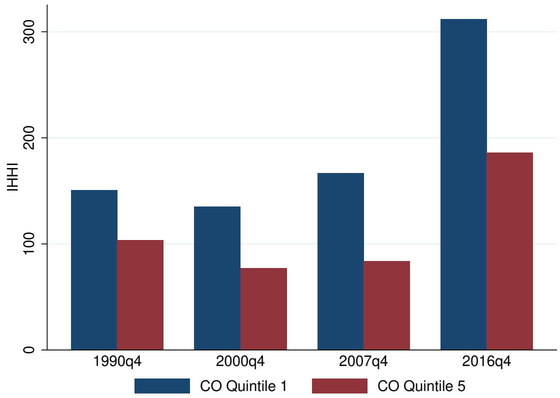
(a) CO



(b) Cosine Similarity



(c) Relative IHHI



(d) Lead IHHI

The figure reports the average values of syndicate common ownership (a) and its decomposition (b) and (c) for the highest and lowest quintile of the common ownership distribution over time. Syndicate common ownership (CO) is defined in Equation 2.2 and the decomposition in Equation 2.3. Panel (d) reports the average shareholders' concentration of lead banks (Lead IHHI) for the highest and lowest quintile of the common ownership distribution over time.

The blue bar represents the lowest quintile of our measure of common ownership, and the red bar represents the highest quintile. The decomposition shows the two underlying forces driving the growth in profit weights over the sample period. Panel (a) depicts the clear increase in profit weights, $\kappa_{ab_i}(\beta)$, over time. Panel (b) shows that cosine similarity, $\cos(\beta_a, \beta_{b_i})$, is, as expected, higher at high levels of common ownership and increasing over time as common investor positions in lenders have become larger over time. Panel (c) depicts the relative investor concentration, $\frac{IHHI_{b_i}}{IHHI_a}$, and Panel (d) represents the average concentration level of investors in lead banks only, $IHHI_a$. Taken together, panels (c) and (d) show that while relative investor concentration is rather constant over time, control rights in lead banks characterized by high common ownership have become somewhat cheaper: investor concentration for the lead banks is lower at the top quintile of common ownership, and the gap in investor concentration between the bottom and the top quintiles has increased over time. Such a shareholder structure allows common investors to influence the lead banks' strategies more effectively. With the lead bank having several small investors, $IHHI_a$ will be small and control rights cheaper. This is partly driven by the growth of retail shares at higher levels of common ownership: as retail investors do not have incentives to engage in active governance, they leave more room for common owners to influence the lead banks' strategies.

A variance decomposition for all lead bank-member pairs of profit weights reveals that around 70% of the variation in profit weights comes from overlapping concentration, and relative investor concentration never falls below 30%. Investor concentration has an impact in shaping the variation in profit weights both in the cross-section and over time; for example, at the lowest quintile of common ownership, institutional investors tend to be large and undiversified, thus the lead banks put more weight on their own profits.

2.4.4 Motivating Empirical Evidence

We begin by documenting two key empirical facts. The first one shows that, after a loan deal with high common ownership between the lead bank and the syndicate member banks, those member banks present a stronger lending relationship with a given borrower with respect to lenders participating in a low common ownership deal with the same borrower. According to our model, as lenders in the high common ownership loan possess superior information on the creditworthiness of the borrower, they will be more likely to engage with that borrower afterward.

Second, we look at connected directors as a simple mechanism of information transmission across lenders. Indeed, we find a positive association between the degree of common ownership and connected directors.[13]

These facts provide suggestive evidence that common ownership can serve as a mechanism to overcome asymmetric information problems.

Common ownership and the intensity of lending relations We empirically compare the intensity of the lending relationship to a given borrowing firm between two types of lenders: lenders that experienced high common ownership with the lead bank and members that experienced low common ownership with the lead bank. We measure intensity in terms of number of deals and dollar amount. We first select a panel at syndicate member-borrower and year-quarter level according to three criteria: (i) a given borrower is granted at least two loans at the origination date, where one of the loans is characterized by a high level of common ownership and the other one by a low level of common ownership; (ii) borrowers are granted at least one loan before and after the loan origination date; and (iii) the loans are not refinancing loans. Second, for each borrower, we calculate the total number of loan facilities and the total dollar amount of these facilities in which the same syndicate member participates before and after a given loan deal date, scaled by the borrower's total newly initiated number of loans or the loan amount during the same period. The before/after period covers 16 quarters, reflecting the average loan duration in our sample. We conduct the comparison between these two groups as follows:

$$Intensity\ Lending\ Relations_{fbt} = \beta_0 + \beta_1 I^H_{CO} I^{Post}_t + \beta_2 I^{Post}_t + \varepsilon_{fbt}, \tag{2.4}$$

where f indexes the borrower firm, b the syndicate member bank, and t indexes the quarter; I^H_{CO} takes a value of one for members in the loan with high common ownership

[13] The literature has amply documented the role of directors on the success of acquisitions (Hilscher and Şişli-Ciamarra, 2013), especially directors with investment banking experience sitting on a board of non-financial firms (Huang et al., 2014), and the implications of conflicts of interest when a bank's relationship with a borrower is affected by extra control rights (Kroszner and Strahan, 2001; Santos and Rumble, 2006; Jagannathan et al., 2020).

and zero otherwise; I_t^{Post} takes a value of one after the date of the loan origination and zero otherwise. The coefficient of interest is β_1.

Table II: **Lending intensity to a borrower with loan with high versus low common ownership**

	(1) # Loans	(2) # Loans	(3) # Loans	(4) Amount	(5) Amount	(6) Amount
Member CO High	0.093	0.075	-0.076**	0.102*	0.083	-0.076**
	(1.643)	(1.507)	(-2.202)	(1.777)	(1.613)	(-2.065)
Post	-0.133**	-0.142***	-0.151***	-0.113*	-0.125**	-0.140**
	(-2.459)	(-2.755)	(-2.678)	(-1.947)	(-2.230)	(-2.285)
Member CO High X Post	0.133*	0.138**	0.161**	0.126*	0.132*	0.162**
	(1.966)	(2.099)	(2.234)	(1.748)	(1.885)	(2.091)
Year-Quarter of Loan FE	Yes	Yes	Yes	Yes	Yes	Yes
Member FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	Yes	Yes	No	Yes	Yes
Member X Borrower FE	No	No	Yes	No	No	Yes
Observations	826	826	820	806	806	801
Adjusted R-squared	0.105	0.116	0.207	0.106	0.116	0.202

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.4). The dependent variable is number of loan underwritten by a syndicate member normalized by the total newly initiated number of loans (Column 1-3) and the amount of loan underwritten by a syndicate member normalized by the total newly initiated number of loans (Column 4-6). The coefficient of interest is the one of *Member CO High X Post*, an indicator variable taking the value of one for syndicate members in the loans with high common ownership and after the date of the loan origination. Standard errors are clustered by lender and year-quarter. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Panel (a) of Table II reports the coefficient estimates of Equation (2.4), where the intensity of financial relationships between the borrower and the syndicate member is measured in the number of loans normalized by the total number of newly initiated loans. In the most saturated specification, with member-borrower, and year-quarter fixed effects (column 3), syndicate members in the high common ownership deal increase their participation after the origination date by 16 percentage points relative to the control group. When measuring the intensity of financial relationships in dollar amount (column 6), we find the same effect (an increase of 16 percentage points).

Connections between lenders and common ownership We investigate the association between common ownership and directorship interconnections (interlocks) in our setting. For each pair of lead bank-potential syndicate members, we define a direc-

Table III: **Board connections and common ownership**

	(1)	(2)	(3)	(4)
CO	0.202***	0.054**	0.152***	0.076**
	(6.675)	(2.049)	(3.954)	(2.027)
Distance Lead-Member		-0.156***	-0.153***	-0.079*
		(-4.368)	(-3.291)	(-1.934)
Relationship Lead-Member		0.249***	0.225***	0.203***
		(6.182)	(5.830)	(5.684)
Lead Size		0.053***		
		(5.394)		
Lead Market Equity		0.024		
		(0.233)		
Lead Book Leverage		0.076*		
		(1.681)		
Lead ROA		0.525		
		(0.642)		
Member Size		0.059***	0.073***	0.049
		(8.858)	(10.884)	(1.624)
Member Market Equity		0.121	-0.085	-0.338***
		(1.419)	(-0.934)	(-2.664)
Member Book Leverage		0.088*	-0.078	-0.029
		(1.887)	(-1.602)	(-0.336)
Member ROA		-0.020	-0.123	0.479
		(-0.026)	(-0.147)	(0.669)
Year FE	No	No	No	No
Lead X Year FE	No	No	Yes	Yes
Member FE	No	No	No	Yes
Observations	10,405	10,126	10,126	10,126
Adjusted R-squared	0.018	0.119	0.184	0.214

The table reports the OLS regression parameter estimates and t-statistics. The dependent variable is as an indicator equal to one if a pair of banks have a board connection. The coefficient of interest is the one of CO, a measure of common ownership between each lead-member pair. *Distance Lead-Member* is the portfolio distance between the lead bank and the syndicate participant in the previous four quarters, *Relationship Lead-Member* is the number of loans arranged by the lead bank where the member bank participated in the previous four quarters divided by the number of loans arranged by the lead bank in the previous four quarters. Standard errors are clustered by member bank. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

tor interlock as an indicator equal to one if: (i) at least one director sits on the boards of both banks or (ii) at least one director from each bank in the pair serves on the board of a common third firm. Information on directors and their joint employment is retrieved from BoardEx, with yearly frequency, for the period 1999-2017.[14] We then describe the probability of director interlocks by regressing the indicator on a measure of common ownership and an extensive set of covariates capturing characteristics of the lender pair.

Table III presents the results of a linear probability model. We empirically document a positive relationship between common ownership and shared directors; that is, pairs of lead bank-potential syndicate members with higher levels of common ownership are more likely to exhibit interlocking directorships. This positive association remains significant after controlling for: (i) characteristics of the lenders (their size, equity, book leverage, return on assets, and whether they belong to the S&P 500); (ii) characteristics of the lender pairs (their portfolio similarity and their past relationships); and (iii) year dummies. These results support the hypothesis that, in our setting, common ownership can constitute a communication device between firms if it is sufficiently large, as common directors are more likely at higher levels of common ownership. Our findings complement the work of Azar (2012), who provides descriptive evidence that firms with common owners are more likely to share directors, and Nili (2020), who documents the rise of so-called horizontal directors, serving on the boards of multiple companies within the same industry.[15]

2.5 Estimation and Results

We now investigate whether the three predictions of Proposition 1 are verified in the data. For each prediction, we first present the empirical specification. We then discuss the identification strategy, highlighting the key sources of identifying variation in the data. Finally, we present the results.

[14]Our common ownership measure is built at the quarter-year level. Because the information on directors is at yearly frequency, we use the measure of common ownership from the last quarter of each year.

[15]In a similar vein, Ferreira and Matos (2012) find that in the presence of common directors between bank-borrower pairs, the bank is more likely to be chosen as a lead arranger because of the informational advantage that the connected bank retains over other banks.

2.5.1 Interest Rates

Empirical Design

According to Prediction 1 of Proposition 1, the interest rate paid to the syndicate members will be lower at higher levels of common ownership. We test the prediction by estimating the following equation:

$$Spread_{iat} = \beta_0 + \beta_1 CO_{iat} + \beta_2 X_{iat} + \varepsilon_{iat}, \tag{2.5}$$

where the dependent variable $Spread_{iat}$ is the all-in-drawn spread paid to syndicate members of facility i arranged by bank a in quarter t. We omit the subscript for the borrowing firm to simplify the notation. The variable of primary interest, CO_{iat}, is the average weight that the lead bank a puts on the profits of other syndicate members present in a specific facility i, as defined in Equation (2.2). Prediction 1 translates into the prediction that the coefficient β_1 is negative when common ownership is high enough, where the threshold $\kappa \geq \underline{\kappa}$ is empirically identified. Our estimated β's do not estimate either the parameters of the demand curve or those of the supply curve, but instead the effect of each covariate on the equilibrium outcomes.

The vector of variables X_{iat} includes an extensive set of controls related to: (i) the loan and the facility; (ii) the borrower; and (iii) the lender. We also account for relationships of common ownership between lenders and borrowers: under the lens of a vertical integration model, common ownership between lenders and borrowers may result in lower prices for the borrower. Other facility and loan-related controls include facility amount, the number of participants, the arranger's past relations with syndicate participants and with the borrower, the presence of collateral, and the maturity of each facility. The rationale for using the facility amount and other non-pricing features of the loans as controls is that those characteristics are fixed before the syndication process. If we remove those controls, our estimates are essentially unchanged. We also control for the three-month LIBOR rate at origination, as the literature documents a relationship between the LIBOR rate and loan spreads (Roberts and Schwert, 2020).

Borrower-related controls include the borrower's size measured in assets, profitability, and a measure of leverage defined as book debt over total assets. Finally, lenders' related variables include their size, capital, and profitability. Following Antón et al. (2023), in our specifications, we use quintile dummies of the lender's size to address the concern that the common ownership variable may be picking up non-linear effects of the lender's size. The full set of controls X_{iat} is listed in Table B.II.

In addition to our time-varying set of controls, we employ multiple fixed effects to differentiate out alternative interpretations, such as confounding effects of demand and supply variations. The inclusion of fixed effects for facility type and loan purpose ensures that our results are not driven by omitted characteristics at the facility level. In our baseline specification, we also include industry-year-quarter fixed effects to control for aggregate variation in demand for syndicated loans in each sector, as well as the aggregate time-varying propensity towards risk in each sector. We, therefore, base our inferences on within industry and year-quarter variations so as to difference out the fact that important events, such as the financial crisis of 2008, may have had differing impacts across industries. Borrower fixed effects account for unobserved time-invariant heterogeneity across borrowers. Finally, to capture time-invariant supply factors (for example the fact that the lead arranger may specialize in loans with specific features or hold a certain reputation), we add lead bank fixed effects.

Our coefficient of primary interest (the one on common ownership) is mainly identified by the cross-sectional variation that arises from differences in the composition of the syndicate both across facilities and across loans. Specifically, as we use quarter-year fixed effects, interacted with the industry in which the borrower operates, the coefficient is identified by the within variation in common ownership among facilities and loans that differs from the average common ownership level faced by borrowers in a certain industry and period. Persistent differences in common ownership across borrowers and lead arrangers are absorbed by our fixed effects at the borrower and lead arranger level.

Before presenting the coefficient estimates, we assess the importance of each source of variation. We regress our common ownership measure on all the covariates included in the main specification, and then partition the variance of the residual into three components: (i) variance in industry-year-quarter, borrower, lead arranger, facility type and loan purpose; (ii) variance across loans within an industry-year-quarter; and (iii) variance across facilities within a loan. We find that the first component explains around 69.0% of the total variance in common ownership: this is the portion of variance absorbed by our fixed effects and time-varying controls. Variability in common ownership across loans and facilities, after accounting for the fixed effects and the controls, accounts for 24.9% of the variance in common ownership. The remaining 6.1% arises from differences in common ownership attributable to variation across facilities within a loan, and this is the variation that we will exploit in the within-loan specifications (see below).

Panel-regression Estimates

Table IV presents the estimation results for the coefficients of primary interest. Columns 1 and 2 of Table B.III in Appendix A.3 report the full set of coefficient estimates. The estimated coefficient indicates that an increase of one standard deviation in common ownership is associated with a lower spread of 5.07 basis points (column 1).

To understand how price reductions vary across the range of common ownership, we discretize our common ownership measure into five indicator variables corresponding to the quintiles of its support. Column 2 of Table IV shows that reductions in the spread are relevant only for high levels of common ownership (quintiles 3 to 5, corresponding to 60% of the facilities in our sample), and those reductions are monotonically increasing in common ownership. Assuming no changes in spread for the omitted category (the first quintile), the point estimates represent the average change in spread for loans in each quintile. Our results are not only statistically significant but also economically significant: within a quintile, a change in common ownership in a facility from the minimum to the maximum level reduces the price by 7 to 15 basis points. The average facility spread in quintiles 3, 4, and 5 of common ownership is around 195 points.

Non-investment grade loans and common ownership Recent literature has focused on the market of non-investment grade loans, which is a rapidly growing segment characterized by originate-to-distribute loans.

Table IV: **Interest rates**

	Full Sample		*Same Facility Type - Same Loan*	
	(1)	(2)	(3)	(4)
CO	-26.647***		-44.447**	
	(-4.008)		(-2.235)	
CO Quintile 2		-2.657		-1.275
		(-0.732)		(-0.155)
CO Quintile 3		-8.853**		-19.660**
		(-2.151)		(-2.061)
CO Quintile 4		-10.584***		-23.596**
		(-3.057)		(-2.492)
CO Quintile 5		-15.627***		-23.182**
		(-3.762)		(-2.134)
Loan Purpose FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Year-Quarter FE	No	No	Yes	Yes
Lead FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	No	No
SIC2 X Year-Quarter FE	Yes	Yes	No	No
Observations	25,466	25,466	1,431	1,431
Adjusted R-squared	0.790	0.790	0.723	0.724

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5). The dependent variable is the all-in-drawn loan spread, expressed in basis points. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). The specification also controls for facility-loan, lender, and borrower characteristics. Standard errors are clustered by lead bank. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Pipeline risk, the risk that the loan becomes a "hung" deal, may arise when the market is unwilling to absorb the loan under the conditions arranged by the lead bank: Bruche et al. (2020). Table B.IV in Appendix A.3 presents our empirical analysis that deals with pipeline risk.

First, in column 1, we exclude from our sample non-investment grade loans. Our results hold; an increase in common ownership decreases loan prices, with a smaller effect with respect to the main specification as asymmetric information plagues investment-grade loans to a lesser extent. Second, in column 2, we include time-on-the-market as a control, namely the number of days from the start to completion of syndication, as a proxy for the mismatch between the loan pricing of the loan and market demand (hot or cold deals). Our results are strengthened by the inclusion of the variable; the coefficient of common ownership is larger in magnitude and significant, notwithstanding the limited sample size. Third, based on our theoretical model, high common ownership should be associated with lower average time-on-the-market as information asymmetries between the lead arranger and investors should be mitigated. The hypothesis is empirically verified, with a negative relationship between common ownership and time-on-the-market for non-investment grade loans, for which pipeline risk is most relevant (column 3).

Robustness Appendix A.3 contains the results of several robustness tests. Table B.V reports the same empirical specification using an alternative definition of common ownership as the average of the minimum commonly held shares between the lead arranger and the syndicate members (Newham et al., 2022). Here, the parameter estimates suggest an even stronger effect of common ownership on spread.

Our results are also robust to the inclusion of different sets of fixed effects, as reported in Table B.III. In particular, in column 3, we include the interaction of lead indicators and year-quarter fixed effects (rather than the additive specification with lead bank and year-quarter fixed effects). The interaction rules out possible sorting based on unobservable variations in the risk preferences in each lead arranger; the resulting coefficient has roughly the same magnitude. In column 4, we consider borrower-year fixed effects to control for unobserved time-varying borrower heterogeneity, where estimates indicate an even larger reduction in spread associated with high common ownership.[16] The syndicated loan market is concentrated. JP Morgan and the Bank of America are the most active lead arrangers, with around 63% of the loans

[16]Following Degryse et al. (2019), we prefer the use of quarter-year-industry fixed effects as our main specification. The use of borrower-year fixed effects implies the loss of single-period borrowers which could bias our results.

in the sample (77% in value). We repeat our analysis excluding the loans arranged by these two banks, with the results reported in column 5. The coefficient estimate of common ownership is negative, larger in magnitude, and somewhat noisier given the reduction in sample size; the result confirms the effectiveness of our controls at the lead arranger level and that the negative effect of common ownership on prices is not driven only by the two main actors in this market, but impacts the market as a whole.

Finally, we consider the pricing structure of loans more holistically, particularly the comprehensive total-cost-of-borrowing measure developed by Berg et al. (2016), which accounts for fees, spreads, and the likelihood that they will have to be paid. Fees are used to price options included in loan contracts and to screen borrowers, as those borrowers self-select into a specific fee structure based on private information. Column 6 of Table B.III shows that our results are robust when using this alternative measure of the cost of debt.

Within-loan Estimates

We now focus on pricing differentials between different facilities of the same type *within* a loan with varying degrees of common ownership. This identification strategy was first used by Ivashina and Sun (2011) and later adopted by Lim et al. (2014). It rules out the possibility that the variation in spread associated with common ownership reflects omitted characteristics related, for example, to borrower risk that systematically correlates both with price and common ownership. As a credit event on one or more facilities within a loan triggers the default of the entire loan (loans with split control rights are removed from the sample), facilities of the same type and in the same loan essentially reflect the same underlying risk characteristics. We also control for any other remaining differences across facilities of the same type (size and maturity) that may influence their pricing.

We exploit the variation in pricing arising from the set of 463 loans with multiple facilities of the same type. We estimate Equation (2.5) on this subsample, with results reported in columns 3 and 4 of Table IV. The estimates again confirm our hypothesis that price reduces as common ownership increases. Our estimates imply a spread reduction of an even greater magnitude with respect to the above estimation; that is, within a quintile, a change in common ownership in a facility from the minimum to the maximum level reduces the spread by roughly 20 basis points.

An even more demanding test of the hypothesis comes from cases in which we have the contemporaneous presence of facilities of the same type displaying high and low common ownership within a particular loan. We only have 135 facilities satisfying the requirement, so we run into issues of small sample size. Nevertheless our results hold: Table B.VI shows that when common ownership is high, syndicate members receive a lower spread on the particular facility relative to a facility with low-common ownership, and the coefficient magnitude is consistent with the above specifications.

2.5.2 Funds Committed by the Lead Bank

Empirical Design

Prediction 2 of Proposition 1 says that at higher levels of common ownership, information sharing between the lead bank and the members of the syndicate implies that the lead bank retains a lower share of funds for each facility in the loan. We test Prediction 2 by estimating the following equation:

$$Percent\ Lead\ Amount_{iat} = \beta_0 + \beta_1 CO_{iat} + \beta_2 X_{iat} + \varepsilon_{iat}, \tag{2.6}$$

where the dependent variable is the percent of facility i's amount retained by lead bank a in quarter t. The term X_{iat} includes the same extensive set of controls used in Equation (2.5) related to: (i) the loan and the facility; (ii) the borrower; and (iii) the lender. As before, we account for variation in facility type and loan purpose by including industry-year-quarter fixed effects to control for aggregate variation in demand for syndicated loans in each sector, and use lead bank fixed effects to capture time-invariant supply factors.

Information on the share retained by the lead arranger is available for only half of the facilities in our sample. Blickle et al. (2020), using an alternative database, document that, for 12% of all loans, the lead arranger sells the entire share within four months, while the average loan duration is four years. These sales are concentrated among term B loans (48%) and leveraged loans (41%). Moreover, in the DealScan data, the retained share is missing not at random. In particular, reported shares at origination tend to under-represent loans for which the lead arranger sales occur (4% in this sample).

We address both challenges in our empirical analysis. First, we exclude all term B and leveraged loans from the analysis; for those loans, the lead share at origination may not be a good measure for the lead arranger's exposure to the borrower over the loan's duration. The exclusion of leveraged loans also allows us to address pipeline risk. Most of the literature notes that lead arrangers hold larger shares in loans provided to opaque borrowers to avoid adverse selection and mitigate moral hazard; instead, for originate-to-distribute loans, loan retention could be the result of a "hung" deal, which may happen when the market is not willing to absorb the loan under the conditions arranged by the lead bank: Bruche et al. (2020). Second, we correct for sample selection bias using a probit selection equation ((Wooldridge, 2010)). In particular, we model the probability of missing information on the retained share for a specific loan as a function of the reported retained shares on the total number of loans syndicated by the same lead arranger in the previous quarter. In the selection equation, we also use loan and lead arranger characteristics included in the estimating Equation (2.6).[17]

Coefficient Estimates

Prediction 2 implies that β_1 is negative. Table V presents the coefficient estimates of Equation (2.6): column 1 of Table V reports the effect of our common ownership measure on the share of loan retained by the lead bank without controlling for the issue of selection and misreporting; column 2 reports the effect excluding all term B and leveraged loans from the sample; and column 3 reports the effect accounting for selection and excluding term B and leveraged loans. Table B.VII in Appendix A.3 reports the full set of coefficient estimates, including the ones related to the selection

[17]In the selection equation, we exclude lead arranger fixed effects to avoid endogeneity issues.

equation (the probit).

