The Importance of Networks for Career Success: Evidence from the Real Estate Industry*

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July 2025

Preliminary results - Please contact authors for updates before citing

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Abstract

The impact of initial network exposure on career success is difficult to identify due to endogenous network formation. Using quasi-random matching among residential real estate agents, we estimate the causal effect of counterparty network centrality on new agents' survival. A one standard deviation increase in initial counterparty centrality raises one-year survival by 26 percent. New agents matched with well-connected counterparts also complete more transactions. These effects are strongest among agents with low first-year volume. Our dynamic Bayesian network model formalizes how counterparty centrality enhances early productivity and long-run outcomes, underscoring the importance of initial relational capital in shaping career trajectories.

Keywords: Network Centrality, Career Success, Mentorship, Survival, Real Estate

JEL Codes: D85, J24, R30, C78, L85

*We thank Fikri Pitsuwan, Jennifer Grootegoed for constructive feedback.
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1 Introduction

Various factors influence an individual's career success, including personal abilities, organizational environments, and external opportunities. Recent research has increasingly emphasized the importance of networks. However, isolating the impact of an individual's network on their career success is difficult due to the endogenous nature of network formation. For example, an agent may possess a strong network as a result of career success. Conversely, a strong network may also facilitate the agent's achievement of career success. We address this endogeneity issue by exploiting the quasi-random matching of *new* real estate agents with counterparty agents to examine the effect of network connections on early career success in the U.S. residential real estate brokerage market.

Three characteristics of the residential brokerage market make it the ideal setting to examine the role of networks in shaping agents' early career success. First, there are relatively few barriers to entry into the industry (Hsieh and Moretti, 2003). Individuals who want to obtain a real estate agent license must take an exam, but the requirements to pass the exam are limited. Second, the relatively low barrier to entry results in high turnover and a low survival rate. Only a fraction of new agents remain active for more than one year.[1] Third, and most importantly, new agents' trading networks are quasi-randomly assigned. Housing markets are notoriously thin (Bayer et al., 2008; Han and Strange, 2015), so new agents cannot choose which agents they transact with. Instead, new agents' network connections depend on which other agents are *active* in the market (i.e., representing a buyer or seller) and their clients' housing preferences. We exploit these characteristics to examine how new agents' initial trading network connections affect their future performance.

To motivate our empirical analysis, we develop a dynamic Bayesian network model of real estate brokerage careers, where new agents are quasi-randomly matched to incumbent agents with heterogeneous network centrality. Each new agent internalizes the centrality of their initial counterpart through a shared, strictly concave internalization technology,

[1] For instance, a recent industry report finds nearly half of new real estate agents who closed their first transaction in 2022 were unable to close another transaction in 2023 (Relitix, 2024). We find new agent one-year survival rates ranging from 50 to 80% in our data from 2004 through 2021.

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generating future network opportunities and compounding spillover benefits. The model captures how career paths diverge based solely on the initial network position of one's first counterparty, rather than innate agent differences, and formalizes how early matching dynamics influence future connectivity, transaction outcomes, and survival.

Our model yields four key predictions. First, new agents initially matched with well-connected counterparties exhibit greater long-run survivability and career longevity. Second, these agents complete more transactions over time, as early exposure to central nodes improves future deal flow and visibility. Third, the benefits of high-centrality matches are most pronounced among agents with low first-year volume, for whom network spillovers serve as a critical substitute for early productivity. Fourth, initial transactions with in-house or dual-agent counterparts—while potentially offering onboarding support or higher commissions—fail to deliver the same network propagation benefits, resulting in no long-run survival advantage relative to arms-length, external matches. These predictions provide clear testable implications for the role of initial network position in shaping heterogeneous career outcomes in brokerage markets.

We test these theoretical hypotheses using transaction-level data from the Cotality Multiple Listing Service (MLS) for Charlotte, North Carolina from 2001 to 2023.[2] The data includes over 417,000 residential real estate transactions. Each record captures a completed sale involving a listing agent and a buyer agent, allowing for the construction of agent-to-agent interaction networks. Transactions missing agent identifiers were excluded to ensure network completeness. To capture the dynamic evolution of professional ties, we segment the dataset into rolling three-month intervals and construct backward-looking three-year networks for each window. Within each network, nodes represent agents and directed edges represent transactions from listing to buyer agents. Repeated interactions form a directed multigraph, which we then collapse into a weighted directed graph that aggregates transaction counts and volumes, allowing for a richer relational characterization. We compute eigenvector centrality as our primary network measure, emphasizing the recursive importance of agents connected to other influential agents.

We find empirical evidence consistent with our theoretical predictions: new real es-

[2]The next version of this paper will incorporate MLS data from several large U.S. cities.

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tate agents who transact with well-connected counterparty agents in their first deal are significantly more likely to survive in the industry than new agents who transact with less-connected counterparty agents. A one-standard-deviation increase in the network centrality of the initial counterparty raises the probability of surviving one year by 24%, two years by 22.5%, and three years by 18.9%. These results are robust to additively and multiplicatively separable sale year and zip code fixed effects, ensuring comparisons are drawn among agents operating in similar temporal and spatial contexts.

We interpret the higher survival rate as evidence that new agents benefit from transacting with well-connected counterparty agents. It seems intuitive that transacting with a well-connected agent would positively impact the career trajectory of a new agent more than a less-connected counterparty agent. The benefits of a network connection may be explicit; a well-connected counterparty agent can provide mentorship and offer access to their professional network. Or the benefits of the network connection could be implicit in that the new agent observed the actions and behavior of the well-connected counterparty agent and mirrored them in subsequent transactions. Regardless, the transaction with the well-connected counterparty agent increased the new agent's likelihood of survival.

Typically, when examining networks' impact on an outcome, other factors that might be correlated with position in the network and the outcome itself must be carefully accounted for. We are not overly concerned about these factors in our study because the new agents we focus on are not yet, by definition, part of the trading network. They enter the trading network via a quasi-random matching process – where the counterparty's position determines theirs. One could argue that new agents already have social (but not trading) connections to the other agents in their brokerage office. We mitigate this potential confounding effect by including fixed effects for the brokerage office, thereby controlling for differences in organizational environments (e.g., training, equipment, within-office mentorship, etc.). We continue to find that new real estate agents who transact with well-connected counterparty agents in their first deal are significantly more likely to survive in the industry than new agents who transact with less-connected counterparty agents.

We also account for the potential confounding effect of time-invariant characteristics of counterparty agents by including counterparty agent fixed effects. Our results show

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that new agents' survival rates improve with the time-varying connectedness of the initial counterparty agent they engage with - underscoring the importance of network position over the counterparty agent's fixed attributes. Finally, we extend the analysis to longer-term outcomes. Agents who begin their careers by transacting with highly central counterparty agents enjoy longer careers and higher cumulative earnings, driven by increased transaction volumes. These results reinforce the lasting impact of early exposure to network influence and highlight how initial relational capital shapes long-term professional trajectories in decentralized markets.

Our study contributes to several strands of economics and finance literature on the role of early-career connections in shaping long-term professional outcomes and the internalization of network spillover effects. First, we advance this literature by leveraging the quasi-random initial matching of new agents in residential brokerage networks to causally identify the impact of transacting with a well-connected counterparty on agent survival. In contrast to prior studies on employment and leadership outcomes—which often rely on observational data or field experiments without plausibly exogenous variation, thereby limiting causal inference (Montgomery, 1991; Calvó-Armengol and Jackson, 2004; Hwang and Kim, 2009; Beaman and Magruder, 2012; Fracassi and Tate, 2012; Galeotti and Merlino, 2014; Cai et al., 2022)—our approach provides a more credible identification strategy. Our setting is unique in that it captures real-world matching processes in a high-stakes professional context while allowing us to isolate the long-run consequences of initial network exposure.

Second, our findings complement the growing economics of talent literature that emphasizes the compounding benefits of early opportunities and mentorship (Becker, 1964; Mincer, 1974; Heckman and Mosso, 2007; Beaman and Magruder, 2012; Fracassi and Tate, 2012; Agarwal and Gaule, 2020; Megalokonomou et al., 2024; Card and Giuliano, 2024; Cohodes et al., 2024) . In line with recent evidence from Calaway (2024) and Megalokonomou et al. (2024) on the power of mentorship and peer interventions, we show that social capital and early professional connections exert persistent, long-term effects on the new entrant's survivability and performance. Our model formalizes how early take-off stage advantages—such as an initial transactional tie to a central agent—can shift

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individuals onto higher career trajectories. By highlighting the sustained internalization of counterparty influence and network embeddedness over time, our findings align with recent evidence from Agarwal and Gaule (2020), Card and Giuliano (2024), and Cohodes et al. (2024), which underscores the importance of path dependence in shaping academic and professional success.

Our study provides a distinct and complementary perspective to the literature on network centrality and peer effects in trading, hiring, and productivity (Sacerdote, 2001; Calvó-Armengol et al., 2009; Blume et al., 2015; Rossi et al., 2018; Di Maggio et al., 2019). Unlike prior work that focuses on information flows within existing networks, we model the internalization of centrality spillovers from the first outside-to-inside node match, generating persistent outcome heterogeneity that remains robust after controlling for a set of stringent fixed effects. While Rossi et al. (2018) show that central fund managers outperform in delegated investment settings and Di Maggio et al. (2019) document that brokers' network positions influence trading performance, our study uniquely links initial network exposure to survival trajectories and cumulative productivity. By structurally modeling network information spillovers in a Bayesian framework, we offer a micro-founded explanation for how early-career network position shapes long-term professional success in information-sensitive markets.

The rest of this paper is organized as follows. Section 2 develops a dynamic Bayesian network framework for modeling the impact of network influence. Section 3 describes our real estate broker data and construction of network measures and our sample. Section 4 outlines our empirical strategy and results. Section 5 presents robustness tests. Section 6 concludes.

2 Theoretical Framework

In this section, we develop a dynamic Bayesian network model to study how real estate agents' initial professional connections shape long-term survival and career success. New agents are randomly matched to established agents with varying network centrality and internalize their counterpart's influence through a strictly concave internalization

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technology. Those matched with high-centrality peers benefit from spillover effects that compound over time, producing heterogeneous trajectories from symmetric entry. We extend the model along three dimensions: (1) the positive effect of initial centrality is strongest among agents with low first-year transaction volume; (2) in-house transactions offer no survival advantage relative to arms-length deals when network quality is similar; and (3) dual-agent transactions provide higher immediate commissions but forego long-run network benefits. Together, these features generate testable predictions linking early match quality, transaction volume, and strategic behavior to agent survival outcomes.

2.1 The Model

2.1.1 Set-up

Suppose there are two new entrant agents. There is an existing network (graph) $G = (V^\theta, E; \Theta)$, where node $v_i^\theta \in V^\theta$ represents agent i in the sub-network V^θ where $\theta \in \Theta$ with $\Theta = \{H, L\}$. The agents in the existing network are partitioned into two mutually exclusive groups with the network centrality measure such that $V^H \cup V^L = V$ and

$$c_i = \frac{1}{\lambda} \sum_{j=1}^{n} \alpha_{ij} c_j \tag{1}$$

$$v_i^\theta \in \begin{cases} V^H & \text{if } c_i \geq c^* \\ V^L & \text{otherwise.} \end{cases} \tag{2}$$

Given agents i and j are in V^θ, the network centrality of agent i is denoted as c_i with constant λ and relative centrality score c_j where $A = [\alpha_{ij}]$ denote its adjacency matrix where $\alpha_{ij} = 1$ if there is an edge from node i to node j, and $\alpha_{ij} = 0$ otherwise.[3] For an exogenous critical threshold c^*, an agent with a network centrality measure exceeding c^* is classified as belonging to the high-centrality group, otherwise, the agent is considered part of the low-centrality group. The partitioning of the network reflects a key feature of the real estate brokerage industry, which is markedly bifurcated between well-connected,

[3] In the context of our analysis, we use the weighted eigenvector centrality measure. Importantly, the use of alternative centrality metrics does not affect the model's key outcomes.

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highly successful agents and those who are less established with weaker links.

2.1.2 Initial Connection & Centrality Internalization

In the first stage, nature draws from a uniform distribution $[0, 1]$ a private assignment of each new entrant agent v_i^θ exactly one unique edge a_{ij} connecting to an existing node $v_j^\theta \in V^\theta$ where $i \in \{a, b\}$.[4] Once the edge is formed, the new entrant agent i learns whether it is connected to a high or low network centrality counterparty.[5] The new entrant agent i is endowed with a strictly concave, continuously differentiable internalization technology $\varphi_i \in [0, 1]$. Thus, new entrants strategies are their internalization technologies, which are determined following the realization of their assigned counterparty types and are symmetric in equilibrium. When new agents form connections (e.g., close a transaction) for the first time, they internalize the network centrality of their counterparties. These spillovers are internalized by the new agents as part of their own payoff function. We define new agent i's payoff function as

$$\pi_i = \varphi_i^* c_j \tag{3}$$

where $\varphi_i \in [0, 1]$ represents new agent i internalization technology, which converts a fraction of the initially connected counterparty agent j's centrality measure. In other words, the new agent i internalizes the positive spillover effect of its initial counterparty j's centrality measure.[6]

[4]The direction of the edge is not of first-order importance in this environment; what matters is whether the new agent forms a connection with a well-connected existing agent. In our empirical analysis, we distinguish the edge's direction to identify whether a given node represents the listing agent or the buying agent per edge.

[5]Note in order to internalize the counterparty agent's centrality measure, we assume the information revealed contains this piece of information.

[6]Figure 1 illustrates an example of network entry in which the existing structure comprises five established agents. New Agent B is randomly matched with Agent 2, a low-centrality agent, while New Agent A is matched with Agent 4, a highly central agent. Figure 2 illustrates a sample one-stage network evolution in which New Agent A forms significantly more transactions with Agents 1 and 5, while New Agent B adds a single additional transaction with Agent 2. These random initial matches, assigned by nature, shape each entrant's future trajectory after internalizing the network spillover effects embedded in their counterparties' network positions.

