Soon Hyeok (Steve) Choi, Ph.D.
Assistant Professor of Real Estate Finance
Rochester Institute of Technology
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September 15, 2026

Dear Professors Breza, Chandrasekhar, and Viviano:

I am applying for the NBER Workshop on Development Economics and Networks for Early-Career Researchers, to be held in Cambridge, Massachusetts on December 5, 2026.

I am currently an Assistant Professor of Real Estate Finance at Rochester Institute of Technology. In summer 2026, I served as a visiting professor at the MIT Center for Real Estate. I received my Ph.D. from Cornell University in 2023.

I would like to present my working paper, "The Importance of Networks for Career Success: Evidence from the Real Estate Industry", with Patrick Smith and Ali Tosyali.

The paper asks whether the network position of a new market entrant's first counterparty causally affects the entrant's career survival. Using more than six million MLS residential real estate transactions across ten U.S. metropolitan areas, we construct rolling agent-to-agent trading networks. We exploit plausibly exogenous variation in first counterparty matches to identify its effects on subsequent deal flow and survival. Moving from the least- to the most-central first counterparty raises one-year survival by 2.8 to 4.5 percentage points, and the effect operates largely through the early deal flow the connection generates.

My research sits at the intersection of contract design and valuation, and the highly intermediated structure of real estate markets, both commercial and residential, has drawn me toward how relationships and network position shape economic outcomes. Brokerage is a natural laboratory for these questions: entry is frequent, counterparty matching is observable at the transaction level, and careers depend on the flow of deals through a network. The questions at the center of this workshop, including network formation, peer and referral effects, and interventions that operate through networks, map directly onto my current work and the projects I hope to build from it. I would value learning from participants working on these problems in development settings, and I believe the brokerage data and identification strategies in my paper can contribute to that exchange.

Should I be shortlisted, Professor Robert Jarrow, Ronald P. and Susan E. Lynch Professor of Investment Management at Cornell University, can provide a recommendation and may be reached at raj15@cornell.edu.

Thank you for your time and consideration. My application includes this letter, my curriculum vitae with a list of completed Ph.D. courses, a one-page statement of motivation and research interests, and the working paper.

Sincerely,



Soon Hyeok (Steve) Choi, Ph.D.

Soon Hyeok Choi Ph.D.

steve-sh-choi.com
Status: U.S. Permanent Resident

Academic Appointment

Rochester Institute of Technology - Saunders College of Business — Rochester, NY
Assistant Professor of Real Estate Finance (tenure-track) — 2023-Present

Visiting Appointment

Massachusetts Institute of Technology — Cambridge, MA
Visiting Assistant Professor - MIT Center for Real Estate — 2026 Summer

Service Appointment

Real Estate Economics - American Real Estate and Urban Economics Association
Director of Research Outreach — 2025-Present
Member, Communications Committee — 2026-Present

Education

Cornell University - SC Johnson College of Business — Ithaca, NY
Nolan School of Hotel Administration - Ph.D. — 2019-2023
Department of Economics - M.A. — 2016-2019
Department of Statistical Science - M.P.S. — 2009-2011

Bowdoin College — Brunswick, ME
B.A. in Economics with High Honors & magna cum laude — 2004-2009

Research Interest

Asset Pricing, Contracts, Networks, Household & Real Estate Finance

Publication

"Applying the Local Martingale Theory of Bubbles to Cryptocurrencies" with Robert Jarrow. *International Journal of Theoretical and Applied Finance*, 2022.

Working Papers

Working Papers

- "Pricing Government Contract Risk Premia: Evidence from the 2025 Federal Lease Terminations" with Cameron LaPoint (Yale)

  Conferences (scheduled†): SFS Cavalcade (UVA Darden), EFA, Pre-WFA Symposium, AREUEA Virtual Seminar, FSU RMI Research Symposium, UGA Critical Issues in Real Estate Symposium, UNC CREDA Real Estate Symposium, UCF-JRER Current Issues in Real Estate Symposium, Baruch-NUS Real Estate Conference, REALPAC/TMU CRE Research Symposium, AREUEA-ASSA†

- "The Winner's Curse in Housing Markets" with Adam Nowak (WVU), Patrick Smith (UNC Charlotte), Alexei Tchistyi (Cornell)