Table V: **Facility amount retained by the lead bank**

	(1) Full Sample	(2) Exclude Term B And Leveraged	(3) Selection
CO	-2.698***	-2.965*	-4.641**
	(-2.874)	(-1.897)	(-2.134)
Loan Purpose FE	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes
SIC2 X Year-Quarter FE	Yes	Yes	Yes
Lead FE	Yes	Yes	Yes
Observations	8,110	2,753	2,746
Adjusted R-squared	0.743	0.805	0.804

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.6). The dependent variable is the percentage facility amount retained by each lead bank in the syndicate. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). The specification also controls for facility-loan, lender, and borrower characteristics. Standard errors are clustered by lead bank. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

The coefficient estimates of our preferred specification (column 3) indicate that an increase of one standard deviation in common ownership as measured by CO_{iat} implies a 0.75 percentage point decrease in the amount retained by the lead bank, holding all other variables constant at their mean values. Lead arrangers retain on average 13% of the facility amount for the sample excluding term B and leveraged loans. We therefore find empirical support for our hypothesis of reduction in the amount retained by the lead bank for each facility when common ownership is sufficiently high.

2.5.3 Rationing

Empirical Design

According to Prediction 3 of Proposition 1, we expect to observe rationing at issuance with low levels of common ownership, as lead arrangers need to commit larger funds in the loans and their funding resources are limited. On the contrary, as lead banks with high common ownership do not need to signal their type of borrower by committing funds in the loans, they should be able to fund multiple and larger projects. We test the prediction by empirically comparing the intensity of lending relationships between two types of lead arrangers: first, arrangers that in a given quarter experience a prevalence of loans with high common ownership in their portfolio; and second, arrangers with fewer loans in high common ownership in their portfolio. We define I_{CO}^{H} taking a value of one for lead arrangers with more than 60 percent of the loans in high common ownership and zero with 40 to 60 percent of the loans in high common ownership. We exclude lead arrangers with loans that always present a low level of common ownership (quintiles 1 to 3). Doing so ensures that the two groups that we are comparing present similar characteristics. For the four bank-related variables (bank leverage, profitability, size, and market equity), we verify that the differences between the two groups (high and low common ownership in the portfolio) are low. In particular, we use the normalized differences in the average values; we find test statistics between 0.01 and 0.17 for the variables, well below the rule of thumb of one quarter suggested by Imbens and Wooldridge (2007) and Imbens and Wooldridge (2009). In other words, we select two groups of lead arrangers whose difference in the level of common ownership in a quarter is driven by quasi-random circumstances tied to the differences in fund inflows of potential investors, which in turn determines a slightly different composition in the syndicate and, as a consequence, the level of common ownership in their portfolio.

Following Jiang et al. (2010), we measure the intensity of lending relationships in terms of the number of deals and the dollar amount, both normalized by the size of the lead arranger. We conduct the comparison between these two groups and test Prediction 3 by estimating the following equation:

$$Intensity\ Lending\ Relations_{at} = \beta_0 + \beta_1 I_{CO}^{H} + \beta_2 X_{at} + \varepsilon_{at}, \tag{2.7}$$

where the dependent variable is the number of loans or the dollar amount underwritten by a lead bank a in quarter t normalized by the lead bank size. In all specifications, we include lenders' related controls such as size, capital, profitability, and quarter-year fixed effects.

Coefficient Estimates

Prediction 3 implies that β_1 is positive. Table VI presents the estimations of Equation (2.7).

Table VI: **Rationing**

	CO Threshold [0.4,0.6];(0.6,max(CO)]		CO Threshold [0,0.5];(0.5,max(CO)]	
	(1)	(2)	(3)	(4)
	# Loans	Amount Lent	# Loans	Amount Lent
CO High Lead	0.168**	492.425***	0.156***	274.182***
	(2.243)	(4.631)	(3.571)	(4.197)
Bank Size	1.094***	1,191.518***	0.630***	505.464***
	(19.674)	(14.818)	(9.573)	(7.336)
Bank Market Equity	-6.533***	-6,439.994***	-0.079	619.380
	(-5.516)	(-3.907)	(-0.212)	(1.588)
Bank Book Leverage	-4.882***	-3,053.603***	-0.123	654.518**
	(-13.318)	(-6.554)	(-0.660)	(2.149)
Bank ROA	2.842	-9,600.885	-5.272*	-11,042.869***
	(0.307)	(-0.758)	(-1.868)	(-2.827)
Year-Quarter FE	Yes	Yes	Yes	Yes
Lead FE	No	No	Yes	Yes
Observations	477	477	1,861	1,861
Adjusted R-squared	0.706	0.683	0.768	0.664

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.7). The dependent variable is the number of loans (odd columns) and the dollar amount (even columns) underwritten by a lead bank in a quarter, normalized by the lead bank size. The coefficient of interest is the one of *CO High Lead*, an indicator variable taking the value of one for lead arrangers with prevalence of high common ownership in their portfolio and zero otherwise. The specification also controls for lead bank characteristics and year-quarter fixed effects. Standard errors are clustered by year-quarter. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Based on the regression results, lead arrangers with a prevalence of high common ownership in their portfolio underwrite 0.17 more loans in a quarter than lead arrangers with a low prevalence, or \$492 in terms of amount (columns 1 and 2). The median number of loans is 0.9 and the median amount is \$751 (both figures are normalized by the size of the lead arranger). In other words, lead banks with a prevalence of high common ownership underwrite 17% more loans in a quarter on average than lead banks with low prevalence, or 65% more in terms of amount.

Finally, we consider a specification with all lead arrangers present in the sample, and add lead bank fixed effects to account for persistent differences across lead arrangers. Columns 3 and 4 report the results of the specifications; results are robust to this alternative specification.

2.6 Additional Results

Our findings are consistent with the predictions of the theoretical model in Section 2.3. In this section, we conduct additional tests whose results confirm our theory.

2.6.1 New Versus Repeated Borrowers

In our analysis, we have so far considered the overall effect of common ownership on the financing terms of syndicated loans. We expect that the role of common ownership will be stronger when information asymmetries are pronounced. Following Sufi (2007), we consider the reputation of borrowers, measured by their past access to the loan market, as a proxy of heterogeneity in information asymmetry between the informed lead arranger and the uninformed syndicate members.

Table VII reports the results of regressing the all-in-drawn spread against the common ownership measure for the subsamples of new borrowers and repeated borrowers. We find that common ownership matters only for borrowers whose reputation is less established. Those borrowers have practically no history in the loan market; thus, the lead arranger carrying out the due diligence will be more likely to hold an informational advantage over the uninformed syndicate participants. For borrowers forming new relationships with the lead arrangers in the market, we find statistically significant decreases in quintiles 3 to 5. Within a quintile, an increase in common ownership from the minimum to the maximum level implies a reduction in spread corresponding to 5.5 basis points in quintile 3, 12.7 basis points in quintile 4, and 16.9 basis points in quintile 5. In contrast, common ownership does not appear to impact the spread of repeated borrowers.

Table VII: **Interest rates and common ownership - New versus repeated borrowers**

	(1)	(2)	(3)	(4)
	New Borrower		Repeated Borrower	
CO	-29.407***		-6.518	
	(-3.147)		(-0.936)	
CO Quintile 2		-4.906		-2.222
		(-1.242)		(-0.587)
CO Quintile 3		-8.221*		-9.438*
		(-1.999)		(-1.818)
CO Quintile 4		-16.644***		-6.238
		(-3.649)		(-1.282)
CO Quintile 5		-19.553***		-6.419
		(-4.329)		(-1.418)
Loan Purpose FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Lead FE	Yes	Yes	Yes	Yes
SIC2 X Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	12,685	12,685	12,653	12,653
Adjusted R-squared	0.729	0.730	0.744	0.744

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5). The dependent variable is the all-in-drawn loan spread, expressed in basis points. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). Column (1) and (2) contain loans issued to new borrowers. Column (3) and (4) report the effect of syndicate common ownership on facility spreads for repeated lending relations. Standard errors are clustered by lead bank. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

2.6.2 Falsification Test: Common Ownership Member-Lead

We now present the results of a falsification test that leverage the testable implications of our hypothesis of common ownership as a mechanism of information transmission *from* the lead *to* the member banks. The falsification test exploits the asymmetry in our measure of common ownership between pairs of banks; that is, lead-member κ_{ab_i}, and member-lead $\kappa_{b_i a}$. As discussed in Backus et al. (2021b), any difference in the

Table VIII: **Falsification test: common ownership member-lead and member-member**

	(1) Spread	(2) Spread	(3) Lead Amount	(4) Lead Amount
CO Member-Lead	-6.472	-6.753	-1.549	0.830
	(-0.801)	(-0.834)	(-0.933)	(0.492)
CO Lead-Member	-26.626***		-2.326**	
	(-3.962)		(-2.415)	
CO Quintile 2		-2.335		-2.463**
		(-0.637)		(-2.526)
CO Quintile 3		-8.515**		-4.713***
		(-2.064)		(-3.439)
CO Quintile 4		-10.295***		-3.920**
		(-2.934)		(-2.628)
CO Quintile 5		-15.397***		-4.494***
		(-3.650)		(-2.829)
Loan Purpose FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Lead FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	No	No
SIC2 X Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	25,420	25,420	8,083	8,066
Adjusted R-squared	0.791	0.791	0.742	0.742

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5) in Column (1) and (2) and Equation (2.6) in Column (3) and (4). The dependent variable is facility loan spread (Column 1 and 2) and the percentage of loan retained by the lead bank (Column 3 and 4). The coefficient of interest is the one on *CO Member-Lead*, a measure of common ownership between the member and the lead in the same facility. The specification also controls for facility-loan, lender, and borrower characteristics. Standard errors are clustered by lead bank. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

value of these two measures is entirely driven by differences in relative investor concentration.[18] Such asymmetry is a feature of our common ownership measure and results

[18]In Appendix A.3, we provide a decomposition of the profit weights member-lead into cosine similarity and relative lender concentration: see Equation (2.3). Figure B.1 shows the results. Panel

in the following testable implication: since only the lead arranger holds superior information on the borrower, the level of common ownership *from* the syndicate member *to* the lead arranger ($\kappa_{b_i a}$) should not impact the lending conditions once we control for the weight that the lead arranger puts on the profit of the syndicate member (κ_{ab_i}).

This test allows us to conclude that pipeline risk is unlikely to explain our results. In the demand-discovery model of Bruche et al. (2020), it is the market that holds superior information. Thus, if common ownership mitigates pipeline risk through the transmission of information from the investors to the lead bank on the demand state, then the falsification test we propose here should give the same results as in our main analysis.

We estimate Equation (2.5) and Equation (2.6) by regressing both the all-in-drawn spread and the amount of loan retained by the lead on our measure of average common ownership between the lead arranger and syndicate members in a facility (CO_{ia}), as before, and a measure of the average common ownership between syndicate members and the lead arranger in a facility (CO_{ib}). The expectation is that adding CO_{ib} should not impact the lending conditions. Table VIII shows the results: in all specifications, the magnitude of the coefficient of common ownership lead-member (CO_{ia}) is practically unchanged. Most importantly, the coefficient of common ownership member-lead (CO_{ib}) is small in magnitude and not statistically different from zero.

2.7 Common Ownership and Syndicate Participation

Our variable of interest (that is, common ownership) is a function of the syndicate structure, namely the set of lenders participating in the syndicate. As the lender's decision to enter the syndicate is not random and may depend, among other factors, on the level of common ownership with the lead arranger and other unobservables

(a) shows that the cosine similarity member-lead is identical to the lead-member, as reported in Figure 2.2. Panel (b) depicts the relative concentration of lenders in the measure of common ownership member-lead, which differs from Panel (c) of Figure 2.2.

collected in the error term, we extend our model to account for this form of self-selection. We assume that the utility maximization problem of potential members can be characterized by a reservation interest rate (spread) or reservation return. The reservation interest rate will depend on the characteristics of the member, along with the assessment on the riskiness of the borrower, as follows:

$$Spread^r_{iabt} = \gamma_0 + \gamma_1 \kappa_{iabt} + \gamma_2 X_{iabt} + \upsilon_{iabt}, \tag{2.8}$$

where i indexes the facility, a the lead arranger, b the potential syndicate member. The term κ_{iabt} is the weight that the lead arranger a puts on the profit of each potential syndicate member b in facility i arranged in quarter t, as defined in Equation (2.1). Finally, X_{iabt} is a vector of controls including characteristics of: (i) the potential member; (ii) the lead arranger; (iii) the loan and the facility; and (iv) the borrower. As above, we omit the subscript for the borrowing firm to simplify the notation.

If the actual interest rate offered to the potential members is below the reservation interest rate, $Spread^r_{iabt}$, the potential member does not participate in the syndicate. The participation decision of a potential member bank (p_{iabt}) is therefore:

$$\begin{aligned} p_{iabt} &= 1 \text{ if } Spread_{iat} - Spread^r_{iabt} > 0 \\ &= 0 \text{ if } Spread_{iat} - Spread^r_{iabt} \leq 0. \end{aligned}$$

Using a slightly different version of the definition of $Spread_{iat}$ in Equation (2.5), the inequality can be expressed as follows:

$$\begin{aligned} p^*_{iabt} &= (\beta_0 - \gamma_0) + (\beta_1 \kappa_{iabt} - \gamma_1 \kappa_{iabt}) + \\ &\quad (\beta_2 X_{iat} - \gamma_2 X_{iabt}) + (\varepsilon_{iabt} - \upsilon_{iabt}) \\ &= \delta_0 + \delta_1 \kappa_{iabt} + \delta_2 X_{iabt} + \eta_{iabt}. \end{aligned}$$

The participation equation is therefore:

$$p_{iabt} = 1[\delta_0 + \delta_1\kappa_{iabt} + \delta_2 X_{iabt} + \eta_{iabt} > 0]. \tag{2.9}$$

The resulting outcome equation is:

$$\begin{aligned} Spread_{iat} &= \beta_0 + \beta_1\kappa_{iabt} + \beta_2 X_{iat} + \varepsilon_{iabt} \text{ if } p^*_{iabt} > 0 \\ &= \text{not observed if } p^*_{iabt} \leq 0, \end{aligned} \tag{2.10}$$

where we modify Equation (2.5) to use a more granular unit of observation at member-facility level rather than facility level as in the main specification.[19] Clearly, the error term η_{iabt} involves the unobserved determinants influencing the interest rate offered to the members ε_{iabt}. To account for the correlation between unobservable drivers of participation and the resulting interest rate offered to the syndicate members, we assume a joint normal distribution for the two error terms:

$$\begin{pmatrix} \eta_{iabt} \\ \varepsilon_{iabt} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}\right).$$

We estimate the model using the standard Heckman two-step procedure. The joint normality of the errors implies that the error in the pricing equation, ε_{iabt}, is a multiple of the error in the participation decision equation (σ_{12}) plus some noise that is independent of the participation decision equation.

While the sample selection model is theoretically identified without any restriction on the regressors, we use exclusion restrictions to allow for the identification of the parameters attributable to variation in the data rather than parametric assumptions. We argue that the following variables should impact participation, but should not affect the resulting prices: (i) the characteristics of potential members (except for the profit weight κ_{iabt}); and (ii) a variable capturing the portfolio similarity between the

[19] The dependent variable, $Spread_{iat}$, is set at facility level and does not vary across members of the same facility.

potential member and the lead (Euclidian distance). Interest rates are a function of a variety of determinants linked to the lead bank, the borrower and the loan, but the characteristics of potential members should not directly influence the final price. Within the characteristics of potential members, we include trading liquidity of potential members as a determinant of equity ownership by mutual funds. While the validity of exclusion restrictions cannot be directly tested, we perform numerous sensitivity analyses and the results do not change. Finally, all the variables included in the outcome equation are also present in the participation equation. Table IX presents

Table IX: **Interest rates: selection into the syndicate**

	No Selection	Heckman Selection	
	(1) Spread	(2) Member	(3) Spread
CO	-5.322**	0.105**	-5.382***
	(-2.090)	(1.983)	(-4.734)
λ			8.828**
			(2.364)
Loan Purpose FE	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
SIC2 FE	Yes	Yes	Yes
Member FE	Yes	Yes	Yes
Observations	75,778	75,544	75,544

The table reports the the regression parameter estimates and t-statistics of a one-step OLS estimation of Equation (2.10) (Column 1) and a two-step estimation of Equation (2.9) and Equation (2.10) accounting for sample selection (Column 2 and 3). The dependent variable is the all-in-drawn loan spread, expressed in basis points. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks given in Equation (2.1). The specification also controls for facility-loan, syndicate member bank, and borrower characteristics. Standard errors are clustered by member bank. All variables are defined in Table B.II in Appendix A.3. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

the results without the correction for selection (column 1) and with the correction (columns 2 and 3). Results from the selection model indicate that participation is not random. Table IX presents the results using the full sample of observations. In column 2, we present the results of the participation equation. As expected, potential members with higher common ownership with the lead bank are more likely to enter the syndicate, confirming that high levels of common ownership can mitigate information asymmetries. As those potential members are more aware of investment opportunities, or hold superior information to other uninformed participants, their reservation price is lower, and they are more likely to participate in the syndicate. Other statistically important drivers of participation include the level of common ownership between the potential member and the borrower (positive), and the portfolio distance between the lead and the member (negative).

We find evidence of selection, with a significant sample selection term, λ, and an implied correlation coefficient of 0.16. We have unobserved attributes that positively affect both the probability of participating in the syndicate and the prices offered to the syndicate members. These results do not appear to be different from those without correction, especially with regard to the impact of common ownership on prices. We conclude that common ownership increases the demand for loans, which would per se reduce the spread through the book building process. However, even after accounting for selection, common ownership reduces the loan spread, which is an effect that we attribute to the role of common ownership in mitigating information asymmetries between the lead arranger and members.

2.8 Conclusion

We study the impact of common ownership in the syndicated loan market, focusing on the connection between the lead bank and the syndicate members. Our novel hypothesis is that high levels of common ownership facilitate the transmission of private information on the borrowing firms between the lead bank and other members of the syndicate. Common ownership is therefore a tool to ease information asymmetries.

We propose a signaling model in which a lead bank detains private information on the riskiness of a project while seeking funding to finance it. Signaling is costly in that it requires a larger commitment of funds by the lead bank. We conjecture that common ownership allows the lead bank to credibly transmit information about the borrower, and solve the model accordingly. The model provides three empirical predictions. At higher levels of common ownership: (i) the interest rate paid to the syndicate members is lower; (ii) the lead bank retains lower funds; and (iii) we observe less rationing at the issuance.

We use data on the syndicated loan market to empirically verify these predictions and find empirical support for all of them. Our identification strategy leverages the cross-sectional variation in the level of common ownership arising from differences in the composition of the syndicate both across facilities within a loan and across loans. An increase of one standard deviation in common ownership between the lead arranger and members of the syndicate is associated with a decrease equal to 5 basis points in interest rates (the average spread is 170 basis points) and 0.75 percentage points in the amount retained by the lead (the lead arranger retains on average 13% of the loan amount). Lead arrangers with a prevalence of high common ownership in their portfolio experience stronger lending relationship. They underwrite 17% more loans in a quarter with respect to lead arrangers with a low prevalence, and 65% more in terms of the amount. These results are robust to a variety of robustness and falsification tests.

Regulators recognize that common ownership can be conducive to the transmission of information about the borrower. We provide empirical evidence consistent with the presence of this flow of information and quantify the impact of common ownership on the contractual terms of the loan.

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Appendix A

In this section, we present the formal details of the model and solve the results we present in Section 2.3.

Recall that the economy is populated by a penniless borrower that owns a project but lacks financial resources to carry it out. The borrower delegates the lead bank (L) to form a syndicate for a loan of size 1; it then shares with the lead bank the returns of the investment. A continuum of potential members of the syndicate (M) operate in perfectly competitive financial markets and have the financial resources to fund the project. A, with $0 < A < 1$, is the maximum amount of the loan that the lead bank can pledge.

The borrower's project can be one of two types. The good type (G) has a probability of success equal to p. The bad type (B) has a probability of success $q < p$. Independently of the type, the project yields R in the case of success and 0 in the case of failure. The lead bank knows the type of the borrower's project. We denote by α and $(1-\alpha)$ the potential syndicate members' prior probabilities that the borrower's project is of type G and type B, respectively.

We make the following parametric assumptions.

Assumption 1.

$$pR > 1 > 1 - A > qR, \tag{A.1}$$

$$qR - A > \frac{q}{p}\left(\frac{1-\kappa\theta qR}{1-\kappa\theta}\right). \tag{A.2}$$

In Assumption 1.(A.1), $pR > 1$ implies that the good borrower's project has a positive net present value (NPV). $1 - A > qR$ means that the bad borrower's project has a negative NPV despite the use of the lead bank's funds A. At the right-hand side of the condition in Assumption 1.(A.2), parameter $\kappa \in [0,1]$ captures the weight that the lead bank attaches to the utility of the fraction $\theta \in (0,1)$ of commonly owned syndicate members. At the left-hand side, $qR - A$ is the project return of a lead bank representing a bad type (qR), net of the "inside liquidity" A. The condition implies that the value of such net utility is large, which, as we will see, makes signaling the good type particularly costly for the lead bank. Taken together, Assumptions 1.(A.1) and 1.(A.2) imply that $0 < A < 1/2$ and an upper bound on θ. Both are satisfied in our data.

All agents are risk neutral, the lead bank is protected by limited liability, and the risk-free interest rate is nil. The contract we consider is $(x_j, R^s_{j,L}, R^f_{j,L}, R^s_{j,M}, R^f_{j,M}, \mathcal{A}_j)$, with $j \in \{G, B\}$. We denote by $x_j \in [0,1]$ the decision on whether a lead bank representing a borrower of type j receives funding by the potential syndicate members. The share of the returns on a project of type $j = G, B$ received by $i = L, M$ in the case of success (s) is $R^s_{j,i}$, it is $R^f_{j,i}$ in the case of failure (f). We assume for simplicity that $R^f_{j,L} = 0$; $R^f_{j,M} = 0$ follows from limited liability. Finally, $\mathcal{A}_j \leq A$ is the amount of cash invested by L in the loan. Suppressing the notation for success, the contract can be rewritten as $(x_j, R_{j,L}, R_{j,M}, \mathcal{A}_j)$, with $j \in \{G, B\}$.[20]

L holds all the bargaining power. It designs contracts that can be accepted or rejected by M. When indifferent, L will prefer not to commit any cash in the loan (i.e., $\mathcal{A}_j = 0$). We will analyze the perfect Bayesian equilibrium of the contract design game. We use $\kappa \in [0,1]$ to denote the level of common ownership between the lead bank and the syndicate member, where κ is the weight that the lead bank L places on the utility of the commonly owned syndicate members. Similarly to Antón et al. (2023), we restrict κ within values in the unit interval. However, values of κ larger than one are empirically possible: they correspond to situations in which the lead bank places more weight on the utility of the commonly owned syndicate members than on its own utility. As a consequence, the lead bank would have the incentive to transfer its funds to the syndicate members.

To begin with, we solve a funding game without common ownership ($\kappa = 0$). We then introduce common ownership. In our model, the lead bank uses common ownership to truthfully channel its private information regarding the borrower's probability

[20] $R_{j,L}$ is then split between the lead bank and the borrower according to a bargaining game that is outside the model.

of success to the commonly owned syndicate members. We derive empirical predictions on the interest rate paid to the syndicate members ($1 + r = R - R_{j,L}$) and the amount of the loan retained by the lead bank ($\mathcal{A}_j$).