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2.1.3 Uncertainty: Network Evolution and Agent Survival

Following the initial connection, we model the agent's subsequent career trajectory as a dynamic Bayesian network formation process unfolding over discrete time periods $t \in \mathbb{N}$. Two sources of uncertainty shape this dynamic path: (1) the stochastic evolution of the agent's network position and (2) the agent's own survival process.

We formalize the agent's network evolution using a time-homogeneous Markov chain. Given the partition of the network into high-centrality (V^H) and low-centrality (V^L) groups, the transition probabilities are defined as:

$$\Pr(v^\theta_{i,t} \in V^H \mid v^\theta_{i,t-1} \in V^H) = \xi_{HH}, \quad \Pr(v^\theta_{i,t} \in V^L \mid v^\theta_{i,t-1} \in V^H) = \xi_{HL}, \tag{4}$$

$$\Pr(v^\theta_{i,t} \in V^H \mid v^\theta_{i,t-1} \in V^L) = \xi_{LH}, \quad \Pr(v^\theta_{i,t} \in V^L \mid v^\theta_{i,t-1} \in V^L) = \xi_{LL}. \tag{5}$$

The key feature of this structure is that agents previously matched with high-centrality nodes are more likely to encounter high-centrality counterparts in the future, i.e., $\xi_{HH} > \xi_{LH}$. This captures a positive feedback loop from early exposure to central agents, generating compounding network benefits over time.

Second, we model the agent's own survivability as a discrete-time Markov process. The probability that agent i survives to period $t+1$ conditional on being active in period t is given by $\mathbb{P}(i \text{ survives at } t+1 \mid i \text{ survives at } t) = \rho_t$ with $\rho_t \in (0,1)$. The cumulative survival probability up to period t is:

$$S_i(t) = \prod_{\tau=1}^{t} \rho_\tau. \tag{6}$$

This formulation implies monotonicity of the survival function since $\rho_{t+1} < 1$. Therefore, under standard assumptions, survival probability is weakly decreasing over time. Together, these two layers of uncertainty—dynamic shifts in network access and declining survival probability—jointly determine the agent's lifetime payoff and the stochastic evolution of their career success.

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2.1.4 Initial Expected Payoff

We begin by characterizing the agent's initial expected payoff, which depends on the probability that the assigned counterparty j belongs to the high-centrality subgraph, along with the associated conditional expected payoff, and similarly for the low-centrality subgraph. We establish below that the resulting expected payoff function is linear in the agent's internalization technology φ_i, and reduces to a scalar multiple of φ_i. Since new agents are rational and forward-looking, the symmetric equilibrium entails full commitment of effort at entry.

Proposition 1 In a symmetric Bayesian Nash equilibrium, all new agents fully commit effort to internalize their counterparties' network centrality. Specifically,

$$\varphi_i^* = 1 \quad \text{with} \quad \pi_i^* = \frac{\varphi_i^*}{2}. \tag{7}$$

Proof. *See Appendix Section A.*

2.1.5 Lifetime Expected Payoff

We define the agent's lifetime expected payoff as the discounted sum of future expected payoffs weighted by the probability of survival at each time t:

$$\mathbb{E}[W_i] = \sum_{t=1}^{\infty} \delta^t S_i(t) \pi_i, \tag{8}$$

where $\delta \in (0, 1)$ is the network-wide discount factor, $S_i(t)$ denotes the cumulative probability that agent i survives up to period t, and π_i is the per-period expected payoff resulting from initial matching and internalization.

Proposition 2 In a symmetric Bayesian Nash equilibrium, the marginal contribution of initial counterparty centrality to the lifetime expected payoff decreases over time, such that $\frac{\partial}{\partial t}\left(\delta^t S_i(t) \pi_i^*\right) < 0$ for all $t \in \mathbb{N}$. The agent's cumulative lifetime expected payoff is given by $\mathbb{E}[W_i^*] = \sum_{t=1}^{\infty} \delta^t S_i(t) \frac{1}{2}$, where $S_i(t)$ is the cumulative survival probability at time t and $\delta \in (0, 1)$ is the discount factor.

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The intuition behind Proposition 2 is that although being matched with a high-centrality counterparty at entry provides a valuable initial boost to an agent's career survivability, the marginal impact of that initial centrality diminishes over time. This occurs because the lifetime payoff stream is both discounted through the factor δ^t and weighted by the agent's survival probability $S_i(t)$, which declines over time.

2.2 Long-run Spillover Effects

2.2.1 Persistent Impact of Counterparty Centrality

We extend the baseline model by allowing the agent's survival probability to depend not only on the independent survival probability but also on the initial counterparty's network centrality and agent's own first-year transaction volume. Let $V_i^{(1)}$ denote the total number of transactions agent i completes in the first year, and let $c_{j,0}$ denote the centrality of the counterparty in agent i's initial match at $t = 0$. Based on the survival framework in network diffusion models (Mortensen and Pissarides, 1994; Jackson, 2008; Banerjee et al., 2013), we define the expected lifetime payoff as:

$$\mathbb{E}[\tilde{W}_i] = \varphi_i \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) c_{j,t} \quad \text{with} \quad S_i(t) = \left(1 - e^{-\nu \frac{c_{j,0}}{V_i^{(1)}+1}}\right) \rho^t. \tag{9}$$

where $S_i(t)$ is the probability that agent i survives until period t. The variable $c_{j,0} \in [0, 1]$ denotes the centrality of agent i's initial counterparty j, while $V_i^{(1)} \geq 0$ captures the total number of transactions agent i completes in their first year. The parameter $\nu > 0$ governs the strength of network spillovers, and $\rho \in (0, 1)$ represents the constant per-period probability of survival, encoding time decay.

Proposition 3 Initial exposure to high-centrality counterparties has a persistent effect on agent outcomes by increasing both long-term survival probability and cumulative transaction value. For all $t \in \mathbb{N}$, we have $\frac{\partial S(c_{j,0}, V_i^{(1)}, t)}{\partial c_{j,0}} > 0$, which implies that $\frac{\partial \mathbb{E}[\tilde{W}_i]}{\partial c_{j,0}} > 0$.

This proposition formalizes the idea that early exposure to well-connected counterparties delivers durable career advantages through enhanced network access, reputational

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spillovers, and knowledge transfer. High-centrality agents act as gateways to more valuable parts of the transaction network, enabling new agents to establish credibility and access further opportunities more rapidly. These early connections compound over time by increasing the likelihood of future high-quality matches, thereby improving long-term survival and cumulative productivity. The result underscores the enduring role of early-career luck—particularly the advantage of being matched with influential peers—in shaping success, with implications for talent development and mentorship interventions.

2.2.2 Heterogeneous Returns to Centrality

Proposition 4 The marginal effect of counterparty network centrality on agent survival is decreasing in first-year transaction volume. Suppose $\frac{\alpha c_{j,0}}{1+V_i^{(1)}} < 1$. For all t, the cross-partial derivative of survival satisfies $\frac{\partial^2 S(c_{j,0}, V_i^{(1)}, t)}{\partial c_{j,0}\, \partial V_i^{(1)}} < 0$, which in turn implies that $\frac{\partial^2 \mathbb{E}[\tilde{W}_i]}{\partial c_{j,0}\, \partial V_i^{(1)}} < 0$.

The condition $\frac{\alpha c_{j,0}}{1+V_i^{(1)}} < 1$ captures diminishing returns to network centrality as early productivity increases. When first-year transaction volume $V_i^{(1)}$ is low, the survival benefit from initial counterparty centrality $c_{j,0}$ is large. However, as $V_i^{(1)}$ grows, agents become less reliant on network spillovers, reducing the marginal value of $c_{j,0}$. This reflects a substitutability between external social capital and internal productivity, consistent with theories of early-career human capital accumulation.

This result captures the idea that high-centrality counterparties provide the greatest benefit to agents who otherwise lack momentum in their early career (i.e., those with low first-year transaction volume). These agents are especially dependent on the spillover effects from high-quality initial matches to jumpstart their network position and increase survival prospects. In contrast, agents with high early volume already signal strong underlying productivity and thus rely less on the centrality of their initial connections.

2.3 Extensions

We extend the baseline model in two key directions. First, we incorporate in-house equilibrium, allowing agents to transact with colleagues from the same brokerage. While such deals may offer modest bonuses, they provide limited exposure to

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external network spillovers. We show that in-house and arms-length transactions yield similar survival outcomes when in-house bonuses are small and network centrality is comparable, reinforcing the idea that organizational affiliation alone does not drive survivability. Second, we analyze a myopic equilibrium where agents engage in dual-agent transactions to earn higher immediate commissions but forgo the long-term benefits of arms-length network formation. While dual-agent deals offer short-term payoffs, they do not confer a survival advantage unless the commission premium is large, highlighting the critical role of early external connections in shaping long-run success.

2.3.1 In-House Equilibrium

We extend our baseline model to include the possibility that new agents transact with in-house counterparties—such as colleagues within the same brokerage—rather than external arms-length agents. While in-house deals may offer modest bonus incentives, they limit exposure to broader network spillovers. We examine whether such internal transactions meaningfully alter expected lifetime payoffs or survival outcomes, relative to matches with externally connected peers. We formalize the lifetime expected payoff for an in-house and external arms-length transactions as

$$\mathbb{E}[\tilde{W}_i^{\text{in}}] = \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) \left(\underline{a} + \varphi_i c_{j,t}^{\text{in}}\right), \tag{10}$$

$$\mathbb{E}[\tilde{W}_i^{\text{ext}}] = \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) \left(\varphi_i c_{j,t}^{\text{ext}}\right) \tag{11}$$

where $\underline{a}$ captures the additional spillover benefits of being within the same brokerage firm, reflecting improved communication, a streamlined office culture, and institutional support.

Proposition 5 Let agent i choose between transacting with an in-house counterparty or an arms-length external counterparty. If $\underline{a} \approx 0$ and $c_{j,t}^{in} \approx c_{j,t}^{ext}$, then the agent's expected lifetime payoff is approximately equal across the two transaction types: $\mathbb{E}[W_i^{in}] \approx \mathbb{E}[W_i^{ext}]$. Moreover, the difference in lifetime payoff, $\Delta W_i = W_i^{in} - W_i^{ext}$, is increasing in the centrality gap $(c_{j,t}^{in} - c_{j,t}^{ext})$, implying that external matches dominate when $c_{j,t}^{ext} > c_{j,t}^{in}$.

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This proposition captures two key insights. First, in-house and arms-length matches yield similar long-term outcomes when in-house bonuses are small and network centrality is comparable, suggesting affiliation alone does not drive survivability. Second, external matches become increasingly advantageous when the external counterparty is more central, as the agent benefits from richer network spillovers over time. Thus, external network quality—rather than organizational affiliation—plays a more pivotal role in shaping career outcomes.

2.3.2 Myopic Equilibrium and Dual-Agent Transactions

We now extend the benchmark model to incorporate the possibility that new agents may opt for dual-agent transactions—acting as both buyer and seller agent in a single deal—thereby bypassing the opportunity to form arms-length connections. While such transactions yield immediate commission benefits, they forgo long-term network spillovers. This setting gives rise to a *myopic equilibrium*, in which agents maximize present-period payoffs without internalizing future gains from networking.

Let φ_i represent agent i's baseline commission from a transaction. We assume that dual-agent deals yield a multiplicative premium $\kappa > 1$ relative to single-sided deals, capturing the fact that the agent earns both sides of the commission. However, dual-agent deals inherently preclude arms-length interaction and thus forgo any network-based continuation value. The agent's per-period payoff function is now:

$$\pi_i = \kappa\varphi_i + \varphi_i c_j \mathbb{1}_{\{\text{arms-length}\}} \tag{12}$$

The term $\mathbb{1}_{\{\text{arms-length}\}}$ is an indicator that equals 1 if the transaction is arms-length and 0 if the transaction is dual-agent. Hence, dual-agent transactions yield immediate payoffs of $\kappa\varphi_i$ but no network benefits. In contrast, arms-length transactions yield φ_i in direct commissions plus a spillover benefit $\varphi_i c_j$ based on the centrality of the counterparty j. Then, it follows that the

$$\mathbb{E}[\tilde{W}_i^{\text{arms}}] = \sum_{t=0}^{\infty} \beta^t \delta_t \left(\varphi_i + \varphi_i c_j\right) \tag{13}$$

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$$\mathbb{E}[\tilde{W}_i^{\text{dual}}] = \kappa\varphi_i + \sum_{t=1}^{\infty} \beta^t \delta_t \varphi_i. \tag{14}$$

Proposition 6 Let $\mathbb{E}[W_i^{\text{arms}}]$ and $\mathbb{E}[W_i^{\text{dual}}]$ denote the lifetime expected payoff under an arms-length and a dual-agent transaction, respectively. Suppose $\kappa < \frac{\delta_0(1+c_j)-\beta\delta_1}{1-\beta}$, then $\mathbb{E}[W_i^{\text{arms}}] > \mathbb{E}[W_i^{\text{dual}}]$.

The inequality $\kappa < \frac{\delta_0(1+c_j)-\beta\delta_1}{1-\beta}$ captures the trade-off between short-term gains from dual-agent transactions and long-term benefits of forming arms-length network ties. The left-hand side, κ, represents the immediate commission premium from closing both sides of a deal. The right-hand side reflects the discounted future value of an external match, which includes both standard commission and the centrality-based spillover c_j. When κ is small relative to the continuation value of external connections, agents have a greater incentive to forgo the immediate gain in favor of building relationships that enhance survival and productivity over time.