  Award: 2026 American Real Estate Society Housing Research Manuscript Award
  Conferences: AFA, AREUEA, ARES, APAD, Behavioral Science & Policy Association (Harvard Kennedy), FSU–UF Critical Issues in Real Estate Symposium, Georgia Tech–Atlanta Fed Household Finance Conference, UNC CREDA Real Estate Symposium, Indiana University Holden Conference in Finance and Real Estate†

- "The Importance of Networks for Career Success: Evidence from the Real Estate Industry" with Patrick Smith (UNC Charlotte), Ali Tosyali (RIT)
- "The Shape of Price Bubbles: Evidence from U.S. Equity Markets" with Robert Jarrow (Cornell)
- "Pricing the Upside Potential to Downside Risk" with Robert Jarrow (Cornell), Daniel Lebret (Cornell), Crocker Liu (Cornell)
- "A Theory of Durable Asset Leasing" with Crocker Liu (Cornell)

Early Stage

- "Co-ethnic Intermediation in Housing Markets" with Jiro Yoshida (Penn State), Siqi Zheng (MIT)
- "Decline in Residential Mortgage Lending by National Banks" with Dongshin Kim (Pepperdine)

Awards and Honors

Housing Research Manuscript Award, American Real Estate Society	2026
Faculty Education and Development Grant, Rochester Institute of Technology	2025
Innovative Thinking Award - "Thinking Out of the Box", American Real Estate Society	2024
Best Practitioner Research Award (Non-residential), American Real Estate Society	2023
NSF Travel Award, SIAM Conference on Financial Mathematics & Engineering	2021
Best Paper Award, Korean Association of Financial Engineering	2020
High Honors & Noyes Political Economy Prize, Bowdoin College	2009
Converse Prize for Excellence in Mathematics, Tabor Academy	2004
Fred Tuttle Prize for Excellence in Physics, Tabor Academy	2004

Teaching

Rochester Institute of Technology - Instructor

Microeconomic Theory (PhD)	2023-Present
Hospitality Asset Management (UG, MS)	2024-Present
Personal Financial Management (UG)	2024-Present

Cornell University - TA

Fixed Income Securities (MBA)	2016-2022
Real Estate Statistical Modeling (MMH, MS)	2021
Introductory Micro & Macroeconomics (UG)	2017-2019

Conferences & Presentation

*Presenter, ○ Co-author Presenter, § Discussant, † Scheduled, ‡ Chair/Service

2027 AREUEA-ASSA*†

2026 AREUEA-ASSA*, U. of Rochester (Simon)*, UT San Antonio (Alvarez)*, Baruch (Zicklin)*, 4th FSU Risk Management & Insurance Research Symposium*, Mortgage Bankers Association*, MIT Center for Real Estate*, 2026 FSU-UF-UGA Critical Issues in Real Estate Symposium○§, SFS Cavalcade North America 2026 (UVA Darden) ○, 42nd ARES Annual Meeting*○‡, DePaul (Driehaus)*, Behavioral Science Policy Association Annual Conference (Harvard Kennedy School)*, NBER SI Real Estate/Urban Economics, MIT-Inha Asian Urban Futures Workshop§, European Finance Association Annual Meeting○†, Penn State (Smeal)*†, 5th Annual Holden Conference in Finance and Real Estate (Indiana Kelley)*†, UNC CREDA Real Estate Research Symposium

2025 AREUEA-ASSA*, AFA*, Nicholas Kiefer Memorial Conference*, FSU-UF Critical Issues in Real Estate Symposium○, 3rd Georgia Tech-Atlanta Fed Household Finance Conference*, Yeshiva University*, 41st American Real Estate Society Annual Conference○, Cornell Real Estate and Urban Economics Symposium○, William & Mary Real Estate Research Symposium*, FMA Applied Finance§, AREUEA-National○§‡, Pre-WFA Summer Real Estate Research Symposium§, WFA, 21st Annual Conference of the Asia-Pacific Association of Derivatives*, 31st European Real Estate Society○, 2025 Asia-Pacific Association of Finance International Conference*, 19th North American Meeting of the Urban Economics Association○, Miami University Finance & Real Estate Conference§, UNC CREDA RE Research Symposium○, Oklahoma (Price)*, ODU RE Research Symposium*§, Cambridge/UF/HKU Real Estate Finance & Investment Symposium§