Before continuing, it is important to note that, with symmetric information, the lead bank rejects the loan to the bad type ($x_B = 0$) and grants the loan to a good type ($x_G = 1$). Moreover, it does not pledge its funds in the loan to the good type ($\mathcal{A}_G = 0$), and sets the reward to investors so to satisfy their break-even condition ($R_{G,M} = 1/p$). If these symmetric-information contracts were available under asymmetric information, a lead bank representing a bad borrower mimics the good borrower and its utility would be positive (because $pR - 1 > 0$). However, the syndicate members would not break even in expectation.[21]

A.1 Funding Without Common Ownership

We now solve the contract design game without common ownership. As discussed in the main text, we focus on the *low-information-intensity* optimum of the contract design game (Rothschild and Stiglitz, 1976; Wilson, 1977).

Proposition 2. *Without common ownership, the separating contracts offered by the lead bank are* $(x_B, R_{B,L}, R_{B,M}, \mathcal{A}_B) = (0, 0, 0, 0)$ *and*

$$(x_G, R_{G,L}, R_{G,M}, \mathcal{A}_G) = (1, A/q, R - A/q, A).$$

Only the lead bank representing the good borrower chooses $(x_G, R_{G,L}, R_{G,M}, \mathcal{A}_G)$.

Proof. We solve for the separating allocation featuring a contract $c = (x_G, R_{G,L}, R_{G,M}, \mathcal{A}_G)$ for the good borrower and the symmetric information contract $\bar{c} = (x_B, R_{B,L}, R_{B,M}, \mathcal{A}_B) = (0, 0, 0, 0)$ for the bad borrower. Contract c will maximize the good borrower's utility subject to M breaking even for the good borrower and to the bad borrower not preferring c to $\bar{c}$. Under a condition equivalent to Assumption 1.(A.1), Tirole (2006) Lemma

[21] Upon accepting, and given their priors, investors' expected utility is $\alpha p(1/p) + (1 - \alpha)q(1/p) < 1$ because of Assumption 1.(A.1).

6.2 proves that this separating allocation is the low-information-intensity optimum. In what follows, we construct the low-information-intensity optimum in our setting.

Contract c solves the following maximization problem:

$$\max_{\{x_G, R_{G,L}, R_{G,M}, \mathcal{A}_G\}} x_G p R_{G,L} - \mathcal{A}_G \tag{A.3}$$

subject to

$$x_G(pR_{G,M} - 1) + \mathcal{A}_G \geq 0, \tag{A.4}$$

$$x_G q R_{G,L} - \mathcal{A}_G \leq 0, \tag{A.5}$$

$$R = R_{G,L} + R_{G,M}, \tag{A.6}$$

$$x_G \in [0,1],\ \mathcal{A}_G \leq A. \tag{A.7}$$

Condition (A.4) is the participation constraint of the potential syndicate members; Condition (A.5) is the mimicking constraint of the lead bank representing a bad borrower.

To begin with, $x_G > 0$ as otherwise the contract would yield a zero payoff for L, despite a type-G borrower holds a positive-NPV project. Moreover, were $x_G < 1$, then increasing x_G slightly, keeping $x_G R_{G,L}$ constant, does not affect neither the maximand nor the left-hand side of Condition (A.5), but increases the left-hand side of Condition (A.4) (because $pR > 1$ and $R_{G,M} = R - R_{G,L}$). Then, $x_G = 1$.

Since with symmetric information the utility of the bad borrower is equal to zero, Constraint (A.5) must be binding. That is, $qR_{G,L} = \mathcal{A}_G$. Plugging $R_{G,L} = \mathcal{A}_G/q$ into Expression (A.3), we obtain:

$$\mathcal{A}_G \left(\frac{p}{q} - 1 \right),$$

which increases in $\mathcal{A}_G$; thus, $\mathcal{A}_G = A$ (L commits its entire funds in the loan) and $R_{G,L} = A/q$.

Finally, the participation constraint of M can be rewritten as

$$pR - 1 > A \left(\frac{p}{q} - 1 \right), \tag{A.8}$$

which hods true under Assumption 1.(A.2). □

To sum up, without common ownership, the lead bank (L) representing a good borrower will underwrite the loan by committing $\mathcal{A}^* = \mathcal{A}_G = A$. The syndicate members (M) receives an interest rate equal to $1 + r^* = R - A/q$.

A.2 Funding with Common Ownership

Consider now the case in which the lead bank places a weight κ on the utility of the commonly owned potential syndicate members. Specifically, there is a fraction $\theta \in (0, 1)$ of commonly owned potential syndicate members (M_{Co}) and a complementary fraction $(1 - \theta)$ that are not commonly owned with the lead bank (M_{NCo}). Any contract offered by the lead bank features the same reward to M_{Co} and M_{NCo} (so that $R_{j,M} = R_{j,M_{Co}} = R_{j,M_{NCo}}$, with $j = G, B$).

We equate common ownership to an information transmission device. We let the lead bank channel its private information regarding the borrower's probability of success to the commonly owned syndicate members (M_{Co}). We say that information transmission can happen only if $\kappa \geq \underline{\kappa}$. As a consequence of information transmission, M_{Co} are perfectly informed about the type of the borrower. M_{NCo} know that the lead bank shares its private information with M_{Co}, but do not observe the type of the firm represented by the lead bank L.

The timing of the game with common ownership is as follows. Having shared with M_{Co} its information about the type of borrower it is representing, L designs the contracts to offer to investors. Subsequently, M_{Co} accept or reject. Finally, after observing M_{Co}'s decision, it is M_{NCo}'s turn to accept or reject the contracts offered by L.[22] In approaching the informed potential investors first, the lead bank implements a cheaper form of signaling, through the acceptance decision of the commonly owned syndicate members instead of contract design. This timing is consistent with

[22]We obtain the same results if we consider a model in which L's decision to share information with M_{NCo} is an equilibrium outcome, M_{NCo} only observe L's decision to share information (not the type of the borrower), and the decision to accept the contract is taken simultaneously by M_{Co} and M_{NCo}. In this alternative model, M_{NCo} update their beliefs on the type of borrower represented by L only based on the latter's decision to share information (and the contract it designs).

the institutional setting of loan syndication. Post-mandate, the lead bank informally contacts a group of potential investors to target; the lead bank first presents the loan and shares information about the loan terms and the borrower's creditworthiness to these potential investors. This process is described in Ivashina and Sun (2011) and Bruche et al. (2020).

We find the following:

Proposition 3. *With common ownership, the lead bank representing a good borrower will offer the equilibrium contract with symmetric information, namely:* $x_G = 1$*,* $R_{G,L} = R - 1/p$*,* $R_{G,M} = 1/p$ *and* $\mathcal{A}_G = 0$*. The lead bank representing a bad borrower, will never get access to funding (*$x_B = 0$*).*

Proof. We solve the contract design game with common ownership by assuming that L offers $c_j = (\mu_j, x_j, R_{j,L}, R_{j,M}, \mathcal{A}_j)$, with $j = G, B$, where μ_j denotes the probability that the commonly owned investors M_{Co} accept c_j, $x_j \in [0, 1]$, $R = R_{j,L} + R_{j,M}$ and $0 \leq \mathcal{A}_j \leq A$. The timing of the game is:

1. The lead bank L formulates its offer to M_{Co} and M_{NCo}.

2. M_{Co}, being informed about the type of borrower represented by L, accept or reject the offer.

3. Conditional on observing the decision taken by M_{Co}, M_{NCo} update their priors α. We denote M_{NCo}'s posteriors by $\hat{\alpha}$; they depend on the contract offer (including the decision by M_{Co}, μ).

4. Given $\hat{\alpha}$, M_{NCo} decide whether to accept or reject L's offer.

We first show that any equilibrium contract must feature the acceptance decision of M_{Co}. In particular, we prove that the the utility of a lead bank L representing type j increases in μ_j. Take the objective function of L:

$$\mathcal{M}_{j,L}(c_j) \equiv x_j \omega_j R_{j,L} - \mathcal{A}_j + \mu_j \theta \kappa [x_j(\omega_j R_{j,M} - 1) + \mathcal{A}_j]$$

where $\omega_G = p$ and $\omega_B = q$. Consider two rewards $R_{j,M}$ and $\tilde{R}_{j,M}$ such that

$$\mu_j R_{j,M} = \tilde{\mu}_j \tilde{R}_{j,M}, \tag{A.9}$$

where μ_j and $\tilde{\mu}_j$ are the probabilities that M_{Co} accept when their reward is $R_{j,M}$ and $\tilde{R}_{j,M}$, respectively, with $\mu_j > \tilde{\mu}_j$ and $R_{j,M} < \tilde{R}_{j,M}$. Since $R = R_{j,L} + R_{j,M}$, setting $R_{j,M} < \tilde{R}_{j,M}$ implies that $R_{j,L} > \tilde{R}_{j,L}$. Hence,

$$\mathcal{M}_{j,L}(c_j) \geq \mathcal{M}_{j,L}(\tilde{c}_j),$$

where $\tilde{c}_j = (\tilde{\mu}_j, x_j, \tilde{R}_{j,L}, \tilde{R}_{j,M}, \mathcal{A}_j)$.

Moreover, Condition (A.9) implies that considering $R_{j,M}$ or $\tilde{R}_{j,M}$ does not affect the participation constraint of M_{Co}:

$$\mu_j \theta[x_j(\omega_j R_{j,M} - 1) + \mathcal{A}_j] \geq 0,$$

because $\mu_j \theta[x_j(\omega_j R_{j,M} - 1) + \mathcal{A}_j] = \tilde{\mu}_j \theta[x_j(\omega_j \tilde{R}_{j,M} - 1) + \mathcal{A}_j]$. All this means that a higher value of μ_j increases the utility of L and leaves the participation constraint of M_{Co} unaffected.

Consider then two candidate equilibrium contract offers such that $\mu_G = \mu_B = 1$. Specifically, we consider the symmetric-information contracts and the low-information-intensity contracts. By comparing the two, we will show that signaling via the acceptance decision of M_{Co} (as it happens under the acceptance of the symmetric-information contracts) is preferred by the lead bank L to the signaling via the contract design that takes place in the low-information-intensity contracts.

Symmetric information equilibrium contracts. Let the lead bank representing type $j \in \{B, G\}$ offer:

$$\begin{aligned}
c_G^{SI} &= (\mu_G, x_G, R_{G,L}, R_{G,M}, \mathcal{A}_j) = (1, 1, R - 1/p, 1/p, 0), \\
c_B^{SI} &= (\mu_B, x_B, R_{B,L}, R_{B,M}, \mathcal{A}_j) = (1, 0, 0, 0, 0).
\end{aligned}$$

Since they observe the type of the borrower, M_{Co} accept these contracts. After observing the contract offer and M_{Co}'s decision, M_{NCo} will also accept because, since $\hat{\alpha}|c_G^{SI} = 1$ and $\hat{\alpha}|c_B^{SI} = 0$, their participation constraint (PC) is always satisfied with equality:

$$PC(c_G^{SI}): \ (1-\theta)[x_G(pR_{G,M} - 1) + \mathcal{A}_G] = 0,$$
$$PC(c_B^{SI}): \ (1-\theta)[x_B(qR_{B,M} - 1) + \mathcal{A}_B] = 0.$$

It follows that, at the symmetric information contracts, the utility of a lead bank representing a good type is $U_L^{SI} = pR - 1$; the utility of a lead bank representing a bad type is equal to zero.

<u>Low-information-intensity optimum contracts.</u> We now construct the separating allocation corresponding to the low-information-intensity optimum of the game with common ownership. Assumption 1.(A.2) guarantees that this optimum allocation exists in this setting.

For the same reason as in the proof of Proposition 2, the lead bank L sets

$$(\mu_B, x_B, R_{B,L}, R_{B,M}, \mathcal{A}_B) = (1, 0, 0, 0, 0),$$

and maximizes $\mathcal{M}_{G,L}(c_G)$ with respect to $c_G = (1, x_G, R_{G,L}, R_{G,M}, \mathcal{A}_G)$, subject to:

$$x_G(pR_{G,M} - 1) + \mathcal{A}_G \geq 0, \tag{A.10}$$
$$x_G qR_{G,L} - \mathcal{A}_G + \theta\kappa\tilde{U}_{B,M_{Co}} \leq 0. \tag{A.11}$$

Condition (A.10) is M_{NCo}'s participation constraint, Condition (A.11) is the mimicking constraint, and $\tilde{U}_{B,M_{Co}} \equiv x_G(qR_{G,M} - 1) + \mathcal{A}_G$. Proceeding as in the analysis without common ownership, we find that $x_G = 1$, $\mathcal{A}_G = A$, and

$$R_{G,L} = \frac{A}{q} - \frac{\theta\kappa}{(1-\theta\kappa)q}(qR - 1). \tag{A.12}$$

Plugging these values into $\mathcal{M}_{G,L}(c_G)$ we find that, with common ownership, the utility of the lead bank representing a good borrower at the low-information-intensity optimum separating allocation is

$$U_L^{SE} = (1 - \theta\kappa)A\left(\frac{p}{q} - 1\right) - \frac{\theta\kappa p}{q}(qR - 1) + \theta\kappa(pR - 1).$$

Finally, the participation constraint of M_{NCo} in (A.10) can be rewritten as

$$U_L^{SI} \geq U_L^{SE}, \tag{A.13}$$

which holds true by Assumption 1.(A.2).

Equilibrium contracts. Given the results above, and, in particular, Condition (A.13), it follows that: (i) a lead bank L representing a good borrower strictly prefers offering c_G^{SI} to the low-information-intensity optimum contracts; (ii) a lead bank L representing a bad borrower will never get access to funding. □

To sum up, if common ownership is an information transmission device, we find that, as with symmetric information, only the good projects will be funded ($x_G = 1$,$x_B = 0$), the loan is fully underwritten by the members of the syndicate ($\mathcal{A}^{**} = \mathcal{A}_G = 0$) in exchange of an interest rate equal to $1 + r^{**} = 1/p$. In analogy to the case without common ownership, the contract targeting a good type can be interpreted as a debt contract in which the members of the syndicate transfer 1 upfront and get $1/p$ in the case of project success or else the borrower goes bankrupt.

In the proof, we also show that signaling through the acceptance decision of the commonly owned syndicate members is preferred by the lead bank L to the signaling via the contract design that takes place in the low-information-intensity contracts.

A.3 Empirical Predictions

The following proposition gives the three empirical predictions of the model (also listed in Proposition 1), and formally proves them. Our null hypothesis is that common ownership facilitates information transmission; thus, our predictions are based on the comparison of the results in Proposition 2 and Proposition 3.

Proposition 4. *Comparing the lending conditions* ($1 + r$ *and* $\mathcal{A}$) *with and without common ownership, we find the results in Proposition 1.*

Proof. For the first prediction,

$$r^* - r^{**} = R - \frac{A}{q} - \frac{1}{p} > 0 \tag{A.14}$$

$$\iff A < \frac{q(pR-1)}{p} \tag{A.15}$$

follows from Assumption 1.

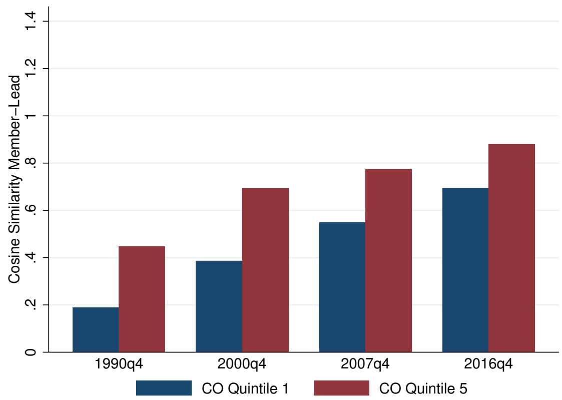
The second prediction directly follows from $\mathcal{A}^{**} = 0 < A = \mathcal{A}^*$.

For the third prediction, we assume that there are many lead banks in the economy, each with funds A distributed according to some CDF $F(A)$. Then, only the lead banks with sufficiently large funds such that the bad firm will find mimicking unappealing will be able to obtain funding at the conditions of the separating equilibrium with asymmetric information.

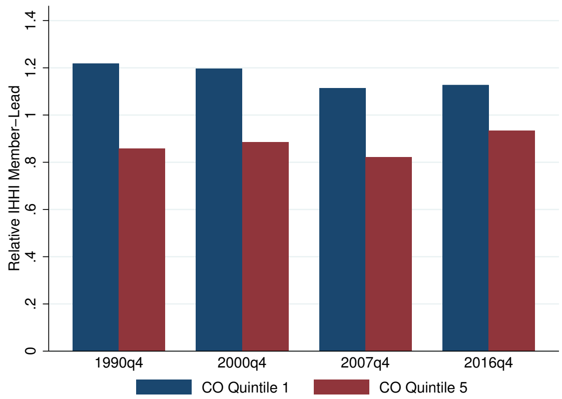
□

Appendix B

Figure B.1: **Decomposition of member-lead common ownership measure**



(a) Cosine Similarity



(b) Relative IHHI

The figure reports the decomposition of the average values of syndicate common ownership (Member-Lead) for the highest and lowest quintile of the common ownership (Member-Lead) distribution over time. Syndicate common ownership (CO) is defined in Equation 2.2 and the decomposition in Equation 2.3.

Table B.I: **Largest Shareholders of Three Largest Banks**

JP Morgan

2002		2007		2014	
CAPITAL RESEARCH & MANAGEMENT	8%	HANSON INVESTMENT MANAGEMENT	6%	BLACKROCK INC	6%
BARCLAYS GLOBAL INVESTORS	4%	AXA	5%	VANGUARD GROUP INC	5%
STATE STREET CORP	3%	STATE STREET CORP	4%	STATE STREET CORP	5%
DEUTSCHE BANK	3%	FMR LLC	3%	FMR LLC	3%
AXA	3%	DAVIS SELECTED ADVISERS	2%	CAPITAL WORLD INVESTORS	3%

Citigroup

2002		2007		2014	
STATE STREET CORP	5%	STATE STREET CORP	3%	BLACKROCK INC	6%
BARCLAYS GLOBAL INVESTORS	4%	CAPITAL RESEARCH GLOBAL INVESTORS	3%	VANGUARD GROUP INC	5%
MANUFACTURERES LIFE INSURANCE	4%	CAPITAL WORLD INVESTORS	3%	STATE STREET CORP	5%
FMR CORP	4%	FMR LLC	2%	FMR LLC	3%
AXA	3%	AXA	2%	WELLINGTON MANAGEMENT GROUP	2%

Bank of America

2002		2007		2014	
MANUFACTURERES LIFE INSURANCE	8%	STATE STREET CORP	3%	BLACKROCK INC	6%
BARCLAYS GLOBAL INVESTORS	4%	FMR LLC	3%	VANGUARD GROUP INC	5%
FMR CORP	4%	AXA	2%	STATE STREET CORP	5%
DEUTSCHE BANK	3%	CAPITAL RESEARCH GLOBAL INVESTORS	2%	FMR LLC	4%
AXA	3%	WELLINGTON MANAGEMENT GROUP	2%	JPMORGAN	2%

This table reports the five largest shareholders of the three largest lead arrangers in the U.S. syndicated loan market. Ownership data comes from the Thomson Reuters s34 database.

Table B.II: **Variable Definition**

Variable	Description
	Loan Variables
All-in-Drawn Spread	Facility all-in-drawn spread over the LIBOR rate
CO	Average common ownership (profit weight) between syndicate lead arranger and syndicate members
CO Quintile Q1,...,5	Common ownership quintile dummy
CO Member-Borrower	Average common ownership (profit weight) between borrower and syndicate banks
Facility Amount	Facility amount divided by borrower's total assets
Loan Amount $	Loan amount in million dollars
Lead Amount	% of the facility amount retained by the lead bank
# Facilities within Loan	Number of facilities within the same loan
Log Maturity	Natural logarithm of the maturity of the facility in months
Secured Loan	Dummy variable equal to 1 if the facility is secured
Refinancing	Dummy variable equal to 1 if the purpose of the facility is refinancing
Log Number of Members	Natural logarithm of the number of syndicate members
Time-on-the-Market (TOM)	Number of days between syndication start (launch) and closing date.
Guarantor	Dummy variable equal to 1 if the facility has a guarantor
Relationship Score	$\frac{\frac{1}{N} \times \sum_j^N \text{Number of facilities between lead}_i \text{ and participant}_j \text{ in the past 3 years}}{\text{Number of facilities arranged by lead}_i \text{ in the past 3 years}}$
New Lending Relation	Dummy equal to 1 if the borrower has not received a loan from the lead arranger(s) in the syndicate before
LIBOR 3M	LIBOR 3-months rate at the time of the loan origination
Non-Bank Syndicate Member	Dummy variable equal to 1 if the facility has a non-bank lender in the syndicate
Prob. Default	Borrower default risk as in Bharath and Shumway (2008)
Volatility	SD of the borrower's stock return over the 12 months period before loan issuance
Credit Line	Dummy variable equal to 1 if the facility is a credit line
Term Loan A	Dummy variable equal to 1 if the facility is a term loan A
Term Loan B	Dummy variable equal to 1 if the facility is a term loan B or higher (C,D,...,H)
	Borrower Variables
Size	natural logarithm of the borrower's total assets
ROA	EBIT over total assets
Book Leverage	Debt over total assets
Tangibilities	PP&T over total assets PP&T over total assets
S&P Rating AAA, AA, ... C	S&P credit rating of the borrower.
High Yield	Dummy variable equal to 1 if the borrower has a high-yield rating
Unrated Borrower	Dummy variable equal to 1 if the borrower is unrated
Tobin's Q	Market to book value
Log Int. Cov.	Log of 1 plus interest coverage truncated at 0
Liquidity Ratio	Cash over total asset
	Bank Variables
Lead Size	Natural logarithm of the bank's total assets
Lead Size Q1,...,5	Lead size quintile dummy
Lead Market Equity	Market value of equity capital over total assets
Lead Book Equity	Book value of equity capital over total assets
Lead Leverage	Bank debt over total assets
Lead ROA	EBIT over total assets

Table B.III: **Interest rates - full results and robustness checks**

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	All	No Top2	TCB
CO	-26.647***		-22.226***	-42.004***	-40.265*	-10.236**
	(-4.008)		(-3.673)	(-3.609)	(-1.881)	(-2.088)
CO Quintile 2		-2.657				
		(-0.732)				
CO Quintile 3		-8.853**				
		(-2.151)				
CO Quintile 4		-10.584***				
		(-3.057)				
CO Quintile 5		-15.627***				
		(-3.762)				
Facility Amount	-14.894***	-15.100***	-15.160***	-20.792***	-11.525**	3.852
	(-4.099)	(-4.260)	(-4.487)	(-5.267)	(-2.167)	(1.098)
CO Member-Borrower	-11.256***	-10.927***	-17.430***	-10.999	-33.567**	-6.003***
	(-2.882)	(-2.785)	(-5.020)	(-1.035)	(-2.380)	(-2.821)
Log Maturity	0.665	0.633	-0.209	-3.009*	2.545	-20.717***
	(0.476)	(0.452)	(-0.134)	(-1.943)	(1.195)	(-12.075)
Secured Loan	17.026***	16.894***	18.258***	-6.801	23.940**	22.197***
	(4.818)	(4.772)	(5.716)	(-1.156)	(2.533)	(10.289)
Refinancing	-11.081***	-10.946***	-9.100***	-21.805***	-11.710*	-4.804***
	(-10.569)	(-10.360)	(-7.668)	(-9.261)	(-1.889)	(-4.755)
Log Number of Members	-20.747***	-20.855***	-17.333***	-20.569***	-20.883***	-14.137***
	(-11.795)	(-11.675)	(-11.134)	(-7.888)	(-3.644)	(-10.411)
Guarantor	-3.292*	-3.202*	-2.700*	-14.329**	-16.187**	-4.642**
	(-1.764)	(-1.751)	(-1.878)	(-2.501)	(-2.210)	(-2.426)
Relationship Score	-249.224***	-244.311***	-230.246***	-305.425***	-81.032	-62.202
	(-4.230)	(-4.244)	(-4.937)	(-3.298)	(-1.011)	(-1.554)
New Lending Relation	-0.348	-0.369	1.052	-4.665**	6.144	2.811***
	(-0.352)	(-0.356)	(1.342)	(-2.135)	(1.055)	(2.921)
LIBOR 3M	-229.214	-234.374	-740.952**	-1,478.401***	821.599	130.822
	(-0.419)	(-0.423)	(-2.183)	(-6.341)	(0.592)	(0.272)
Non-Bank Synd. Member	11.730***	11.843***	10.091***	6.140	24.638***	9.151***
	(4.316)	(4.349)	(4.752)	(0.998)	(4.062)	(5.029)
Prob. Default	34.378***	34.229***	36.397***	13.930	8.646	39.532***
	(3.313)	(3.347)	(3.623)	(0.925)	(0.293)	(6.715)
Stock Volatility	96.457***	96.167***	98.555***	165.150***	123.181***	61.670***
	(8.558)	(8.555)	(8.991)	(4.246)	(7.067)	(7.139)
Size	-6.885***	-7.013***	-4.246***		11.721	-1.009
	(-5.401)	(-5.489)	(-2.673)		(1.316)	(-0.918)
Profitability	-108.616***	-108.759***	-100.801***		-150.958	-69.932***