Dual-agent transactions generate immediate returns by capturing both sides of the commission, but they sacrifice the long-term benefits of network formation. Arms-length deals, particularly with highly central counterparties, provide compounding value through enhanced visibility, reputation, and connectivity. The proposition shows that unless the dual-agent commission premium κ is very large, the strategic benefit of entering the network through arms-length ties outweighs the short-term gain—emphasizing that early relationship-building is critical for long-run survival and success.

2.4 Theoretical Hypotheses

Hypothesis 1 New agents who are initially matched with high-centrality counterparties will exhibit superior survivability compared to those matched with low-centrality counterparties.

This prediction is grounded in Proposition 3, which shows that initial exposure to central counterparties increases long-term survival probability. The intuition is that high-centrality agents serve as conduits of information and deal flow. A new agent linked to

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a well-connected peer enters a denser part of the transaction network, accelerating their access to future opportunities and increasing visibility among potential collaborators.

Hypothesis 2 The positive effect of initial counterparty centrality on new agent survival will diminish over time as agents become more embedded in the transaction network.

This prediction follows from Proposition 2, which establishes that the marginal contribution of early centrality declines with time. While network spillovers are critical during early career stages, agents eventually generate their own connections and reputation, reducing reliance on their initial counterpart's network position.

Hypothesis 3 Initial exposure to high-centrality counterparties will have lasting effects, increasing new agents' long-term survival duration and cumulative transaction volume.

Also supported by Proposition 3, this prediction reflects the persistent role of early network placement. Central partners create a favorable trajectory in the Markovian evolution of connections, leading to cumulative advantage as agents repeatedly access well-connected peers. Early centrality thus compounds over time through preferential attachment.

Hypothesis 4 The effect of counterparty network centrality on survival will be stronger among agents with lower first-year transaction volume, indicating that centrality may facilitate early productivity.

This prediction is formalized in Proposition 4, which shows that the cross-partial of survival with respect to initial centrality and early volume is negative. When endogenous productivity is low, external spillovers compensate by amplifying visibility, referrals, and network legitimacy—providing crucial momentum during the formative stages of career development.

Hypothesis 5 New agents who transact with in-house counterparties will not exhibit significantly different survival outcomes than those transacting with arms-length counterparties, suggesting external networks play a more pivotal role.

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This prediction is grounded in Proposition 5, which shows that if the in-house bonus is modest and centrality levels are similar, then organizational affiliation alone does not generate a survival advantage. Economic gains from internal deals stem mainly from coordination benefits, but these are outweighed by the broader market access afforded by external connections when spillovers matter most.

Hypothesis 6 Dual agent transactions, which prevent network formation, will not confer a survival advantage despite providing higher immediate commissions.

This follows from Proposition 6, which compares arms-length and dual-agent lifetime payoffs. While dual-agent deals offer high upfront earnings, they forgo long-run network benefits that sustain career relevance. The trade-off reflects a classic short-term versus long-term dynamic: without external ties, agents miss out on compounding spillovers essential for survivability.

3 Data and Networks

This section outlines the dataset and the methodology used to build the panel dataset and agent network from MLS transaction records.

3.1 Data

Our primary dataset consists of Cotality's MLS housing transaction data in Charlotte, North Carolina, from 2001 through 2023. Transactions missing information in key fields, such as a listing agent ID or a buyer agent ID, are excluded from the dataset. The filtered dataset contains 417,094 single-family housing transactions involving 40,344 unique real estate agents. Panel A of Table 1 displays summary statistics for the filtered housing transaction dataset.

3.2 Constructing Networks

To capture the evolving structure of agent interactions, we construct a series of dynamic networks over rolling time windows. We segment the full sample period into sequential

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three-month intervals, starting in January, April, July, and October of each calendar year. For each time window, we define a backward-looking three-year observation period and include all transactions completed during that window to construct the agent network.

In each resulting network, nodes represent individual real estate agents, and directed edges represent housing transactions, oriented from the listing agent to the buyer agent. Because agents may transact multiple times with the same counterparty agent, the network takes the form of a directed multigraph, allowing multiple edges between agent pairs. Each edge reflects a distinct transaction and is labeled with the corresponding sale price, thereby capturing both the frequency and economic value of interactions.

Figure 6 illustrates an example of our constructed network. The left graph shows the raw directed multigraph where repeated interactions between agents are represented as multiple edges. This detailed representation enables a fine-grained view of market behavior, such as patterns of repeated cooperation or agent specialization. The right graph presents a reduced-form version of the multigraph, in which multiple edges between the same agent pair are aggregated into a single directed edge. Each edge in the collapsed graph is annotated with the number of transactions (n), total transaction volume (TP), and average transaction price (AP), summarizing the intensity and economic scale of the relationship.

While the multigraph preserves the granularity of individual interactions, we use the reduced-form directed graph as the input for centrality analysis. This transformation allows us to capture both the presence and intensity of agent relationships, facilitating the computation of weighted network measures. Economically, frequent and high-value repeated transactions between two agents may signal trust, shared clientele, or strategic alignment. These relational dynamics, in turn, shape agents' access to information, client flows, and future opportunities, all of which are critical for understanding influence within the marketplace.

3.3 Measuring Network Centrality

The centrality of a node in a network is a micro-level structural feature that facilitates comparisons among nodes by quantifying their relative importance within the network

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(Jackson, 2008). Various centrality measures exist, each capturing a different notion of importance, such as degree, closeness, or betweenness. In this study, we employ eigenvector centrality to assess an agent's influence, not only through its direct connections but also through the centrality of the agents it is connected to. This recursive structure is particularly relevant in the residential real estate brokerage setting, where indirect connections and the prominence of counterparty agents' neighbors can enhance visibility, information access, or market power.

Our network is a directed multigraph, where edges point from listing agents to buyer agents. To reflect this structure, we compute eigenvector centrality based on incoming edges; that is, an agent is central if it frequently transacts as a buyer agent with other highly central listing agents. The eigenvector centrality of agent i is defined as:

$$C_i = \frac{1}{\lambda} \sum_{j \in \mathcal{N}^-(i)} A_{ji} C_j, \tag{15}$$

where $\mathcal{N}^-(i)$ denotes the set of agents with directed edges pointing to agent i (i.e., its in-neighbors), A_{ji} is the adjacency matrix entry indicating the presence and weight of an edge from agent j to agent i, and λ is the largest eigenvalue of the adjacency matrix. This formulation emphasizes that an agent's centrality is recursively determined by the centrality of those agents who transact with it as listing agents.

In addition to the unweighted specification, we compute weighted eigenvector centrality in which the adjacency matrix entries A_{ji} are defined by the number of transactions from agent j to agent i. This approach captures not only the presence of a connection but also its intensity. Specifically, repeated interactions between the same pair of agents—such as multiple transactions initiated by a listing agent toward the same buyer agent—are weighted more heavily in the centrality calculation.

Incorporating transaction frequency as a weight provides richer economic interpretation. In real estate markets, repeated collaborations may reflect underlying information channels, professional trust, or brokerage networks that facilitate more efficient dealmaking. Agents who are repeatedly selected by other central agents are likely to have stronger reputational capital, broader market reach, or superior client matching capabil-

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ities. By capturing both the structure and depth of relationships, the weighted version of eigenvector centrality offers a more nuanced measure of influence within the agent network.

3.4 New Agents

Panel B of Table 1 presents summary statistics for the 19,904 new agents who entered the real estate trading network between 2004 and 2021. The counterparty network centrality reflects the normalized weighted eigenvector centrality of the first counterparty agent each new agent transacts with. We normalize these rolling quarterly centrality measures to account for variation in the timing of new agents' entry into the network. The summary statistics indicate that 70% of the new agents survive more than one year, 58% survive more than two years, and 47% survive more than three years. The average survival length of new agents in the data is 1,642 days or roughly four and a half years. Figure 7 highlights how new agents' survival length varies over time with market conditions.

4 Methodology and Results

We exploit the quasi-random matching of real estate agents in housing transactions to examine whether new agents who transact with well-connected counterparty agents have a higher survival rate than new agents who transact with less connected counterparty agents. We estimate agent-level regressions of the following form:

$$Survive_{i,j,t} = \beta_1 Centrality_{j,t} + \beta_2 Dual_{i,t} + \beta_3 Inhouse_{j,t} + \lambda_t + \varepsilon_{i,j,t} \tag{16}$$

The dependent variable in Equation 16, $Survive_{i,j,t}$, is a binary indicator that equals one if real estate agent i survives — that is, has another transaction in the data — after a specified duration following their initial transaction with counterparty agent j at time t; otherwise, it takes a value of zero. In most analyses, we examine relatively short-term survival lengths of one, two, or three years. In subsequent analysis, we also examine new agents' survival length where $Survive_{i,j,t}$ is a continuous variable that measures the the number of days

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between new agent i's first and last transaction in the data.

In Equation 16, the primary variable of interest, $Centrality_{j,t}$, captures the time-varying network centrality of the first counterparty agent j that the new agent i transacts with in the data. Equation 16 also includes controls identifying whether the agents involved in the transaction have an "arms-length" relationship. The first control, $Dual_{i,t}$, is an indicator variable that equals one if new agent i represents both the buyer and seller in the transaction; otherwise, it equals zero. These transactions, which are commonly referred to as dual agent transactions, are illegal in some states. By definition, $Centrality_{j,t} = 0$ when $Dual_{i,t} = 1$ since new agent i does not transact with a counterparty agent. The second control, $Inhouse_{j,t}$, is an indicator variable that equals one if new agent i works for the same brokerage office as counterparty agent j; otherwise, it equals zero. These transactions are commonly referred to as in-house transactions. We set $Inhouse_{j,t} = 0$ when $Dual_{i,t} = 1$.

To avoid perfect multicollinearity, we omit the final control, $ArmsLength_{j,t}$, from Equation 16. $ArmsLength_{j,t}$ is an indicator variable that equals one if new agent i has an arms-length relationship with counterparty agent j; otherwise, it equals zero. New agent i and counterparty agent j have an arms-length relationship if they work for different brokerage offices. We set $ArmsLength_{j,t} = 0$ when $Dual_{i,t} = 1$ or $Inhouse_{j,t} = 1$. Finally, Equation 16 also includes additively or multiplicatively separable zip code and sale year fixed effects, λ_t, for the new agent's first transaction at time t. Including the location and time fixed effects allows us to isolate the impact of network connections on the early career success of new real estate agents who work in the same area and enter the profession at the same time.

4.1 New Agent Survival

Table 2 reports regression results from Equation 16. The counterparty network centrality coefficient estimates in all six columns of Table 2 vadliate Hypothesis 1. They indicate that new agents' probability of survival increases with the connectedness of the first counterparty agent they transact with. In columns 1 and 2, a one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 24-27.9%. As the length of the new agent survival window increases

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from one year to three years in columns 3 to 6, the magnitude of the network centrality coefficient estimate decreases, which supports Hypothesis 2. In columns 5 and 6 of Table 2, a one-standard-deviation increase in the counterparty agents' network centrality increases new agents' three-year survival rate by 18.9-26.1%. This finding indicates that the impact of counterparty agent j's network connectedness on the survival of new agent i decreases over time. This outcome is expected because new agents likely grow less dependent on their initial connection as they become more embedded in the trading network.

Overall, the results in Table 2 indicate that new agents benefit from forming network connections with well-connected agents. These benefits are particularly significant during the early stages of their real estate careers. The benefits may be explicit — through mentorship and direct access to the counterparty agents' network connections — or implicit, as new agents learn by observing and emulating the more experienced counterparty agents' behavior. In either case, transactions with well-connected counterparty agents significantly increase new agents' chances of survival.

Table 2 also reports the coefficient estimates for the agent relationship controls in Equation 16. The first control for dual agent transactions highlights an interesting tradeoff that new agents face when representing both the buyer and seller in their first transaction. On the one hand, the new agent earns a larger commission for representing both the buyer and seller. The larger commission should arguably increase the new agent's probability of survival. On the other hand, the new agent does not develop a network connection with a counterparty agent. Assuming networks matter - which we show in this paper - the lack of network connectivity will decrease the new agent's probability of survival relative to new agents that transact with well-connected counterparty agents.

The coefficient estimates for dual agent transactions are negative but not statistically significant across all six specifications in Table 2. These findings indicate that new agents whose initial transaction does not involve a counterparty agent are not significantly more likely to survive than those who transact with counterparty agents from different brokerage offices. In terms of new agent survival, this implies that the initial loss of network connectivity counterbalances the higher commission earned in the dual agent transaction. Together, these results support Hypothesis 6, showing that dual-agent transactions provide

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short-term commission gains but do not improve long-run survival due to the lack of network formation.

One could argue that new agents already have network (but not trading) connections with the other agents in their brokerage office. Accordingly, the brokerage office that the new agent joins could impact their probability of survival. We include an in-house agent indicator variable in Equation 16 to partially address this concern. Including the indicator variable also addresses concerns that new agents may receive referrals from other, more experienced agents in their brokerage office. This is especially a concern in states where dual agent transactions are illegal.

The coefficient estimates for in-house agent transactions are not statistically significant in all six specifications in Table 2. This suggests that new agents whose initial transaction is with a counterparty agent in the same brokerage office are not significantly more likely to survive than those who transact with counterparty agents from different brokerage offices. This implies that new agents' likelihood of survival is primarily driven by the counterparty agents' network connectedness, not whether the counterparty is outside their brokerage office. In other words, while cross-office transactions may introduce agents to a broader set of the trade network, it is unclear whether the mere fact of transacting across brokerage boundaries is a key determinant of new agents' survivability.

4.2 Brokerage Office Fixed Effects

While not statistically significant, the coefficient estimates for in-house agent transactions in Table 2 are positive in five out of six columns, suggesting that within-brokerage office trading connections may enhance the likelihood of new agents' survival. However, this indicator likely understates the true effect of such connections, as it only captures cases where a new agent's first transaction involves a counterparty from the same office. To investigate this relationship further, we incorporate brokerage office fixed effects into Equation 16. The brokerage office fixed effects control for pre-existing brokerage office network connections as well as differences in organizational environments (e.g., training, equipment, within-office mentorship, etc.).

