September 10, 2026

Emily Breza, Arun Chandrasekhar, and Davide Viviano
Workshop Organizers
National Bureau of Economic Research

Dear Professors Breza, Chandrasekhar, and Viviano,

I am a fifth-year PhD student in economics at the University of Virginia, currently writing my dissertation. For the 2026 NBER Workshop on Development Economics and Networks, I propose to present "The Value of Network Position: Evidence from Taiwan's Top Investors," coauthored with Ming-Jen Lin.

The paper studies whether changes in an investor's position within a co-investment network affect wealth accumulation. Using administrative data from Taiwan, we construct a private-firm co-investment network and exploit deaths of connected investors as plausibly exogenous shocks to its structure. In a stacked difference-in-differences design, surviving co-investors who are not the deceased's spouse, parent, or child lose approximately 0.07 in log wealth after three years. This decline is concentrated among survivors whose PageRank centrality falls because their access to the rest of the network ran through the deceased; survivors whose centrality rises experience no detectable loss. Because every survivor of the same death loses a direct tie, this contrast suggests that the cost of a lost connection depends on the change it induces in network position, not on the lost tie alone.

Workshop feedback at this stage could strengthen the interpretation of the paper's findings and guide its next steps. I hope to refine how death-induced link losses translate into changes in network position and to distinguish information from investment-opportunity channels. I also want to understand how far the results travel. Business in Taiwan runs to an unusual degree through family groups and long-standing personal relationships, where network position is plausibly most valuable; the same disruption may matter less where investment is more arm's-length. The workshop would provide a valuable setting to discuss these questions with researchers working on development economics and economic networks.

If I am shortlisted, Lee M. Lockwood, Professor of Economics at the University of Virginia, has agreed to provide a recommendation and may be contacted at leelockwood@virginia.edu.

Sincerely,

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RESEARCH FIELDS

Economics of Networks, Household Finance, Behavioral Economics

EDUCATION

University of Virginia, Charlottesville, VA 2022–Present
PhD Economics

Syracuse University, Syracuse, NY 2021–2022
Ph.D. studies in Economics

National Taiwan University, Taipei, Taiwan 2017–2019
M.A. Economics

National Chengchi University, Taipei, Taiwan 2010–2014
B.A. Economics

WORKING PAPERS

The Value of Network Position: Evidence from Taiwan's Top Investors with Ming-Jen Lin

We study whether changes in network position affect wealth accumulation among top investors. Using administrative data from Taiwan, we build a co-investment network and exploit deaths of connected investors as plausibly exogenous shocks to network structure.

The Optimal Menu Mechanisms in a Market for Lemons with Cursed Traders with Po-Hsuan Lin

We study mechanism design in a market for lemons under Cursed Sequential Equilibrium. Within a menu mechanism framework, we characterize buyer-optimal, seller-optimal, and socially optimal mechanisms and show how trade and surplus depend on cursedness.

PhD COURSEWORK

Syracuse University PhD Economics

Core and Methods: Mathematics for Economists; Foundations of Econometrics; Microeconomic Analysis; Microeconomics I; Econometrics I

University of Virginia PhD Economics

Current (Fall 2026): Experimental Economics

Core and Methods: Mathematical Economics I; Microeconomic Theory I; Macroeconomic Theory I; Econometrics I; Microeconomic Theory II; Macroeconomic Theory II; Econometrics II; Microeconomic Theory III; Cross-Section Econometrics

Fields and Electives: Development Economics; Labor Economics and Development; Public Economics I (separate offerings in Fall 2023 and Spring 2024); Economics of Labor Markets; Industrial Organization I; Industrial Organization II; Empirical Industrial Organization: Demand and Retail

Workshops: Public Economics Workshop; Industrial Organization Workshop

HONORS AND AWARDS

Graduate Study Fulbright Partial Grant 2020
J. William Fulbright Foreign Scholarship Board

College Student Research Scholarship 2013
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RESEARCH EXPERIENCE

Research Assistant 2025
Alexander J. MacKay, Associate Professor, University of Virginia

Research Assistant 2019–2021
Ming-Jen Lin, Professor, National Taiwan University

Research Assistant 2018–2019
Wen-Jen Tsay, Research Fellow, Academia Sinica

TEACHING EXPERIENCE

Teaching Assistant 2023–2025
University of Virginia: Intermediate Microeconomics, Principles of Economics

Teaching Assistant 2017–2019
National Taiwan University: Principles of Economics

SKILLS

Stata, Python, Julia, LaTeX

LANGUAGES

Mandarin (native), English (fluent)

Motivation and Current Research Interests

Pin-Chao Wang

My interest in networks began with my undergraduate thesis on peer effects. That project first led me to consider how individual decisions depend on the people around them. I later worked as a research assistant for Professor Ming-Jen Lin on a project studying social influence on household equity investment. The project examines whether peers formed through random assignment to military units affect investment decisions later in life. These experiences showed me how social relationships can have lasting economic consequences and motivated me to study networks more systematically.

When I began studying network economics, I was drawn to the way its mathematical structure, especially its use of linear algebra, translates complicated patterns of interaction into clear economic intuition. Network theory also gave me a broader way to think about peer effects. An individual's outcomes may depend not only on direct connections, but also on the individual's position within a larger system of relationships. This shifted my interest from asking whether peers matter to asking how network structure affects access to information, opportunities, and capital.

While developing my dissertation research, I recognized that Taiwan's administrative records offer an unusual opportunity to study these questions. Ownership records for registered firms, including private firms, make co-investment relationships observable when they would ordinarily be difficult to measure. Linked household-registration records also identify each investor's spouse, parents, and children, which separates inheritance from the disruption of business connections. These features led to my current paper, "The Value of Network Position: Evidence from Taiwan's Top Investors." The paper uses deaths of connected investors as plausibly exogenous shocks to study whether changes in an investor's co-investment network position affect wealth accumulation. Its findings suggest that the cost of losing a connection depends on how the loss changes an investor's position in the network, not on the lost tie alone.

Because this research lies at the intersection of network economics and household finance, the workshop would provide a valuable opportunity to receive specialized feedback on the measurement and interpretation of network position, the mechanisms behind its effects, and the extent to which the findings may extend to other populations and institutional settings. It would also help me develop a broader research agenda on how social and business networks shape investment, access to capital, and wealth accumulation.

The Value of Network Position: Evidence from Taiwan's Top Investors

Pin-Chao Wang Ming-Jen Lin*

September 10, 2026

Preliminary results. Please do not cite or circulate without the authors' permission.

Abstract

We estimate how changes in network position affect wealth accumulation among top investors. Using Taiwanese administrative data, we build a co-investment network from private firms and use deaths of connected investors as plausibly exogenous shocks to it. In a stacked difference-in-differences design, exposure to the death of an inheritance-relevant tie raises log wealth by about 0.14 after three years, while exposure to a non-heir connection's death lowers it by about 0.07. Among non-heirs, the loss falls on survivors whose access to the rest of the network ran through the deceased; those left more central to what remains show no detectable loss. The cost of a lost connection depends on the change it induces in the survivor's network position, not on the lost tie alone.

Keywords: investment networks, network position, wealth accumulation, causal identification

JEL Codes: D85, G11, Z13

*Wang: University of Virginia (pcwang@virginia.edu); Lin: National Taiwan University (mjlin@ntu.edu.tw). The data are provided by Taiwan's Ministry of Finance through a data-sharing agreement with Academia Sinica. The authors thank the AI assistants for their support. All generated content was fully verified by the authors, and any remaining errors are solely our own.

1 Introduction

Economic activity is embedded in networks of social and business relationships. Information and investment opportunities often travel through personal ties, and those ties can also facilitate coordination. A large literature shows that who people know affects what they learn, how they behave, and what opportunities they receive (Bailey et al. 2018; Kuchler and Stroebel 2021). But direct contacts are only part of the story. Economic outcomes may also depend on where an individual sits in the broader network.

Network position is distinct from direct peer exposure or the mere presence of a connection. It is a structural property of an individual's location in the overall graph. Theory gives reason to expect such position to matter for behavior, learning, and economic outcomes (Ballester, Calvó-Armengol, and Zenou 2006; Golub and Jackson 2010). Empirically, however, its effect is hard to identify. Successful individuals may also be better able to form valuable ties, making network position endogenous to economic success.

We study this question among top investors in Taiwan, a setting in which network position is likely to be economically consequential and empirically visible. These top investors are selected by equity wealth, placing them in an investment space where access to partners, information, and opportunities may be especially important. The administrative records combine individual wealth, firm ownership, and mortality, allowing us to observe both the co-investment ties that define the network and the wealth paths that follow connection loss. We use private firm co-investment ties to construct the network and total wealth accumulation as the main outcome.

Our empirical design exploits deaths of wealthy co-investors as shocks to network structure. Using a stacked difference-in-differences design, we compare investors exposed to the death of a connected investor with otherwise similar top investors who are not exposed to that event. In the main event-study specification, exposure to the death of an inheritance-relevant tie raises log wealth by 0.140 after three years (SE = 0.035). By contrast, non-heir deaths reduce log wealth by 0.074 at the same horizon (SE = 0.021). These two estimates highlight different channels. The positive effect of inheritance-relevant deaths is consistent with wealth transfers within families, while the negative effect of non-heir deaths is consistent with evidence that losing connections reduces subsequent outcomes (Azoulay, Graff Zivin, and Wang 2010; Waldinger 2012).