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	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	All	No Top2	TCB
	(-5.926)	(-5.913)	(-6.208)		(-1.567)	(-6.647)
sd of profitability	18.533	19.133	-20.391		22.698	5.944
	(0.544)	(0.566)	(-0.679)		(0.188)	(0.312)
Book Leverage	44.236***	43.914***	41.308***		80.132**	37.490***
	(6.864)	(6.846)	(9.008)		(2.248)	(5.546)
Tangibilities	44.728***	43.691***	13.308		38.253	30.252**
	(3.358)	(3.342)	(1.268)		(0.997)	(2.425)
Tobin's Q	-6.462***	-6.519***	-6.113***		-6.801	-2.651**
	(-5.870)	(-6.025)	(-5.673)		(-1.485)	(-2.449)
Log Int. Cov.	-5.112***	-5.073***	-5.434***		6.256	-5.587***
	(-5.555)	(-5.584)	(-6.023)		(1.126)	(-6.700)
Liquidity Ratio	57.549***	56.767***	19.723**		40.593	41.782***
	(4.865)	(4.901)	(2.014)		(0.742)	(4.714)
Current Ratio	-1.077**	-1.049**	-0.877**		-3.135***	-0.210
	(-2.136)	(-2.117)	(-2.436)		(-4.119)	(-0.613)
S&P Rating C	33.688	32.923	113.262***			-4.565
	(0.815)	(0.786)	(5.586)			(-0.169)
S&P Rating CC	32.422	32.245	-23.797			163.795***
	(1.566)	(1.543)	(-0.499)			(9.989)
S&P Rating CCC	49.991**	50.708**	9.298			25.924**
	(2.396)	(2.435)	(0.776)			(2.274)
S&P Rating B	-2.851	-2.764	5.740*		-45.588***	-2.002
	(-0.872)	(-0.855)	(1.854)		(-3.991)	(-0.632)
S&P Rating BB	-2.010	-1.964	-4.179*		-15.578	-11.314***
	(-0.859)	(-0.846)	(-1.677)		(-1.659)	(-9.014)
S&P Rating BBB	-23.987***	-24.117***	-28.214***		-11.727	-23.503***
	(-8.840)	(-8.924)	(-6.679)		(-0.923)	(-15.695)
S&P Rating A	-36.722***	-37.278***	-47.619***		-26.217*	-20.520***
	(-7.884)	(-7.925)	(-9.218)		(-1.783)	(-7.705)
S&P Rating AA	-21.881***	-22.456***	-31.902***		35.615	-12.847***
	(-4.346)	(-4.460)	(-4.203)		(1.151)	(-3.334)
S&P Rating AAA	-12.695	-13.255	-16.133**		207.071**	-11.512
	(-1.442)	(-1.516)	(-2.154)		(2.563)	(-1.649)
Lead Size Q2	-1.441	-0.945		-2.319	-8.556	0.151
	(-0.337)	(-0.222)		(-0.660)	(-0.954)	(0.043)
Lead Size Q3	-9.006	-8.109		-5.099	-27.960**	-6.124
	(-1.593)	(-1.434)		(-1.046)	(-2.506)	(-1.483)
Lead Size Q4	-8.644	-7.404		-7.492	-31.064**	-4.367
	(-1.479)	(-1.267)		(-1.378)	(-2.524)	(-0.983)
Lead Size Q5	-13.396**	-12.090*		-8.917	-56.066***	-6.265
	(-2.104)	(-1.917)		(-1.528)	(-4.681)	(-1.448)

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	(1) All	(2) All	(3) All	(4) All	(5) No Top2	(6) TCB
Lead Market Equity	-0.766	-0.201		0.706	-29.853	-9.869
	(-0.029)	(-0.007)		(0.065)	(-0.723)	(-0.532)
Lead Book Leverage	7.811	8.017		2.164	45.700**	9.521
	(0.639)	(0.652)		(0.345)	(2.112)	(0.962)
Lead ROA	80.750	90.864		19.297	355.135	0.262
	(0.433)	(0.489)		(0.197)	(0.931)	(0.002)
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes	Yes	Yes
SIC2 FE	No	No	No	No	No	No
Year-Quarter FE	No	No	No	No	No	No
Lead FE	Yes	Yes	No	Yes	Yes	Yes
Borrower FE	Yes	Yes	No	No	Yes	Yes
SIC2 X Year-Quarter FE	Yes	Yes	No	No	Yes	Yes
Lead X Year-Quarter FE	No	No	Yes	No	No	No
Borrower X Year FE	No	No	No	Yes	No	No
Observations	25,466	25,466	26,096	25,166	5,351	22,809
Adjusted R-squared	0.790	0.790	0.746	0.875	0.825	0.854

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5). The dependent variable is the all-in-drawn loan spread, expressed in basis points. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). The specification also controls for facility-loan, lender, and borrower characteristics. Standard errors are clustered by lead bank. Columns (1)-(2) report the main results with the full set of controls. Column (3) and (4) report results on the full sample with a different set of fixed-effects. Column (5) excludes all the loans that had Bank of America or JP Morgan as lead arrangers. Column (6) reports the results using total-cost-of-borrowing (TCB) measure developed by Berg et al. (2016) as dependent variable. All variables are defined in Table B.II. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.IV: **Common Ownership and Time-on-the-Market (TOM)**

	Spread (1) Invest. Grade	*Spread* (2) All with TOM	*Time-on-the-Market* (3) Leveraged
CO	-8.338**	-49.849**	-32.389**
	(-2.622)	(-2.329)	(-2.191)
Time-On-the-Market	-	0.007	
		(0.068)	
Loan Purpose FE	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes
Lead FE	Yes	Yes	Yes
Borrower FE	Yes	No	No
SIC2 X Year-Quarter FE	Yes	Yes	Yes
Observations	9,592	2,558	2,072
Adjusted R-squared	0.938	0.797	0.783

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5) in columns 1 and 2. In column 1, the dependent variable is the all-in-drawn loan spread, expressed in basis points; the OLS regression is performed on the subsample of investment-grade loans. In column 2, the dependent variable is the all-in-drawn loan spread, expressed in basis points; the OLS regression is performed on the subsample of loans for which we have information on time-on-the-market, namely the number of days from the start to completion of syndication. The variable is also used as a control in the regression. In column 3, the dependent variable is time-on-the-market. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). Standard errors are heteroscedasticity-robust. All variables are defined in Table B.II. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.V: **Facility Loan Spread and Common Ownership - Alternative definitions of common ownership**

	(1)	(2)	(3)	(4)
	Spread		Amount	
CO	-88.257***		-15.841***	
	(-3.667)		(-3.090)	
CO Quintile 2		-1.652		-2.386**
		(-0.490)		(-2.639)
CO Quintile 3		-8.180**		-4.682***
		(-2.542)		(-3.497)
CO Quintile 4		-10.396***		-3.833**
		(-2.902)		(-2.392)
CO Quintile 5		-10.729**		-4.349***
Loan Purpose FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Lead FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	No	No
SIC2 X Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	25,467	25,467	8,090	8,090
Adjusted R-squared	0.790	0.790	0.743	0.744

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5). The dependent variable are: the all-in-drawn loan spread, expressed in basis points in column (1) and (2); and the percent of facility amount retained by the lead bank in column (3) and (4). The coefficient of interest is the one of CO, a measure of common ownership defined as the sum of the minimum commonly held shares by investors between the lead arranger and other syndicate members. Standard errors are clustered by lead bank. All variables are defined in Table B.II. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.VI: **Interest rates - Within-group estimates**

	(1)	(2)
	Same Facility Type - Same Loan	*Same Facility Type - Same Borrower-Year*
CO High	-13.715*	-10.079**
	(-1.824)	(-2.450)
Loan Purpose FE	Yes	Yes
Facility Type FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	229	1,740
Adjusted R-squared	0.964	0.596

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.5) on a sample of loans containing facilities of the same type displaying high and low common ownership within a given loan. The dependent variable is the all-in-drawn loan spread, expressed in basis points. The coefficient of interest is the one of *CO High*, an indicator variable taking the value of one when common ownership between the lead and member banks in the same facility is high (quintile 4 and 5) and zero otherwise. All variables are defined in Table B.II. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.VII: **Facility amount retained by the lead bank - full results and robustness checks**

	(1) Full Sample	(2) Full Sample	(3) Not Term B Not Leveraged	(4) Not Term B Not Leveraged	(5) Selection 1st Stage	(6) Selection 2nd Stage
CO	-2.698***		-2.965*		-0.351**	-4.641**
	(-2.874)		(-1.897)		(-2.419)	(-2.134)
CO Quintile 2		-0.847		-2.340		
		(-1.215)		(-1.337)		
CO Quintile 3		-2.593***		-2.813**		
		(-2.723)		(-2.495)		
CO Quintile 4		-2.701***		-2.764**		
		(-3.124)		(-2.184)		
CO Quintile 5		-1.758*		-2.368*		
		(-1.986)		(-1.873)		
Facility Amount	0.256	0.258	3.657***	3.381***	-0.249**	2.732***
	(0.317)	(0.329)	(4.583)	(4.403)	(-2.136)	(2.911)
CO Member-Borrower	-0.805*	-0.682	0.777*	0.882**	0.106*	1.209**
	(-1.715)	(-1.414)	(1.908)	(2.089)	(1.790)	(2.343)
Log Maturity	0.433**	0.446**	-0.314	-0.322	-0.096***	-0.671**
	(2.050)	(2.091)	(-1.425)	(-1.409)	(-3.623)	(-2.563)
Secured Loan	1.182***	1.195***	-1.165**	-1.200**	-0.141**	-1.707***
	(3.569)	(3.552)	(-2.277)	(-2.442)	(-2.293)	(-2.740)
Refinancing	-0.276	-0.233	-0.061	0.046	0.347***	1.651*
	(-0.881)	(-0.722)	(-0.139)	(0.098)	(8.860)	(1.768)
Log Number of Members	-15.350***	-15.279***	-13.479***	-13.365***	0.822***	-9.916***
	(-14.676)	(-14.610)	(-8.808)	(-9.194)	(22.489)	(-5.834)
Guarantor	0.981***	0.884**	-0.266	-0.396	0.359***	1.194
	(2.848)	(2.580)	(-0.992)	(-1.237)	(7.281)	(1.432)
Relationship Score	8.931	8.588	-119.880***	-117.622***	-4.736***	-140.518***
	(1.138)	(1.135)	(-3.846)	(-3.857)	(-2.691)	(-3.945)
New Lending Relation	0.168	0.273	-0.166	-0.035	0.169***	0.491
	(0.630)	(1.032)	(-0.601)	(-0.122)	(5.150)	(1.662)
LIBOR 3M	-15.026	-16.078	-325.126***	-313.361**	0.285	-333.515***
	(-0.160)	(-0.165)	(-2.793)	(-2.694)	(0.290)	(-2.899)
Non-Bank Synd. Member	2.317***	2.335***	1.084	1.148	0.128***	1.447**
	(8.973)	(8.778)	(1.645)	(1.649)	(2.703)	(2.089)
Prob. Default	1.267	1.153	6.321**	6.525***	-0.420	5.961***
	(0.437)	(0.396)	(2.421)	(3.258)	(-1.427)	(2.760)
Stock Volatility	5.029***	4.849***	9.694**	9.593**	-0.208	8.124*
	(3.122)	(2.923)	(2.444)	(2.435)	(-1.283)	(1.918)
Size	0.381**	0.400***	0.697***	0.599**	-0.229***	-0.307
	(2.601)	(2.799)	(2.878)	(2.504)	(-11.818)	(-0.726)

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Table B.VII: **Facility amount retained by the lead bank - full results and robustness checks**

	(1) Full Sample	(2) Full Sample	(3) Not Term B Not Leveraged	(4) Not Term B Not Leveraged	(5) Selection 1st Stage	(6) Selection 2nd Stage
Profitability	-1.517	-1.492	-1.002	-0.383	0.056	-0.892
	(-1.241)	(-1.219)	(-0.630)	(-0.249)	(0.375)	(-0.605)
sd of profitability	10.457***	10.539***	3.061	2.307	-0.976*	0.811
	(3.748)	(3.633)	(0.632)	(0.468)	(-1.692)	(0.147)
Book Leverage	0.737	0.934	1.265	1.037	0.050	1.385
	(0.324)	(0.403)	(0.408)	(0.327)	(0.322)	(0.435)
Tangibilities	-2.465**	-2.642**	2.003	1.531	0.204**	2.777**
	(-2.254)	(-2.420)	(1.596)	(1.152)	(2.519)	(2.050)
Tobin's Q	-0.480**	-0.497**	0.091	-0.004	-0.051**	-0.151
	(-2.210)	(-2.297)	(0.208)	(-0.008)	(-2.367)	(-0.306)
Log Int. Cov.	0.275	0.282	-0.027	-0.110	-0.014	-0.121
	(1.189)	(1.202)	(-0.089)	(-0.347)	(-0.468)	(-0.389)
Liquidity Ratio	-2.209	-1.947	2.774*	3.323*	0.158	4.225*
	(-0.696)	(-0.588)	(1.712)	(2.014)	(0.614)	(2.001)
Current Ratio	0.263*	0.275*	0.200	0.151	0.001	0.125
	(1.773)	(1.850)	(0.974)	(0.602)	(0.052)	(0.616)
S&P Rating C			-	-	-	-
S&P Rating CC			-	-	-	-
S&P Rating CCC	-5.791*	-6.002*	-	-	-	-
	(-1.769)	(-1.896)				
S&P Rating B	-1.676***	-1.604***	-12.250***	-12.571***	-0.370**	-14.206***
	(-3.736)	(-3.474)	(-5.006)	(-4.761)	(-2.023)	(-4.483)
S&P Rating BB	-0.931	-1.000*	-0.164	-0.372	-0.150*	-1.098
	(-1.609)	(-1.715)	(-0.135)	(-0.306)	(-1.679)	(-0.798)
S&P Rating BBB	-0.898**	-1.080***	-1.005	-1.244	-0.001	-1.149
	(-2.352)	(-2.777)	(-0.841)	(-1.021)	(-0.013)	(-0.977)
S&P Rating A	-0.140	-0.438	-0.708	-0.917	0.163**	-0.039
	(-0.195)	(-0.582)	(-0.723)	(-1.015)	(2.021)	(-0.046)
S&P Rating AA	0.174	-0.011	-0.293	-0.227	-0.024	-0.600
	(0.242)	(-0.015)	(-0.230)	(-0.194)	(-0.206)	(-0.420)
S&P Rating AAA	1.707	1.364			-0.154	0.608
	(1.398)	(1.231)			(-0.892)	(0.458)
Lead Size Q2	-0.776	-0.804	-4.550***	-4.825***	-0.104	-5.657***
	(-0.930)	(-0.954)	(-4.300)	(-4.430)	(-1.587)	(-5.629)
Lead Size Q3	-1.004	-0.972	-5.098***	-5.324***	-0.114	-6.368***
	(-1.014)	(-0.983)	(-5.765)	(-5.408)	(-1.564)	(-6.433)
Lead Size Q4	-0.488	-0.673	-5.861***	-6.129***	0.041	-6.437***

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Table B.VII: **Facility amount retained by the lead bank - full results and robustness checks**

	(1) Full Sample	(2) Full Sample	(3) Not Term B Not Leveraged	(4) Not Term B Not Leveraged	(5) Selection 1st Stage	(6) Selection 2nd Stage
	(-0.491)	(-0.639)	(-5.086)	(-4.802)	(0.528)	(-5.339)
Lead Size Q5	0.013	-0.216	-5.962***	-6.228***	0.078	-6.362***
	(0.012)	(-0.193)	(-5.234)	(-4.968)	(0.968)	(-5.508)
Lead Market Equity	-2.704	-1.973	-3.504	-2.113	-0.245	-4.602
	(-0.704)	(-0.524)	(-0.745)	(-0.516)	(-0.528)	(-0.978)
Lead Book Leverage	-1.381	-2.154	5.563*	5.112*	0.351	7.168**
	(-0.471)	(-0.769)	(1.936)	(1.961)	(1.554)	(2.460)
Lead ROA	-36.055	-31.431	56.305*	49.322*	-6.140	20.211
	(-0.945)	(-0.841)	(2.022)	(1.847)	(-1.171)	(0.677)
Perc. Missing Facilities					-1.115***	
					(-6.855)	
Mills Ratio						6.560**
						(2.137)
Loan Purpose FE	Yes	Yes	Yes	Yes		Yes
Facility Type FE	Yes	Yes	Yes	Yes		Yes
SIC2 X Year-Quarter FE	Yes	Yes	Yes	Yes		Yes
Lead FE	Yes	Yes	Yes	Yes		Yes
Observations	8,110	8,110	2,753	2,753	7,489	2,746
Adjusted R-squared	0.743	0.744	0.805	0.806		0.804

The table reports the OLS regression parameter estimates and t-statistics of Equation (2.6). The dependent variable is the percentage facility amount retained by each lead bank in the syndicate. The coefficient of interest is the one of CO, a measure of common ownership between the lead and member banks in the same facility given in Equation (2.2). The specification also controls for facility-loan, lender, and borrower characteristics. Standard errors are clustered by lead bank. Columns (1)-(2) report the main results with the full set of controls. Columns (3)-(4) exclude all Term-Loan B and Leveraged facilities. Columns (5)-(6) report the results of the selection model. All variables are defined in Table B.II. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Chapter 3

Early Life Conditions, Patience, and Savings

Effrosyni Adamopoulou, Mattia Colombo and Eleftheria Triviza

Abstract

This paper studies the effects of early life exposure to food scarcity on individuals' patience and savings in the long run. To this end, we combine hand-collected historical data at the province level on the drop in the availability of livestock during World War II with rich survey data on elicited patience and precautionary savings. By exploiting cohort and local variation in a difference-in-differences framework, we show that individuals who as children were more exposed to scarcity exhibit higher levels of patience and increase precautionary savings in the aftermath of recessions. Our results suggest that exposure to food scarcity early in life can lead to a long-lasting increase in individuals' prudence.

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3.1 Introduction

Time preferences play an important role in various economic decisions and are a key determinant of consumption, savings, and investment. There is substantial heterogeneity in time preferences across countries and socioeconomic groups, with cultural and institutional differences accounting for a fair portion of it. However, a significant part of this variation remains unexplained. While existing research has primarily focused on the short-term effects of socioeconomic disparities on time preferences (mainly in experimental settings), the effects of early life experiences have largely been understudied. In this paper, we fill this gap and show that early-life experiences have a long-lasting impact on individuals' time preferences.

To do so, we exploit an early-life shock that is arguably exogenous, that is, food scarcity during World War II (WWII) in Italy. Our analysis utilizes newly digitized historical data at the province level on the availability of different categories of food with a special focus on meat. Food scarcity and hunger was prevalent during WWII. Meat scarcity is of particular interest for our analysis as a substantial portion of livestock was excised by the German army to meet their dietary needs. We argue that the decline in the number of livestock resulted in a significant reduction in local meat availability during those years and estimate an Intention-To-Treat (ITT). Given that rationing and the prices in the black market were a function of the local availability of food, our measure is likely to capture well the overall scarcity of meat during the war.

In our analysis, we use a difference-in-differences framework and leverage provincial and cohort variation in the number of animals slaughtered for meat across Italy. Specifically, we compare the time preferences of individuals belonging to different cohorts (passed their childhood during or after WWII) who were born in provinces with varying levels of meat scarcity (measured on a continuous scale) during WWII. To measure time preferences, we utilize uniquely elicited information from the 2004 Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy. Within the survey, household heads were asked to indicate the percentage of a hypothetical lottery prize, equivalent to their household's net annual income, that they would be willing to forego in order to receive the prize immediately instead of waiting for a year. Consequently, we can observe the different levels of patience among respondents and classify those who are willing to sacrifice the highest percentage as “Impatient”. We then further investigate the impact of meat scarcity on households’ annual savings and on an elicited measure of precautionary savings.

We find that individuals who have experienced meat scarcity during childhood exhibit greater patience later in life. In our benchmark specification, a 10% decrease in the number of livestock slaughtered for meat reduces the probability of being impatient in adulthood by 2.3 p.p. This effect is economically significant, as about 10% of people in our sample are classified as ”impatient”. We obtain this result in specifications that account only for demographics (gender, age, parental education) or for other factors that may affect patience but are potentially endogenous, such as individuals’ socio-economic conditions (e.g., own education, income, and wealth). We are also able to exploit for identification the fact that some individuals reside in a different province than the province of birth. We do so by including province of residence dummies to control for unobserved differences across Italy while the shock refers to the province of birth (where the individuals passed their early childhood).

We carefully conduct several robustness tests to rule out the possibility that the relationship between exposure to meat scarcity during childhood and patience later in life reflects omitted characteristics. First, we include in the set of controls the number of WWII casualties per 1000 population at the province level to account for other direct consequences of the war. Second, we control for individuals’ financial literacy and add employment-sector dummies to control for an indirect channel through which the war could affect patience. Third, we control for the different speed of recovery in meat availability across Italian provinces after the end of the war. None of the above poses a threat to the causal relationship between meat scarcity and patience.

Moreover, we redefine our measure of meat scarcity, i.e. the percentage change in the number of slaughtered animals for meat between 1941-1942 and 1945 at the province level. First, we use the weight rather than the headcount of slaughtered animals to measure the availability of meat. Second, we employ data from the 1942 and 1944 censuses in the Italian liberated territories to account for the overall supply of livestock across Italian provinces. Both definitions do not change the estimated effect of meat scarcity on patience.

Finally, we make sure that the disruption of trade during WWII is not the main driver of our results. We do so by excluding provinces with a production of meat per capita in 1941-1942 above the 90th percentile of the distribution. The idea is that a share of meat production in these provinces was intended for trade purposes rather than local consumption and a drop in the number of animals for meat did not necessarily trigger meat scarcity at the local level. Furthermore we aggregate our measure of meat scarcity at the region of birth level to account for possible spillovers across adjacent provinces. In both cases, we obtain similar estimates to our benchmark specification.

Next, we exploit several sources of heterogeneity in our data to document potential asymmetries in the impact of childhood meat scarcity on treated individuals. First, we observe that the effect is driven by people born during WWII (ages 0-3), suggesting that early-life or in-utero experiences may have long-term consequences on individuals' time preferences. Second, we find that meat scarcity affected mainly people coming from relatively poorer families, as proxied by their parent's level of education. Third, we do not find any statistically significant differences between males and females, and across provinces with different infant mortality rates.