Table 3 displays results where we regress the one-year survival variable on the coun-

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terparty agent network centrality measure for a subsample of new agents whose first transaction was with an arms-length counterparty agent. In other words, the new agent's first transaction was not a dual agent or in-house agent transaction. Column 1 of Table 3 includes zip code and sale year fixed effects. The network centrality coefficient estimate in column 1 of Table 3 is comparable to the estimate for the full sample in column 1 of Table 2, suggesting the subsample of arms-length agent transactions is similar to that of the larger sample.

Columns 2 and 3 of Table 3 introduce brokerage office fixed effects in addition to additively or multiplicatively separable zip code and sale year fixed effects. Including the brokerage fixed effects reduces the magnitude of the network centrality coefficient estimate, yet it remains sizable and statistically significant. Even after controlling for differences in organizational environments among new agents, we find that a one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 18.5-24.2%.

Column 4 of Table 3 includes brokerage office-by-sale year fixed effects. This allows us to compare the effect of network connections on the survival rate of new agents that work for the same brokerage office and enter the profession during the same calendar year. In other words, we can isolate the impact of network-connectedness among new agents who have access to the same organizational resources and support. Our results remain unchanged when we include the brokerage office-by-sale year fixed effects in column 4. We continue to find new agents who transact with well-connected counterparty agents have a higher survival rate than new agents who transact with less connected counterparty agents. This supports Hypothesis 5, indicating that in-house transactions do not significantly affect survival outcomes relative to arms-length deals, underscoring the importance of external network exposure. A one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 17.9%.

4.3 Counterparty Agent Fixed Effects

We further isolate the effect of network connectedness on new agents' early career success by modifying Equation 16 to regress the one-year survival variable on the counterparty

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agent network centrality measure and counterparty agent fixed effects. The results in Table 4 use a subsample of arms-length agent transactions that do not include dual agent or in-house agent transactions. Even after including counterparty agent fixed effects in columns 2 and 3 of Table 4, we continue to find that new agents' probability of survival increases with the connectedness of the first counterparty agent they transact with. This finding implies that new agents benefit from the counterparty agents' connectedness – which is time-varying – and not necessarily just from working with the counterparty agent themselves.

4.4 New Agent Cohort Analysis

The findings from the previous sections suggest that the network connectedness of the first counterparty agent a new agent transacts with influences their likelihood of survival. Additional factors — such as the number of transactions a new agent completes in their first year — are also likely to affect their survival. Intuitively, a higher transaction count in the first year should increase a new agent's survival chances by increasing both commission earnings (holding transaction prices constant) and connections within the counterparty agent network. We analyze the impact of first-year transaction volume on agent survival using two approaches.

First, we modify Equation 16 to include indicator variables for first-year transaction cohorts that identify new agents with 3-5, 6-10, and 11-20 first-year sales. We omit the transaction cohort indicator variable for new agents with 1-2 first-year sales. Column 1 of Table 5 displays the regression results from the modified equation using the full sample of new agents. As expected, the coefficient estimates for the first-year transaction cohorts monotonically increase with the new agents' first-year transaction volume. New agents with 3-5 first-year sales are 29% more likely to survive their first year than new agents with 1-2 first-year sales. Whereas new agents with 6-10 or 11-20 first-year sales are 40.7-44.3% more likely to survive their first year than new agents with 1-2 first-year sales. Importantly, the counterparty network centrality measure remains statistically and economically significant. A one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 22.2%.

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Second, we run subsample analyses using Equation 16 for each of the first-year transaction cohorts. Columns 2 to 4 of Table 5 display the subsample analyses results for the new agent cohorts with 1-2, 3-5, 6-10, and 11-20 first-year sales. In column 2 of Table 5, a one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 37.6%. Not surprisingly, the magnitude of the counterparty network centrality coefficient estimate monotonically decreases with the first-year transaction volume of the cohorts. In columns 3 to 5, a one-standard-deviation increase in the counterparty agents' network centrality increases new agents' one-year survival rate by 24.4% for new agents with 3-5 first-year sales, 8% for new agents with 6-10 first-year sales, and is statistically insignificant for new agents with 11-20 first-year sales.

The subsample analyses in columns 2 to 4 of Table 5 underscore the significance of network connections in shaping new agents' early career outcomes. Supporting Hypothesis 4, the findings suggest that the network centrality of the initial counterparty agent is more critical for new agents with lower transaction volumes in their first year, indicating that the importance of this initial connection diminishes for agents with higher transaction volumes. However, the network centrality of these counterparties likely contributed to the higher transaction volumes to begin with. We examine this relationship in greater detail in the next section.

4.5 Long-Term Effects

The preceding sections establish the significant role that network connections have on new agents' survival within the real estate industry. Table 6 extends this analysis by evaluating the extent to which these relatively short-term effects persist over the longer term. To facilitate this examination, the analysis uses a subsample of agents who entered the industry between 2004 and 2017, providing a minimum five-year post-entry observation window for assessing long-term performance outcomes.

Column 1 of Table 6 reports results from a regression using a modified version of Equation 16 where the dependent variable is the log of new agent i's survival length. The new agents' survival length equals the number of days between their first and last transaction date in the data. In column 1, a one-standard-deviation increase in the counterparty agents'

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network centrality almost doubles new agents' survival length. This finding shows that transacting with well-connected counterparty agents significantly increases new agents' career length. These findings support Hypothesis 3 in that initial exposure to central counterparties yields persistent survival benefits over the agent's career trajectory.

Columns 2 to 5 of Table 6 examine the effect of counterparty agents' network connectedness on the new agents' short and long-term transaction volume. Each column regresses the log of new agents' transaction volume over the specified period on the counterparty agents' network centrality, non-arms-length agent relationship controls, and zip code-by-year fixed effects. The counterparty network centrality coefficient estimates in all four columns indicate that new agents' subsequent transaction volume increases with the connectedness of the first counterparty agent they transact with. In column 2, a one-standard-deviation increase in counterparty agents' network centrality increases new agents' first-year transaction volume by just under 40%.

The short-term effect on new agents' transaction volume in column 2 is unsurprising, given that new agents' survival rate and transaction volume are interrelated. The longer a new agent survives, the more transactions they can complete. The more transactions a new agent completes, the longer they will likely survive. The results in columns 3 and 4 of Table 6 support this conjecture, showing that the magnitude of the network centrality coefficient estimate increases with the transaction window length. In column 3, a one-standard-deviation increase in counterparty agents' network centrality increases new agents' three-year transaction volume by 52.1%. Similarly, in column 4, a one-standard-deviation increase in counterparty agents' network centrality increases new agents' total transaction volume by 72.5%. These findings jointly reinforce Hypothesis 3 in that the long-run effects of initial network quality are not transitory and accumulate over time through compounding opportunity and gains in early productivity.

The final column in Table 6 adjusts for differences in new agents' survival length using the log of transactions per year as the dependent variable. Similar to the preceding columns, we find new agents' average annual transaction volume increases with the network centrality of the first counterparty agent they transact with. A one-standard-deviation increase in counterparty agents' network centrality increases new agents' average

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annual transaction volume by 42%.

The coefficient estimates for the non-arms-length agent relationship controls in column 1 of Table 6 are similar to those reported in Table 2. The dual agent coefficient estimate is negative, the in-house agent is positive, and both are statistically insignificant. These findings indicate that new agents whose first transaction is either a dual agent or an in-house agent transaction have a similar survival length as new agents whose first transaction is with an arms-length counterparty agent. These results are consistent with Hypothesis 5 and Hypothesis 6 in that neither in-house nor dual-agent match types yield a distinct long-run survival advantage.

However, when we examine new agent transaction volume in columns 2 to 5, the non-arms-length agent relationship control coefficient estimates are statistically significant. In column 5, we find new agents whose first transaction is a dual agent transaction have a 10.9% lower average annual transaction volume than new agents that first transact with an arms-length counterparty agent. In contrast, new agents whose first transaction is an in-house agent transaction have a 14% higher average annual transaction volume than new agents that first transact with an arms-length counterparty agent. These findings further support Hypothesis 5 and Hypothesis 6 in that while alternative match types may affect early productivity, they do not substitute for external network-based spillovers that drive survival.

5 Robustness Tests

In this section, we present three robustness checks. First, the Cox proportional hazard model shows that initial counterparty centrality significantly reduces exit risk, validating our use of eigenvector centrality based on incoming ties. Second, the network evolution analysis reveals that treatment agents gain sustained connectivity—especially in-degree—supporting reputational spillovers and path dependence. Third, a simulation confirms these dynamics, showing that early exposure to central agents leads to persistent and reinforcing network advantages over time.

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5.1 Survival Analysis

We document the survival analysis results in Table 7 using the Cox proportional hazard model. Among the centrality measures, indegree and eigenvector centrality stand out with the largest risk reductions—28.3% and 24.1%, respectively—indicating that connections to well-networked and influential buyer-agents generate substantial survival benefits. We plot the visualization of the agent survivability in Figure 8 and Figure 9 using the Kaplan-Meier Survival estimate results. These results align with the intuition that being introduced into a broader and more active segment of the network early on confers lasting informational and reputational advantages. More importantly, our findings justify the use of incoming directional edges as the basis for our eigenvector centrality construction for the empirical analysis.

In contrast, some centrality measures exhibit minimal or statistically insignificant effects. For instance, outdegree and clustering. These findings suggest that not all forms of network activity translate equally into survival advantages. The overall pattern supports the interpretation that it is not mere transaction volume or activity level, but the position within the network—especially in terms of connectivity to influential or bridging agents—that governs the long-term professional trajectory of new entrants in the residential brokerage market.

5.2 Evolution of the networks

To understand how early network positioning influences long-term connectivity, we analyze the structural evolution of agents' networks over time, with a particular focus on treatment and control groups defined by initial exposure to central agents. We begin by identifying agents whose first recorded transaction occurs within a selected reference window (Q2 2006) in Union County. Using these transactions, we construct a baseline agent network and compute centrality measures for all counterpart agents involved. Agents whose first transaction is with a counterpart in the top 25th percentile of eigenvector centrality are classified as the treatment group, while all others are assigned to the control group.

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Figure 10 illustrates the longitudinal evolution of average degree, in-degree, and out-degree for treatment and control agents. In the baseline period, both groups exhibit similar levels of network connectivity. However, over time, treatment agents demonstrate a systematically higher degree growth compared to control agents. This divergence is particularly pronounced for in-degree, suggesting that treatment agents become increasingly prominent as recipients of transactions, possibly due to reputational spillovers or preferential attachment mechanisms. These dynamics imply that early access to well-connected agents may serve as a catalyst for sustained integration and influence within the network.

Figure 11 provides a complementary visualization of network evolution by displaying snapshots of the agent network at four time points: Q2 2006, 2012, 2018, and 2023. Red nodes represent treatment agents, green nodes represent control agents, and gray nodes correspond to all other agents. Node size is scaled by degree to reflect each agent's connectivity in the network. In the initial period (Q2 2006), treatment and control agents exhibit relatively similar node sizes, indicating comparable levels of engagement. However, as time progresses, treatment agents show visibly larger node sizes compared to control agents, reflecting a more substantial increase in transaction volume and network participation. This growth suggests that treatment agents become more active over time, while control agents tend to exhibit more modest changes in degree.

Together, these patterns highlight the persistent effect of early network positioning. Agents who begin their careers transacting with central market players appear more likely to build and sustain a broad and active set of connections. These findings support the notion that early relational capital—measured through network centrality—plays a critical role in shaping long-term professional success in decentralized markets such as real estate.

5.3 Simulation

We perform a set of Monte Carlo simulations that follows a dynamic Bayesian network from our theoretical framework governed by a reasonable regularity condition on the Markov process and evolves stochastically over a 10-year horizon (120 months). Figure 3 presents a simulated evolution of two agents, New Agent A and New Agent B, who enter an existing real estate intermediary network consisting of 10 established brokers. New

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Agent A is initially matched with a high-centrality counterparty, whereas New Agent B is paired with a low-centrality counterparty.

Two salient patterns emerge from this simulation. First, being matched with a high-centrality counterparty in the previous period increases the probability that agent i will form new edges in the current period (e.g., through more transactions), implying that the edge formation process is state-dependent and conditioned on the centrality group of the current counterparty. Second, this dependence induces persistence in network dynamics: agents initially matched with a high-centrality counterparty are more likely to be paired with similarly central counterparties in future periods, thereby reinforcing and amplifying their network position over time.

Figure 5 illustrates a simulated trajectory of new agent survivability measured as a normalized, discounted sum of internalized centrality from counterparty transactions based on the survivability function in (8). The simulation begins with a network of 10 incumbent agents, where New Agent A is initially matched with a high-centrality counterparty and New Agent B with a low-centrality one. Vertical dashed lines indicate key temporal milestones at the 1-, 2-, 3-, and 5-year marks. Similarly, Figure 4 plots the same exercise with 100 and 1,000 simulated survival probability trajectories. These simulation results reinforce our study's key results in that the initially high-centrality counterparty-connected agent has a superior survivability.

6 Conclusion

This paper investigates the long-term impact of initial network exposure on career success in real estate brokerage, leveraging a unique setting in which new agents are quasi-randomly matched to incumbent counterparties. We develop a dynamic Bayesian network model in which agents internalize the centrality of their initial connections, generating compounding spillover benefits over time. The model yields clear predictions: early exposure to highly connected agents boosts survival, enhances transaction volume, and especially benefits low-performing entrants by substituting for early productivity. These predictions are strongly supported by empirical evidence from transaction-level data in the

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Charlotte MLS, where new agents randomly paired with central counterparties experience significantly longer careers and greater cumulative performance.