We next ask whether the negative non-heir effect depends on how the death changes the survivor's network position. We measure position with PageRank centrality. Because PageRank sums to one across investors, removing an investor's links lowers some positions and raises others. For each death we recompute PageRank on the base-year network with the deceased's ties removed and compare it with the survivor's position before the death. A survivor whose access to the rest of the network ran through the deceased loses position; one who absorbs the routing role the deceased used to play gains it.

Among non-heir exposures, the effect three years after the event is -0.104 when the survivor's PageRank falls (SE = 0.028), compared with -0.014 when it rises (SE = 0.024), an estimate statistically indistinguishable from zero. Thus, the cost of losing a connection depends on the induced change in network position, not only on the disappearance of a direct co-investment tie.

The paper relates first to work showing that social and financial networks shape economic decisions and opportunities. Measures of social connectedness are strongly related to economic mobility (Chetty et al. 2022a; Chetty et al. 2022b); social interactions shape household and investor financial decisions (Kuchler and Stroebel 2021); and randomly assigned military peers affect equity-market participation in Taiwan (Chi et al. 2025). These papers show that relationships can affect economic behavior, but they do not identify how changes in an investor's position in an investment network affect wealth accumulation.

The closest empirical literature links network centrality to investment performance. Better-networked venture-capital firms have better investment outcomes (Hochberg, Ljungqvist, and Lu 2007), and more central stock-market investors earn higher returns and trade earlier around information events (Ozsoylev et al. 2014). These relations may partly reflect successful investors becoming central. Rossi et al. (2018) address this concern with a natural experiment, in which a merger of two pension-fund consultants shifts the centrality of the fund managers attached to them. Our variation comes instead from the deaths of connected investors. Survivors of the same death all lose a direct tie, yet some gain network position while others lose it, so comparing them separates the change in position from the loss of the tie.

The remainder of the paper is organized as follows. Section 2 describes the data and the co-investment network, and Section 3 defines network position. Sections 4 and 5 present the design and results, Section 6 examines alternative explanations, and Section 7 concludes.

2 Setting, Data, and Measurement

2.1 Data

We use administrative records collected by Taiwan's Ministry of Finance. The data cover five main registers. The equity-holdings registry records the shareholders of all registered firms in Taiwan, including both listed and private firms, together with their ownership stakes and associated capital each year. Registered asset records identify individual holdings of land, houses, and bonds. Personal income tax records report interest income paid by financial institutions, which we use to infer savings. Corporate income tax records provide annual balance sheets for registered firms. Finally, household registration records give birth dates, death dates, spousal and parental links, sex, and residential information for citizens. The sample period is 2006 to 2021.

2.2 Effective Ownership

We observe direct ownership in registered firms, but this is not always the final ownership of an individual. Wealthy investors often hold firms through shell companies or other private companies. If an individual owns Company A, and Company A owns Company B, then the individual also indirectly owns Company B. Ownership chains can also involve cross-holdings, where firms own each other directly or indirectly. These circular structures make it difficult to infer an individual's final exposure from direct shareholdings alone.

We trace these corporate layers using a Neumann-series expansion. Let A record direct ownership by companies in all registered firms. Let S record the subset of these links where the firm being owned is also a company that owns other firms. Effective corporate holdings are then

$$E = A + SA + S^2A + \cdots .$$

We then assign these holdings back to individuals. Let D_{pF} be individuals' direct ownership in firms, and let D_{pC} be individuals' direct ownership in corporate intermediaries. Each individual's effective ownership is

$$H = D_{pF} + D_{pC}E,$$

which combines direct ownership with ownership held through companies.

2.3 Measuring Wealth

The outcome of interest is individual wealth, which we measure using administrative records. Land and housing are valued using government-assessed values adjusted with transaction records. Savings are inferred from interest income paid by financial institutions, and registered bonds are observed in asset records.

For listed firms, equity holdings are valued at market prices. Valuing private firms is more difficult because they are not publicly traded. We use corporate tax records to estimate firm value. For each private firm, we start from an adjusted book-value measure based on its annual financial statement. Some private firms also hold listed stocks. For these firms, we calculate the market value of the listed-stock portfolio and use the larger of this portfolio value and the adjusted book value as the firm's value.

We assign private-firm value to investors in proportion to their effective ownership stakes. Equity wealth is the sum of listed-firm holdings and effective stakes in private firms. Individual wealth is the sum of equity wealth, land, housing, registered bonds, and savings.

2.4 Investor Sample

The empirical analysis focuses on the top 10,000 Taiwanese personal investors by equity wealth in the 2010 base year. We focus on natural persons because they are the individuals behind many corporate holding chains, including shell and investment companies. Restricting the sample to Taiwanese citizens allows us to link investment records to household-registration records, including demographics, family ties, and mortality.

This population is useful for the paper's question for two reasons. First, selection by equity wealth focuses the analysis on investors with meaningful stakes in firms, rather than on wealthy individuals whose assets are primarily held outside business activity. These investors operate in a setting where access to partners, information, and private investment opportunities is especially likely to matter. Second, they control economically meaningful amounts of capital, so their wealth trajectories are directly relevant for capital allocation at the top of the distribution. These investors' business relationships are embodied in jointly held private firms, while the consequences of losing a relationship can surface anywhere in their portfolios; we accordingly measure relationships with co-investment in private firms and outcomes with total wealth.

2.5 The Co-Investment Network

We construct an undirected co-investment network among the top 10,000 personal investors in 2010. Two investors are linked if they jointly hold effective ownership stakes of at least 5% in the same private firm. We call this a *co-investment tie*. Ties are undirected because co-ownership is mutual: both parties hold a stake in the same firm, so neither side of the tie comes first.

Formally, let $\mathcal{I}$ denote the set of investors and $\mathcal{F}$ the set of all private firms. Investor i and investor j are connected in the base year if there exists at least one firm $f \in \mathcal{F}$ such that both $s_{if} \geq 0.05$ and $s_{jf} \geq 0.05$, where s_{if} is the effective shareholding of investor i in firm f, resolved through indirect ownership chains via the Neumann-series algorithm. The resulting graph $G = (\mathcal{I}, E)$ captures the structure of co-committed private capital in the base year.

This definition has two important properties. First, co-investment ties represent realized capital commitments: both parties have meaningful ownership stakes in the same enterprise. Unlike social-network links inferred from communication records, geographic proximity, or correlated trading (Ozsoylev et al. 2014), these edges are economically consequential by construction. Second, indirect shareholding chains are resolved before edge formation. If investor i controls firm A, which in turn holds a stake in firm B alongside investor j, the indirect exposure is credited to i before the threshold test.

Figure 2.1 illustrates the construction. Investors A, B, and C each hold at least 5% of firm F_1, while investors C and D each hold at least 5% of firm F_2. The resulting investor network contains edges AB, AC, BC, and CD, with investor C acting as the bridge between the two clusters. Every

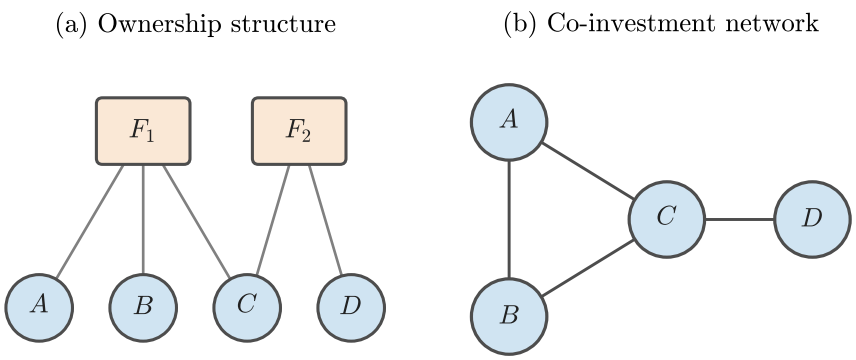


Figure 2.1: Toy Illustration of Network Construction

Notes: Panel (a) shows the ownership structure: investors A, B, and C each hold an effective stake of at least 5% in firm F_1, and investors C and D each hold at least 5% in firm F_2. Stakes are effective shareholdings, with indirect ownership chains resolved before the threshold test. Panel (b) shows the induced co-investment network: an edge connects two investors whenever both pass the 5% threshold in the same firm, producing edges AB, AC, BC, and CD, with investor C bridging the two clusters.

tie here is symmetric, yet C and D do not occupy the same position: what separates them is where their ties lead in the rest of the graph. The next section uses this measured co-investment graph to define network position.

3 Network Position and Counterfactual Disruption

The previous section defined the co-investment network from administrative ownership records. This section introduces two objects built from that graph: a measure of network position and the counterfactual disruption generated by the death of a connected investor. The goal is to build intuition before the formal identification argument in the Empirical Design section.

3.1 Network Position

The co-investment network among 10,000 investors is in principle a 10,000-by-10,000 adjacency matrix. Working with the raw matrix is not feasible; we need a scalar statistic that summarizes each investor's position within that structure.

The simplest position measure is degree centrality, the number of direct co-investment ties. But degree centrality treats all connections as equally valuable, regardless of who is on the other end of the tie. A link to a well-connected investor counts exactly the same as a link to a peripheral investor with no further connections.