To shed light on the main mechanism behind our results, we further use information from the Annual Agricultural Statistics on the availability of other food groups, namely other sources of proteins beyond meat (legumes), carbohydrates (wheat, corn, and potatoes), and vitamins (tomatoes and apples). For each food category, we then compute a measure of scarcity, defined as the percentage change in the available quantity between 1941-1942 and 1945, and re-estimate our benchmark specification. We find that only the scarcity of high-protein foods (i.e., meat and legumes) affected individuals' patience levels, suggesting a potential biological mechanism. Nevertheless, a potential behavioral channel may also be at work given the vast evidence on the importance of early life conditions in the formation of preferences (Cunha and Heckman, 2007).

Lastly, we find that exposure to meat scarcity during childhood increases individuals' propensity to save later in life. First, people that presumably experienced meat scarcity as children show a higher level of yearly total household savings during adulthood. In particular, a 10% decrease in the number of animals slaughtered for meat increases total savings by 7.4%. This could be driven by higher levels of patience. Second, treated individuals that have experienced as adults a local recession in the previous year report a higher level of precautionary savings. Overall, our results suggest that individuals that were exposed to scarcity during childhood exhibit a higher degree of prudence in adulthood: they are more patient, save more as a household, and increase precautionary savings in the aftermath of recessions at the local level.

Related literature. The literature on time preferences documents considerable heterogeneity across countries, cultures and socio-economic groups. Falk et al. (2018) attribute this heterogeneity to cultural, historical and institutional differences. Harrison et al. (2002) show that while constant discount rates are a reasonable assumption for certain types of households, it is not appropriate to assume that the same discount rates apply to all households. Our study contributes to the understanding of the origins of heterogeneity in time preferences by shedding light on the role of early life experiences.

Previous studies have found that time preferences and scarcity of goods are strongly correlated. Lawrance (1991) shows that poverty may lead to present-oriented preferences, while Golsteyn et al. (2014) find that individuals with higher socioeconomic status tend to be more patient. Moreover, scarcity may lead to increased risk aversion (Dohmen et al., 2011), a preference for immediate rewards over delayed costs (Lawrance, 1991), and engagement in risky behaviours such as smoking (WHO, 2004). The underlying mechanism behind this behavioural shift is the experience of scarcity itself (Haushofer and Fehr, 2014; Mullainathan and Shafir, 2013), and recent research has explored the potential moderating role of the size of individual's choice set in this relationship (Gneezy et al., 2020). All the above papers primarily focus on the short-term effects and the contemporaneous relationship between poverty and current levels of patience. Our study instead investigates the causal, long-term effects of early life experiences on time preferences and savings.

Our study also adds to the literature that analyzes the relationship between poverty and economic behavior (Bertrand et al., 2004; Blalock et al., 2007; Yesuf and Bluffstone, 2009; Agarwal et al., 2009; Shah et al., 2012; Fehr et al., 2022). While this literature mainly focuses on the scarcity of financial resources (Carvalho et al., 2016; Ananyev and Guriev, 2018), our study specifically investigates the impact of food scarcity on economic behavior (Agneman et al., 2023).

Traumatic events such as wars, recessions, or the death of a relative are also factors that can impact economic behavior later in life. Research shows that experiencing this type of events can lead to a decrease in risk-taking behavior (Malmendier and Nagel, 2011) and trust (Kesternich et al., 2020) and a deterioration of labor market outcomes (Ichino and Winter-Ebmer, 2004; Atella et al., 2022). The impact of natural disasters extends beyond physical damages by affecting survivors emotionally and psychologically thus resulting in changes in patience (Callen, 2015) and economic behavior (Filipski et al., 2019). Our study contributes to this literature by focusing on the traumatic event of food scarcity during WWII in Italy. Our empirical design allows us to isolate the effect of food scarcity from the general deprivation and the casualties due to the war.

Early life experiences and exposure to stressors and environmental factors may have long-lasting effects on individual economic behavior and outcomes (Almond et al., 2018). These effects can manifest in changes in health, cognitive development, and behavior (Kesternich et al., 2020; Adamopoulou et al., 2021). Our study uncovers a direct link between early life experiences and time preferences–a key parameter for most economic decisions, including saving. Moreover, our study adds to the literature that examines the long-term effects of events, such as malnutrition and weather conditions, in utero or during infancy on various economic outcomes. Jürges (2013) focuses on cohorts born during the German food crisis after World War II and finds that those exposed to severe undernutrition during early pregnancies have lower educational attainment and occupational status. Scholte et al. (2015) examine the Dutch Hunger Winter and demonstrate negative effects of in utero exposure during the first trimester on employment outcomes and increased hospitalization rates later in life. Maccini and Yang (2009) links early-life rainfall to adult outcomes in Indonesia and highlights the positive effects on women's height, schooling grades, and socioeconomic status. Hoynes et al. (2016) investigates the impact of a positive policy-driven change in economic resources in utero and during childhood and find a reduction in metabolic syndrome and increased economic self-sufficiency for women. Lastly, Neelsen and Stratmann (2011) examine the Greek famine and show that adverse outcomes are most significant for infants, with urban-born cohorts experiencing larger negative impacts on educational outcomes compared to rural-born cohorts. Our study contributes to the understanding of the long-lasting effects of early-life conditions, also in utero, on patience and savings.

The rest of the paper is organized as follows. Section 2 describes the data and Section 3 outlines our identification strategy. Section 4 presents the results for both patience and savings. Section 5 concludes.

3.2 Data

We combine unique historical data on meat availability in different provinces of Italy with comprehensive survey information on individuals' patience, savings, and precautionary savings. We focus on Italy because it was one of the countries that experienced a plausibly exogenous adverse impact on meat availability. Moreover, we have access to detailed historical records on meat availability at the province level during WWII, as well as detailed survey data that provide insights into the characteristics of different cohorts.

To estimate the scarcity of meat in each province, we hand-collect data on the number of animals slaughtered for meat from ISTAT's Annual Agricultural Statistics reports from ISTAT (1948) and ISTAT (1950a).[1] We also digitize information from

[1] Figure A.1 in Appendix 3.5 shows an extract of the historical reports that we digitize.

the livestock censuses held in 1941, 1942, and 1944, which are obtained from ISTAT (1945) and ISTAT (1948) reports. Since our dataset includes the number of breed animals classified by species, we determine the availability of meat in each province by adding up the total number of cattle, pigs, goats, and sheep. We choose to use a simple sum, as the distribution of these species has remained relatively constant over time (cattle in the North, goats, and sheep in the South). We also use quintals instead of the number of slaughtered animals to aggregate the different species as a robustness check. In addition, we utilize unique information from the 1944 census which recorded the number of livestock the German army confiscated in Central and Southern provinces. This approach allows us to estimate the scarcity of meat in each province during the relevant time period.

The impact of WWII on provinces extended beyond the availability of livestock. We thus use an indicator to measure the severity of the war at the province level, which can serve as a control variable for the effects of the war. More specifically, we make use of data on the number of war victims by firearms and explosives in each province during the entire duration of WWII (i.e., before and after the armistice of September 8, 1943), which are obtained from ISTAT (1957) reports. To express the number of war victims per 1000 population in each province in 1936, we utilize the ISTAT (1976) report.

Different provinces experienced varying levels of meat scarcity during WWII. However, after the war, the availability of meat started to recover. To account for differences in the speed of recovery across provinces, we gather data on the number of slaughtered animals for meat at the province level in 1946 and 1947. We then create a variable that measures the change in the number of slaughtered animals between 1946-1947 and its levels in 1941-1942. This allows us to determine whether, by 1946-1947, the availability of meat had returned to pre-war levels and to what extent each province had recovered.

We collect data on several measures of food scarcity, including proteins (legumes such as beans and chickpeas), carbohydrates (such as wheat, maize, and potatoes), and fruits (such as apples and tomatoes), derived from the censuses conducted in 1941, 1942, and 1944. This data iss obtained from ISTAT's 1945 and 1948 reports with the aim of addressing potential concerns regarding the impact of overall food scarcity on our results.

Furthermore, we address potential concerns regarding sample selection by incorporating data from the Supplemento Straordinario alla Gazzetta Ufficiale n. 63 del 15 marzo 1948, specifically focusing on infant mortality rates. This additional data allows us to examine the potential correlation between meat scarcity and infant mortality, providing a comprehensive analysis of the underlying factors at play.

For our analysis, we use historical data along with information from the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy in 2004. This biennial survey provides information about households including their savings behavior, total income, wealth, home ownership, and characteristics of household members such as age, gender, educational level, marital status, sector of activity, and retirement status.

Another advantage of the SHIW is that it provides information on both the province of birth and the province of residence of household members. This enables us to determine the level of meat scarcity in the province where each individual is most likely to have been born and spent their childhood. Table A.I reports the summary statistics of the main variables we use in the analysis.

In the 2004 wave of the survey, there are questions that elicit the level of patience of the household's head and the precautionary savings of the household. The measure of patience is based on a six-point scale ranging from "least patient" to "most patient". The survey asked respondents to indicate the percentage of a hypothetical lottery gain that they would be willing to renounce in order to receive it immediately instead of waiting for a year. Respondents were offered a hypothetical lottery gain equivalent to their annual net household income and were asked whether they would be willing to forego 20, 10, 5, 3, or 2 percent of it to receive it immediately. We analyze patience as both a categorical variable and as a binary variable called "impatient," which is equal to 1 if the individual is willing to forego 20 percent.

A possible concern is that patience may reflect differences in financial literacy. To address this, we control for individuals' educational level and whether they worked in the financial sector. Additionally, the survey in 2004 includes a question about the amount of time individuals spent each week seeking out financial news. Based on the responses to this question, we construct a categorical variable ranging from 0 to 5, representing the amount of time dedicated to staying informed about financial matters each week, from no time to 4 hours per week. This allows us to account for the potential confounding factor of financial literacy in our analysis.

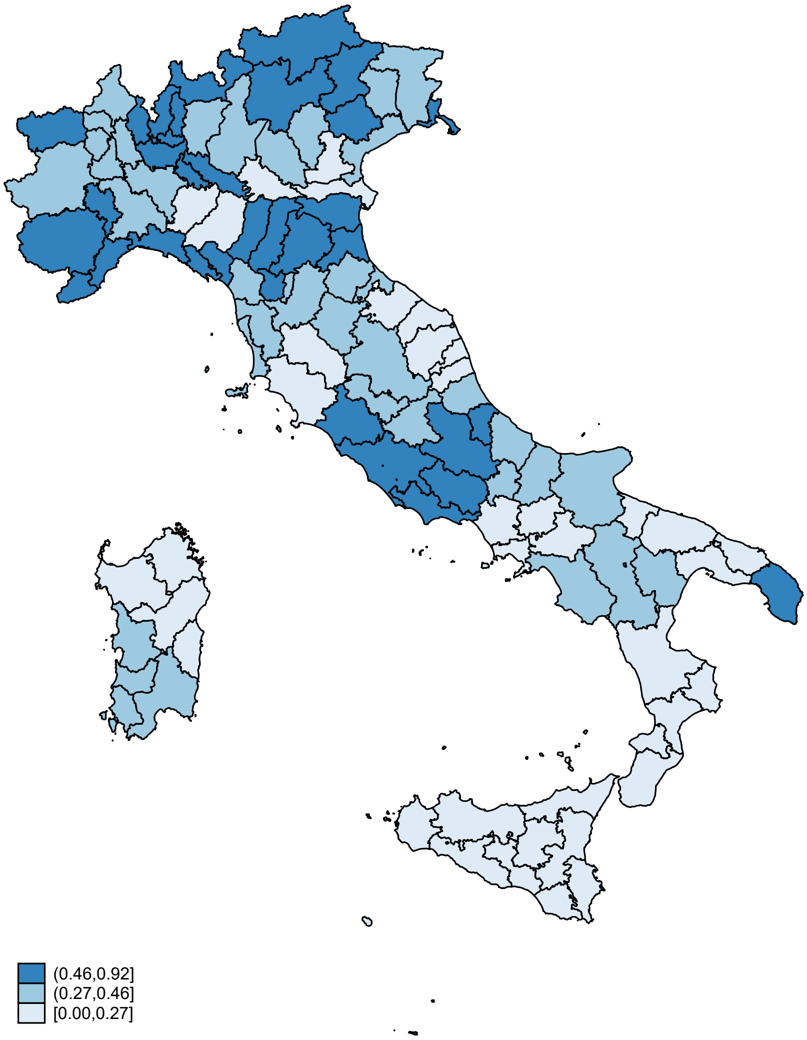
The SHIW in 2004 also elicits an amount of precautionary savings. The question is formulated as follows: "People save in various ways (depositing money in a bank account, buying financial assets, property, other assets) and for different reasons. The first reason is to prepare for a planned event, such as the purchase of a house, their children's education, etc. Another reason is to protect against contingencies, such as increased uncertainty about future earnings or unexpected outlays (owing to health problems or other emergencies). Approximately how much do you think your household should have available to meet such unexpected events?". The respondents are free to reply to the amount that they think is needed. Therefore, this question elicits a sufficient amount of savings that would act as insurance against unforeseen events.

3.3 Identification

3.3.1 Construction of the meat scarcity shock at the local level

As a first step, we construct a measure of meat scarcity at the province level using historical data from the annual agricultural statistics in 1941 and 1942 (before the start of the harshest phase of the war) and in 1945 (end of WWII in Italy). We calculate the percentage difference in the number of animals slaughtered for meat between the 1941-1942 average and that of 1945 in each province and obtain a measure in absolute value, with higher values denoting more severe scarcity levels.[2] Figure 3.1 shows that meat scarcity increased sharply during WWII. There is considerable variation across provinces, ranging from 0 to 92%.

Figure 3.1: **Our measure of meat scarcity**

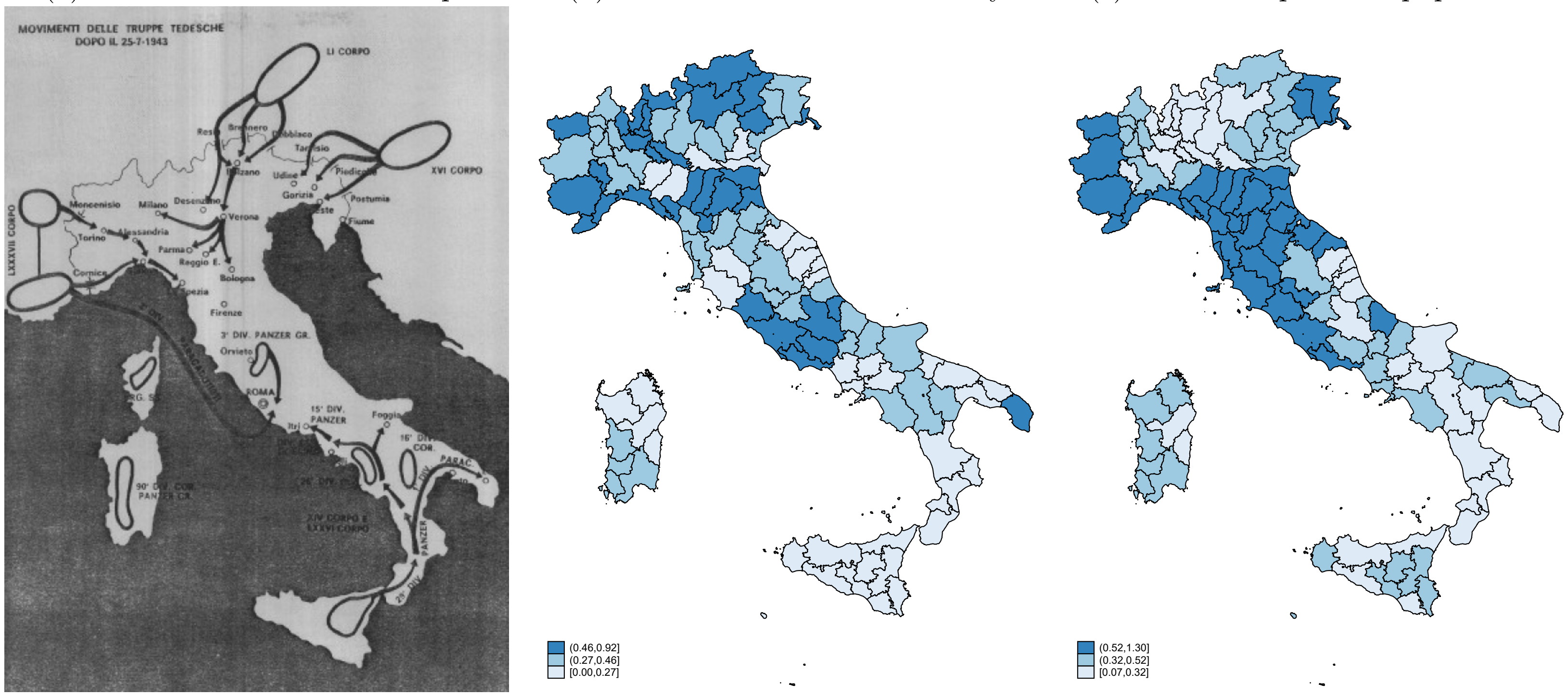


Notes: Percentage difference in the number of animals slaughtered for meat between 1941-1942 and 1945 as a proxy of meat scarcity at the regional level. The drop ranges between 0 and 92%.
Sources: Annual Agricultural Statistics 1941, 1942 (ISTAT, 1948) and 1945 (ISTAT, 950a).

[2] As a robustness check we use i) quintals of slaughtered animals, ii) the number of animals according to the livestock census of 1942 and 1944. The latter was only conducted in the central-southern area of the country, which was at the time already liberated.

Figure 3.2: **Movement of German troops after 1943, meat scarcity and casualties per 1000 population**

(a) Movement of German troops (b) Our measure of meat scarcity (c) Casualties per 1000 population



Notes: The figure compares the movement of German troops after the armistice signed on September 8, 1943 (a), our measure of meat scarcity as reported in Figure 3.1 (b), and the number of war casualties per 1000 population at the province level.
Sources: (a) Gandini (1995), (b) see notes of Figure 3.1, (c) ISTAT (1957)

We argue that the main driving factor of meat scarcity was the German army's livestock excise, aimed at fulfilling their dietary needs. As Figure 3.2 illustrates, meat scarcity at the province level (panel b) closely resembles the movements of the German troops after the fall of Mussolini on July 25, 1943, and upon the Allied invasion in September of 1943 (panel a). A possible confounding factor is that these provinces were directly affected by the war. However, in many cases, the German troops excised meat from certain provinces while battles and bombings took place elsewhere. Indeed, as Figure 3.2 shows, casualties per 1000 population (panel c) and meat scarcity (panel b) at the province level do not perfectly coincide–see the example of Lecce in the "heel" of Italy. To address the concern that the war may act as a confounding factor, we control for casualties per 1000 population throughout our empirical analysis.

We further corroborate that livestock excise was key for meat scarcity by using unique information from the 1944 census on the number of livestock excised by the German army in the central-southern provinces (liberated territory).[3] We express it as a share of the number of livestock in 1942 and correlate it with the total drop in the number of livestock between 1942 and 1944 (proxy of meat scarcity). Figure 3.3 shows the scatter plot along with the linear fit and confidence interval of the share of excised livestock and meat scarcity at the province level. As the figure shows, the German army excised up to 70% of the livestock in certain provinces (Frosinone, Latina). Moreover, the correlation between the share of excised livestock and meat scarcity is very high (above 80%), which supports the hypothesis that meat scarcity was mainly due to the excise by the German troops.[4]

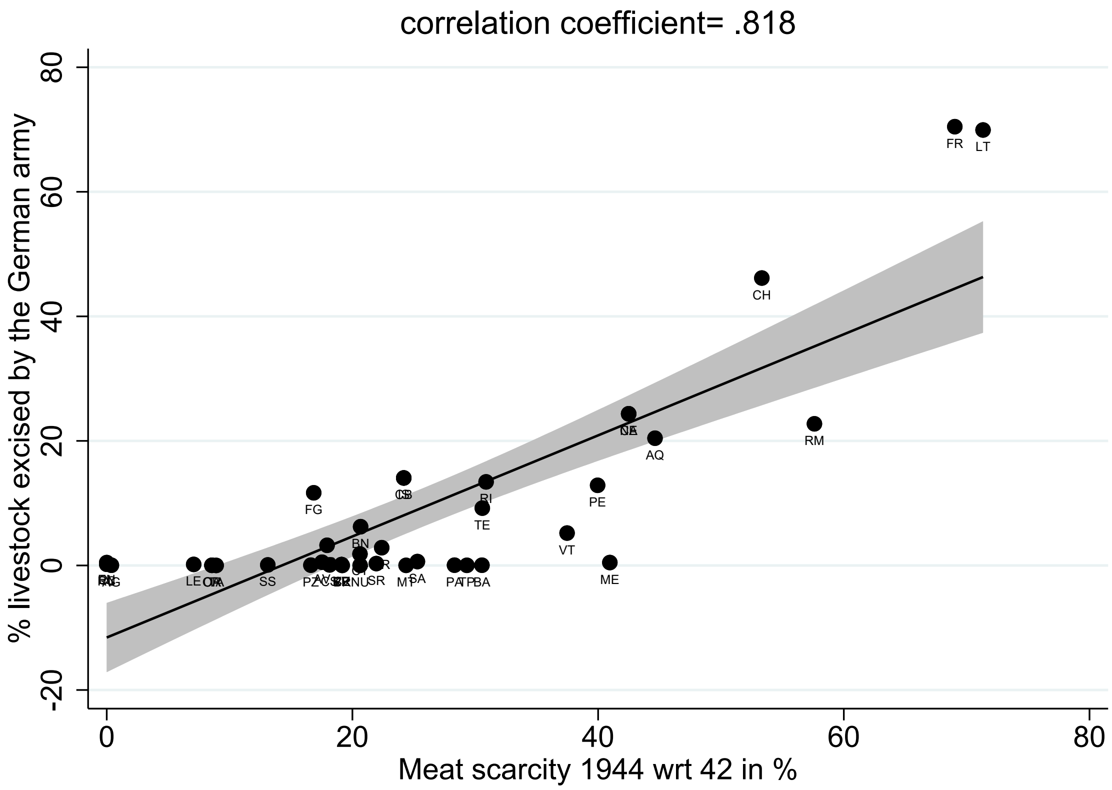
We use the number of slaughtered animals for meat as this treatment has several advantages. First, we do not need to rely on retrospective self-reported incidences of hunger that may suffer from recall bias and depend on the socio-economic status of the family of origin. The decrease in the number of slaughtered animals is arguably

[3]The liberated territory in 1944 included the following regions: Umbria, Lazio, Abruzzo, Campania, Apulia, Lucania (Molise), Calabria, Sicily, and Sardinia.