Our empirical design overcomes common challenges in network research by exploiting the quasi-random nature of early agent matching in a decentralized and thin market. Fixed effects for brokerage offices and counterparties help isolate the causal influence of network position from confounding organizational and agent-level characteristics. We further show that network centrality—not static traits—drives long-run outcomes, and that these effects persist even after adjusting for first-year performance. Agents who begin with in-house or dual-agent transactions, by contrast, do not enjoy similar long-run benefits, underscoring the importance of external network propagation over internal coordination or short-run commissions.

These findings offer important implications for how careers unfold in information-sensitive markets. They reveal that seemingly minor early differences—such as transacting with a more central agent—can have long-lasting effects on professional trajectories. By formalizing this mechanism through a Bayesian framework, we provide a micro-founded account of how social capital is internalized, reinforcing the path-dependent nature of talent development and organizational survivability. In doing so, our study bridges theories of human capital, mentorship, and network economics within a structural, data-rich setting.

Overall, our results contribute to the literature on the economics of talent, social networks, and peer spillovers by offering credible causal evidence of how early relational capital shapes long-run performance. They suggest that improving access to high-centrality connections—particularly for lower-volume entrants—could serve as a powerful lever for broadening participation and increasing retention in competitive, attrition-prone industries such as real estate brokerage. More broadly, our findings imply that talent development policies—whether in vocational trades, professional services, or education—should prioritize early exposure to influential peers or mentors. Structured onboarding, targeted matching programs, or incentive-based network interventions may yield non-trivial returns by shifting initial conditions that compound over time. Even modest early investments in network access can have persistent effects on economic inclusion and career mobility.

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7 Tables

Table 1: Summary Statistics

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel A: MLS Transaction Data					
List Price (000s)	306.79	235.22	159.00	242.08	374.99
Sale Price (000s)	295.48	224.34	152.75	235.00	362.00
Days on Market	76.70	120.85	8	35	95
House Age (Years)	26.01	23.83	8	18	38
Bedrooms	3.51	3.25	3	3	4
Bathrooms	2.74	1.74	2	3	3
Observations	417,094				
Unique Agents	40,344				
Panel B: New Agent Data					
Counterparty Network Centrality	0.003	0.03	0.0000	0.0000	0.0002
Dual Agent	0.05	0.22	0	0	0
In-house Agent	0.06	0.24	0	0	0
Arms-Length Agent	0.89	0.31	1	1	1
Survive One Year	0.70	0.46	0	1	1
Survive Two Years	0.58	0.49	0	1	1
Survive Three Years	0.47	0.50	0	0	1
Survival Length (Days)	1,642.84	1,810.36	211.8	994.5	2,392
First Two Years Transactions	6.30	7.01	2	4	8
Total Transactions	21.77	47.02	2	7	21
New Agents	19,904				

Note: Table 1 displays summary stats for the data used in the empirical analysis. Panel A displays summary stats for the MLS transaction data used to construct the real estate agent trading network. Panel B displays summary stats for the new agent data.

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Table 2: New Agent Survival

	One Year (2004-2021)		Two Years (2004-2019)		Three Years (2004-2017)	
	(1)	(2)	(3)	(4)	(5)	(6)
Network Centrality	0.279***	0.240***	0.279***	0.225***	0.261**	0.189*
	(0.052)	(0.055)	(0.069)	(0.066)	(0.103)	(0.100)
Dual Agent	−0.020	−0.024	−0.026	−0.027	−0.014	−0.015
	(0.019)	(0.019)	(0.017)	(0.017)	(0.018)	(0.019)
In-house Agent	0.013	0.002	0.015	0.007	0.008	−0.002
	(0.015)	(0.016)	(0.017)	(0.019)	(0.019)	(0.020)
Observations	19,904	19,904	18,030	18,030	16,488	16,488
Adjusted R^2	0.038	0.036	0.030	0.030	0.029	0.029
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓

*p<0.1; **p<0.05; ***p<0.01

Note: Table 2 reports regression results from Equation 16. Columns 1 and 2 use a one-year survival period, columns 3 and 4 use a two-year survival period, and columns 5 and 6 use a three-year survival period. Odd-numbered columns include additively separable zip code and sale year fixed effects. Even-numbered columns include multiplicatively separable zip code and sale year fixed effects. Standard errors are clustered by zip code.

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Table 3: Brokerage Office Fixed Effects

	One Year Survival (2004-2021)			
	(1)	(2)	(3)	(4)
Network Centrality	0.277***	0.242***	0.185***	0.179***
	(0.054)	(0.056)	(0.063)	(0.069)
Observations	17,692	17,692	17,692	17,692
Adjusted R^2	0.038	0.075	0.070	0.071
Zip+Year FE	✓	✓		
Zip×Year FE			✓	
Office FE		✓	✓	
Office×Year FE				✓

*p<0.1; **p<0.05; ***p<0.01

Note: Table 3 reports regression results from a modified version of Equation 16 that uses a one-year survival period and a subsample of "arms-length" agent transactions. Columns 1 to 4 differ only in their use of zip code, sale year, and brokerage office fixed effects. Standard errors are clustered by brokerage office.

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Table 4: Counterparty Agent Fixed Effects

	One Year Survival (2004-2021)		
	(1)	(2)	(3)
Network Centrality	0.277***	0.318***	0.281***
	(0.057)	(0.056)	(0.076)
Observations	17,692	17,692	17,692
Adjusted R^2	0.038	0.052	0.052
Zip+Year FE	✓	✓	
Zip×Year FE			✓
Counterparty FE		✓	✓

*p<0.1; **p<0.05; ***p<0.01

Note: Table 4 reports regression results from a modified version of Equation 16 that uses a one-year survival period and a subsample of "arms-length" agent transactions. Columns 1 to 3 differ only in their use of zip code, sale year, and counterparty agent fixed effects. Standard errors are clustered by counterparty agent.

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Table 5: New Agent Cohort Survival Analysis

	Full Sample	Subsample Analyses Based on First-Year Transaction Volume			
		1-2	3-5	6-10	11-20
	(1)	(2)	(3)	(4)	(5)
Network Centrality	0.222***	0.376**	0.244***	0.080***	−0.001
	(0.055)	(0.152)	(0.075)	(0.028)	(0.022)
Dual Agent	0.0002	0.009	−0.021	0.009	0.017*
	(0.016)	(0.022)	(0.027)	(0.020)	(0.009)
In-house Agent	−0.003	−0.009	−0.002	0.014	0.004
	(0.014)	(0.025)	(0.020)	(0.013)	(0.014)
3-5 First-Year Sales	0.290***				
	(0.007)				
6-10 First-Year Sales	0.407***				
	(0.008)				
11-20 First-Year Sales	0.443***				
	(0.009)				
Observations	19,904	9,769	6,004	3,153	978
Adjusted R^2	0.180	0.036	0.032	0.012	0.048
Zip+Year FE	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01

Note: Column 1 of Table 5 reports regression results from a modified version of Equation 16 that uses a one-year survival period and includes a series of first-year transaction cohort indicator variables. Columns 2 to 5 report regression results from Equation 16 using a one-year survival period for subsamples of the first-year transaction cohorts. Every column includes additively separable zip code and sale year fixed effects. Standard errors are clustered by zip code.

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Table 6: Long-term Effects

	Survival	Transactions			
	Length	Year 1	Years 1-3	Total	Per Year
	(1)	(2)	(3)	(4)	(5)
Network Centrality	0.967**	0.397**	0.521***	0.725**	0.420**
	(0.447)	(0.176)	(0.198)	(0.324)	(0.187)
Dual Agent	−0.195	−0.119***	−0.139***	−0.147**	−0.109***
	(0.133)	(0.031)	(0.035)	(0.063)	(0.027)
In-house Agent	0.171	0.144***	0.169***	0.165***	0.140***
	(0.110)	(0.037)	(0.042)	(0.061)	(0.030)
Observations	13,415	13,415	13,415	13,415	13,415
Adjusted R^2	0.023	0.078	0.082	0.029	0.041
Zip×Year FE	✓	✓	✓	✓	✓

*p<0.1; **p<0.05; ***p<0.01

Note: Table 6 reports regression results from a modified version of Equation 16 that uses a subsample of new agent data from 2004 through 2017 and several different dependent variables. The dependent variable in column 1 is the log of the new agent's survival length. The dependent variable in columns 2 through 5 is the log of the new agent's transaction over different periods. Column 2 uses the first year of transactions, column 3 uses the first three years of transactions, column 4 uses the new agent's total transactions, and column 5 uses the new agent's transactions per year. Every column includes multiplicatively separable zip code and sale year fixed effects. Standard errors are clustered by zip code.

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Table 7: Cox Proportional Hazard Model Estimates

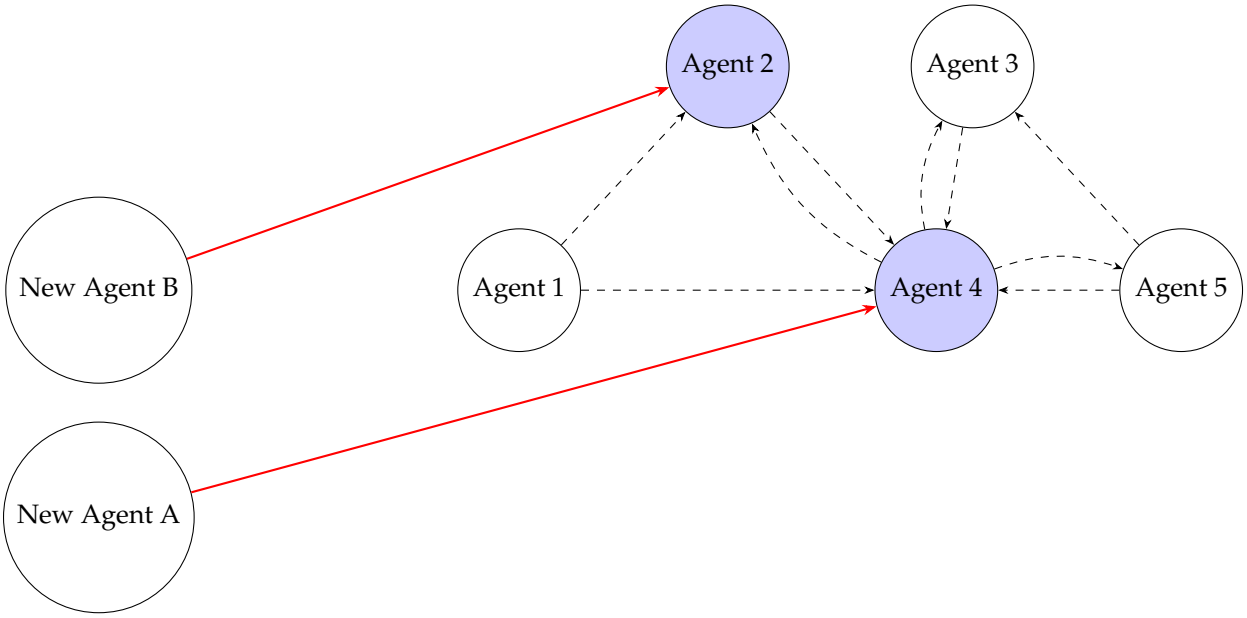
Centrality Measure (Top 5%)	Coef.	Hazard Ratio	Risk Reduction	Impact on Agent Survival (by Counterparty Centrality)
Outdegree	-0.059^{*}	0.943	5.7%	Active seller-agent marginally improves survival
Indegree	-0.333^{***}	0.717	28.3%	Active buyer-agent strongly improves survival
Eigenvector	-0.275^{***}	0.759	24.1%	Influential counterparty strongly improves survival
Clustering	-0.099^{***}	0.906	9.4%	Tight-knit counterparty moderately improves survival
Betweenness	-0.191^{***}	0.826	17.4%	Being a bridge agent strongly improves survival

Note: Table 7 reports regression results from the Cox proportional hazard model for a set of centrality measures. The treatment group for the survival analysis is defined as top 5% of the counterparty's corresponding centrality measure. The model includes dual agent and in-house covariates.

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8 Figures

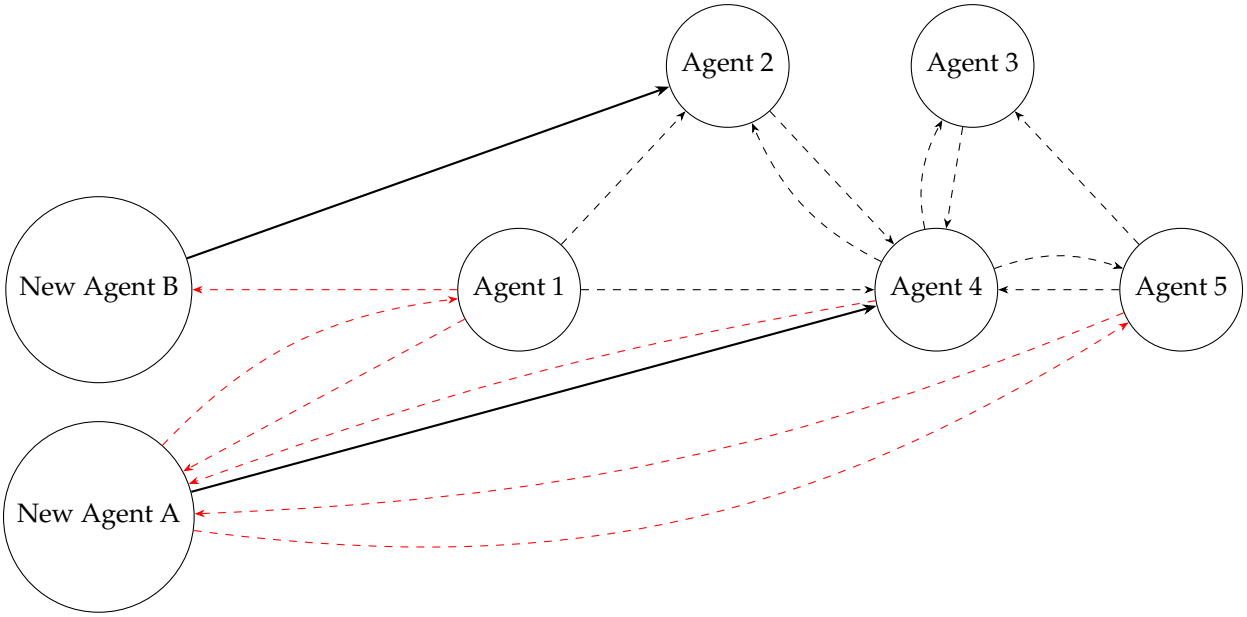
Figure 1: New Agents Entering an Existing Network



Note: Figure 1 plots an illustrative example of two new agents entering an existing real estate brokerage network. New Agent B is initially connected to a low-centrality counterparty (Agent 2), whereas New Agent A is matched with a high-centrality counterparty (Agent 4). The directed edges represent transactions flowing from the selling agent to the buying agent.