Figure 3.1 illustrates why degree centrality is incomplete. Investors x and v each have one tie and therefore identical degree centrality. Yet their ties lead to different parts of the network: x is connected to y, while v is connected to z, whose position reflects additional connections to u and

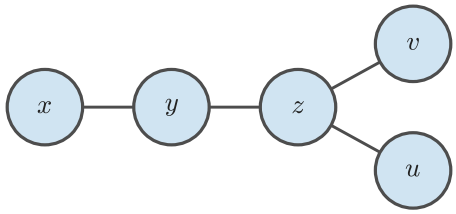


Figure 3.1: Same Degree, Different Network Position

Notes: The figure shows a five-investor network in which x and v each have exactly one co-investment tie and therefore identical degree centrality. PageRank differs because it depends on the position of the neighbor and on how that neighbor's position is divided across its own ties: x is connected to y, while v is connected to z, whose position reflects additional connections to y and u but is spread across three ties. At $\alpha = 0.85$, PageRank is 0.134 for x and 0.131 for v.

y. Degree centrality cannot distinguish these second-order differences.

A recursive centrality measure addresses this first limitation by allowing an investor's position to depend on the position of their neighbors; measures in the Katz-Bonacich tradition have exactly this structure (Bonacich 1987). But recursion alone is not enough. Being one of many business partners of a highly connected investor may provide less access than that investor's centrality alone suggests: private information, attention, and exclusive opportunities are diluted across many relationships, whereas being one of a few partners of the same investor implies a more concentrated claim on them. Katz-Bonacich centrality sums neighbors' positions without adjusting for how many partners share each neighbor, so it values both relationships identically. PageRank (PR) combines recursive position with this concentration adjustment, dividing each neighbor's position by the neighbor's number of ties (Page et al. 1999; Gleich 2015). Formally, we define network position as the fixed point

$$\mathrm{PR}_i = \frac{1-\alpha}{|\mathcal{I}|} + \alpha \sum_{j \in \mathcal{N}(i)} \frac{\mathrm{PR}_j}{d_j},$$

where $\alpha = 0.85$ is the damping parameter, $\mathcal{N}(i)$ is the set of direct neighbors of i, and d_j is the degree of neighbor j. The PageRank vector is the dominant eigenvector of the row-normalized adjacency matrix, scaled to sum to one. Because the vector sums to one, position gains for some investors must be offset by losses elsewhere, a property that will matter when we trace how centrality redistributes after a death event.

3.2 The Counterfactual Disruption

The empirical design exploits a specific disruption to an investor's network position: the death of a direct co-investment partner. When investor d dies after the base year, the ties that d maintained dissolve. Each surviving neighbor $i \in \mathcal{N}(d)$ experiences a change in network position as a result.

We make this precise with a counterfactual graph. For each death event, define $G^{(-d)}$ as the

base-year network G with all edges incident to d removed; d is retained as an isolated node. Keeping d in the graph preserves the node count, so PageRank values remain on the same scale across G and $G^{(-d)}$. Recomputing PageRank on $G^{(-d)}$ yields the position each survivor would occupy absent d's connections. The induced position change for survivor i is

$$\Delta \mathrm{PR}_i^{(d)} = \mathrm{PR}_i\left(G^{(-d)}\right) - \mathrm{PR}_i(G).$$

We scale this change by 10^4 in the regressions to work with coefficients of readable magnitude.

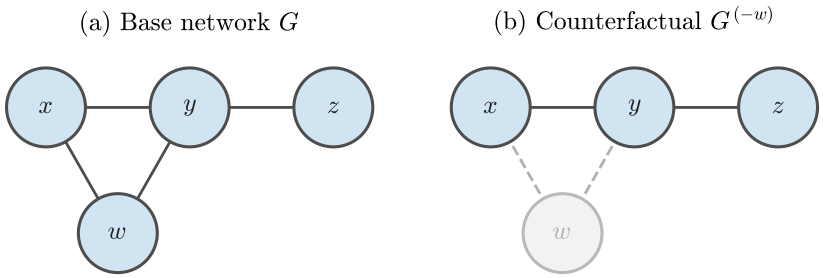


Figure 3.2: Counterfactual Disruption from the Death of a Connected Investor

Notes: Panel (a) shows the base network G, with edges xy, yz, xw, and yw. Investors x and y are both direct neighbors of w. Panel (b) shows the counterfactual graph $G^{(-w)}$ after w's death: the dashed edges incident to w are removed and w is retained as an isolated node, preserving the node count. Recomputing PageRank on $G^{(-w)}$, investor y gains position (0.367 to 0.463), while investor x loses slightly (0.246 to 0.245).

Figure 3.2 illustrates the counterfactual logic. In the base network, w is directly connected to both x and y. When w dies, the edges xw and yw dissolve, so x and y each lose exactly one tie: measured by degree, the two survivors experience the same shock. Their positions nonetheless move in opposite directions. Investor y becomes the sole bridge between x and z, absorbing the routing role that previously ran through w, and its PageRank rises from 0.367 to 0.463. Investor x inherits no part of w's role, and its remaining access to the network now runs entirely through y; its position declines from 0.246 to 0.245.

This within-event heterogeneity is determined by the pre-existing topology of the base-year network, conditional on the identity of the deceased, and it provides the key contrast exploited in the Empirical Design section.

4 Empirical Design

The empirical strategy exploits variation in whether a top investor loses a direct co-investment partner to death. The key features of the design are: the shock is plausibly exogenous to the survivor's own wealth trajectory; the same death event induces heterogeneous changes in network position across neighbors; and all variation used for the mechanism comparison is determined by

pre-existing network topology, not by any attribute of the survivor or the deceased.

4.1 Event Definition

The base network is the 2010 co-investment network at the 5% ownership threshold. All network distances and centrality measures, including the counterfactual PageRank changes constructed in Section 3, are anchored to this snapshot.

A connection-loss event is defined as the death of a base-year investor who held at least one co-investment tie in the 2010 network, occurring strictly after 2010. A surviving investor i is treated by event d if i was a direct neighbor of the deceased d in the base network. The primary specifications restrict treated investors to direct neighbors, who themselves lose a co-investment partner; we refer to the resulting estimation sample as the primary sample. Specifications that add second-step neighbors, the neighbors of the deceased's neighbors, are reported as robustness checks, since those investors are indirectly exposed through the network but do not themselves lose a direct tie to the deceased.

Controls are drawn from non-isolated investors in the 2010 base network, those with at least one co-investment tie, who have no exposure to any connection-loss event within the focal event window, from three years before to three years after the death, including never-exposed investors. Restricting controls to the non-isolated pool ensures that treated and control investors are comparable: both had active co-investment relationships in the base year; in the primary sample, only the treated group lost a direct partner during the event window. To address pre-existing differences, each treated investor is matched to control candidates from the same death cohort. Matching is exact on sex and requires the control to be within five years of the treated investor's age and within 500 positions of their pre-event wealth rank.

4.2 Sample Construction

The estimation uses a stacked design: one panel per death event, stacked into a single dataset. Each observation is an (i, d, t) triple, indexed by event time $\tau = t - t_d \in \{-3, \ldots, 3\}$, where t_d is the year of death.

Two sample restrictions apply before estimation. First, a completeness restriction: we retain only stacks in which the investor has strictly positive, nonmissing wealth in all seven event years. This ensures each stack contributes a balanced panel and prevents attrition from contaminating the event-time profile. Second, an outlier restriction: observations in the 1st and 99th percentiles of annual log-wealth change are dropped; the completeness condition is re-checked on the trimmed sample.

The main outcome is log total wealth:

$$Y_{i,d,t} = \log W_{i,t},$$

where $W_{i,t}$ is total wealth of investor i in year t. Although the dependent variable is log wealth rather than a baseline difference, the investor-by-deceased fixed effect absorbs each pair's permanent wealth level. In the event-study specification, omitting $\tau = -1$ normalizes coefficients to the last pre-event year. Equivalently, subtracting $\log W_{i,t_d-1}$ within each investor-event pair would leave the treatment coefficients unchanged.

Two fixed-effect identifiers and one clustering identifier are constructed. The investor-by-deceased pair fixed effect absorbs all time-invariant characteristics of the dyad. The deceased-by-event-time fixed effect absorbs the average wealth trajectory of each death cohort at each point in event time. Standard errors are clustered at the investor level.

4.3 Event-Study Specification

The event-study regression estimates the dynamic treatment effect separately for each event-time period:

$$Y_{i,d,t} = \sum_{\tau \neq -1} \beta_\tau \big(\text{Treat}_{i,d} \times \mathbf{1}[t - t_d = \tau]\big) + \alpha_{i,d} + \gamma_{d,\tau} + \varepsilon_{i,d,t}. \tag{1}$$

where $\tau \in \{-3, -2, 0, 1, 2, 3\}$, $\tau = -1$ is the omitted reference period, $\alpha_{i,d}$ are investor-by-deceased pair fixed effects, and $\gamma_{d,\tau}$ are deceased-by-event-time fixed effects. Identification comes from within-cohort variation between treated and control investors at each event-time relative to their common pre-event baseline.

We run the event study separately on two subsamples. We refer to treated investors who are immediate family of the deceased, spouse, parent, or child, as heirs; all other treated investors are non-heirs.

The heir subsample captures the inheritance margin: wealth may flow to the survivor upon the partner's death. The non-heir subsample isolates the network disruption margin. We check pre-trends by plotting $\hat{\beta}_\tau$ for $\tau \in \{-3, -2\}$ against the omitted period $\tau = -1$. Flat pre-period coefficients support the parallel-trends interpretation. The full coefficient path, including post-event divergence, allows us to compare how the wealth path differs across heirs and non-heirs.