[4]Although there is no available data for the northern provinces, several historical sources report that livestock was almost entirely excised in several areas of Friuli Venezia Giulia (Liuzzi, 2004) and Emilia Romagna (Arbizzani, 1976) after numerous German divisions entered the Italian territory.

exogenous, as the German army excised a large share of the available livestock as they moved throughout the territory. Indeed, the provinces that experienced the largest meat scarcity (Belluno or Gorizia, Figure 3.2, panel c) were not among those that saw the highest number of casualties per capita (e.g., Ravenna or Bologna, Figure 3.2, panel b) and vice versa. Second, at that time, meat could be obtained either through

Figure 3.3: **Correlation between meat scarcity and share of livestock excised by the German army**



Notes: The figure depicts the correlation between the % change in the number of animals slaughtered for meat between 1941-1942 and 1945 and the share of livestock excised by the German army at the province level.

rationing or the black market. Both rations and the prices in the black market, in turn, were depending on the availability of meat at the local level. More specifically, during WWII, a ration card was introduced in Italy and different types of food, including meat, could only be purchased in established quantities using this special card. Rations differed by province depending on local availability (Massola, 1951). The collection and distribution of food were administered by the State exclusively at the local level through the so-called *Sezioni Provinciali dell'Alimentazione* (Provincial Food Sections, see Luzzatto-Fegiz (1948)), leading many to rely on the black market to acquire basic goods ((Luzzatto-Fegiz, 1948) and (Daniele and Ghezzi, 2019)). As the black market was also predominantly local (at most between city and countryside), the number of slaughtered animals at the province level likely captures the overall local availability of meat (both through rationing and the black market), providing a good measure of the meat scarcity individuals experienced during the war.[5]

The inefficiency of the rationing system (Morgan, 2007) and the very high inflation rate intensified the food shortage.[6] In certain places, some items were completely missing because they could not get in from the outside, while for others (e.g., milk) trade between provinces was completely forbidden. Moreover, transport infrastructures suffered substantial damage, further hampering the trade and provision of products (Daneo, 1975). Therefore, in our setting, spillover effects between the treated and control provinces (the so-called SUTVA) are unlikely to pose a threat to identification. Lastly, to address the concern that a drop in the number of slaughtered animals may also capture reduced trade, we conduct a robustness exercise by excluding meat-intensive provinces (i.e., provinces with a very high number of slaughtered animals per capita in 1941-42). Moreover, as an alternative check, we use meat scarcity aggregated at the region rather than at the province of birth.

3.3.2 Definition of the treated and control cohorts

As a second step, we use household heads' year of birth to pin down the treated and control groups for our analysis.[7] Italy entered WWII in 1940 but most of the casualties (severe phase) occurred after 1942. We thus define as "treated" the cohort born in

[5]It is reasonable to assume that the number of slaughtered animals also proxies for the availability of milk/butter and other animal products, for which no information exists in the historical archives.

[6]In 1943, the consumer price index increased by 67.7% compared to the previous year, and in 1944 by 344.4% (ISTAT, 2012).

[7]Patience is only elicited among household heads and savings refer to the household as a whole. Given that the household head is typically the member responsible for family finances, we consider the cohort and the province of birth of the household head to study the effects on both patience and savings.

1942-1945, i.e., individuals who passed their early childhood during the harshest years of WWII. The "control" cohort comprises those born in 1946-1957, i.e., individuals who were born and passed their childhood after the end of WWII. In the first part of the analysis, we compare the 1942-1945 cohort to the 1946-1957 cohorts (aggregated). In the second part, we conduct event studies with more disaggregated cohort groups and also consider earlier cohorts (born in 1934-1941).

As explained in section 3.3.1, the decrease in the number of animals slaughtered for meat is employed to proxy meat scarcity at the province level. Figure A.2 in Appendix 3.5 shows that livestock were present all across the Italian territory before the severest phases of WWII. This implies that people used to consume meat in all provinces and as a result, a decrease in livestock would be detrimental to individual consumption. As Figure A.3 in Appendix 3.5 shows, the average daily protein intake in the liberated territory in 1944 was around 30% lower than the minimum required intake for a person doing heavy muscular work. Therefore, it is reasonable to assume that individuals born in provinces that saw a large drop in the number of animals slaughtered for meat were more exposed to meat scarcity. In this way, we compare a cohort that was subject to varying levels of meat scarcity during childhood (depending on their province of birth) to cohorts who did not and estimate an intention to treat (ITT).[8] Our final sample includes around 2,500 individuals.

Table I displays some descriptive statistics for the treated and control cohorts born in provinces subject to more and less severe scarcity. We see that individuals born in high-scarcity provinces are more patient and save more on average than those born in low-scarcity provinces. Moreover, this difference is larger for the treated than the control cohort (compare columns 3 and 7 in Table I), suggesting that treated individuals exposed to more severe meat scarcity are relatively more patient and save more. We test this formally in the following subsection.

Individuals from high and low-scarcity provinces also differ in terms of income,

[8] By 1946-1947, the number of animals slaughtered for meat had recovered to its pre-WWII levels in most provinces (see Figure A.4 in Appendix 3.5), suggesting that the observed fall in meat consumption during WWII was a deviation from its "steady state." We include the recovery of animals slaughtered for meat at the province level as an additional control in a robustness check.

wealth, and number of war victims. However, this is true both for the treated and control cohort and the differences are almost identical. In our empirical analysis, we account for these differences by controlling for socioeconomic variables and casualties per capita and by exploiting provincial variation *within* cohorts in a difference-in-difference setting.

Table I: **Differences in Means**

	Cohort 1942-1945				Cohort 1946-1957			
	Scarcity High (1)	Scarcity Low (2)	Diff. (3)	N (4)	Scarcity High (5)	Scarcity Low (6)	Diff. (7)	N (8)
Patience	3.6	3.3	0.3*	593	3.8	3.6	0.2**	1965
Impatient	0.1	0.1	-0.0	593	0.1	0.1	0.0	1965
log(1+Savings)	8.5	7.8	0.7***	492	8.4	8.0	0.4***	1541
log(Precaut. Savings)	9.9	9.5	0.3**	592	9.8	9.4	0.4***	1955
War Victims	0.6	0.4	0.1***	585	0.6	0.4	0.1***	1914
Female	0.3	0.3	-0.0	593	0.4	0.3	0.0*	1965
Age	60.4	60.5	-0.1	593	52.6	52.8	-0.2	1965
Parental High Education	0.2	0.2	0.0	593	0.3	0.2	0.1***	1965
log(Net Income)	9.8	9.5	0.3***	593	9.8	9.5	0.3***	1963
log(Wealth)	12.0	11.5	0.5***	580	11.9	11.4	0.5***	1884
Retired	0.6	0.6	0.1	593	0.2	0.2	-0.0	1965
Home Owner	0.8	0.8	0.0	593	0.8	0.7	0.0*	1965
Finance	0.0	0.0	-0.0	593	0.0	0.0	0.0	1965
Health Insurance	0.1	0.1	0.0	593	0.1	0.1	0.0*	1965
Education	3.2	2.9	0.3**	593	3.5	3.2	0.2***	1965
Marital Status	1.6	1.6	-0.0	593	1.5	1.4	0.1*	1965

The table reports differences in means for the main variable of the analysis between treated (born in 1942-1945) and control (born in 1946-1957) cohorts. Scarcity High and Scarcity Low respectively identify provinces with values of $\Delta(Slaughtered)$ above and below the median. The definition of all variables is in Table B.II.

3.3.3 Methods

In order to estimate the causal effect of meat scarcity during early childhood on patience and savings later in life, we exploit cohort and provincial variation in a continuous difference-in-differences framework (DD). We estimate the following specification:

$$\begin{aligned} y_{i,p} = & \beta_0 + \beta_1 cohort_i + \beta_2 \Delta(Slaughtered)_p \\ & + \beta_3 (cohort \times \Delta(Slaughtered))_{i,p} \\ & + \beta_4 X_i + \eta_p + u_{i,p}, \end{aligned} \tag{3.1}$$

where i stands for the individual and p for the province. When we analyze patience, the dependent variable is a dummy=1 for household heads who are classified as impatient (willing to forego 20 percent of a hypothetical lottery gain equivalent to their annual net household income to receive it immediately) and 0 otherwise. The variable *Cohort* is equal to 1 if the household head is born in 1942-1945 and 0 if born in 1946-1957, and $\Delta(Slaughtered)$ is the drop in the number of animals slaughtered for meat during WWII, which is continuous and ranges between 0% and 92%. It is expressed in absolute value, with higher values denoting more severe scarcity levels.[9] The coefficient of interest is β_3, i.e., that of the interaction between the cohort dummy and meat scarcity.

In the most parsimonious specification, the vector X_i includes only exogenous controls, i.e., demographics of the respondent (age, age squared, gender) and socioeconomic characteristics of their family of origin (a dummy if at least one of their parents had a middle school degree). Given that WWII had long-run consequences for individuals' education and earnings (Ichino and Winter-Ebmer, 2004), our benchmark specification additionally controls for individuals' educational attainment, log(Net Income), log(Wealth), retirement status, home ownership, working in the financial sector as a proxy of financial literacy, having a private health insurance as a proxy of health status, and marital status. However, the results do not depend on the inclusion/exclusion of these potentially endogenous controls.[10,11] To avoid that WWII acts as a potential confounding factor, the benchmark specification also includes the war casualties per

[9] As a robustness check we use i) quintals of slaughtered animals and ii) the number of animals according to the livestock census of 1942 and 1944. The latter was only conducted in the central-southern area of the country, which was at the time already liberated.

[10] Net income, wealth, and precautionary savings are adjusted using an equivalence scale.

[11] In a robustness check we also include the amount of time individuals spent each week seeking out financial news as another proxy of financial literacy, dummies for different retirement age groups, and occupation dummies.

capita at the province level. This ensures that the treatment at the province level indeed captures meat scarcity rather than the overall hardship of WWII.

SHIW is one of the few Italian surveys that contain information both on individuals' province of birth and residence. We exploit this feature of the survey for identification by exploiting movers, i.e., individuals whose province of birth and current residence do not coincide. More specifically, we define the scarcity shock based on the province of birth but include in the specification province of residence dummies, η_p. In this way, we compare individuals that reside in the same province but were born in different provinces. We thus cluster standard errors at the province of birth level (102 provinces).

Given that the dependent variable "impatient" is binary, we estimate a linear probability model. We conduct robustness exercises by estimating a probit model and by considering the ordered variable "patience". Furthermore, we consider a binary instead of continuous treatment (high vs low scarcity) and estimate regressions with the scarcity defined at the regional level to account for possible spillovers. To better link the drop in the number of livestock to a drop in meat consumption rather than reduced trade, we estimate a specification excluding provinces with a high (above the 90^{th} percentile) per capita number of animals slaughtered for meat in 1941-1942.

We also carry out a more disaggregated analysis by 4-year cohorts in the spirit of an event study analysis. This allows us to check whether the effect is stronger among a particular treated group and to confirm that the control cohorts were unaffected. In the event study we cluster standard errors by province and cohort and the omitted cohort comprises of individuals born in 1954-1957. In this way, we ensure that the cohort of reference lived their childhood during a period of full recovery.

One potential concern is infant mortality. If the most vulnerable infants did not survive due to meat scarcity, there could be issues of selection in our sample. To address this issue, we correlate historical statistics on infant (first year of life) mortality at the province level with our measure of meat scarcity. Figure A.5 in Appendix 3.5 shows that there is no correlation between meat scarcity and fetal/infant mortality during WWII. A possible explanation is that breastfeeding is more important than meat intake for survival at this early age. Moreover, infants were entitled to more generous rations in terms of calories than were adults or older children (Daniele and Ghezzi, 2019). Therefore, infant mortality is unlikely to affect our results for those aged 0-2 during WWII.[12].

To understand whether the underlying mechanism is partly biological, we use additional information from the Annual Agricultural Statistics on the availability of other types of food and estimate the effects of scarcity on impatience by food category, namely, proteins (meat and legumes), carbohydrates (wheat, corn, potato) and vitamins (tomato and apple).

We then move to the analysis of savings and estimate 3.1 via OLS with log annual household savings as the dependent variable. To take into account households with 0 savings we compute log(1+Savings) in the benchmark specification and conduct a robustness exercise using the inverse hyperbolic function.

In the case of precautionary savings, local business cycles may also play a role. In particular, individuals who experienced scarcity during early childhood may react more in the aftermath of an adverse economic shock. To explore this possibility, we estimate the following specification:

$$\begin{aligned} y_{i,p} =& \beta_0 + \beta_1 cohort_i + \beta_2 \Delta(Slaughtered)_p \\ &+ \beta_3 (cohort_i \times \Delta(Slaughtered)_p) \\ &+ \beta_4 (Recession_{t-1} \times \Delta(Slaughtered)_p) \\ &+ \beta_5 (Recession_{t-1} \times Cohort_i) \\ &+ \beta_6 (Recession_{t-1} \times Cohort_i \times \Delta(Slaughtered)_p) \\ &+ \beta_7 X_i + \eta_p + u_{i,p}, \end{aligned} \tag{3.2}$$

where $Recession_{t-1}$ takes the value 1 if the respondent experienced a local recession the year before the survey took place. We define local business cycles using the unemployment rate of the province of residence (increase for recessions and decrease

[12] A similar type of bias could arise from selective fertility. However, contraception was quite ineffective in the period of analysis (Greenwood et al., 2021)

for expansions).

3.4 Results

3.4.1 Effects on patience

We examine the effect of exposure to meat scarcity during childhood on the individuals' probability of being impatient in later life by estimating the linear probability model specified in equation 3.1. Table II reports the results. The coefficient β_3 associated with the interaction term, $Cohort_i \times \Delta(Slaughtered)_p$, is negative and statistically significant. A 10% decrease in the number of livestock slaughtered for meat reduces the probability of being impatient in adulthood by 2.3 p.p. in our first specification, column (1). Given that about 10% of the individuals in our sample are defined as "impatient", this effect is economically significant. Previous studies have shown how social and economic conditions affect individuals' time preferences. For example, poorer individuals show a higher propensity to be impatient, Lawrance (1991). In column (2), we show that the estimated effect is not driven by differences in individuals' socio-economic conditions (e.g., income, wealth, and education). In addition, the inclusion of province dummies controls for unobserved geographical differences.

As described in Section 3.3.1, our measure of meat scarcity is based on the decline in meat availability during WWII. Thus, the estimated effect may be driven by those provinces more severely affected by the war as a whole, and our measure, $\Delta(Slaughtered)_p$, may be capturing the overall wartime hardship and not just meat scarcity. To address this concern, in our benchmark specification and throughout the rest of the analysis, we add to the set of controls "War Victims", i.e., a variable that measures the number of WWII casualties per 1000 population at the province level. Table II column (3) reports the results. The coefficient of interest β_3 remains negative and statistically significant also after controlling for the direct consequences of WWII.

Table II: **Effect of Meat Scarcity on Impatience**

	(1) Impatient	(2) Impatient	(3) Impatient
Cohort i	0.184***	0.186***	0.186***
	(3.699)	(3.952)	(3.951)
$\Delta(Slaughtered)$	0.034	0.067	0.070
	(0.843)	(1.605)	(1.574)
Cohort i $\times$ $\Delta(Slaughtered)$	-0.226***	-0.243***	-0.243***
	(-3.374)	(-3.394)	(-3.384)
Female	0.009	-0.024	-0.024
	(0.478)	(-1.116)	(-1.115)
Age	0.154***	0.154***	0.154***
	(2.629)	(3.185)	(3.183)
Age^2	-0.002***	-0.001***	-0.001***
	(-2.724)	(-3.282)	(-3.280)
Parents high Education	-0.051***	-0.028	-0.027
	(-3.767)	(-1.588)	(-1.588)
log(Net Income)		-0.056***	-0.056***
		(-2.628)	(-2.632)
log(Wealth)		-0.012	-0.012
		(-1.419)	(-1.420)
Retired		0.004	0.004
		(0.234)	(0.245)
Home Owner		0.045*	0.045*
		(1.915)	(1.917)
Finance		-0.004	-0.004
		(-0.126)	(-0.134)
Health Insurance		0.001	0.001
		(0.070)	(0.067)
Education		-0.007	-0.007
		(-0.644)	(-0.634)
Marital Status		0.021**	0.021**
		(2.269)	(2.267)
War Victims			-0.009
			(-0.251)
Province FE	Yes	Yes	Yes
Observations	2498	2414	2414
Adjusted R-squared	0.065	0.084	0.084

The table reports Linear Probability Model estimates of meat scarcity during childhood on the probability of being impatient during late adulthood. Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. Col. (1) includes only exogenous controls (demographics and socioeconomic of the family origin), Col. (2) includes additional controls: education, log(Net Income), log(Wealth), retirement status, home ownership, working in the financial sector, having private health insurance, marital status, Col (3) also controls for the per capita casualties during the entire period of WWII at the province level. The definition of all variables is in Table B.II.

3.4.2 Robustness

In Table III, we conduct various robustness tests to ensure the causality of our main result in Table II.

First, differences in individual financial literacy may explain the negative effect between childhood meat scarcity and impatience. Previous studies have shown that individuals who collect financial information tend to have higher discount rates than those who do not, Meier and Sprenger (2013). Therefore, we include "Fin. Literacy", a categorical variable ranging from 0 to 6 based on the number of hours per week that each individual spends reading financial news. The results reported in column (2) show that the effect of meat scarcity on impatience is not caused by differences in financial literacy among individuals in our sample. Moreover, the inclusion of employment sector dummies in column (2) controls for other unobserved job-related characteristics (e.g. employment in the financial sector).

Second, we control for the heterogeneity in the recovery of meat availability after WWII. If meat scarcity did not recover after WWII in affected provinces, then individuals born in those provinces after the end of the war would also be treated. We address this concern by including in column (3) the estimates of the following specification:

$$
\begin{aligned}
y_{i,p} = & \beta_0 + \beta_1 cohort_i + \beta_2 \Delta(Slaughtered)_p \\
& + \beta_3 (cohort_i \times \Delta(Slaughtered)_p) \\
& + \beta_4 (Recovery_p \times \Delta(Slaughtered)_p) \\
& + \beta_5 (Recovery_p \times Cohort_i) \\
& + \beta_6 (Recovery_p \times Cohort_i \times \Delta(Slaughtered)_p) \\
& + \beta_7 X_i + \eta_p + u_{i,p},
\end{aligned}
\tag{3.3}
$$

where $Recovery_p$ is a continuous variable measuring the percentage change in the number of slaughtered animals for meat reported in the ISTAT annual agricultural statistics for 1941-1942 and 1946-1947. The main coefficient of interest, β_3, remains negative and statistically significant, while the coefficient of the triple interaction term,

Table III: **Effect of Meat Scarcity on Impatience: Robustness**

	(1) Baseline	(2) Extended Controls	(3) Recovery	(4) Discrete Treatment	(5) $\Delta(Weight)$	(6) $\Delta(Livestock)$	(7) Not Meat Intensive	(8) Regional Treatment
Cohort i	0.186***	0.187***	0.196***	0.144***	0.152***	0.181***	0.199***	0.173***
	(3.951)	(4.034)	(3.454)	(3.789)	(3.489)	(3.704)	(3.927)	(3.255)
$\Delta(Slaughtered)$	0.070	0.065	0.094				0.055	
	(1.574)	(1.478)	(1.226)				(1.042)	
Cohort i $\times$ $\Delta(Slaughtered)$	-0.243***	-0.242***	-0.301**				-0.282***	
	(-3.384)	(-3.372)	(-2.593)				(-3.125)	
Recovery			0.065					
			(0.922)					
Recovery $\times$ $\Delta(Slaughtered)$			-0.078					
			(-0.495)					
Cohort i $\times$ Recovery			0.014					
			(0.114)					
Cohort i $\times$ Recovery $\times$ $\Delta(Slaughtered)$			-0.118					
			(-0.632)					
High Scarcity				0.047**				
				(2.378)				
Cohort i $\times$ High Scarcity				-0.103***				
				(-3.096)				
$\Delta(Weight)$					0.060*			
					(1.928)			
Cohort i $\times$ $\Delta(Weight)$					-0.188***			
					(-2.889)			
$\Delta(Livestock)$						0.058		
						(1.363)		
Cohort i $\times$ $\Delta(Livestock)$						-0.238***		
						(-3.023)		
$\Delta(Slaughtered)_{regional}$								0.071
								(1.274)
Cohort i $\times$ $\Delta(Slaughtered)_{regional}$								-0.203**
								(-2.454)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	No	No	No	No	No
Observations	2414	2414	2414	2414	2414	2414	2187	2414
Adjusted R-squared	0.084	0.084	0.083	0.083	0.081	0.081	0.091	0.081

The table reports Linear Probability Model estimates of meat scarcity during childhood on the probability of being impatient during late adulthood. Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. Recovery is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1946-47 in each province in absolute terms. High Scarcity is a dummy equal to 1 for provinces with $\Delta(Slaughtered)$ values above the sample median. $\Delta(Weight)$ is the % change in the weight of slaughtered meat between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Livestock)$ is the % change in the number of breed animals between 1941-42 and 1944 in each Central-Southern region and the % change in the number of animals slaughtered for meat between 1941-42 and 1945 in each Northern region. $\Delta(Slaughtered)_{regional}$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each region in absolute terms. Col. (1) reports the benchmark estimate of eq. 3.1, Col. (2) controls for financial literacy and employment-sector dummies, Col. (3) presents differences in the effect across provinces with different speed of recovery in the production of slaughtered meat, Col. (4) uses a discretized version of the main treatment, Col (5) redefines treatment using $\Delta(Weight)$, Col. (6) redefines treatment using $\Delta(Livestock)$, Col. (7) excludes provinces with a level of slaughter meat in 1941-42 above the 90th percentile, Col. (8) redefines the main treatment variable at the regional level. The definition of all variables is in Table B.II.

β_6 is not statistically different from zero. Thus, differences in the recovery of meat availability do not pose a threat to our identification strategy.

Third, we estimate equation 3.1 using a discretized version of $\Delta(Slaughtered)_p$. In particular, we define the dummy variable High Scarcity as equal to one for all those provinces with values of $\Delta(Slaughtered)_p$ above the median. By doing so, we ensure that our results are not driven by a few outliers in the distribution of meat scarcity across provinces. The coefficient associated with the interaction term in column (4) remains negative and highly statistically significant.

Next, we report two additional tests regarding our definition of meat scarcity at the province level. In our benchmark specification, we measure meat scarcity as the percentage change in the number of slaughtered animals for meat between 1941-1942 and 1945. As mentioned in Section 3.3.1, we construct our measure of meat scarcity by summing up different species of animals. This is because the various provinces typically specialize in the production of certain species and our treatment variable is based on the percentage difference over time within each province. Still, we can refine our treatment variable using quintals rather than the headcount of slaughtered animals of meat. In column (5) we redefine meat scarcity as the percentage change in the weight of slaughtered meat between 1941-1942 and 1945 at the province level and the results are very similar to the benchmark estimates. Moreover, slaughtered animals for meat represent only a portion of total livestock. Total livestock is available from the livestock census that took place in 1942 and 1944 (only liberated territory). Thus, in column (6) we measure meat scarcity as the percentage difference in the number of total livestock–see Section 3.3.1. Again, we obtain similar estimates to our benchmark specification.

Furthermore, we conduct two tests to rule out the possibility that the disruption of trade during WWII is driving our results rather than the drop in meat consumption. First, we estimate the equation 3.1 excluding the provinces where a large part of the meat production was for trade purposes. To do so, we calculate the per capita number of animals slaughtered for meat in 1941-1942 and exclude those provinces with a value above the 90th percentile. Second, we compute meat scarcity aggregated at the region rather than at the province of birth level to account for possible spillovers between adjacent provinces. We report the results in columns (7) and (8) respectively. In both cases, the coefficient of the interaction term is negative, statistically significant, and similar in size to the benchmark estimate.