2024 AREUEA-ASSA*, FSU Risk Management Research Symposium*, Mortgage Market Research Conference (FRB PHL), 5th Workshop on Credit Card Lending, Consumer Finance and the AI Revolution (FRB PHL), 20th Annual Conference of the Asia-Pacific Association of Derivatives*, 11th Annual Global Forum for Financial Consumers*, Cornell Real Estate Symposium, Finance Hybrid Conference*, 18th Urban Economics Association North America Meeting‡, 2nd MIT Climate and Real Estate Symposium*§, UNC CREDA Real Estate Research Symposium○, ODU Real Estate Research Symposium*, Midwest International Trade and Theory Conference, 34th Conference for Financial Economics and Accounting*, ARES Fall Research Symposium*, Peter Carr Conference on Mathematical Finance*, Federal Housing Finance Agency (FHFA) Econ Summit, REALPAC/TMU CRE Research Symposium

2023 AREUEA-ASSA, FSU-UF Critical Issues in Real Estate Symposium[*], ARES 39th Annual Meeting[*§], Pre-WFA Summer Real Estate Research Symposium[*], WFA Annual Meeting, Cornell ESG Investing Research Conference, MIT Asia Real Estate Symposium[§], Finance Hybrid Conference - Innovation & Sustainability, Financial Management Association Annual Meeting[*§], 6th Annual REALPAC/TMU CRE Research Symposium[*], UMass Amherst CISDM Black-Merton-Scholes Option Pricing Conference, Toronto Metropolitan University Research Seminar[*]

2022 17th Annual Economics Graduate Student Conference of Washington University in St. Louis[*], Financial Management Association Annual Meeting, American Real Estate Society Fall 2022 Research Symposium[*], 35th Australasian Finance and Banking Conference - PhD Forum[*§], 8th Paris Financial Management Conference[*§], 17th Annual Conference on Asia-Pacific Financial Markets[*], World Finance & Banking Symposium 2022[§]

2021 34th Australasian Finance and Banking Conference[*§], 10th International Conference of the Financial Engineering and Banking Society[*], 24th International Congress on Insurance: Mathematics and Economics[*], NUS-HKUST 10th Asian Quantitative Finance Seminar[*], Western Finance Association[*], SIAM Conference on Financial Mathematics and Engineering[*], IBHF Household & Behavioral Finance Symposium

2020 Korea Derivatives Association Conference, Doctoral Consortium[*], Korean Association of Financial Engineering Conference[*], The Cornell Hotel School MS/PhD Research Talk[*]

2019 IBHF Household & Behavioral Finance Symposium, Cornell CREF Real Estate Symposium

Discussions

2026 MIT-Inha Asian Urban Futures - Flooded but Resilient: Frequent Pluvial Floods, Adaptive Infrastructure, and Housing Market Responses in Singapore - Pak, Liao, Chow, Zheng

FSU-UF-UGA Critical Issues in Real Estate Symposium - E-commerce and the Changing Value of Retail Co-location in Cities - Brooks & Meltzer

2025 UF/Cambridge/HKU REFIS - Human Capital and Local Credit Supply: Evidence from the Mortgage Industry - Huang, Mayer, Titman, Xu

ODU RERC - Tradition and Technology: Do Institutional Changes Influence Mortgage Appraisal Practices? - Doerner

Miami U. REFC - Determinants and Consequences of Return to Office Policies - Flynn, Ghent, Nair

Pre-WFA - Diversifying the Suburbs: Rental Supply and Spatial Inequality - Chang

AREUEA Nat'l - Homeowners Insurance and Housing Prices - Eastman, Kim, Zhou

FMA AF - Incomplete Pass-Through in Mortgage Markets - Amornsiripanitch, Ricks

2024 ARES FRS - Accessory Dwelling Units' Contagion Effects: New Spatial Evidence from Los Angeles - Liu, Cohen, Ghosh, Lu-Andrews

39th CFEA - Local Government Valuation - Giesecke, Mateen, Sena

ODU RES - Real Estate Agent Response to Hispanic/Latino Clients in a Large Sample Correspondence Field Experiment - Hanson, Hawley

MIT CCRES - Beyond Asset Losses: Estimating the Economic Cost of Floods - Lee, Wan, Zheng

2023 FMA - Mortgage Default: A Heterogeneous-Agent Model - Kalikman, Scally

FMA - Black Box, Greenleaf:Lender Behavior Under Uncertain Collateral Enforcement - Ahsin

FHB - Automated Benchmark Orientation in Portfolio Selection - Edirisinghe

MIT ARES - Who Bears the Cost of Green Policies? - Das, Banerjee, Fuerst

39th ARES - A Machine Learning Approach to Predicting Industry Types Using Company Names - Syed, Khasar, Lo, Jennings