4.4 Difference-in-Differences Specification

To summarize the event-study coefficient paths in a single set of estimates, we collapse the dynamic profile into a difference-in-differences (DiD) specification. Let $\text{Post}_{d,t} = \mathbf{1}[t \geq t_d]$. Let $\text{Heir}_{i,d}$

indicate that investor i is immediate family of deceased investor d. The estimating equation is

$$Y_{i,d,t} = \beta_1 \big(\text{Post} \times \text{NonHeir} \times \text{Treat}\big)_{i,d,t} + \beta_2 \big(\text{Post} \times \text{Heir} \times \text{Treat}\big)_{i,d,t} + \alpha_{i,d} + \gamma_{d,\tau} + \varepsilon_{i,d,t}, \quad (2)$$

where $\text{NonHeir}_{i,d} = 1 - \text{Heir}_{i,d}$.

The estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ measure the average post-event wealth change for non-heir and heir treated investors, respectively, relative to matched controls within the same death cohort and at the same event-time. The sign contrast is informative about whether inheritance and network disruption operate differently after the same death event. If $\hat{\beta}_1 < 0$ while $\hat{\beta}_2 > 0$, the same physical shock, the death of a connected investor, produces opposite post-event wealth paths depending on the nature of the tie.

4.5 Network-Position Heterogeneity

The DiD results summarize the heir and non-heir contrast. This section sharpens the interpretation by asking whether non-heir losses are more severe when the same death also lowers the survivor's network position, rather than merely removing one tie.

Section 3 showed that the same death can generate heterogeneous position changes: some neighbors gain centrality because they become the new bridge, while others lose it because they lose a routing path without an alternative. This specification compares those PR-loss and PR-gain neighbors within the same death event.

We construct the position change $\Delta\text{PR}_{i,d}^{(-d)}$ using the counterfactual graph defined in Section 3. Define

$$\text{PRloss}_{i,d} = \mathbf{1}\Big[\Delta\text{PR}_{i,d}^{(-d)} < 0\Big]$$
$$\text{PRgain}_{i,d} = \mathbf{1}\Big[\Delta\text{PR}_{i,d}^{(-d)} > 0\Big].$$

The estimating equation is

$$\begin{aligned} Y_{i,d,t} \;=\; & \beta_1 \big(\text{Post} \times \text{NonHeir} \times \text{PRloss}\big)_{i,d,t} + \beta_2 \big(\text{Post} \times \text{NonHeir} \times \text{PRgain}\big)_{i,d,t} \\ & + \beta_3 \big(\text{Post} \times \text{Heir} \times \text{PRloss}\big)_{i,d,t} + \beta_4 \big(\text{Post} \times \text{Heir} \times \text{PRgain}\big)_{i,d,t} \\ & + \alpha_{i,d} + \gamma_{d,\tau} + \varepsilon_{i,d,t}. \end{aligned} \quad (3)$$

Among non-heirs, the contrast between $\hat{\beta}_1$ and $\hat{\beta}_2$ indicates whether post-event wealth losses are concentrated among survivors whose network position falls rather than rises after the same death event. The corresponding heir coefficients show whether the inheritance margin remains positive across the same PR groups.

The key identification argument rests on the deceased-by-event-time fixed effect. Because this

term absorbs all deceased-by-event-time variation, it controls for everything specific to the death event: the deceased's age, wealth rank, centrality, number of ties, and any other attribute. The residual variation in $\Delta \text{PR}_{i,d}^{(-d)}$ across the neighbors of the same deceased is determined by the pre-existing topology of the base-year network, specifically by the structural role the survivor occupied relative to the deceased's other connections. This comparison rules out a purely deceased-level importance story, though it does not eliminate all possible forms of relationship-specific dependence between the deceased and individual neighbors.

5 Results

5.1 Summary Statistics

We present the results in three steps: descriptive facts about the event sample, dynamic event-study estimates, and pooled difference-in-differences summaries. Table 5.1 reports the connection-loss events that enter the regression sample, restricting to 2011–2018 event years because the stacked specifications require a complete event window, from three years before to three years after the death ($\tau \in \{-3, \ldots, 3\}$). The usable regression events are spread across the full 2011–2018 period rather than concentrated in a single cohort. The event counts, mean age at death, and median age at death are event-year statistics. The reported wealth rank, PR rank, and degree are measured in the 2010 base network, so they describe the baseline network position of the deceased investors whose later deaths generate the regression sample.

Table 5.1: Connection-Loss Events by Event Year

Year	Deaths	Mean wealth rank	Mean PR rank	Mean degree	Mean age	Median age
2011	22	4696.2	3472.8	3.91	71.4	76.0
2012	19	3542.8	2349.0	5.89	74.3	80.0
2013	25	4123.7	3266.1	3.32	73.5	71.0
2014	25	4272.2	3278.0	4.20	75.7	77.0
2015	37	4099.4	2688.9	3.76	72.0	69.0
2016	42	4663.9	3119.7	4.43	74.4	74.5
2017	41	3982.0	2696.2	4.95	77.3	79.0
2018	39	3969.3	3620.2	3.28	72.5	70.0

Notes: Regression events are limited to 2011–2018 because the stacked specifications require a complete event window from three years before to three years after the death and the sample period ends in 2021. Counts and ages are event-year statistics. Wealth rank, PR rank, and degree are measured in the 2010 base network.

Table 5.2 describes the investor composition of the primary sample before the shock occurs. Following the construction in the Empirical Design section, log wealth and age are measured at $\tau = -1$, while baseline wealth rank and own degree are base-year variables taken from the 2010 network. Treated and control investors are similar in age and baseline wealth rank, and treated investors are slightly richer, with mean log wealth 20.366 versus 20.105. The clearest difference is connectedness: treated investors have own degree 7.16 versus 3.46. Both groups are drawn

from the non-isolated pool, but degree is not a matching variable, and an investor with more connections is more likely to experience the death of one of them. These level differences do not threaten identification, which rests on parallel trends rather than baseline similarity; the investor-by-deceased pair fixed effects absorb them. The last four rows are defined by treated exposure itself: the PR change $\times 10^4$ is computed only for treated exposure pairs, and the family-link shares are essentially zero for controls because controls are not exposed to a deceased investor. For control investors, the counterfactual PageRank change would in any case be close to zero by construction.

Table 5.2: Pre-Event Summary Statistics

	1st-degree only	
	Treated	Control
Log wealth	20.366	20.105
	(1.189)	(1.107)
Baseline wealth rank	3536.7	3653.2
	(2928.0)	(2744.7)
Age	59.37	58.66
	(11.49)	(8.15)
Female	0.366	0.249
	(0.482)	(0.433)
Own degree	7.16	3.46
	(4.90)	(2.63)
PR change x 10^4	-0.102	.
	(0.244)	(.)
Family (1st)	0.287	0.000
	(0.453)	(0.000)
Family (2nd)	0.173	0.000
	(0.378)	(0.019)
Family (3rd)	0.085	0.005
	(0.280)	(0.070)
Observations	867	52,240

Notes: Log wealth and age are measured in the year just before the death. Baseline wealth rank and own degree are measured in the 2010 base network. PR change $\times 10^4$ is a treated-exposure statistic constructed from the counterfactual-minus-base PageRank change scaled by 10,000.

5.2 Event-Study Estimates

We first trace how heir and non-heir wealth paths evolve around the same connection-loss event. Figures 5.1 and 5.2 report the log-wealth event studies of equation (1) for the primary sample: all PR changes pooled, then PR gains and PR losses as separate panels. In every figure, the omitted base period is $\tau = -1$, so the pre-period comparison comes from $\tau = -3$ and $\tau = -2$, and the plotted post-event coefficients are interpreted relative to the year just before the death.

Figure 5.1 shows the all-PR event study. The pre-period coefficients are comparatively small,

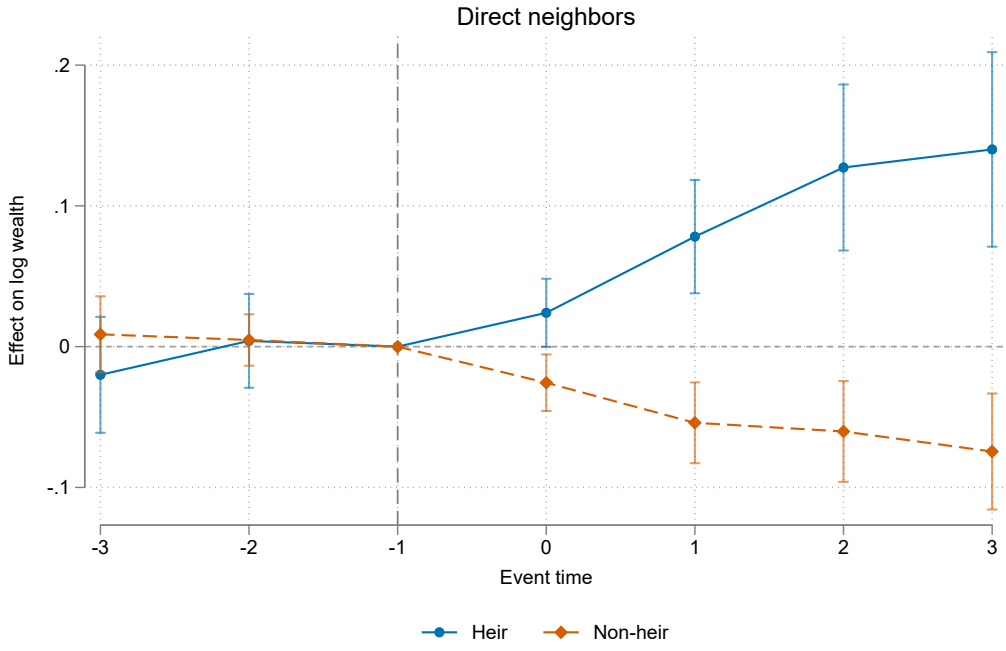


Figure 5.1: Event Study for Log Wealth: All PR Changes, Direct Neighbors

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The treated sample includes direct neighbors of the deceased only, pooling all events regardless of the sign of the induced PageRank change.

with no large divergence between heirs and non-heirs before the event. After the death, the two series separate. The heir path is positive through the post period and reaches roughly 0.14 by $\tau = +3$, while the non-heir path turns negative and falls to roughly -0.07; both endpoint estimates are statistically distinguishable from zero at the 5% level.