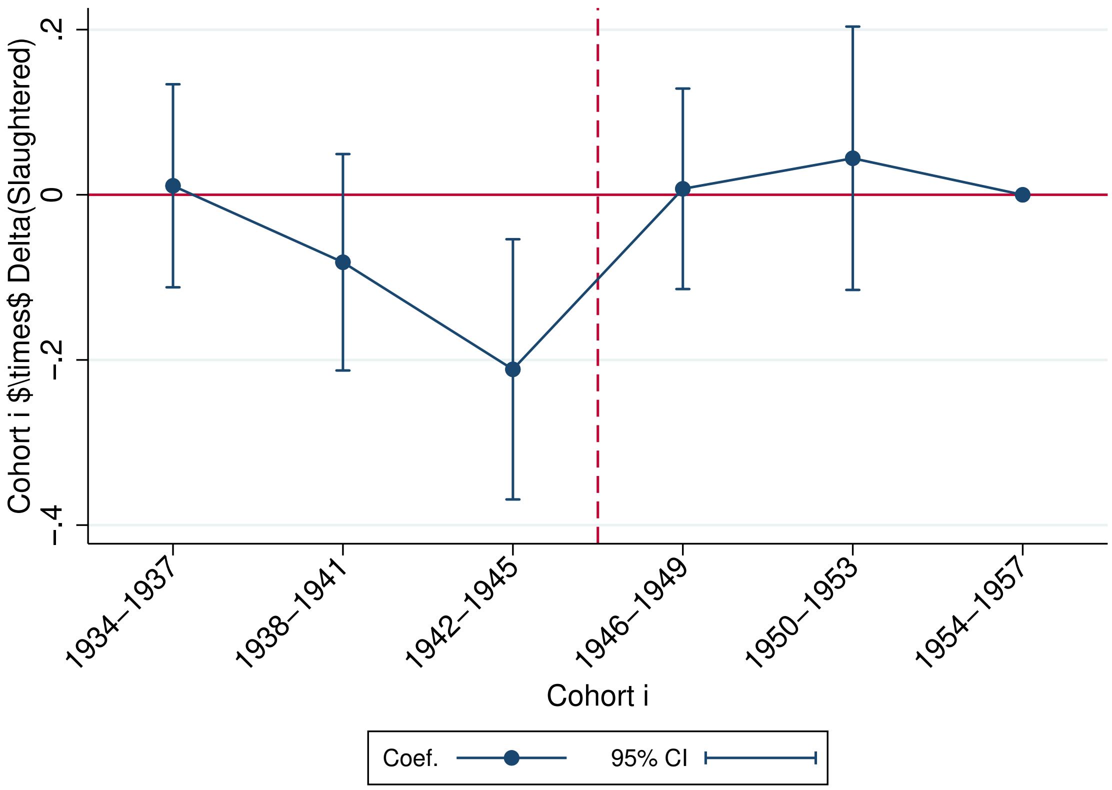
Additionally, we check whether our results are robust to the estimation method and to the way we define our outcome variable. As Table B.I, column 1 in Appendix 3.5 shows, we obtain a marginal effect of similar size as the benchmark estimate if we estimate a probit instead of a Linear Probability Model. In columns 2 and 3 we use the categorical variable "patience" instead of the dummy impatience as an outcome variable and estimate OLS or ordered logit. Patience is measured on a six-point scale ranging from "least patient" to "most patient". We find that an increase in meat scarcity during childhood by 10% leads to an increase of around 1.5 points on the six-point scale of patience.

Finally, we perform an event study analysis that unfolds the overall average effect for different cohorts. In the event study, the control cohort comprises individuals born in 1954-1957, i.e., when Italy had fully recovered from the consequences of WWII. We report the benchmark result by 4-year cohort groups in Figure 3.4. The effect of meat scarcity on the likelihood of being impatient in adulthood is statistically significant for individuals born during WWII (cohort 1942-1945), suggesting that meat scarcity in early childhood (ages 0-3) is pivotal and can have long-lasting effects on individuals' patience levels. Older cohorts (1934-1941) and individuals born after the war show no statistically significant effect. Our result is in line with the economic literature on the long-term effects of childhood experiences (e.g. Almond et al. (2018)) and on the role of early life conditions in the formation of cognitive and non-cognitive skills (Cunha and Heckman, 2007).

3.4.3 Heterogeneous effects and overall food scarcity

In this section, we conduct several sample splits to understand whether our findings are heterogeneous across different groups. First, we use the reported information on the educational level of the interviewees' parents to proxy for the socioeconomic

Figure 3.4: **Effects of meat scarcity on the probability of being impatient**



Notes: Estimated coefficients of the interaction terms in the diff-in-diff specification and 95% confidence intervals. Standard errors are clustered at the province level. The dependent variable is a dummy equal to 1 if the individual is labeled as impatient and 0 otherwise. Treated cohorts are born in 1934-1937, 1938-1941, and 1942-1945. Control cohorts are born in 1946-1949 and 1950-1953. Omitted cohort (comparison category) is born in 1954-1957. $\Delta(Slaughtered)$ is the % change in the number of slaughtered animals for meat consumption between 1941-42 and 1945.

background of the family of origin. Parents with a higher educational level may have had better access to meat through the black market as they were less financially constrained. We thus create the dummy variable "High Parental Education" equal to one if at least one of the interviewee's parents has a middle school certificate or higher. As reported in Table A.I, around 20% of individuals in our sample have a parent with a high level of education. Columns (1) and (2) in Table IV show that childhood meat scarcity affects patience in late adulthood only among individuals

Table IV: **Effect of Meat Scarcity on Impatience: Heterogeneity**

	(1) Low Parental Education	(2) High Parental Education	(3) Male	(4) Female	(5) Low Infant Mortality	(6) High Infant Mortality
Cohort i	0.218***	0.058	0.160***	0.105	0.145**	0.207***
	(4.377)	(0.705)	(2.906)	(1.531)	(2.128)	(2.925)
$\Delta(Slaughtered)$	0.068	0.148**	0.043	0.157**	0.003	0.084
	(1.283)	(2.212)	(0.790)	(2.152)	(0.023)	(1.263)
Cohort i × $\Delta(Slaughtered)$	-0.279***	-0.096	-0.208***	-0.219**	-0.251*	-0.246**
	(-3.681)	(-0.827)	(-2.801)	(-2.251)	(-1.874)	(-2.442)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1925	469	1652	749	1209	1178
Adjusted R-squared	0.079	0.094	0.094	0.110	0.128	0.065

The table reports Linear Probability Model estimates of meat scarcity during childhood on the probability of being impatient during late adulthood. Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. Col. (1) includes only individuals with low parental education (i.e., with an elementary school degree or no degree), Col. (2) contains only individuals with high parental education, Col. (3) includes only male individuals, Col. (4) contains only female individuals, Col. (5) includes only provinces with an infant mortality level in 1942 below the sample median, Col. (6) contains only provinces with an infant mortality level in 1942 above the sample median.

with lower parental education, who probably had greater difficulty in acquiring meat through the black market. Second, we investigate possible differences by gender in the responses to the lack of meat. Columns (3) and (4) show that meat scarcity equally affected both female and male individuals.[13] Third, we study potential heterogeneous effects across individuals born in provinces with different infant mortality rates. For each province, we compute the percentage increase in infant mortality rate between 1940 and 1945. We then create the dummy variable "High Infant Mortality" equal to one if the increase in infant mortality rate in a province was above the sample median. Columns (5) and (6) show that the effect of meat scarcity is similar among low and high infant mortality provinces. Therefore, we are confident that our results are not driven by sample selection issues due to different infant mortality rates across provinces.

[13]Given that our analysis is limited to household heads, females in our sample may not be representative of the entire female population.

3.4.4 Mechanisms

The effect of meat scarcity on patience can be explained both through a behavioral or biological mechanism. To shed light on the existence of a biological channel, we use additional information from the Annual Agricultural Statistics on other food groups' availability. In particular, we collect data on the availability of other sources of

Table V: **Effect of Food Scarcity on Impatience: Food categories**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Proteins		Carbohydrates			Fruits	
	Meat	Legumes	Wheat	Corn	Potato	Tomato	Apple
Cohort i	0.186***	0.152***	0.088*	0.098**	0.089***	0.096***	0.067**
	(3.951)	(3.444)	(1.967)	(2.194)	(2.712)	(3.084)	(2.066)
Treatment	0.070	0.061*	0.054	0.066**	0.072*	0.046***	0.005
	(1.574)	(1.903)	(1.566)	(2.163)	(1.688)	(2.659)	(0.777)
Cohort i × Treatment	-0.243***	-0.110*	0.011	-0.010	-0.001	-0.020	-0.013
	(-3.384)	(-1.870)	(0.152)	(-0.149)	(-0.031)	(-0.545)	(-1.154)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2414	2102	2289	2276	2353	2373	2287
Adjusted R-squared	0.084	0.099	0.077	0.077	0.078	0.082	0.077

The table reports Linear Probability Model estimates of meat scarcity during childhood on the probability of being impatient during late adulthood. Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Legumes)$ is the % change in legumes production between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Wheat)$ is the % change in wheat production between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Corn)$ is the % change in corn production between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Potato)$ is the % change in potato production between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Tomato)$ is the % change in tomato production between the 1941-42 average and that of 1945 in each province in absolute terms. $\Delta(Apple)$ is the % change in apple production between the 1941-42 average and that of 1945 in each province in absolute terms.

proteins beyond meat (legumes), carbohydrates (wheat, corn, potatoes), and vitamins (tomatoes, and apples) at the province level. For each food category, we calculate the percentage difference in the quantity available between the 1941-1942 average and that of 1945 in each province and obtain a measure in absolute value, with higher values denoting more severe scarcity levels. We then estimate equation 3.1 for each of the above food groups. Table V contains the results. Columns (1) and (2) show a negative and statistically significant effect of scarcity of legumes on the probability of being impatient. We do not find any statistically significant effects on carbohydrates (columns 4, 5, and 6) and vitamin scarcity (columns 6 and 7). Thus, our result appears to be related to protein rather than general food scarcity. Even though we cannot rule out a potential behavioral mechanism behind our findings (e.g., the importance of preferences' formation in the first years of life), the documented effect may also be partly driven by a biological channel, as the lack of proteins during gestation and early childhood affects children's cognitive abilities and brain development.

3.4.5 Effects on savings

A higher level of patience may have important implications for individuals' intertemporal saving decisions. We investigate this possibility by estimating the effect of meat scarcity on households' yearly savings as reported in the 2004 wave of the SHIW. In particular, we adopt the same diff-in-diff framework as in equation 3.1 and compare households' savings decisions in the treated and control cohorts, who experienced different degrees of meat scarcity in the province of birth. The dependent variable is $log(1 + savings)$. Table VI, column 1 shows that, conditionally on household income, those who experienced meat scarcity during childhood tend to save more compared to others. The effect is statistically significant and is not driven by differences in individuals' demographic characteristics or socioeconomic status (parental education). Column 2 shows that the estimated effect is robust to the inclusion of additional controls (e.g. wealth, occupation, health, education, marital status).

In Figure 3.5, we repeat the analysis using the same event study methodology as in Section 3.4.2. The control cohort consists of individuals born in 1954-1957, i.e. when Italy had fully recovered from the consequences of WWII. shows the results. The effect of childhood meat scarcity on annual savings is again positive and statistically significant for individuals born during WWII (cohort 1942-1945). Hence, early childhood meat scarcity has an impact not only on the individuals' patience levels (as shown in Figure 3.4) but also on their actual savings decisions. Finally, we conduct an additional robustness test to ensure that the documented effect does not depend on the

Table VI: **Effect of Meat Scarcity on Savings**

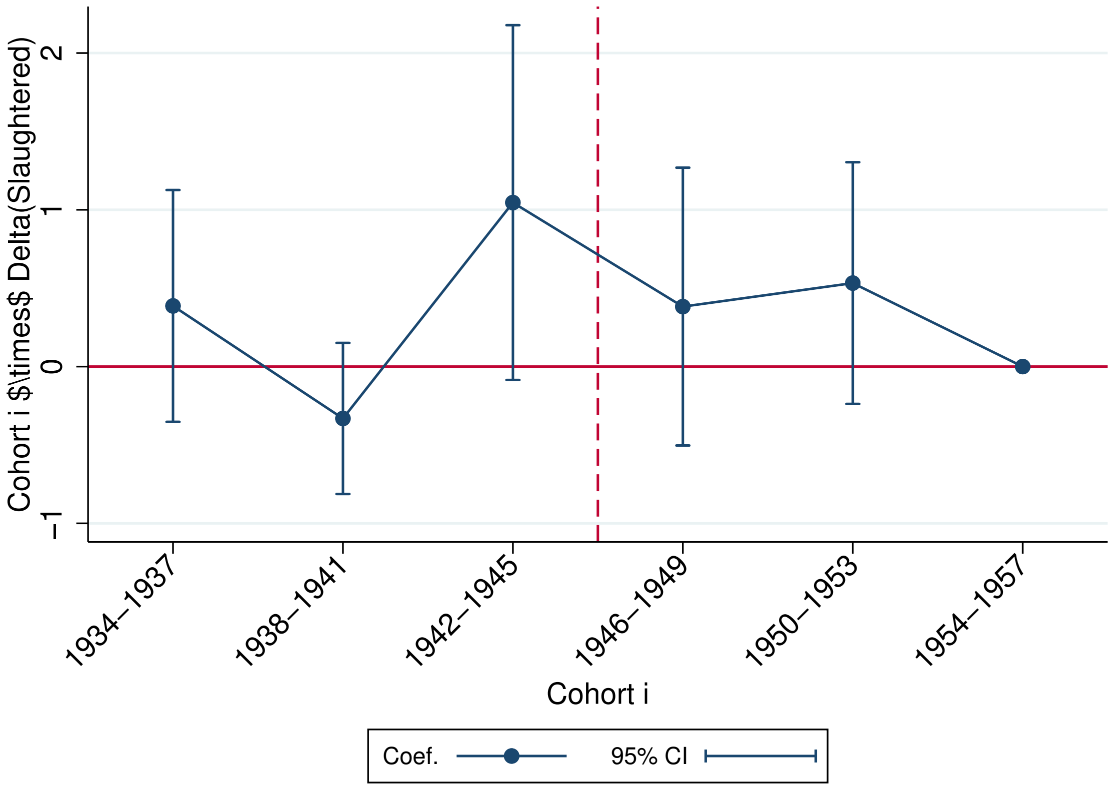
	(1) log(1+Savings)	(2) log(1+Savings)
Cohort i	-0.339	-0.313
	(-1.593)	(-1.627)
$\Delta(Slaughtered)$	-0.325	-0.212
	(-1.411)	(-1.008)
Cohort i $\times$ $\Delta(Slaughtered)$	0.772*	0.741*
	(1.981)	(1.970)
Female	-0.079	-0.084
	(-0.985)	(-1.017)
Age	-0.143	-0.185
	(-0.639)	(-0.854)
Age^2	0.001	0.002
	(0.655)	(0.895)
Parents high Education	-0.154**	-0.130*
	(-2.304)	(-1.918)
log(Net Income)	1.821***	1.976***
	(17.096)	(15.801)
log(Wealth)		-0.065
		(-1.005)
Retired		-0.135*
		(-1.705)
Home Owner		0.112
		(0.898)
Finance		-0.011
		(-0.112)
Health Insurance		-0.054
		(-0.731)
Education		-0.049
		(-1.160)
Marital Status		-0.071**
		(-2.081)
War Victims		-0.282*
		(-1.814)
Province FE	Yes	Yes
Observations	1984	1945
Adjusted R-squared	0.440	0.444

The table reports OLS estimates of meat scarcity during childhood on the amount of reported savings. The dependent variable is log(1+Savings). Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. Col. (1) includes only exogenous controls (demographics and socioeconomic of the family origin) and log(Net Income), Col. (2) includes additional controls: education, log(Wealth), retirement status, home ownership, working in the financial sector, having private health insurance, marital status, and the per capita casualties during the entire period of WWII at the province level. The definition of all variables is in Table B.II.

way we account for zero savings in the dependent variable, $log(1 + savings)$. In Table

B.I column (4), we repeat the benchmark analysis applying the inverse hyperbolic sine (arcsinh) transformation to the individuals' yearly savings. The effect of meat scarcity on savings remains positive and statistically significant.

Figure 3.5: **Effects of meat scarcity on savings**



Notes: Estimated coefficients of the interaction terms in the diff-in-diff specification and 95% confidence intervals. Standard errors are clustered at the province level. The dependent variable is the logarithm of the household's annual savings plus 1, $log(1 + Savings)$. Treated cohorts are born in 1934-1937, 1938-1941, and 1942-1945. Control cohorts are born in 1946-1949 and 1950-1953. Omitted cohort (comparison category) is born in 1954-1957. $\Delta(Slaughtered)$ is the % change in the number of slaughtered animals for meat consumption between 1941-42 and 1945.

Next, we exploit another unique feature of the 2004 SHIW wave, namely elicited information on precautionary savings. As described in section 2, respondents reported the amount of savings they would set aside to insure themselves against unexpected expenses. This allows us to investigate whether exposure to meat scarcity during childhood affects not only total savings but also their precautionary amount. Table

3.2 presents the results. In the baseline specification in columns (1) and (2), we

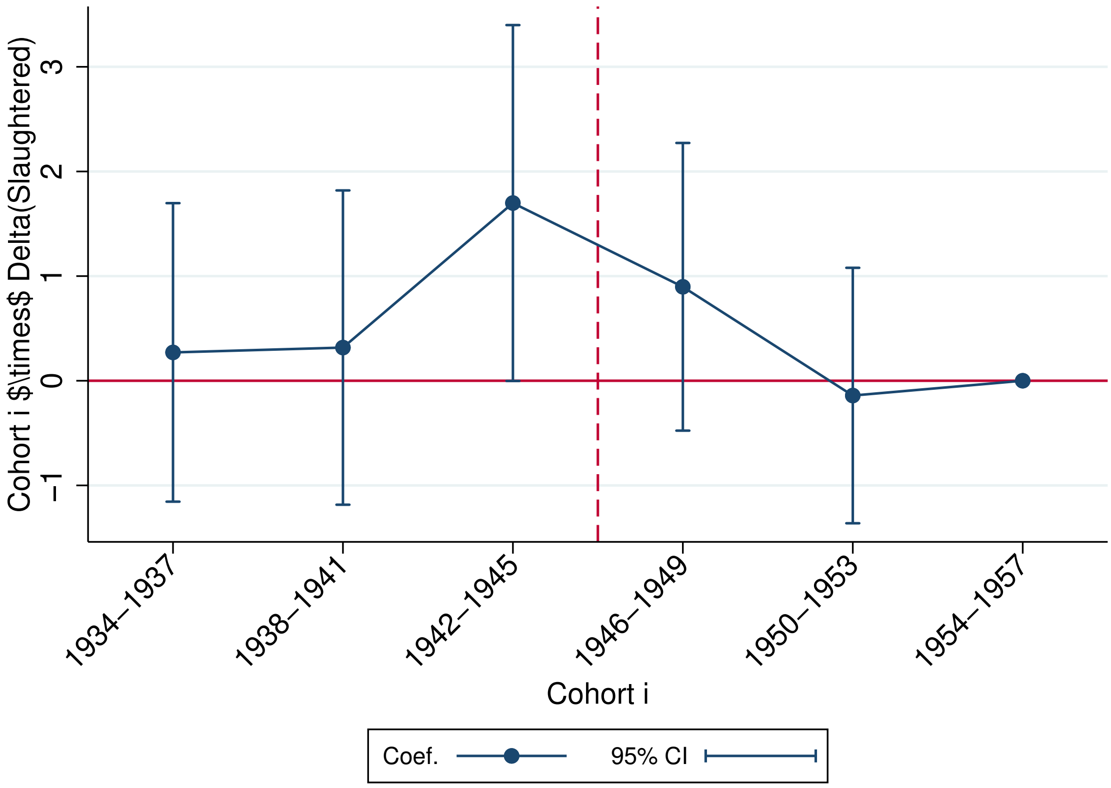
Table VII: **Effect of Meat Scarcity on Precautionary Savings**

	(1) log(Prec. Savings)	(2) log(Prec. Savings)	(3) log(Prec. Savings)	(4) log(Prec. Savings)
Cohort i	-0.011	-0.064	0.341	0.299
	(-0.049)	(-0.259)	(1.613)	(1.346)
$\Delta(Slaughtered)$	0.076	0.073	-0.152	-0.204
	(0.292)	(0.244)	(-0.402)	(-0.509)
Cohort i $\times$ $\Delta(Slaughtered)$	0.032	0.098	-0.998**	-0.985**
	(0.090)	(0.288)	(-2.271)	(-2.225)
$Recession_{t-1}$ $\times$ $\Delta(Slaughtered)$			0.265	0.315
			(0.478)	(0.569)
Cohort i $\times$ $Recession_{t-1}$			-0.619*	-0.623*
			(-1.934)	(-1.907)
Cohort i $\times$ $Recession_{t-1}$ $\times$ $\Delta(Slaughtered)$			1.564**	1.622**
			(2.089)	(2.132)
Female	0.081	0.080	0.077	0.081
	(1.057)	(0.946)	(1.010)	(0.930)
Age	-0.270	-0.211	-0.274	-0.219
	(-1.153)	(-0.805)	(-1.159)	(-0.827)
Age^2	0.003	0.002	0.003	0.002
	(1.130)	(0.795)	(1.137)	(0.819)
Parents high Education	-0.043	-0.111	-0.037	-0.108
	(-0.492)	(-1.258)	(-0.411)	(-1.189)
log(Net Income)	0.468***	0.250***	0.466***	0.246***
	(7.695)	(3.746)	(7.783)	(3.684)
log(Wealth)		0.142***		0.141***
		(4.946)		(4.840)
Retired		0.030		0.032
		(0.427)		(0.457)
Home Owner		-0.308***		-0.312**
		(-2.635)		(-2.625)
Finance		0.189		0.221
		(1.352)		(1.628)
Health Insurance		0.184*		0.182**
		(1.983)		(1.998)
Education		0.035		0.039
		(0.854)		(0.971)
Marital Status		0.051		0.048
		(1.264)		(1.154)
War Victims		-0.020		0.012
		(-0.105)		(0.066)
Province FE	Yes	Yes	Yes	Yes
Observations	2485	2403	2485	2403
Adjusted R-squared	0.293	0.296	0.295	0.298

The table reports OLS estimates of meat scarcity during childhood on the amount of reported precautionary savings. The dependent variable is log(Prec. Savings). Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. $Recession_{t-1}$ is a dummy equal to 1 if the respondent experienced a local recession the year before the survey took place. Cols. (1) and (3) include only exogenous controls (demographics and socioeconomic of the family origin) and log(Net Income), Cols. (2) and (4) include additional controls: education, log(Wealth), retirement status, home ownership, working in the financial sector, having private health insurance, marital status, and the per capita casualties during the entire period of WWII at the province level. The definition of all variables is in Table B.II.

find no statistically significant effect. However, when we account for different phases of the business cycle in a triple difference framework (equation 3.3) we do detect statistically significant effects. As columns (3) and (4) show, we find a positive effect but only among treated individuals who experienced a local recession in the year prior to the interview. Thus, individuals who were exposed to meat scarcity early in life allocate relatively more savings for precautionary purposes in the event of an economic downturn. The event study in Figure 3.6 shows that the effect is positive and statistically significant for the 1942-1945 cohort, i.e., those individuals aged 0-3 during WWII.

Figure 3.6: **Effects of meat scarcity on precautionary savings**



Notes: Estimated coefficients of the interaction terms in the diff-in-diff specification and 95% confidence intervals. Standard errors are clustered at the province level. The dependent variable is the logarithm of the household's reported annual precautionary savings, $log(Precaut.Savings$. Treated cohorts are born in 1934-1937, 1938-1941, and 1942-1945. Control cohorts are born in 1946-1949 and 1950-1953. Omitted cohort (comparison category) is born in 1954-1957. $\Delta(Slaughtered)$ is the % change in the number of slaughtered animals for meat consumption between 1941-1942 and 1945.

3.5 Conclusions

Past experiences exert a significant influence on various economic decisions, including savings and belief formation. Building upon this understanding, our study explores the impact of past experiences on time preferences, specifically patience, which is a critical parameter in economic decision-making. We contribute to the understanding of the heterogeneity of time preferences and show that it is crucial to consider a long-term perspective. We provide compelling evidence that individuals exposed to meat scarcity during childhood exhibit greater levels of patience later in life.

Using hand-collected historical archives and rich survey data, we examine the causal effects of an arguably exogenous local shock to meat availability during childhood on later outcomes, employing a difference-in-differences framework. We find that individuals more exposed to meat scarcity in their early years tend to be more patient and save more in adulthood.