2022 35th AFBC - Deviations from the Law of One Price across Economies - Jung, Jung

8th PFMC - Corporate Leverage Ratio Adjustment under Cash Flow-based Debt Covenants - Becker, Julio, Vodenska, Wang

WFBS - Four Decades of Research on Equity Premium: a Systematic Literature Review - Belloque

2021 34th AFBC - Factor Structure of Cryptocurrencies - Chi, Hao, Hu, Ran

Service

Academic

Rochester Institute of Technology

2025-2026 Faculty Focus Group, Strategic Implementation Committee

2024-Present Finance Area Coordinator, Research Seminar

Faculty Advisor, Real Estate Club

Research Faculty Advisor, Student Research Initiative

Cornell University

2010-2011 Vice President, Behavioral Economics & Finance Organization

2009-2010 Graduate Student Representative, Statistics Department

2009-2010 Appropriation Committee, Graduate Student Assembly

Bowdoin College

2007-2008 Student Volunteer, Maine Volunteer Lawyers Project

2006-2007 Member, Economics Student Advisory Committee

Professional

Committee

2026 AREUEA International - Scientific Committee

2025 AREUEA National - Scientific Committee

2024 ARES Manuscript Prize Committee

Referee

Real Estate Economics, Journal of Empirical Finance, Journal of Real Estate Portfolio Management, Journal of Housing Research, Journal of Real Estate Research, Journal of Housing Economics

Affiliation

American Economic Association, American Finance Association, American Real Estate Society, American Real Estate and Urban Economics Association, Korea America Finance Association

Media & Public Engagement

2026 "Economics Update: A Panel Discussion" by *The Small Business Council of Rochester*

2025 "The Dangers of Overbidding on a House" by *Connections* with Evan Dawson (WXXI, NPR)

"The Truth About Bidding Wars & Home Prices" by *Rochester Living* with Corey Moran (Marc Siwiec)

"Could a buyer's market end bidding wars?", Barefoot, A. *Cotality* (formerly *CoreLogic*)

"The real-estate 'winner's curse': Study of nearly 14 million home sales over 20 years shows you don't want to win that bidding war", Choi, S. *Fortune*

"Winning a bidding war isn't always a win, research on 14 million home sales shows", Choi, S. *The Conversation*

"Early Terminations, Shutdown Shake Confidence in GSA Leases", Hellwig, M. *GlobeSt.*

"Evaluating Federal Government Lease Stability: Opportunities and Insights for CRE Owners and Investors", Hellwig, M & Beck, L. *Northmarq Research & Insights*

"A first connection can make a big difference when it comes to sticking with a career", Choi, S. *The Conversation*

"Research Impact: DOGE Lease Terminations Shaking Real Estate Markets", Smith, N. *Rochester Institute of Technology*

"DOGE's Lease Cancellations Are Already Hitting the Commercial Real Estate Market", Blumberg, D. *Yale Insights*

"DOGE's Lease Cancellations Are Already Causing Real Estate Shocks", Long, C. *Bisnow*

"Government Lease Terminations Expose New CRE Debt Risk", Barrington, T. *Propmodo*

"Federal Government Lease Terminations Hitting CMBS", Hollier, D. *Inside Mortgage Finance*

"Federal lease cuts would only compound Rochester's CRE office sector", Oklobzija, K. *Rochester Business Journal*

2024 "New minor bridges gaps between property development and management", Smith, N. *Rochester Institute of Technology*

Op-Ed Column

2025 "The Unintended Curse of the 50-Year Mortgage"

"Some Winners End Up Losing... in the Housing Market"

"The Illusion of Stability: Rethinking the Risks of the Safest Tenant in Commercial Real Estate"

"Does Your First Handshake Really Matter?"