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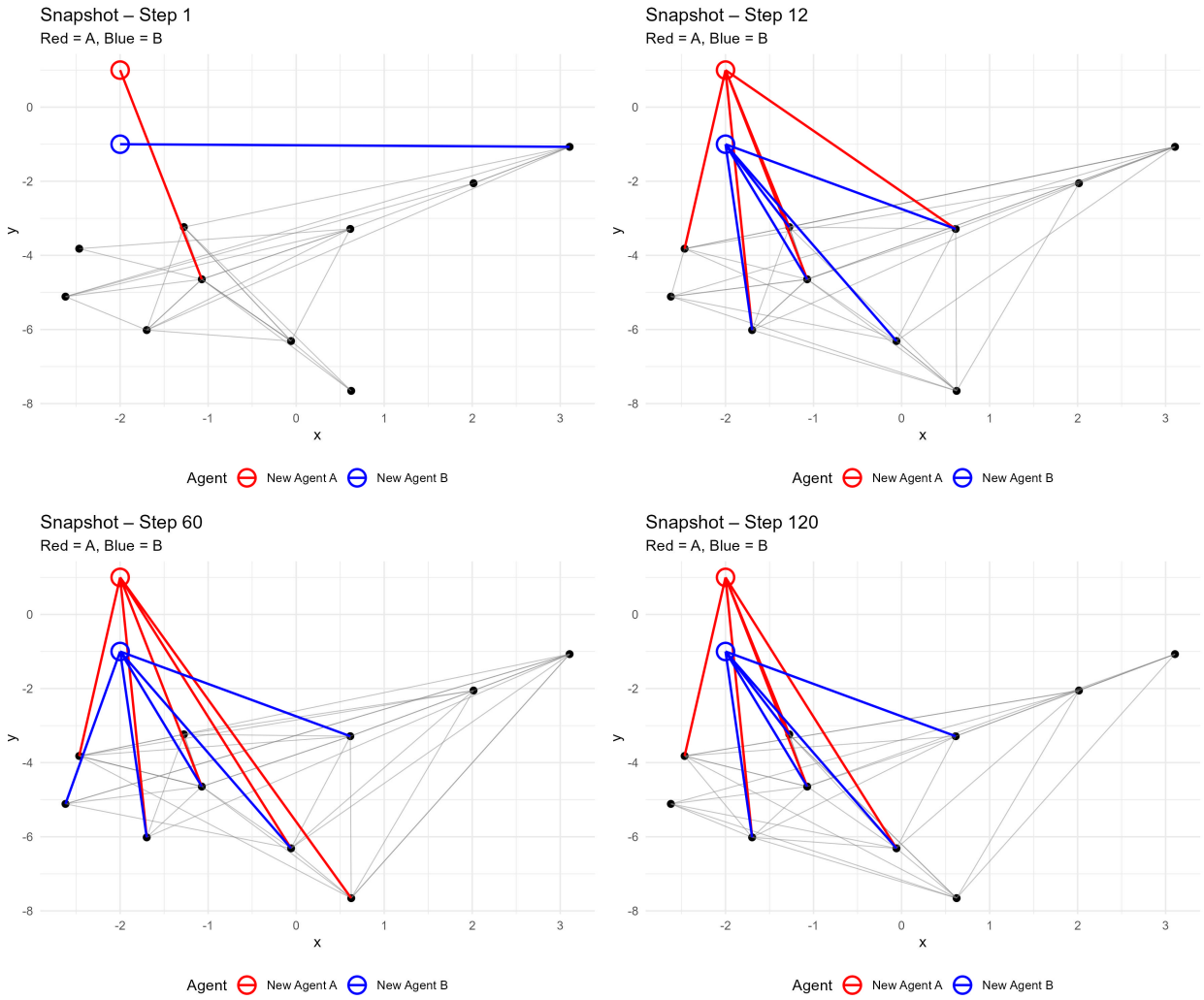
Figure 2: Subsequent Network Formation of Entered Agents



Note: Figure 2 demonstrates a one-stage evolution of two newly entering agents. New Agent A, initially connected to a high-centrality counterparty (Agent 4), internalization of counterparty network centrality leading to the formation of more connections, particularly with other high-centrality nodes. In contrast, New Agent B, whose initial match is with a low-centrality counterparty (Agent 2), generates fewer and less influential connections as a result of lower centrality internalization.

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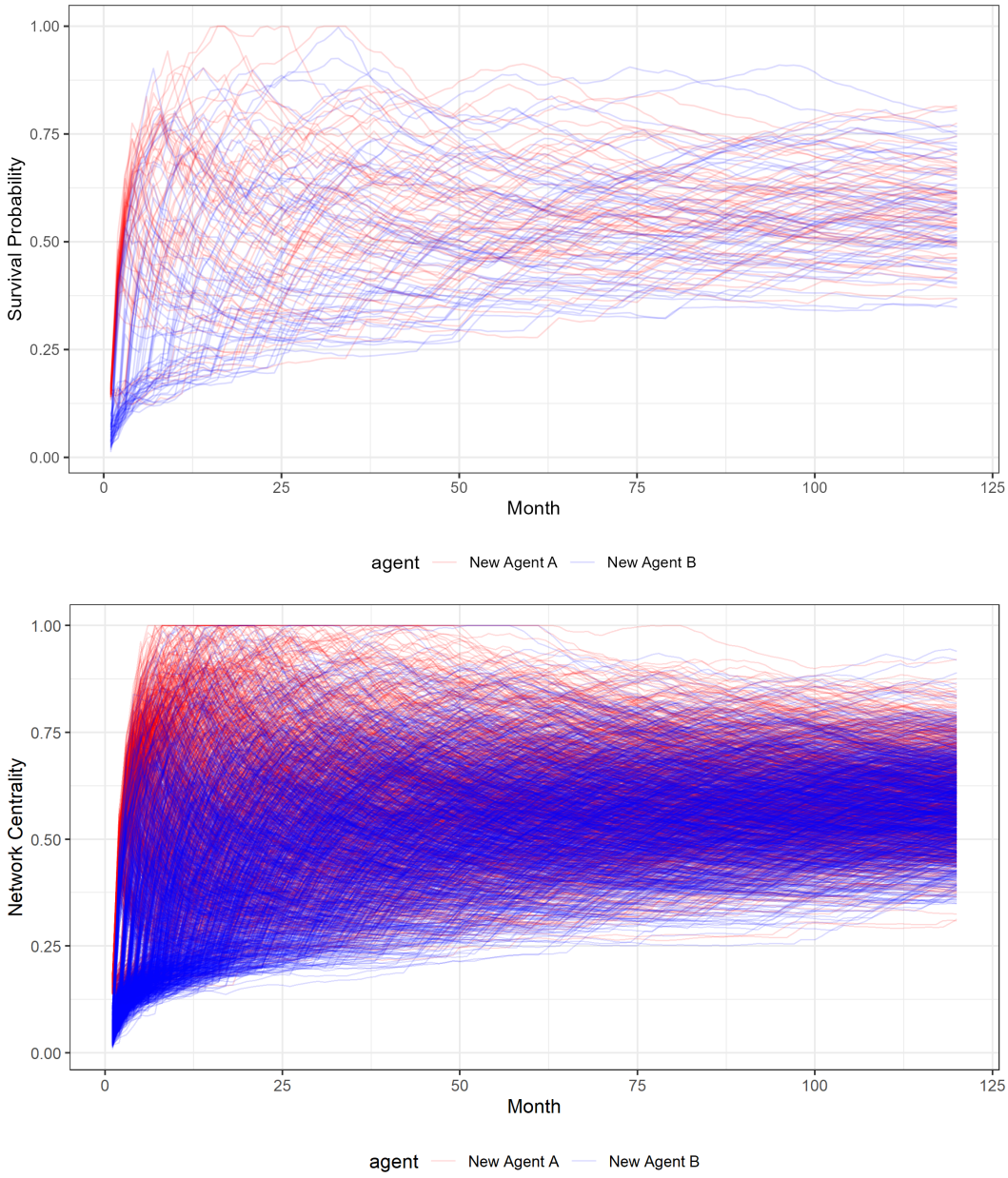
Figure 3: An Evolution of Two New Entrant Agents



Note: Figure 3 plots a sample evolution of two new agents entering a network of 10 existing brokers over 10 years (120 months). New Agent A and New Agent B initially connect to high and low centrality counterparty agents, respectively.

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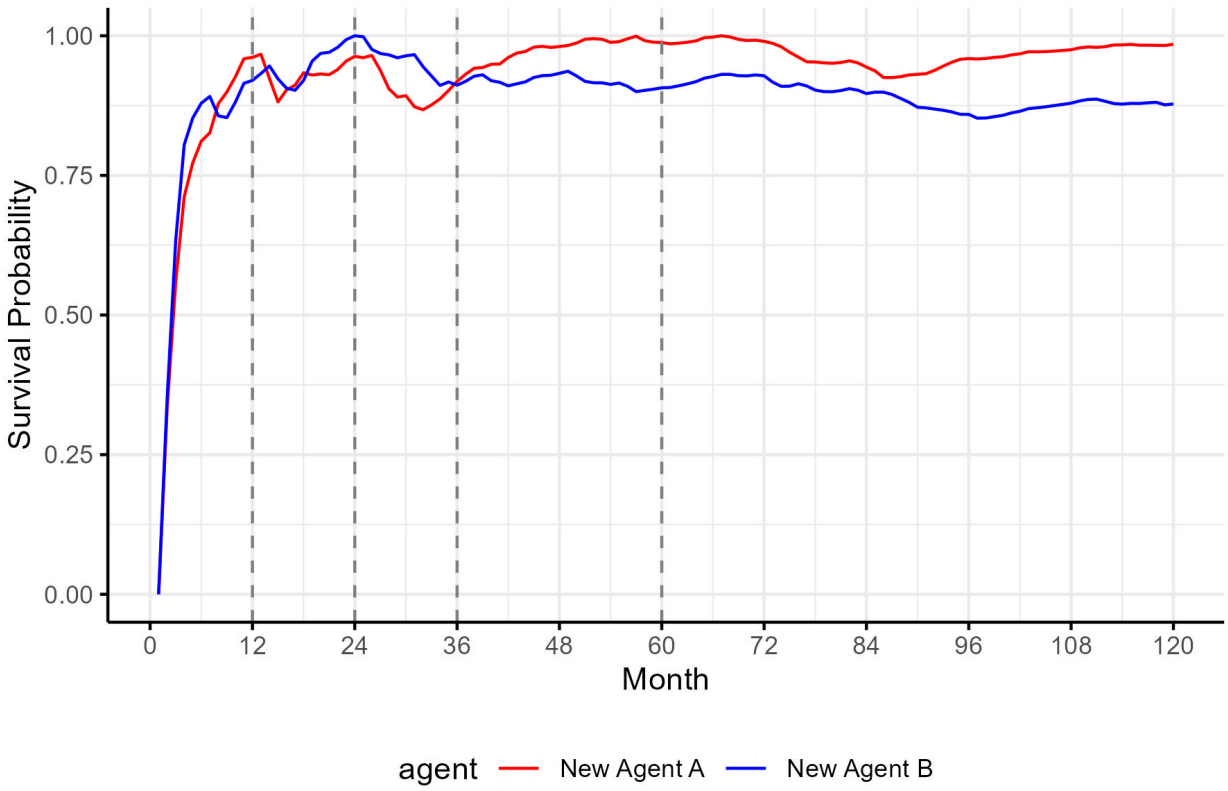
Figure 4: Simulated Survival Trajectories of Two New Entrant Agents' Survivability



Note: Figure 4 plots a 100 (top) and 1,000 (bottom) simulated survival probability trajectories of New Agent A (red) and New Agent B (blue) who transact with a high and low centrality counterparty agent, respectively. For each simulation, the model numerically tracks and compares the centrality growth of both agents over 120 months.