To understand the underlying mechanisms, we consider other food groups' availability (i.e., proteins, carbohydrates, and vitamins). Our results indicate that only the scarcity of high-protein foods, such as meat and legumes, impacts individuals' patience levels. This suggests that a potential biological influence may be at play as the lack of proteins during gestation and early childhood is known to affect children's cognitive abilities and brain development. However, we cannot rule out a potential behavioral channel given the importance of the first years of life in preferences formation.

Furthermore, we find that exposure to meat scarcity during childhood increases individuals' propensity to save later in life. Treated individuals who experienced meat scarcity tend to save more (conditional on income), and increase precautionary savings in the aftermath of a recession at the local level. Our findings provide valuable insights into the intricate relationship between early-life experiences, time preferences, and saving behavior. Understanding the dynamics of this relationship is crucial given the pivotal role of saving behavior in household economic planning and its implications for household poverty and overall economic growth.

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Appendix A

Figure A.1: **An extract of the Annual Agricultural Statistics 1943-1946**

468 ANNUARIO STATISTICO DELL'AGRICOLTURA ITALIANA 1943-1946

Segue : TAV. 228 — Bestiame macellato nei comuni con oltre 5.000 abitanti (*)

Segue : a) NUMERO DEI CAPI, PESO VIVO E PESO MORTO, IN QUINTALI, PER SPECIE NEGLI ANNI 1945 E 1946

Numero d'ordine	CIRCOSCRIZIONI	BOVINI 1945 Capi	BOVINI 1945 Peso vivo	BOVINI 1945 Peso morto	BOVINI 1946 Capi	BOVINI 1946 Peso vivo	BOVINI 1946 Peso morto	EQUINI 1945 Capi	EQUINI 1945 Peso vivo	EQUINI 1945 Peso morto	EQUINI 1946 Capi	EQUINI 1946 Peso vivo	EQUINI 1946 Peso morto
60	Campobasso	2.629	6.080	3.074	2.211	4.998	2.558	33	70	32	35	64	32
61	Chieti	4.203	9.834	5.024	4.081	10.358	5.262	96	195	90	344	684	313
62	L'Aquila	6.610	13.927	6.969	6.156	11.939	6.360	185	385	173	228	457	218
63	Pescara	4.018	11.223	5.676	4.432	11.653	6.048	53	133	62	65	142	71
64	Teramo	4.486	14.190	7.038	8.625	24.293	12.380	—	—	—	1	2	1
65	Avellino	3.564	10.365	5.012	4.339	12.163	6.118	—	—	—	—	—	—
66	Benevento	2.857	6.816	3.441	2.403	5.224	2.729	—	—	—	—	—	—
67	Caserta	6.554	21.342	10.436	7.549	22.911	11.348	1.301	2.812	1.371	914	1.935	939
68	Napoli	45.537	138.992	70.781	51.494	146.036	75.005	938	3.580	1.642	696	2.700	1.239
69	Salerno	9.835	27.131	13.587	12.937	33.360	17.078	946	1.772	831	498	983	454
70	Bari	11.759	31.154	15.491	18.373	49.363	24.743	10.154	24.447	11.194	10.619	24.649	10.810
71	Brindisi	4.442	13.104	6.370	4.836	14.291	6.929	863	1.920	894	1.050	2.232	1.007
72	Foggia	6.199	16.536	8.215	5.260	14.208	7.218	891	2.347	1.056	957	2.367	1.109
73	Ionio (Taranto)	5.520	18.126	8.604	6.592	22.307	10.920	2.314	5.261	2.438	3.226	7.350	3.270
74	Lecce	2.857	8.491	4.213	5.908	16.238	8.266	1.387	3.035	1.405	1.958	4.258	1.913
75	Matera	719	1.916	914	681	1.652	801	17	53	23	15	33	17
76	Potenza	1.816	3.328	1.664	1.400	2.390	1.211	10	27	12	11	26	12
77	Catanzaro	6.321	19.836	9.416	5.250	16.208	7.768	6	23	11	4	13	7
78	Cosenza	3.707	9.407	4.604	3.086	7.932	3.980	38	80	37	31	80	37
79	Reggio di Calabria	6.945	19.543	9.803	7.502	19.120	9.719	372	584	275	146	266	120
80	Agrigento	2.819	8.665	4.244	2.643	8.067	3.982	—	—	—	—	—	—
81	Caltanissetta	2.835	8.373	4.191	2.422	7.470	3.834	103	201	92	92	180	80
82	Catania	18.653	58.849	29.176	17.987	55.164	28.159	1.640	3.496	1.613	859	1.856	836
83	Enna	1.460	4.510	2.156	1.355	4.289	2.041	—	—	—	—	—	—
84	Messina	10.988	34.623	17.761	12.655	37.180	19.121	52	95	46	116	196	92
85	Palermo	15.674	45.992	23.827	15.855	45.222	23.523	2.587	5.924	2.700	1.607	3.449	1.568
86	Ragusa	4.491	11.211	5.725	4.212	10.370	5.461	—	—	—	—	—	—
87	Siracusa	5.731	16.931	8.177	5.208	15.399	7.652	63	123	56	109	248	109
88	Trapani	3.569	10.254	5.148	4.702	13.423	6.915	352	655	304	213	458	201
89	Cagliari	13.626	42.881	20.089	13.354	41.736	19.758	369	829	387	1.028	1.942	958
90	Nuoro	1.744	5.186	2.491	1.352	4.128	2.000	4	7	3	3	7	3
91	Sassari	10.120	28.715	13.757	6.698	19.163	9.336	293	797	375	367	861	409

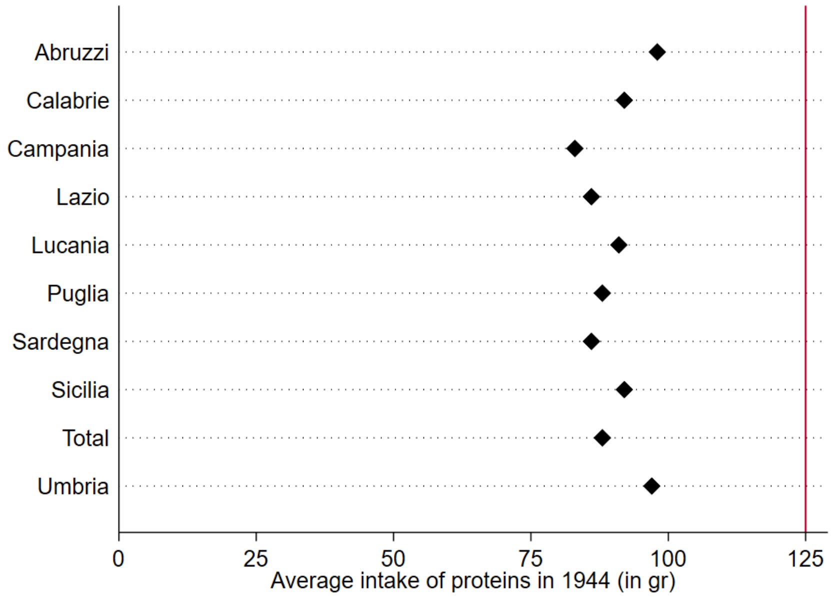
CAPITOLO XI — AMMASSI E CONSUMI ALIMENTARI 469

OVINI E CAPRINI 1945 Capi	OVINI E CAPRINI 1945 Peso vivo	OVINI E CAPRINI 1945 Peso morto	OVINI E CAPRINI 1946 Capi	OVINI E CAPRINI 1946 Peso vivo	OVINI E CAPRINI 1946 Peso morto	SUINI 1945 Capi	SUINI 1945 Peso vivo	SUINI 1945 Peso morto	SUINI 1946 Capi	SUINI 1946 Peso vivo	SUINI 1946 Peso morto	Numero d'ordine
18.535	2.644	1.502	38.280	4.855	2.808	13.384	11.950	9.621	14.954	13.791	10.918	60
14.771	2.400	1.373	23.433	3.821	2.301	6.634	6.098	4.834	12.412	11.817	9.357	61
13.329	2.949	1.523	26.307	5.486	2.931	12.354	13.068	10.599	16.091	15.707	12.522	62
8.195	1.667	890	21.729	4.223	2.387	6.284	6.233	4.630	6.837	7.333	5.823	63
10.952	1.865	997	33.005	4.699	2.621	14.702	15.466	12.694	17.733	20.492	16.496	64
18.018	3.214	1.731	30.805	5.115	2.885	17.989	17.183	13.780	18.632	18.280	14.391	65
18.077	2.723	1.491	27.769	4.413	2.488	11.471	10.681	8.634	11.325	10.705	8.477	66
10.146	1.317	759	12.313	1.490	862	10.622	9.066	7.222	13.234	11.706	9.243	67
109.057	15.383	9.189	115.786	13.681	8.241	44.977	44.815	35.514	56.792	59.154	46.681	68
22.261	2.628	1.502	28.802	3.874	2.185	21.105	18.180	14.447	32.279	29.172	23.066	69
167.827	29.707	15.722	224.911	39.311	20.894	12.861	10.653	8.409	14.249	11.350	8.844	70
23.613	3.867	2.071	29.249	4.646	2.500	2.667	2.148	1.690	4.413	3.513	2.786	71
101.625	17.344	9.367	169.202	30.973	17.044	20.091	18.186	14.597	20.640	17.751	13.975	72
43.102	6.532	3.589	57.626	9.232	4.935	4.718	3.887	3.063	7.422	6.030	4.697	73
7.611	1.023	567	15.044	2.279	1.249	3.303	2.829	2.213	5.460	4.295	3.343	74
24.985	3.765	2.090	29.508	4.573	2.518	10.448	7.358	5.816	7.269	4.840	3.798	75
27.335	3.941	2.163	42.932	5.527	3.097	14.735	11.221	8.800	18.703	13.895	10.980	76
23.732	4.185	2.276	49.104	8.048	4.376	16.745	14.505	11.480	23.538	19.742	15.668	77
28.716	4.918	2.656	61.724	9.190	5.134	21.341	19.006	15.002	24.808	21.453	17.078	78
20.077	3.304	1.800	35.786	5.505	3.038	14.832	12.157	9.722	16.668	13.206	10.389	79
26.147	5.852	2.971	38.717	8.209	4.257	6.989	4.899	3.796	8.454	5.614	4.317	80
16.604	3.776	1.947	24.241	5.337	2.764	6.316	3.879	2.921	6.511	4.351	3.338	81
25.563	3.083	1.725	45.974	4.692	2.656	16.056	11.492	9.108	23.012	17.386	13.540	82
14.452	2.662	1.388	23.033	3.935	2.146	5.980	3.721	2.901	8.089	6.327	4.987	83
25.660	4.333	2.303	33.758	5.686	3.069	13.476	10.966	8.734	13.191	9.693	7.549	84
18.458	4.192	2.129	23.450	4.858	2.571	5.933	4.276	3.231	13.051	9.391	7.429	85
9.681	1.522	823	13.066	2.046	1.110	3.932	2.784	2.180	5.948	4.713	3.716	86
13.131	1.921	1.029	17.599	2.317	1.281	4.356	3.024	2.364	5.940	4.707	3.690	87
10.598	1.411	764	17.398	1.899	1.046	3.346	2.204	1.722	5.680	3.881	3.001	88
63.834	9.406	5.144	135.365	16.039	8.778	14.338	8.267	6.497	11.042	8.198	6.508	89
30.372	3.607	2.050	19.886	2.206	1.195	1.460	1.046	820	1.482	1.286	1.016	90
78.652	8.764	4.957	103.144	9.768	5.370	11.032	7.989	6.245	8.951	7.631	6.105	91

Notes: An extract of the 1943-1946 slaughtered meat that we digitized. We consider the sum of cattle, pigs, poultry, goats and sheep to measure the availability of meat in each province region.

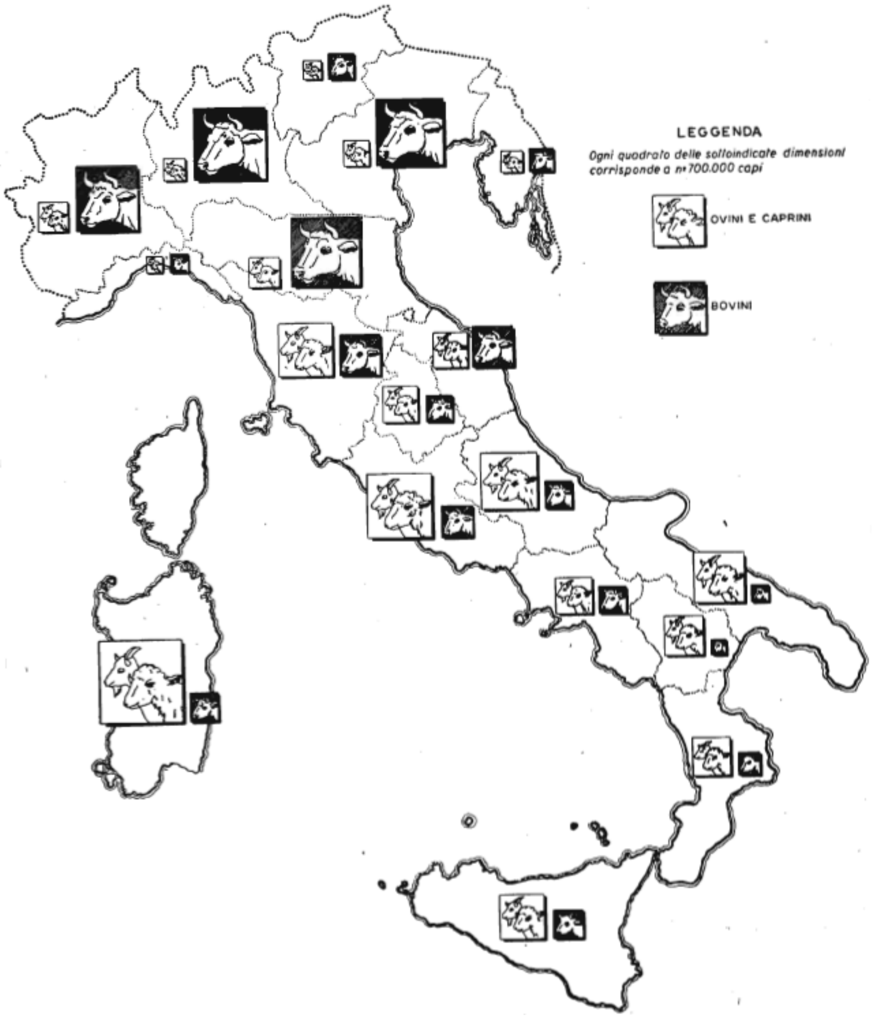
Source: Statistical Summary of the Italian Regions, ISTAT (1947).

Figure A.2: **Average daily protein intake and minimum requirements for heavy labor in 1944**



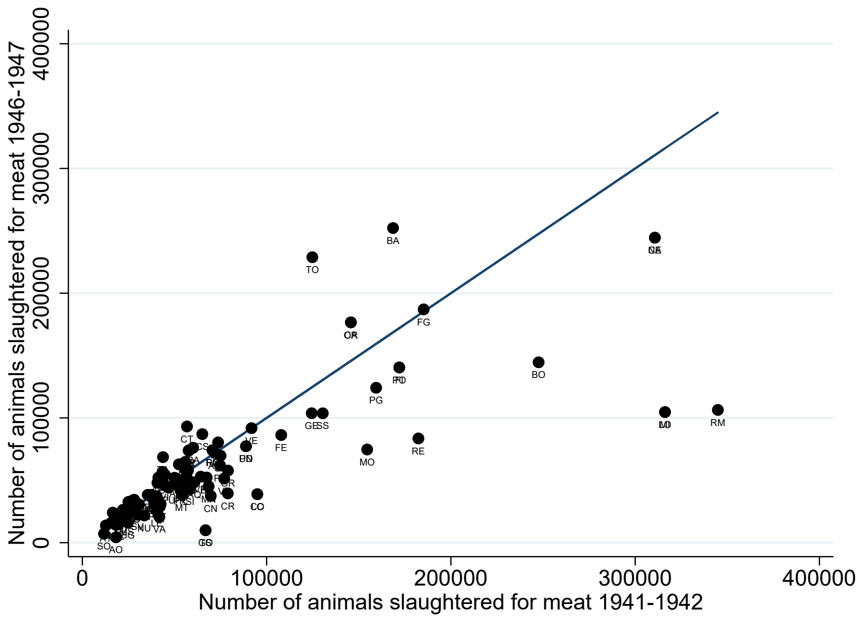
Notes: The figure shows the average daily protein intake in a set of regions with available data (liberated territory) in 1944. The red vertical line represents the minimum requirement for a person who does heavy muscular work. The average daily intake was between 20 and 35% lower than the minimum requirement.
Sources: Census and Surveys for the National Reconstruction, Survey on Living Conditions-Nutrition, p. 137-142, ISTAT (1945).

Figure A.3: **Distribution of livestock across the Italian territory in 1942**



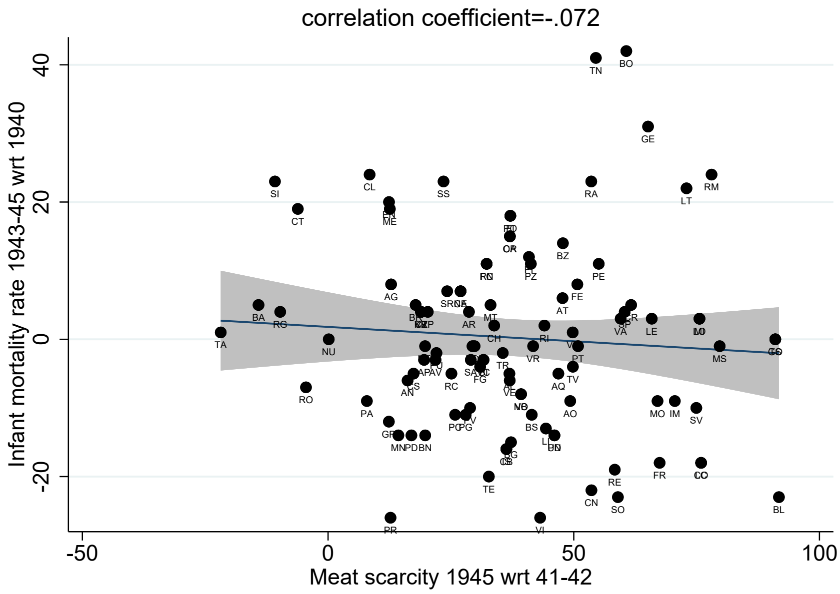
Notes: The figure shows that livestock was widespread all over the Italian territory. Cattle was more common in the North while goats and sheep were more common in the Center-South.
Source: Statistical Summary of the Italian Regions, ISTAT (1947).

Figure A.4: **Recovery of number of slaughtered animals for meat after the end of WWII**



Notes: The figure shows that the number of slaughtered animals for meat in 1946-1947 had recovered to its 1941-1942 "Steady State" in most provinces.
Source: Annual Agricultural Statistics, ISTAT (1948, 950a)

Figure A.5: **Correlation between meat scarcity and infant mortality at the province level**



Notes: The figure shows that infant mortality during WWII was not significantly correlated with meat scarcity at the province level.
Source: Supplemento straordinario alla Gazzetta Ufficiale n. 63 del 15 marzo 1948.

Table A.I: **Summary Statistics**

	Mean	SD	Median	Min	Max	N
Patience	3.63	1.71	3.00	1.00	6.00	2,558
Impatient	0.10	0.30	0.00	0.00	1.00	2,558
log(Savings)	8.30	1.18	8.45	2.06	11.87	2,009
log(Precaut. Savings)	9.65	1.42	9.77	0.39	13.36	2,547
$\Delta(Slaughtered)$	0.35	0.22	0.30	0.00	0.92	2,499
Cohort i	0.23	0.42	0.00	0.00	1.00	2,558
War Victims	0.48	0.25	0.42	0.07	1.30	2,499
Female	0.32	0.47	0.00	0.00	1.00	2,558
Age	54.49	4.46	54.00	47.00	62.00	2,558
Parental High Education	0.20	0.40	0.00	0.00	1.00	2,558
log(Net Income)	9.63	0.63	9.68	5.70	12.11	2,556
log(Wealth)	11.68	1.68	12.09	4.33	15.59	2,464
Retired	0.27	0.44	0.00	0.00	1.00	2,558
Home Owner	0.75	0.43	1.00	0.00	1.00	2,558
Finance	0.02	0.15	0.00	0.00	1.00	2,558
Health Insurance	0.09	0.28	0.00	0.00	1.00	2,558
Education	3.28	1.00	3.00	1.00	6.00	2,558
Marital Status	1.48	0.93	1.00	1.00	4.00	2,558

The table reports the summary statistics for the main variables used in the analysis. The definition of all variables is in Table B.II.

Appendix B

Table B.I: **Effects of Meat Scarcity: Additional Robustness**

	(1) Impatient Probit	(2) Patience OLS	(3) Patience OLogit	(4) asinh(Savings)
Cohort i	1.342***	-0.633***	-0.895***	-0.319
	(5.322)	(-2.685)	(-2.923)	(-1.639)
$\Delta(Slaughtered)$	0.482	-0.421	-0.535	-0.235
	(1.287)	(-1.474)	(-1.557)	(-1.076)
Cohort i $\times$ $\Delta(Slaughtered)$	-1.786***	1.278***	1.725***	0.759*
	(-3.652)	(3.330)	(3.375)	(1.967)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	1930	2414	2415	1945
Adjusted R-squared		0.133		0.425

The table reports the estimates of meat scarcity during childhood on individuals' reported patience and savings. Cohort i is a dummy equal to 1 if born in 1942-1945 and 0 if born in 1946-1957. $\Delta(Slaughtered)$ is the % change in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province in absolute terms. Col. (1) reports the estimates of Eq. 3.1 using a Probit model, Col. (2) reports the OLS estimate of Eq. 3.1 using Patience (an ordinal variable, where higher values indicate greater levels of patience) as the dependent variable, Col. (3) reports the estimate of Eq. 3.1 using Patience as the dependent variable and an Order-Logit model, Col. (4) estimates the effect of meat scarcity on savings applying the inverse hyperbolic sine (arcsinh) transformation to the individuals' yearly savings. The definition of all variables is in Table B.II.

Table B.II: **Variable Definition**

Variable description	Type	Values
Impatient	binary	1 if willing to renounce 20% of a hypothetical lottery win equal to the annual net household income to receive it immediately instead of waiting for a year 0 otherwise
Patience	ordinal	1 if willing to renounce 20% of the hypothetical lottery 2 if willing to renounce 10% of the hypothetical lottery 3 if willing to renounce 5% of the hypothetical lottery 4 if willing to renounce 3% of the hypothetical lottery 5 if willing to renounce 2% of the hypothetical lottery 6 if not willing to renounce 2% of the hypothetical lottery
Household Savings	continuous	annual, nominal, in euros
Precaut. Savings	continuous	annual, nominal, in euros
$\Delta(Slaughtered)$	continuous	absolute percentage difference in the number of animals slaughtered for meat between the 1941-42 average and that of 1945 in each province.
War Victims	continuous	number of casualties per 1000 population at the province level during WWII
Female	binary	1 if female 0 otherwise
Age	continuous	in years
Parental High Education	binary	1 if at least one parent has a middle school degree or higher 0 otherwise
Household Net Income	continuous	annual, nominal, in euros
Household Wealth	continuous	annual, nominal, in euros
Retired	binary	1 if the individual has retired from work 0 otherwise
Home Owner	binary	1 if the household owns the house 0 otherwise
Finance	binary	1 if working in the financial sector 0 otherwise
Health Insurance	binary	1 if own additional private health insurance 0 otherwise
Education	ordinal	1 if no education 2 if elementary school degree 3 if middle school degree 4 if high school degree 5 if university degree 6 if masters/PhD degree
Marital Status	ordinal	1 if married 2 if single 3 if divorced 4 if widow/widower

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Early Life Conditions, Patience, and Savings, with Effrosyni Adamopoulou & Eleftheria Triviza