"Delayed Negotiations in Housing Markets"

"The $10 Lease That Outlived Sears"

Professional Employment

Republic of Korea Air Force — Various AFB
1st Lieutenant — 2012-2015

JP Morgan Chase — New York, NY
Market Risk Analyst, Investment Banking Division — 2011-2012

Reference

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Ph.D. Coursework

Course	*Dept.*	*Status*	*Instructor*
Microeconomic Theory I	Econ	Credit	David Easley
Microeconomic Theory II	Econ	Credit	Larry Blume
Intermediate Mathematical Economics	Econ	Credit	Bruno Salcedo
Macroeconomics I	Econ	Credit	Julieta Caunedo
Macroeconomics II	Econ	Credit	Karel Mertens
Econometrics I	Econ	Credit	Yongmiao Hong
Econometrics II	Econ	Credit	Tom Diciccio
Advanced Topics in Econometrics II	Econ	Credit	Yongmiao Hong
Applied Econometrics I	Econ	Audit	George Jakubson
Ph.D. Seminar in Asset Pricing	Fin	Credit	Robert Jarrow
Ph.D. Seminar in Corporate Finance Theory	Fin	Credit	Murillo Campello
Ph.D. Seminar in Empirical Corporate Finance	Fin	Credit	Murillo Campello
Doctoral Seminar in International Finance	Fin	Credit	Warren Bailey
Real Analysis	Math	Audit	Camil Muscalu
Probability	ORIE	Audit	Pierre Patie

Soon Hyeok (Steve) Choi, Ph.D.

Statement of Motivation and Research Interests

NBER Workshop on Development Economics and Networks for Early-Career Researchers

My interest in development and network economics began in part with Donaldson and Hornbeck (2016) who quantify the economic impact of railroad expansion through changes in market access. What stayed with me was the underlying empirical challenge: transportation networks are endogenously formed, and their effects spill across connected places. The same difficulty runs through the broader networks and development literature. Because agents and links are jointly determined, an association between a node's network position and its outcomes is generally difficult to interpret causally. This led me to look for a setting in which a link forms before an agent has an established network on which to sort. Residential real estate brokerage offers such a setting. Entry barriers are low, first-year turnover is high, and housing search is thin and idiosyncratic, leaving new agents comparatively little scope to select their first transaction counterparty based on pre-existing network position (Han and Strange, 2015).

I am particularly motivated to attend this workshop because I would like to learn how researchers at the frontier of development and network economics currently evaluate this identification strategy. This is also the part of the paper that I am actively developing. We are approaching this in three steps. First, we regress first-counterparty centrality on entrant and transaction observables to test for balance. Second, we test whether the centrality estimate remains stable as entrant, transaction, market, and year controls are added and, following Oster (2019), report how much stronger selection on unobservables would need to be than selection on observables to overturn it. Third, we test the match itself by simulation, comparing the centrality of each entrant's actual first counterparty with what they would obtain if counterparties arrived in proportion to how often incumbents in the same market transact; we find no evidence of systematic upward matching.

My research interests build outward from this paper toward matching, search, and network formation in highly intermediated markets. In residential real estate, I am interested in how buyers and sellers are matched to intermediaries who differ in experience, information, and network capital, and whether those differences translate into unequal access to opportunity and unequal market outcomes. I am extending these questions to commercial real estate, where brokers, owners, tenants, and lenders interact through persistent relationship networks. A related direction connects network position to contract design: real estate transactions are unusually rich in clauses and contingencies, making them a useful setting for studying how access, bargaining, and relationships shape both matching patterns and contractual terms. I see the workshop as an opportunity both to improve the current paper and to learn how the conceptual and empirical tools of network and development economics can inform this broader program

References

Donaldson, Dave, and Richard Hornbeck. 2016. “Railroads and American Economic Growth: A “Market Access” Approach.” *The Quarterly Journal of Economics* 131 (2): 799–858. 10.1093/qje/qjw002.

Han, Lu, and William C. Strange. 2015. “The Microstructure of Housing Markets: Search, Bargaining, and Brokerage.” *Handbook of Regional and Urban Economics* 5 813–886. 10.1016/B978-0-444-59531-7.00013-2.

Oster, Emily. 2019. “Unobservable Selection and Coefficient Stability: Theory and Evidence.” *Journal of Business & Economic Statistics* 37 (2): 187–204. 10.1080/07350015.2016.1227711.

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

Soon Hyeok Choi† Patrick S. Smith‡ Ali Tosyali§

September 2026

Abstract

Identifying the causal effect of networks on career success is challenging because network formation is endogenous. We address this challenge by exploiting plausibly exogenous variation in the network centrality of the first counterparty agent that a new residential real estate agent transacts with when entering the trading network. Moving from the least- to most-central first counterparty raises the probability of surviving one year by 2.8 to 4.5 percentage points. Consistent with a stochastic network exposure model, this effect operates largely through transaction volume, as central initial counterparties increase early deal flow through repeat business and access to their networks.