Figure 5.2 splits the same event study by the sign of the induced PageRank change. The upper panel restricts to survivors whose network position rises after the death. The heir series remains positive, reaching roughly 0.15 by $\tau = +3$. The non-heir series is much closer to zero than in the all-PR figure and, at the end of the horizon, is statistically indistinguishable from zero at the 5% level. This pattern suggests that the negative non-heir response is not a generic response to every connection-loss event. The lower panel shows the PR-loss group, where the non-heir decline is the sharpest. The heir series remains positive, at roughly 0.13 by $\tau = +3$, while the non-heir series falls to roughly -0.10 and is statistically distinguishable from zero at the 5% level. Read together, the all-PR figure and the two panels make the contrast in the Empirical Design section visible: post-event wealth paths diverge most clearly when the same death also lowers the survivor's network position.

5.3 Difference-in-Differences Estimates

We next collapse the dynamic profiles into pooled estimates of equation (2). Table 5.3 reports the main pooled estimates for log wealth, organized by PR group. The pooled coefficients line up closely with the event-study evidence in the previous subsection. In the all-PR column, the non-heir post coefficient is -0.058, while the heir post coefficient is 0.098. The PR-gain column shows that the non-heir estimate is near zero at 0.008 and statistically indistinguishable from zero, while the heir coefficient remains positive at 0.081. The PR-loss column shows the sharpest contrast: the non-heir estimate is -0.090, whereas the heir coefficient is 0.110. All other coefficients are statistically distinguishable from zero at the 5% level.

Table 5.3: Main DiD Estimates for Log Wealth

	Dependent variable: log wealth		
	All PR changes	PR gain	PR loss
Post × Non-heir	-0.0580	0.0083	-0.0898
	(0.0177)	(0.0216)	(0.0232)
Post × Heir	0.0976	0.0812	0.1104
	(0.0248)	(0.0384)	(0.0313)
Observations	371,749	367,843	369,586
Adj. R-sq	0.9418	0.9417	0.9418
Dep. var. mean	20.1174	20.1140	20.1167

Notes: The table reports pooled post-period DiD estimates of equation (2) for log wealth in the primary sample. Columns vary by PR group. Standard errors, reported in parentheses, are clustered at the investor level.

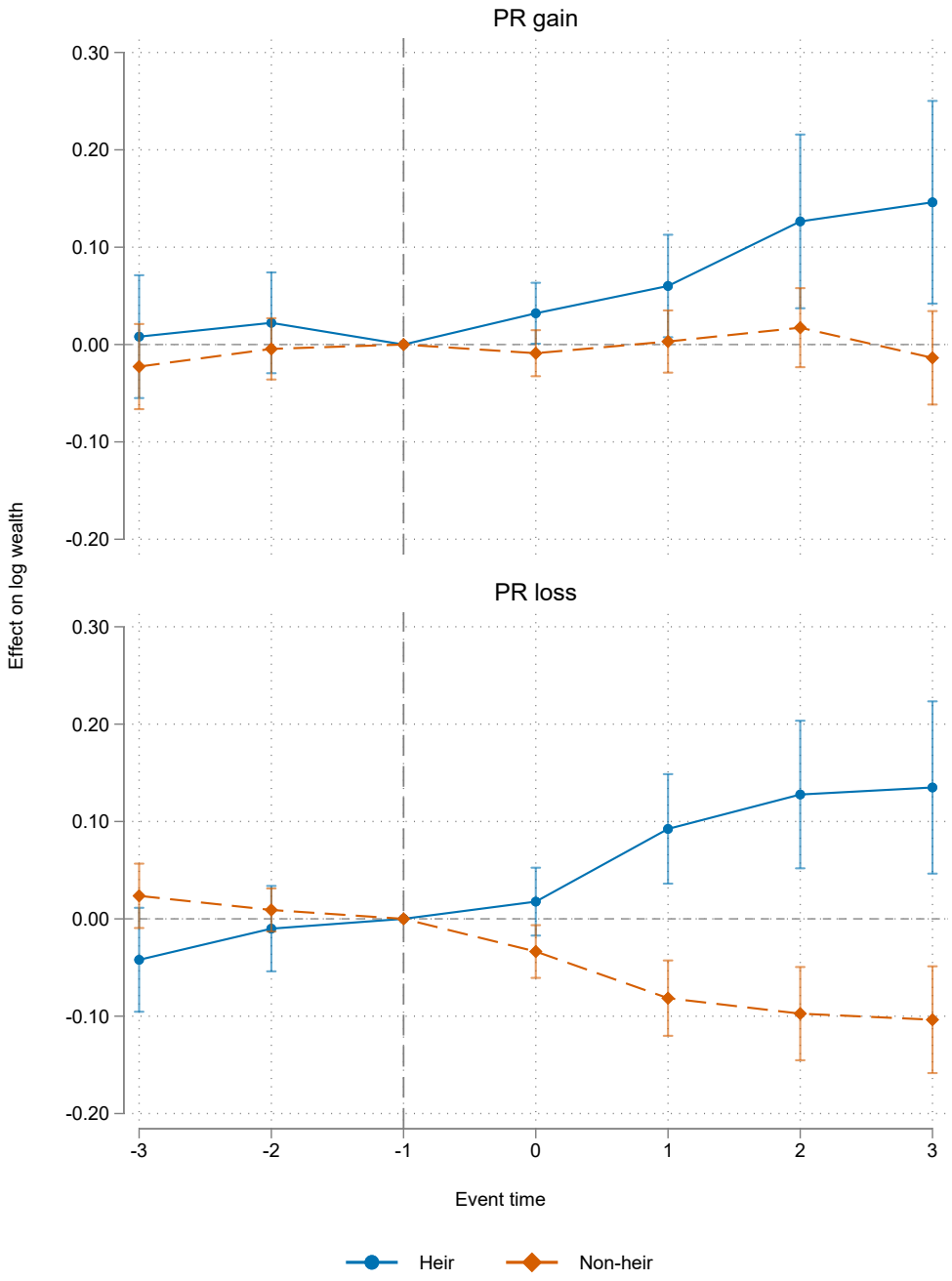


Figure 5.2: Event Study for Log Wealth: PR Gain versus PR Loss, Direct Neighbors

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The treated sample includes direct neighbors of the deceased only. The upper panel restricts to events in which the death induces a counterfactual PageRank gain for the survivor; the lower panel restricts to events that induce a loss. The two panels share a common vertical scale.

Table 5.4 provides the interaction refinement of equation (3), which compares PR-loss and PR-gain exposure within the same specification rather than across split columns. For non-heirs, the PR-loss coefficient is negative at -0.090, while the PR-gain coefficient is near zero at 0.008 and statistically indistinguishable from zero. For heirs, both PR-loss and PR-gain coefficients remain positive. This pooled interaction view shows that the main non-heir loss is concentrated where the death induces a decline in network position, while the heir coefficients remain positive regardless of the PR group.

Table 5.4: PR-Loss versus PR-Gain Interaction Estimates

	Dependent variable: log wealth
Post × Non-heir × PR loss	-0.0895
	(0.0232)
Post × Non-heir × PR gain	0.0083
	(0.0216)
Post × Heir × PR loss	0.1105
	(0.0312)
Post × Heir × PR gain	0.0813
	(0.0383)
Observations	371,749
Adj. R-sq	0.9418
Dep. var. mean	20.1174

Notes: The table reports estimates of equation (3), which refines the main DiD by interacting the post-period indicator with heir status and the sign of the induced PageRank change, in the primary sample. Standard errors, reported in parentheses, are clustered at the investor level.

6 Alternative Explanations and Robustness

Section 5 established that losing a co-investment partner to death reduces the log wealth of non-heir survivors. The loss is not a uniform response to the event: in the estimates of equation (3), it is concentrated among survivors whose induced PageRank falls, the non-heir estimate for PR-gain exposure is statistically indistinguishable from zero, and heir estimates are positive in every PR group. We read this contrast as evidence that connection loss operates through the survivor's network position.

Network-position decline is not, however, the only mechanism consistent with these patterns. The identifying events are deaths, and treatment therefore bundles the loss of a tie with everything else the death sets in motion; any of those consequences that also moves survivor wealth is a potential confounder. We first use heterogeneity in the age of the deceased to separate such death-event side effects from the loss of network position. Two further checks then vary the sample while holding the design fixed: expanding the treated group to second-step neighbors of the deceased, and restricting the stacked sample to each survivor's first connection-loss exposure. Throughout, heir

estimates remain positive after the death, and non-heir losses remain concentrated among survivors whose PageRank falls.

6.1 Age of the Deceased

A connection-loss event is a death, and a death changes more for the survivor than the position of one node in the network. The heir/non-heir contrast already absorbs the most direct side effect, the bequest itself, so the threats that remain are consequences of the death that could depress the wealth of non-heir survivors and masquerade as a network-position effect. Three candidates stand out: the loss of the deceased's operational human capital, a common shock to jointly held firms, and anticipation of the death.