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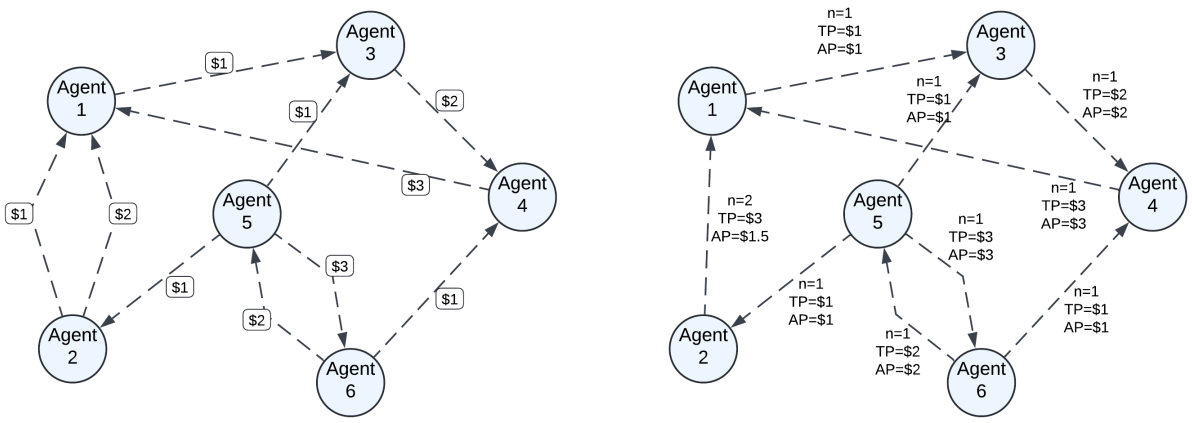
Figure 5: An Evolution of Two New Entrant Agents' Survivability



Note: Figure 5 plots a sample evolution of new agent survivability as a normalized discounted sum of internalized centrality from transactions based on **??** with counterparties over 10 years (120 months) from the initial network of 10 established agents. New Agent A's initial counterparty centrality is high while New Agent B's initial counterparty centrality is low. The vertical dotted lines represent 1, 2, 3, and 5 year-mark.

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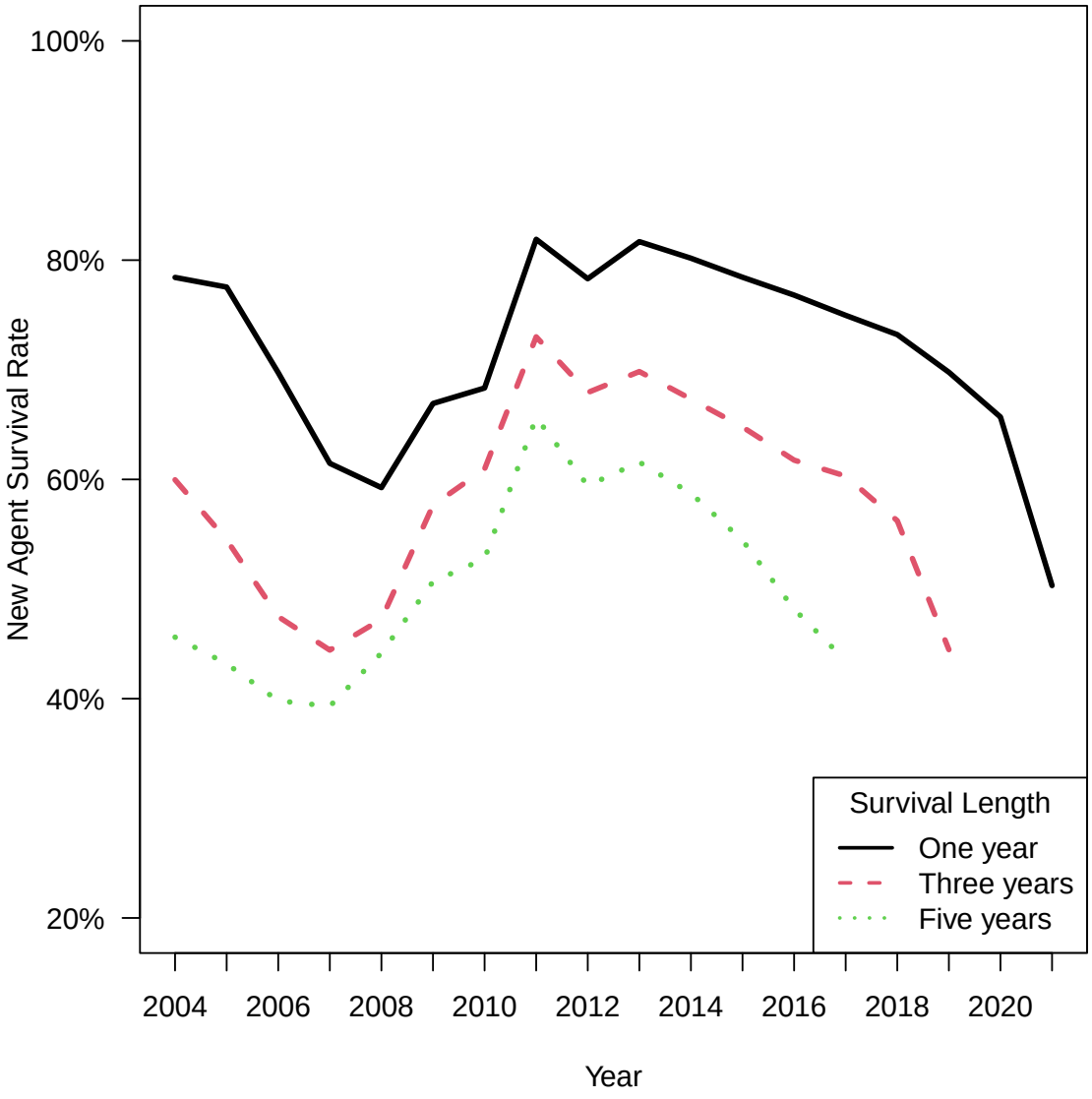
Figure 6: Raw Network Construction & Reduced-Form Graph



Note: Figure 6 plots an illustration of agent transaction networks in the real estate market. The left panel depicts a directed multigraph, where nodes represent agents and each directed edge represents a single transaction from the listing agent to the buyer agent. Edges are labeled with transaction sale prices. The right panel shows the corresponding reduced-form directed graph, where multiple transactions between the same pair of agents are aggregated into a single edge. Each edge is annotated with the number of transactions (n), total transaction price (TP), and average price (AP), summarizing the transactional relationship between agents over the observation window. This collapsed representation supports feature extraction while preserving the directionality and intensity of agent interactions.

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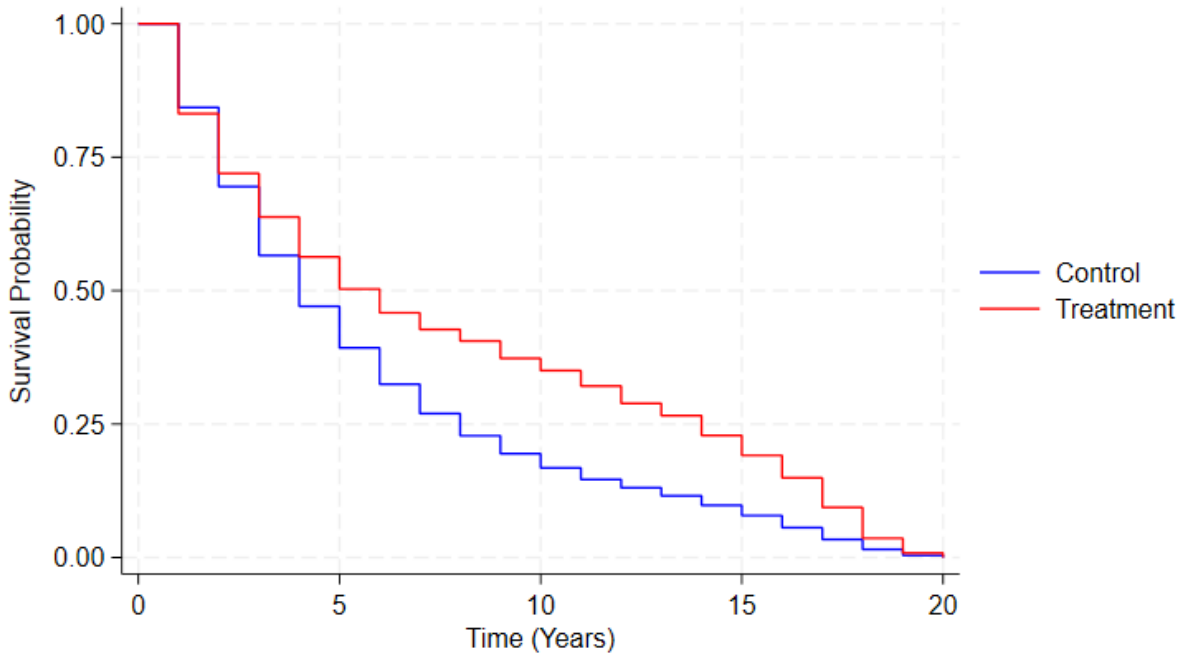
Figure 7: Fraction of New Agents that Survive Each Year



Note: Figure 7 plots the percent of new agents that survive for more than one, three, and five years based on the year the new agent first transacts in the data.

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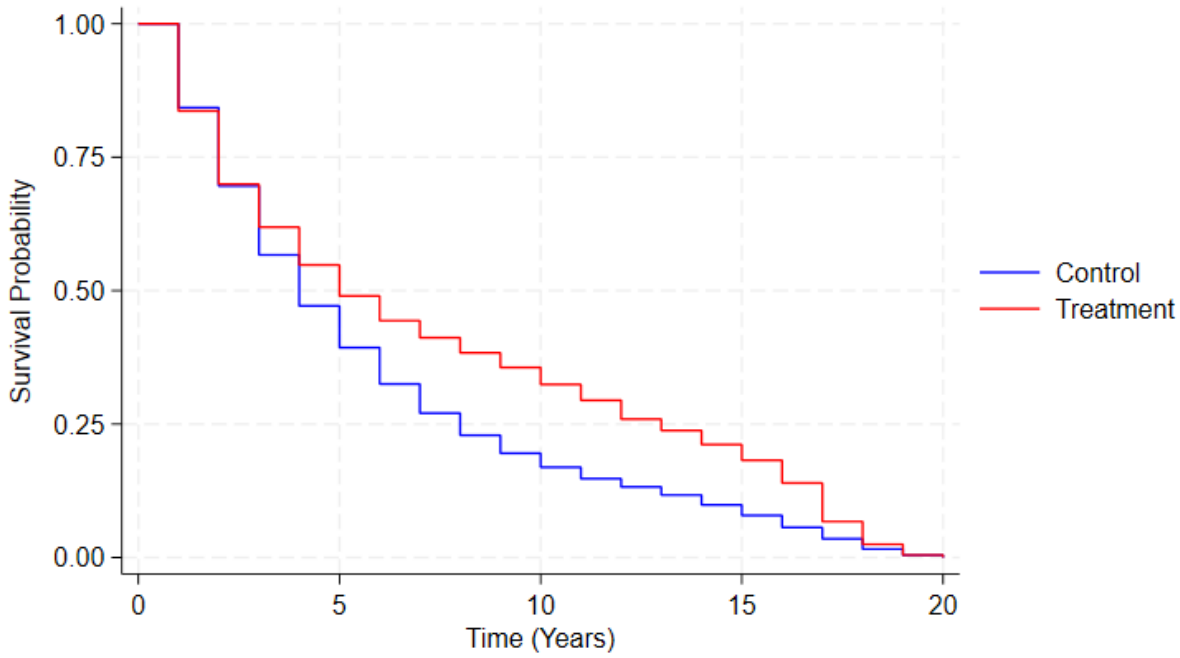
Figure 8: Kaplan-Meier Survival Estimates: In-degree Centrality



Note: Figure 8 plots the Kaplan-Meier Survival estimates for the in-degree centrality. The treatment group represents the counterparty agents whose in-degree centrality is in the top 5%.

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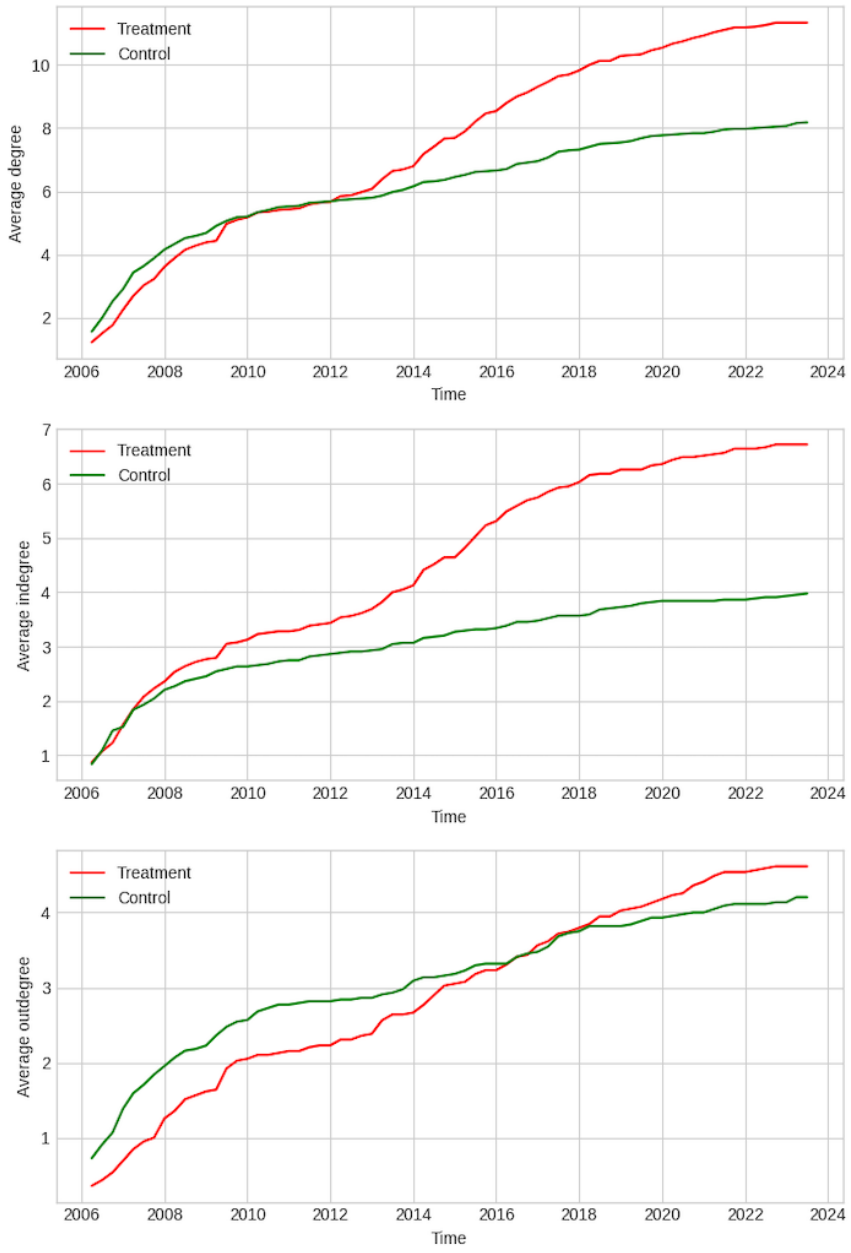
Figure 9: Kaplan-Meier Survival Estimates: Eigenvector Centrality



Note: Figure 9 plots the Kaplan-Meier Survival estimates for the eigenvector centrality. The treatment group represents the counterparty agents whose eigenvector centrality is in the top 5%.