Keywords: Career Success, Centrality, Mentorship, Networks, Real Estate

JEL Classifications: D85, J24, J44, R31

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1 Introduction

Various factors influence an individual's career success, including personal abilities, organizational environments, and external opportunities. Recent research, which we review below, 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 individual may possess a strong network because they are successful. Conversely, a strong network may itself drive an individual's success. We address this endogeneity problem by exploiting plausibly exogenous variation in the network centrality of the first counterparty agent that a *new* real estate agent transacts with to examine the effect of network connections on career success in the U.S. residential real estate brokerage market.

Three characteristics of the residential real estate brokerage market make it an ideal setting for examining the role of networks in shaping new agents' career success. First, there is a relatively low barrier 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 minimal. Second, the relatively low barrier to entry results in high turnover and a low survival rate. In the ten cities we examine, a sizable share of new agents do not survive their first year, with first-year turnover reaching 44%.[1] Third, the network centrality of a new agent's first counterparty agent is plausibly exogenous. We exploit these characteristics to examine how new agents' initial network connections affect their career success.

Our identifying assumption is that, conditional on local market conditions and the timing of entry, the network centrality of a new agent's first counterparty is as good as randomly assigned. This assumption is highly plausible given the institutional structure of residential brokerage and the nature of housing markets. Housing markets are notoriously thin and subject to substantial matching frictions: transactions are infrequent, buyers and sellers have heterogeneous preferences, and agents can only interact with the counterparty agents involved in the listings their clients choose to pursue (Han and Strange, 2015). These frictions leave new agents with little scope to select their initial counterparty strategically. Instead, the identity and network centrality

[1] Between 2004 and 2021, only 56 to 74% of new agents in our sample remain active beyond twelve months. This is broadly consistent with a recent industry report finding that nearly half of new agents who closed their first transaction in 2022 did not close another in 2023 (Relitix, 2024).

of a new agent's first match are largely determined by which counterparty agents happen to be active (i.e., representing a buyer or seller) at the time of the transaction, combined with the idiosyncratic search behavior of their clients.[2]

Two features of our research design further support this assumption. First, any transaction characteristics correlated with the counterparty agent's network centrality are absorbed by our controls, so the identifying variation is the residual network centrality of the first counterparty conditional on the property, the local market, and the transaction year. Second, and most importantly, the network centrality estimate is stable as we progressively add these controls, so that selection on unobservables would have to differ markedly from selection on the rich set of observables to overturn our findings (Oster, 2019).[3]

To motivate our empirical analysis, we develop a stochastic network exposure model in which new agents are randomly matched to established counterparty agents with heterogeneous network centrality. Each new agent internalizes the network capital of their initial counterparty agent, which raises their early transaction volume through preferential access to the counterparty's listings and network. The model captures how career paths diverge based on the network centrality of a new agent's first counterparty and formalizes how early matching dynamics influence deal flow and survival.

The model yields two key predictions. First, new agents initially matched with more central counterparties face a higher post-entry transaction volume distribution. This prediction underscores the role of early network embeddedness in generating an entrant's initial deal flow. Second, greater realized deal flow raises continuation probabilities and cumulative survival. This second prediction identifies transaction volume as the primary channel through which an initial network connection translates into a longer and more productive career.

We test these predictions using transaction-level Multiple Listing Service (MLS) data from ten large Metropolitan Statistical Areas (MSAs) in the U.S. between January 2001 and June 2023. The data includes over 6 million residential real estate transactions.

[2]Our identifying assumption is consistent with the literature. Linden and Rockoff (2008), for example, note that "the nature of the search for housing is also a largely random process at the local level. Individuals may choose neighborhoods with specific characteristics, but, within a fraction of a mile, the exact locations available at the time individuals seek to move into a neighborhood are arguably exogenous."

[3]In Appendix E, we compare actual first counterparties with a simulated benchmark of counterparties drawn in proportion to incumbents' transaction volume and find no evidence of upward matching.

Each record captures a completed sale involving a listing agent and a buyer agent, allowing for the construction of agent-to-agent trading networks for each of the ten MSAs. To capture the dynamic nature of the professional ties in the agent trading network, 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 collapse into a weighted directed graph that aggregates transaction volume, allowing for a richer relational characterization. We compute weighted eigenvector centrality as our primary network centrality measure, which captures the idea that new agents become more influential when they are connected to other agents who themselves occupy prominent positions. To make centrality comparable across MSAs and over time and to limit the influence of a small number of highly central hubs, we express each agent's weighted eigenvector centrality as its percentile rank among all agents active in the same MSA and quarter. The resulting measure ranges from 0 for the least-central agent to 1 for the most-central agent in each cohort.