The first candidate is operational human capital. A death removes not only a node but also the deceased's ongoing managerial input into shared ventures, and the evidence on key-person deaths shows that such losses can be large: sudden executive deaths move firm value in ways that depend on the deceased's role (Johnson et al. 1985), and deaths destroy value when the key person is an operationally active entrepreneur or an irreplaceable employee (Becker and Hvide 2022; Israelsen and Yonker 2017). If the non-heir losses documented in Section 5 reflected this margin, they would be a statement about the deceased's labor, not about the survivor's network position.

The second candidate is a common shock to the firms the survivor and the deceased jointly hold. Even with no change in the survivor's own position, the death of a substantial shareholder can set off succession contests and estate settlement that depress the value of the shared firms; transitions of control in family firms are costly (Pérez-González 2006; Bennedsen et al. 2015). Under this story, non-heir losses would flow mechanically through the shared asset rather than through the survivor's access to the network.

The third candidate is anticipation. When a death is foreseen, survivors can rebalance away from shared ventures in advance, and expected bequests can be partly transferred before the event; both responses shift wealth changes into the pre-period and attenuate post-event estimates, the concern that leads Azoulay, Graff Zivin, and Wang (2010) to restrict attention to sudden deaths.

One implication can be checked without new estimation. Any death-event side effect that is common to the exposed survivors, such as grief, distraction, or a shock to shared ventures, should also depress the wealth of survivors whose induced PageRank rises. It does not: in Section 5, the non-heir PR-gain estimate is statistically indistinguishable from zero. A generic death effect therefore cannot generate the observed pattern; whatever depresses non-heir wealth operates disproportionately where the death also lowers the survivor's network position.

The age of the deceased at death discriminates among the remaining, age-graded versions of these candidates. Day-to-day operational involvement recedes with age, and market reactions to the deaths of old or entrenched executives are neutral or even positive (Salas 2010; Jenter, Matveyev,

and Roth 2023), so the human-capital and common-shock candidates both predict non-heir losses concentrated among the youngest deceased and fading for the oldest. Anticipation points the same way: deaths at older ages may be more often foreseen, which predicts weaker measured effects for the oldest deceased. A network-position effect predicts a weaker gradient: an elderly investor may network less actively but still occupies a position accumulated over a career. Losses that do not shrink when the deceased was elderly therefore favor the network-position interpretation.

The composition of our events makes this test informative. The deceased investors behind the connection-loss events are mostly elderly: Table 5.1 shows that their mean age at death exceeds 70 in every event year, so the sample is dominated by deaths for which operational involvement is the least plausible margin. To use the remaining variation, we split connection-loss events by the age of the deceased in the death year, under 75 versus 75 and older, and re-estimate the pooled DiD specifications within each group on the primary sample.

Table 6.1: Robustness DiD Estimates: Age of the Deceased

	Dependent variable: log wealth					
	All PR changes		PR gain		PR loss	
	Under 75	75 and older	Under 75	75 and older	Under 75	75 and older
Post × Non-heir	-0.0411	-0.0769	0.0211	-0.0118	-0.0783	-0.1007
	(0.0207)	(0.0277)	(0.0257)	(0.0368)	(0.0285)	(0.0346)
Post × Heir	0.1589	0.0771	0.1226	0.0684	0.1856	0.0839
	(0.0557)	(0.0270)	(0.0874)	(0.0422)	(0.0719)	(0.0331)
Observations	177,366	194,383	175,686	192,157	176,330	193,256
Adj. R-sq	0.9407	0.9418	0.9408	0.9416	0.9407	0.9418
Dep. var. mean	20.0071	20.2181	20.0051	20.2136	20.0070	20.2168

Notes: The table re-estimates equation (2), splitting connection-loss events by the age of the deceased investor in the death year: under 75 versus 75 and older. Columns vary by PR grouping and age group. The treated sample includes direct neighbors only. Standard errors, reported in parentheses, are clustered at the investor level.

Tables 6.1 and 6.2 show the opposite of what the human-capital and common-shock candidates predict. Non-heir losses persist among the oldest deceased and are, if anything, larger: the non-heir all-PR estimate is -0.041 when the deceased died under 75 and -0.077 when the deceased died at 75 or older, and in both groups the loss is concentrated among survivors whose PageRank falls, at -0.078 and -0.101. Both the deceased's hands-on input and death-related disruption to jointly held firms should matter least for the oldest deceased; instead the losses grow with age. What survivors lose when an elderly central investor dies is therefore better described as access to the deceased's network position.

Heir estimates are positive in both groups, at 0.159 for deaths under 75 and 0.077 for deaths at 75 or older. The smaller estimate for the oldest deceased is consistent with expected bequests being partly transferred before anticipated deaths, and it does not affect the non-heir contrast. If deaths at 75 or older are also more often anticipated, the persistence of the non-heir PR-loss estimate in this group suggests that the network-disruption channel does not rely on the death arriving as a

Table 6.2: Robustness PR-Loss versus PR-Gain Estimates: Age of the Deceased

	Dependent variable: log wealth	
	Under 75	75 and older
Post × Non-heir × PR loss	-0.0783	-0.1003
	(0.0285)	(0.0346)
Post × Non-heir × PR gain	0.0209	-0.0117
	(0.0257)	(0.0368)
Post × Heir × PR loss	0.1856	0.0841
	(0.0718)	(0.0331)
Post × Heir × PR gain	0.1224	0.0685
	(0.0874)	(0.0421)
Observations	177,366	194,383
Adj. R-sq	0.9407	0.9418
Dep. var. mean	20.0071	20.2181

Notes: The table re-estimates equation (3) separately for events in which the deceased died under age 75 and at age 75 or older, interacting the post-period indicator with heir status and the sign of the induced PageRank change. The treated sample includes direct neighbors only. Standard errors, reported in parentheses, are clustered at the investor level.

surprise.

The biases that survive these tests work against the estimated effect rather than for it. Anticipation shifts part of the response into the $\tau = -1$ base period, and the pooled stacked sample includes survivors already exposed to earlier connection-loss events, whose pre-event baselines embed prior losses; consistent with both forces, restricting the sample to first exposures (Appendix A) yields slightly stronger estimates. Because the confounders that could overstate the effect fade with the age of the deceased while the estimates do not, the non-heir estimates are best read as, if anything, a lower bound on the effect of losing network position.

6.2 Adding Second-Step Neighbors

The primary specifications restrict treated investors to direct neighbors of the deceased, tying treatment to the direct loss of a co-investment partner. The next check adds second-step neighbors, the neighbors of the deceased's neighbors; we refer to the resulting estimation sample as the expanded sample. Second-step neighbors do not share a private firm with the deceased at the ownership threshold that defines a co-investment tie, so the deceased's operational input into jointly run ventures is not a margin for them. They may still hold overlapping positions in public firms, so death-related shocks to commonly held assets are muted rather than eliminated. What the death changes most sharply for them is their network position.

The expanded sample therefore carries a prediction. If the effect operates through network position, the heir/non-heir and PR-loss/PR-gain ordering should survive among the indirectly exposed, with pooled estimates diluted because indirect exposure mixes investors with heterogeneous

induced position changes. If instead the effect required losing a direct tie, whether the partner's input or some relationship-specific dependence, adding investors who lose no tie should push every estimate toward zero alike.

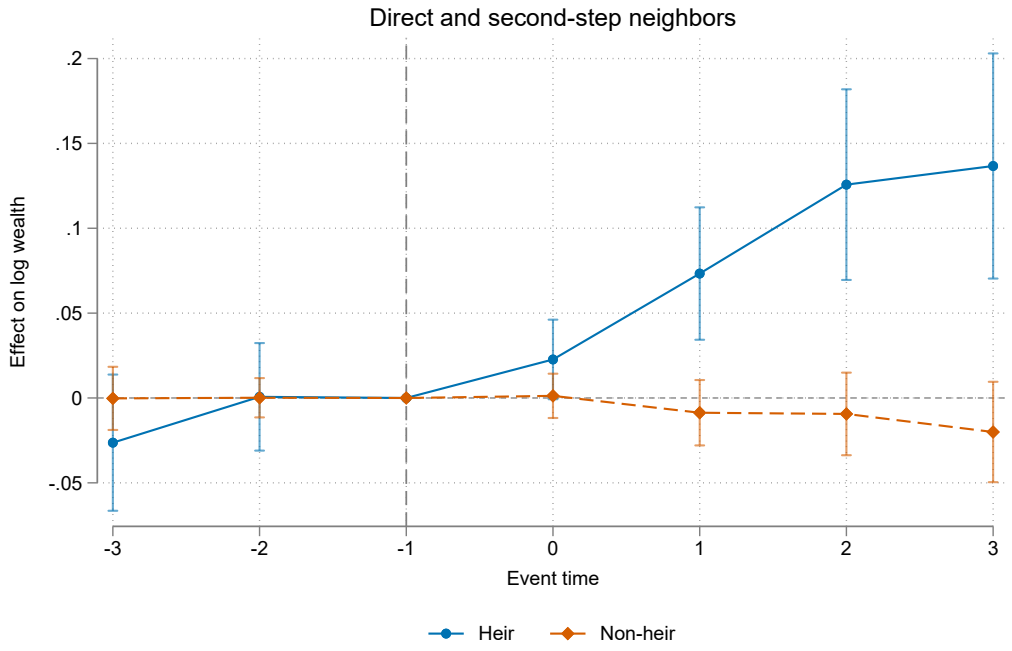


Figure 6.1: Robustness Event Study: All PR Changes, Direct and Second-Step Neighbors

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The treated sample includes direct and second-step neighbors of the deceased, pooling all events regardless of the sign of the induced PageRank change.