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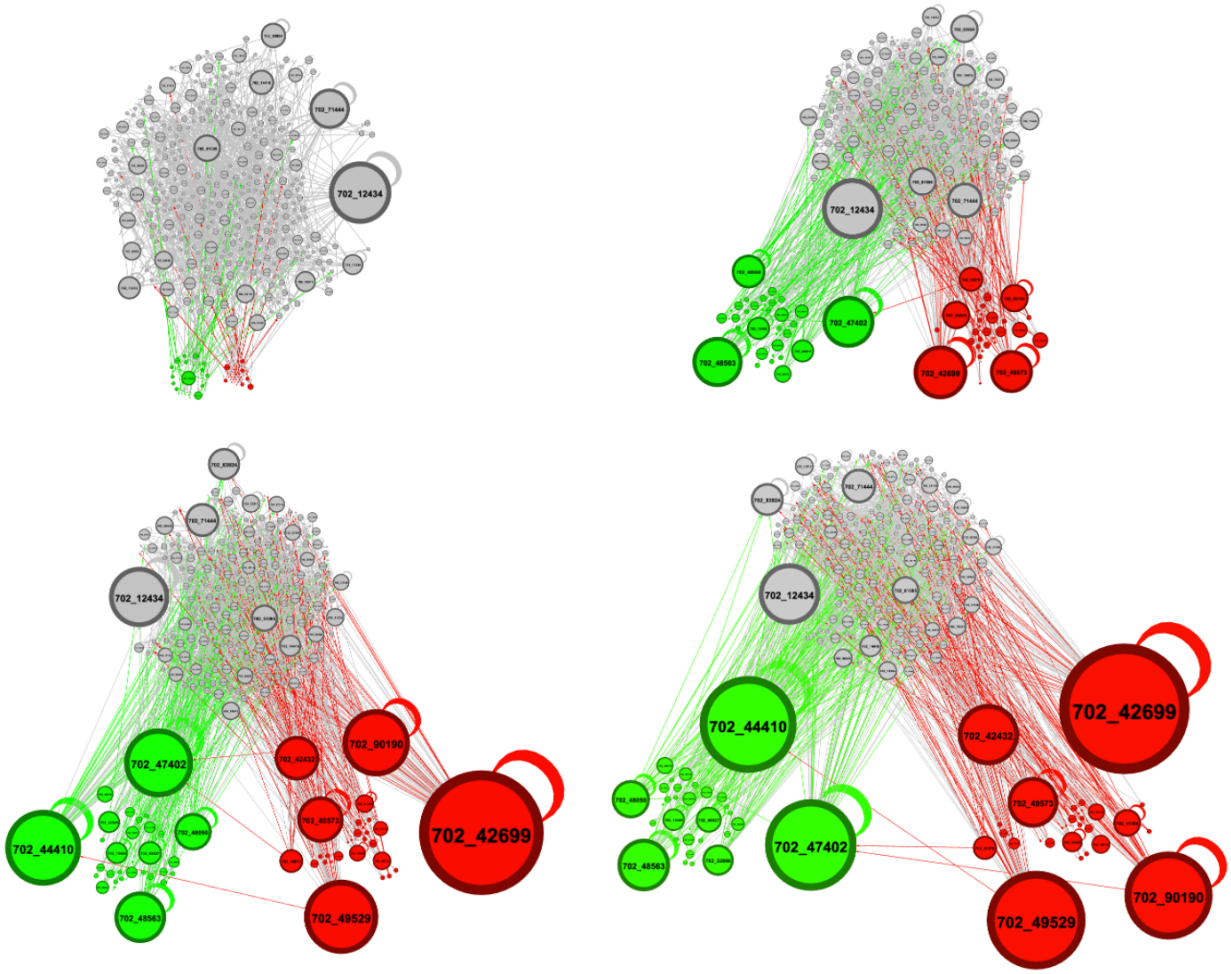
Figure 10: Treatment vs. Control Group (Avg Deg, In-deg, Out-deg)



Note: Figure 10 plots the evolution of average degree, in-degree, and out-degree for treatment and control group agents. We define a baseline network using transactions from Union County in Q2 2006 and identify agents whose first deal occurs in this window. Agents are assigned to the treatment group if their first counterparty ranks in the top 25% of network centrality; others form the control group. We track degree, in-degree, and out-degree over time by sequentially adding transactions and retaining only those involving treatment or control agents, allowing us to analyze the evolution of network positions post-entry.

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Figure 11: Visualization of The Treatment & Control Groups from Figure 10.



Note: Figure 11 displays the baseline agent network and its snapshots at successive time points, illustrating the evolution of network structure for treatment and control groups. This visualization corresponds to the setup described in Figure 10, highlighting how agents' positions change over time relative to their initial classifications. The panels display snapshots of the agent network at four time points: Q2 2006 (top left), 2012 (top right), 2018 (bottom left), and 2023 (bottom right). Red nodes represent agents in the treatment group, green nodes represent agents in the control group, and gray nodes represent all other agents in the network. Node size is scaled proportionally to the agent's degree in the corresponding time-specific network, reflecting each agent's level of connectivity at that point in time.

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Appendices

A Proofs

A.1 Proof of Proposition 1

Proof.

$$\pi_i = \Pr(v_j^\theta \in \theta^H)\,\mathbb{E}[\varphi_i c_j \mid v_j^\theta \in \theta^H] + \Pr(v_j^\theta \in \theta^L)\,\mathbb{E}[\varphi_i c_j \mid v_j^\theta \in \theta^L] \tag{17}$$

$$= (1-c^*)\mathbb{E}[\varphi_i c_j \mid c_j \in [c^*, 1]] + c^*\mathbb{E}[\varphi_i c_j \mid c_j \in [0, c^*]] \tag{18}$$

$$= (1-c^*)\varphi_i\mathbb{E}[c_j \mid c_j \in [c^*, 1]] + c^*\varphi_i\mathbb{E}[c_j \mid c_j \in [0, c^*]] \tag{19}$$

$$= (1-c^*)\varphi_i\frac{c^*+1}{2} + c^*\varphi_i\frac{c^*}{2} \tag{20}$$

$$= \varphi_i\left[(1-c^*)\frac{c^*+1}{2} + c^*\frac{c^*}{2}\right] \tag{21}$$

$$= \varphi_i\left[\frac{(1-c^*)(c^*+1) + (c^*)^2}{2}\right] \tag{22}$$

$$= \frac{\varphi_i}{2} \tag{23}$$

$\therefore \varphi_i^* = 1$ with $\pi_i^* = \frac{\varphi_i^*}{2}$. □

A.2 Proof of Proposition 2

Proof.

$$\mathbb{E}[W_i^*] = \sum_{t=1}^{\infty} \delta^t S_i(t)\pi_i^* \tag{24}$$

$$= \sum_{t=1}^{\infty} \delta^t S_i(t)\frac{1}{2} \quad \text{from Proposition 1} \tag{25}$$

$$\text{Denote the summand } f(t) = \delta^t S_i(t) \tag{26}$$

$$= \delta^t \prod_{\tau=1}^{t} \rho_\tau \quad \text{from (6)} \tag{27}$$

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$$f(t+1) = \delta^{t+1} \prod_{\tau=1}^{t+1} \rho_\tau \tag{28}$$

$$= \delta^{t+1} \left(\prod_{\tau=1}^{t} \rho_\tau \right) \rho_{t+1} \tag{29}$$

$$= \delta \rho_{t+1} f(t) \tag{30}$$

$$\Rightarrow \frac{f(t+1)}{f(t)} = \delta \rho_{t+1} \tag{31}$$

$$\text{Since } \delta, \rho_{t+1} \in (0,1), \quad \delta \rho_{t+1} < 1 \tag{32}$$

$$\therefore f(t+1) < f(t) \Rightarrow \frac{\partial}{\partial t} \left(\delta^t S_i(t) \pi_i^* \right) < 0 \tag{33}$$

□

A.3 Proof of Proposition 3

Proof.

$$\mathbb{E}[\tilde{W}_i] = \varphi_i \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) c_{j,t} \tag{34}$$

$$S(c_{j,0}, V_i^{(1)}, t) = \rho^t \left(1 - e^{-\alpha c_{j,0}/(1+V_i^{(1)})} \right) \tag{35}$$

$$\frac{\partial S(c_{j,0}, V_i^{(1)}, t)}{\partial c_{j,0}} = \rho^t \frac{\partial}{\partial c_{j,0}} \left(1 - e^{-\alpha c_{j,0}/(1+V_i^{(1)})} \right) \tag{36}$$

$$= \rho^t \left(\frac{\alpha}{1+V_i^{(1)}} e^{-\alpha c_{j,0}/(1+V_i^{(1)})} \right) > 0 \tag{37}$$

$$\therefore \frac{\partial \mathbb{E}[\tilde{W}_i]}{\partial c_{j,0}} = \varphi_i \sum_{t=1}^{\infty} \delta^t \frac{\partial S(c_{j,0}, V_i^{(1)}, t)}{\partial c_{j,0}} c_{j,t} > 0 \tag{38}$$

□

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A.4 Proof of Proposition 4

Proof. Suppose $\frac{\alpha c_{j,0}}{1+V_i^{(1)}} < 1$.

$$\frac{\partial S}{\partial c_{j,0}} = \rho^t \frac{\partial}{\partial c_{j,0}} \left(1 - e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}}\right) \tag{39}$$

$$= \rho^t \left(\alpha \frac{1}{1+V_i^{(1)}} e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}}\right) \tag{40}$$

$$\frac{\partial^2 S}{\partial c_{j,0}\, \partial V_i^{(1)}} = \rho^t \frac{\partial}{\partial V_i^{(1)}} \left(\alpha \frac{1}{1+V_i^{(1)}} e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}}\right) \tag{41}$$

$$= \rho^t \left[-\alpha \frac{1}{(1+V_i^{(1)})^2} e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}} + \alpha \frac{1}{1+V_i^{(1)}} \left(\alpha \frac{c_{j,0}}{(1+V_i^{(1)})^2} e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}}\right)\right]$$

$$= \rho^t e^{-\alpha \frac{c_{j,0}}{1+V_i^{(1)}}} \left[-\frac{\alpha}{(1+V_i^{(1)})^2} + \frac{\alpha^2 c_{j,0}}{(1+V_i^{(1)})^3}\right] < 0 \tag{42}$$

□

A.5 Proof of Proposition 5

Proof.

$$\mathbb{E}[\tilde{W}_i^{\text{in}}] = \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) \left(\underline{a} + \varphi_i c_{j,t}^{\text{in}}\right), \tag{43}$$

$$\mathbb{E}[\tilde{W}_i^{\text{ext}}] = \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) \left(\varphi_i c_{j,t}^{\text{ext}}\right), \tag{44}$$

$$\Delta \tilde{W}_i = \mathbb{E}[\tilde{W}_i^{\text{in}}] - \mathbb{E}[\tilde{W}_i^{\text{ext}}] \tag{45}$$

$$= \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) \left(\underline{a} + \varphi_i \left(c_{j,t}^{\text{in}} - c_{j,t}^{\text{ext}}\right)\right). \tag{46}$$

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$$\text{If } \underline{a} \approx 0 \quad \text{and} \quad c_{j,t}^{\text{in}} \approx c_{j,t}^{\text{ext}}, \tag{47}$$

$$\Rightarrow \Delta\tilde{W}_i \approx 0 \Rightarrow \mathbb{E}[\tilde{W}_i^{\text{in}}] \approx \mathbb{E}[\tilde{W}_i^{\text{ext}}], \tag{48}$$

$$\therefore \frac{\partial \Delta\tilde{W}_i}{\partial \left(c_{j,t}^{\text{in}} - c_{j,t}^{\text{ext}}\right)} = \varphi_i \sum_{t=1}^{\infty} \delta^t S(c_{j,0}, V_i^{(1)}, t) > 0. \tag{49}$$

□

A.6 Proof of Proposition 6

Proof. Suppose $\kappa < \frac{\delta_0(1+c_j)-\beta\delta_1}{1-\beta}$.

$$\mathbb{E}[\tilde{W}_i^{\text{arms}}] = \sum_{t=0}^{\infty} \beta^t \delta_t \left(\varphi_i + \varphi_i c_j\right) = \frac{\delta_0 \varphi_i (1+c_j)}{1-\beta}, \tag{50}$$

$$\mathbb{E}[\tilde{W}_i^{\text{dual}}] = \kappa\varphi_i + \sum_{t=1}^{\infty} \beta^t \delta_t \varphi_i = \kappa\varphi_i + \frac{\beta\delta_1\varphi_i}{1-\beta}, \tag{51}$$

$$\therefore \mathbb{E}[\tilde{W}_i^{\text{arms}}] - \mathbb{E}[\tilde{W}_i^{\text{dual}}] = \varphi_i \left(\frac{\delta_0(1+c_j) - \beta\delta_1}{1-\beta} - \kappa\right) > 0. \tag{52}$$

□

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