We find empirical evidence consistent with our theoretical predictions. New real estate agents who transact with more central counterparty agents in their first deal are significantly more likely to survive than new agents who transact with less central counterparty agents. In our baseline specifications, we find that moving from the least- to the most-central counterparty agent increases the probability of surviving one year by 2.8 to 4.5 percentage points, or roughly 4 to 7% of the baseline rate. These estimates come from specifications with additively and multiplicatively separable sale year and zip code fixed effects, so comparisons are drawn among new agents who enter the profession at the same time and work in the same location. These results hold when we model the timing of exit directly. In Cox and Weibull proportional hazards models, moving from the least- to the most-central counterparty reduces a new agent's exit hazard by 6 to 9%.

Typically, when examining networks' impact on an outcome, other factors that might be correlated with network centrality and the outcome itself must be carefully accounted for. These factors are less concerning in our study because the new agents we focus on are, by definition, not yet part of the trading network. One could argue that new agents already have professional (but not trading) connections to the other agents in their brokerage office. We account for the brokerage environment by controlling for in-house transactions, in which the new agent and counterparty agent work in the same brokerage

office, and for whether the new agent works for a national brokerage, which absorbs cross-brokerage differences in training and resources. We also rule out that the higher survival of these agents reflects the size of their first commission. Controlling for the sale price and detailed physical characteristics of the property leaves the magnitude and significance of the centrality effect unchanged.

Initial network connections shape not only whether new agents survive but also how productive they are in the early stages of their careers. We find that new agents who initially transact with more central counterparty agents have significantly higher first-year and longer-term transaction volume. These new agents also become more central in the trading network themselves over time. This early embeddedness, in turn, is a strong predictor of longer-term survival, underscoring the persistent and economically meaningful role of initial network connections in shaping new agents' career trajectories.

We interpret the higher survival rate as evidence that new agents benefit from transacting with a more central counterparty agent. This benefit may operate through several mechanisms. The benefits of a network connection may operate through explicit mechanisms. A more central counterparty agent can provide referrals, preferential access to listings that result in repeat transactions, access to other agents in their network, and mentorship. They may also operate through an implicit mechanism, in which the new agent observes the actions and behavior of the more central counterparty agent and mirrors them in subsequent transactions.

The implicit mechanism is difficult to observe directly, but the explicit mechanisms can be proxied with observable measures in the transaction data. We test three such mechanisms against a randomly selected placebo counterparty agent that is active in the same zip code and calendar year. Relative to this baseline, new agents are significantly more likely to transact with that counterparty again (repeat deal flow), to transact with the counterparty's existing network connections (network access), and to co-locate in the same brokerage office with the counterparty agent (mentorship). Repeat business and network access expand the new agent's future deal flow, which is precisely how an initial transaction with a more central counterparty translates into the higher survival we document.

Our study contributes to several strands of research at the intersection of network, labor, financial, and real estate economics. A substantial literature examines how networks shape career outcomes (Montgomery, 1991; Calvó-Armengol and Jackson,

2004; Beaman and Magruder, 2012; Kramarz and Skans, 2014; Cattan et al., 2025), yet causal interpretation remains difficult because network formation is endogenous (Manski, 1993; Jackson, 2008). A common strategy is to exploit an exogenous shock that removes a connection from an existing network, such as the expulsion of professors in Nazi Germany (Waldinger, 2010) or the sudden death of a superstar coauthor (Azoulay et al., 2010), and to measure the effect of losing that connection. We take a complementary approach that identifies the value of a connection at the point of network entry, before new agents have any network of their own. This setting isolates the causal effect of an initial connection's network centrality without the confounding that a pre-existing network introduces, and it lets us trace not only whether the first network connection matters but also how, through the early deal flow it generates. We thereby provide new evidence that the network centrality of one's first professional connection has a causal effect on career success.