Figures 6.1 and 6.2 show that the expanded sample preserves the same ordering as the main figures. Heir paths remain positive after the event. Non-heir losses are weaker when all PR changes are pooled, but they remain negative in the PR-loss group, falling to roughly -0.08 by $\tau = +3$.

Tables 6.3 and 6.4 show the same pattern in pooled form. Adding second-step neighbors attenuates the non-heir all-PR estimate from -0.058 to -0.009, but the PR-loss estimate remains negative at -0.054. Heir estimates remain positive across both treated-group definitions. The ordering survives with dilution rather than washing out uniformly: the pooled estimate shrinks while the PR-loss estimate persists, consistent with the effect following the induced position change rather than mere proximity to the death event.

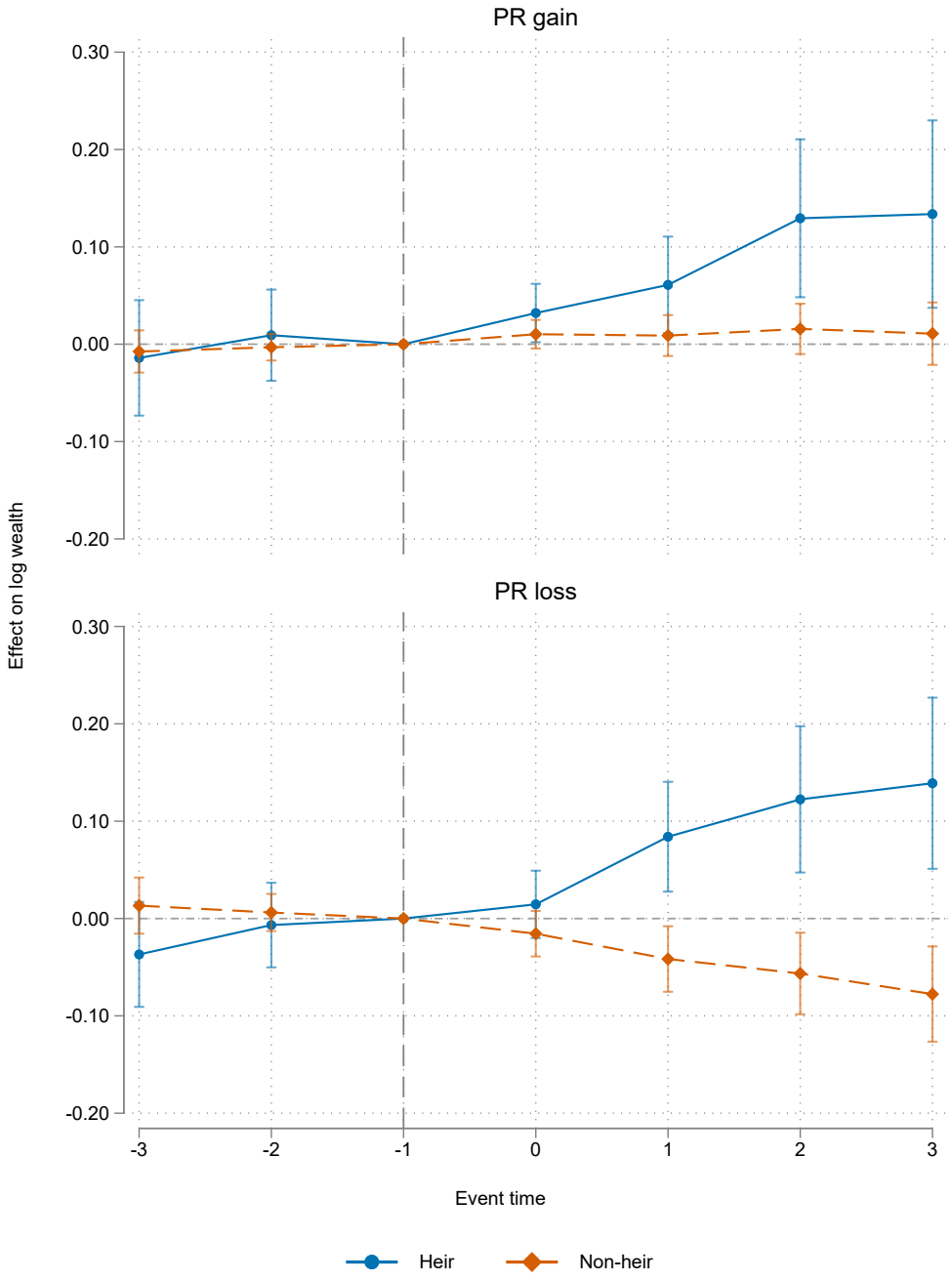


Figure 6.2: Robustness Event Study: PR Gain versus PR Loss, Direct and Second-Step Neighbors

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The treated sample includes direct and second-step neighbors of the deceased. The upper panel restricts to events in which the death induces a counterfactual PageRank gain for the survivor; the lower panel restricts to events that induce a loss. The two panels share a common vertical scale.

Table 6.3: Robustness DiD Estimates: Adding Second-Step Neighbors

	Dependent variable: log wealth					
	All PR changes		PR gain		PR loss	
	1st-degree only	1st + 2nd degree	1st-degree only	1st + 2nd degree	1st-degree only	1st + 2nd degree
Post × Non-heir	-0.0580	-0.0091	0.0083	0.0150	-0.0898	-0.0543
	(0.0177)	(0.0124)	(0.0216)	(0.0129)	(0.0232)	(0.0211)
Post × Heir	0.0976	0.0983	0.0812	0.0907	0.1104	0.1046
	(0.0248)	(0.0236)	(0.0384)	(0.0347)	(0.0313)	(0.0311)
Observations	371,749	693,574	367,843	688,688	369,586	685,482
Adj. R-sq	0.9418	0.9403	0.9417	0.9402	0.9418	0.9401
Dep. var. mean	20.1174	20.0846	20.1140	20.0819	20.1167	20.0814

Notes: The table re-estimates equation (2), comparing the primary sample with the expanded sample that adds second-step neighbors of the deceased. Columns vary by PR grouping and treated-group definition. Standard errors, reported in parentheses, are clustered at the investor level.

Table 6.4: Robustness PR-Loss versus PR-Gain Estimates: Adding Second-Step Neighbors

	Dependent variable: log wealth	
	1st-degree only	1st + 2nd degree
Post × Non-heir × PR loss	-0.0895	-0.0542
	(0.0232)	(0.0211)
Post × Non-heir × PR gain	0.0083	0.0153
	(0.0216)	(0.0129)
Post × Heir × PR loss	0.1105	0.1049
	(0.0312)	(0.0310)
Post × Heir × PR gain	0.0813	0.0909
	(0.0383)	(0.0347)
Observations	371,749	693,574
Adj. R-sq	0.9418	0.9403
Dep. var. mean	20.1174	20.0846

Notes: The table re-estimates equation (3), comparing PR-loss and PR-gain exposure in the primary sample and in the expanded sample that adds second-step neighbors of the deceased. Standard errors, reported in parentheses, are clustered at the investor level.

6.3 First Exposure Only

Some survivors lose more than one connection during the sample period, which complicates the interpretation of the pooled estimates, as noted above. Restricting the sample to each survivor's first connection-loss exposure, the estimated losses grow: from -0.058 to -0.065 for non-heirs overall, and from -0.090 to -0.111 where PageRank falls — the direction the attenuation argument predicts. Appendix A reports the full results.

7 Conclusion

This paper studies whether changes in network position affect wealth accumulation among top investors. Using deaths of connected investors as shocks to the co-investment network, we compare exposed investors with matched, non-exposed investors in a stacked event-study and difference-in-differences design. The main empirical pattern is that heirs and non-heirs diverge after the same class of events: heir exposure is followed by wealth gains, while non-heir exposure is followed by wealth losses.

The non-heir effect is not uniform across exposed investors. It is concentrated among survivors whose PageRank-based network position falls as a result of the death, and it is close to zero when the same death raises the survivor's position. Holding the same death event fixed, exposed investors experience different wealth paths depending on the induced change in their network position, a contrast that is difficult to reconcile with a purely deceased-level importance story. This ordering is stable across the checks we run: splitting events by the age of the deceased, expanding the treated group to second-step neighbors, and restricting the sample to each survivor's first exposure.

Because the identifying events are deaths, we also weighed the leading explanations a death event allows other than network position: the loss of the deceased's operational human capital, common shocks to jointly held firms, and anticipation. The evidence sits uneasily with each of them: non-heir losses grow rather than fade with the age of the deceased, and survivors whose position rises after the same class of events show little response. The biases that remain, anticipation and repeated exposure, push the estimates toward zero. We read the results as favoring the network-position interpretation, while acknowledging that the design cannot rule out every form of relationship-specific dependence between the deceased and individual neighbors.

These findings come with two limits. First, the identification relies on a natural experiment, and a death is never a pure shock to network position: it bundles the position change with the other consequences of the event. The robustness checks address the leading candidates, but a design built on death events cannot unbundle them completely. Second, the setting shapes how far the results travel. Business in Taiwan is organized to an unusual degree around family groups and long-standing personal relationships, an environment in which network position is plausibly at its most

valuable; in economies where investment is more arm's-length, the same disruption may matter less. Within these limits, the results suggest that network position is economically meaningful in this environment, and, more tentatively, that the structure of co-investment relationships may matter for wealth accumulation and capital allocation.

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A First Exposure Only

The stacked design allows the same survivor to appear in multiple death-event stacks if the survivor is exposed to more than one connection-loss event. For such survivors, the pre-event baseline of a later stack already embeds the losses from earlier disruptions, which compresses the treated-control gap and attenuates the pooled estimates, one of the attenuating biases noted in the main text. The first-exposure check restricts the sample to each survivor's first connection-loss exposure, removing this source of attenuation. If earlier disruptions indeed bias the pooled estimates toward zero, the first-exposure estimates should be at least as large.

Figures A.1 and A.2 show that the first-exposure restriction preserves the main dynamic pattern. The non-heir series is again most negative in the PR-loss group, while the heir series remains positive.

Tables A.1 and A.2 show that the first-exposure restriction slightly strengthens the core estimates. The non-heir all-PR coefficient is -0.065, and the non-heir PR-loss coefficient is -0.111. The non-heir PR-gain coefficient remains close to zero, while heir coefficients remain positive across PR groups. The direction of the change is what the attenuation logic predicts: dropping the later stacks whose baselines embed earlier losses strengthens the estimates, supporting the reading of the pooled estimates as conservative.

Table A.1: Robustness DiD Estimates: First Exposure Only

	Dependent variable: log wealth		
	All PR changes	PR gain	PR loss
Post × Non-heir	-0.0655	0.0187	-0.1107
	(0.0186)	(0.0236)	(0.0246)
Post × Heir	0.1010	0.0722	0.1282
	(0.0271)	(0.0398)	(0.0363)
Observations	370,552	367,570	368,662
Adj. R-sq	0.9417	0.9417	0.9417
Dep. var. mean	20.1150	20.1134	20.1149

Notes: The table reports pooled post-period DiD estimates of equation (2) for log wealth after restricting the sample to each survivor's first connection-loss exposure. The treated sample includes direct neighbors only. Standard errors, reported in parentheses, are clustered at the investor level.

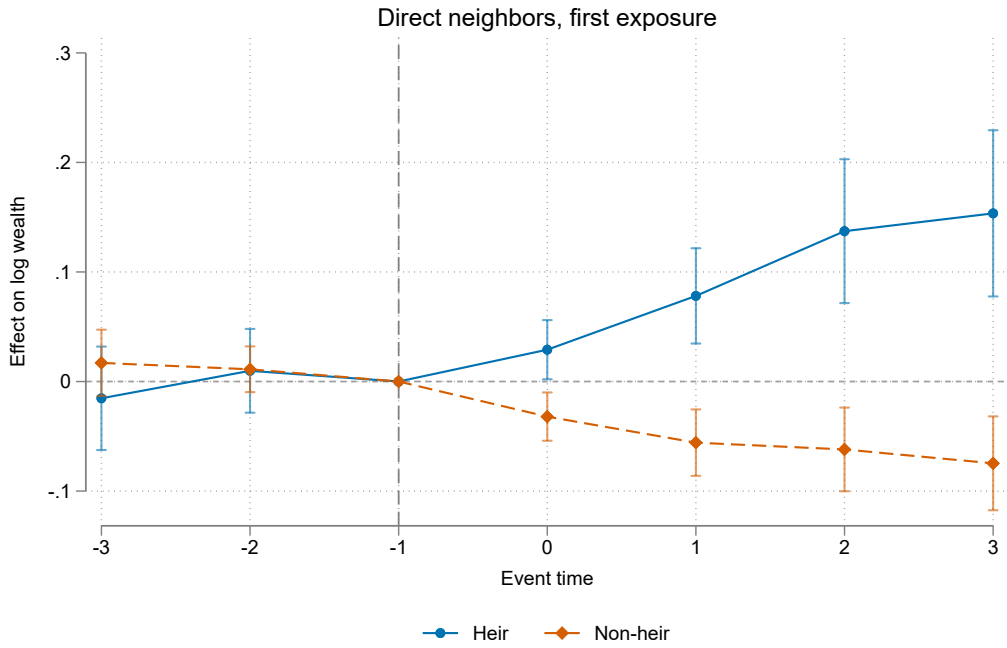


Figure A.1: Robustness Event Study: All PR Changes, First Exposure Only

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The sample is restricted to each survivor's first connection-loss exposure and to direct neighbors of the deceased.

Table A.2: Robustness PR-Loss versus PR-Gain Estimates: First Exposure Only

	Dependent variable: log wealth
Post × Non-heir × PR loss	-0.1104
	(0.0246)
Post × Non-heir × PR gain	0.0186
	(0.0236)
Post × Heir × PR loss	0.1282
	(0.0363)
Post × Heir × PR gain	0.0723
	(0.0397)
Observations	370,552
Adj. R-sq	0.9417
Dep. var. mean	20.1150

Notes: The table refines the first-exposure robustness check by re-estimating equation (3), interacting the post-period indicator with heir status and the sign of the induced PageRank change. Standard errors, reported in parentheses, are clustered at the investor level.

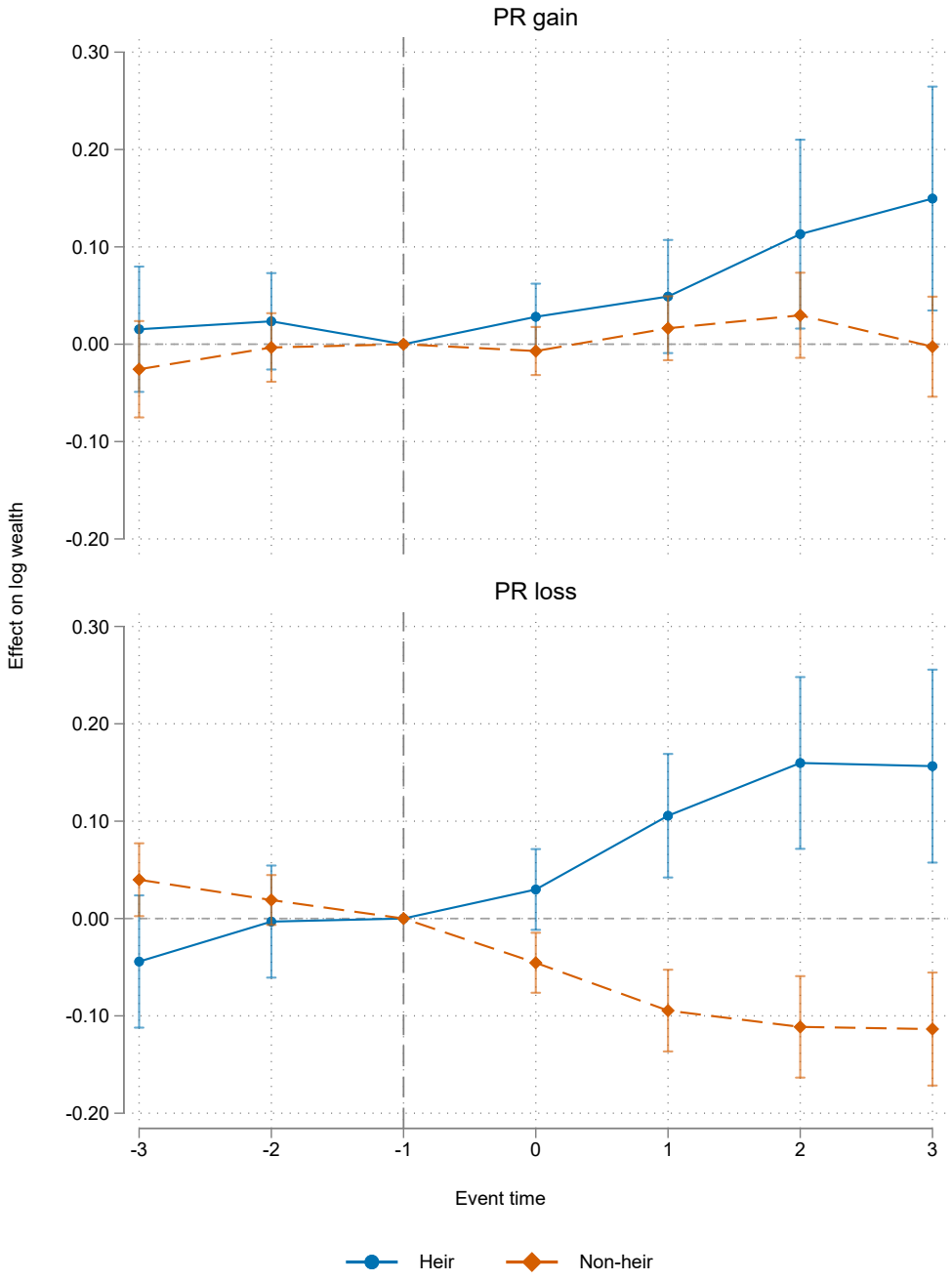


Figure A.2: Robustness Event Study: PR Gain versus PR Loss, First Exposure Only

Notes: Each marker is an event-time coefficient from the stacked log-wealth event study in equation (1), estimated separately for heirs and non-heirs of the deceased. The omitted period is the year before death. Vertical bars show 95% confidence intervals with investor-level clustered standard errors. The sample is restricted to each survivor's first connection-loss exposure and to direct neighbors of the deceased. The upper panel restricts to deaths that induce a counterfactual PageRank gain for the survivor; the lower panel restricts to deaths that induce a loss. The two panels share a common vertical scale.