Our findings also speak to a growing literature on how early opportunities and mentorship shape long-run outcomes (Athey et al., 2000; Cunha and Heckman, 2007; Hilmer and Hilmer, 2007; Blau et al., 2010). Much of this work studies designed interventions, such as assigned mentors, training programs, or structured peer support (Resnjanskij et al., 2024; Falk et al., 2026), where the relationship is deliberately created. Our results suggest that an early advantage need not be designed to matter. We show that an initial arm's-length transactional tie to a more central counterparty agent exerts a lasting influence on a new agent's survival and performance. In doing so, we document that the benefits of early-career network connections extend beyond formal mentorship to the incidental professional ties an entrant happens to form, and that even an incidental initial connection can meaningfully alter an individual's career trajectory.

Our study also contributes to a literature on how networks shape financial outcomes, deal flow, and firm performance (Hochberg et al., 2007; Cohen et al., 2008; Ozsoylev et al., 2014; Rossi et al., 2018; Di Maggio et al., 2019). This work establishes that network centrality confers informational and performance advantages, as central intermediaries gain earlier access to information and opportunities that yield superior performance. A parallel strand of the literature demonstrates that network connections are not always beneficial, since preferential treatment given to ties of powerful or entrenched decision-makers can destroy value (Fracassi and Tate, 2012; El-Khatib et al., 2015). We depart from this literature by shifting the focus from information transmission within established networks to the path-dependent effects of network entry. We show that an

entrant's initial exposure to a more central counterparty affects the trajectory of their subsequent career, extending the study of network centrality from the returns it yields established network participants to the formative advantages it confers on newcomers.

Finally, our study contributes to a literature on real estate agent performance and the industry's market structure (Hsieh and Moretti, 2003; Hendel et al., 2009; Levitt and Syverson, 2008; Liu et al., 2020; Gilbukh and Goldsmith-Pinkham, 2024). This work has emphasized two features of the brokerage market: low barriers to entry that generate high turnover and reduce the returns to brokerage (Hsieh and Moretti, 2003), and substantial heterogeneity in agent productivity that shapes outcomes for their clients and shifts over the housing cycle (Gilbukh and Goldsmith-Pinkham, 2024). Yet this literature has largely characterized agent performance in terms of individual attributes, such as experience, effort, and information, rather than the professional network an agent is embedded in.[4] We bring the agent's network to the center of the analysis, showing that a portion of the heterogeneity in early-career survival and productivity traces to the network centrality of the first counterparty with whom a new agent transacts – a feature present before the new agent enters the network. In a market defined by low barriers to entry and high turnover, we identify the initial network connection as an early, plausibly exogenous determinant of which new agents survive.

2 Theoretical Framework

To motivate our empirical analysis, we develop a stochastic network exposure model in which new agents are randomly matched at entry with established counterparties that differ in network centrality. The model formalizes that connecting with a more central initial counterparty enables an entrant to internalize the counterparty's network capital, thereby increasing the entrant's subsequent deal flow and career survival.

[4]Prior real estate studies of agent networks focus mainly on how repeat interactions between agents affect transaction-level outcomes, such as price and time on market (Smith et al., 2019; Lin et al., 2024). We differ in two respects: our outcome is the agent's own career success rather than a single transaction outcome, and our first-match design, which exploits plausibly exogenous variation in counterparty centrality, addresses the endogeneity of network formation that complicates causal interpretation in this prior work.

2.1 Environment

There is an existing network of established agents at the time a new agent enters the market. For a new agent e, let $t = 0$ denote the time of the agent's first transaction.[5] We denote the established network observed immediately prior to this initial match by

$$G_0 = (V_0, E_0),$$

where the nodes $v_i \in V_0$ are established agents $i \in \{1, \ldots, n_0\}$. Let $A_0 = [\alpha_{ij,0}]$ denote the corresponding weighted adjacency matrix, where $\alpha_{ij,0}$ is the non-negative number of transactions from established agent i to established agent j used to construct the network at the new agent's entry. The weighted eigenvector centrality of established agent i at the time of entry satisfies

$$c_{i,0} = \frac{1}{\lambda_0} \sum_{j=1}^{n_0} \alpha_{ij,0} c_{j,0} \tag{2.1}$$

where λ_0 is the largest eigenvalue of A_0. In the empirical analysis, we transform raw eigenvector centrality into a percentile rank, which preserves agents' ordering by centrality while placing the measure on a common scale across various local networks.[6]

The new agent e is randomly matched to its initial counterparty j with centrality $c_{j,0}$. The new agent internalizes part of the network capital tied to the counterparty's connectedness through an internalization technology φ with $\varphi(c_{j,0}) > 0$ and $\varphi'(c_{j,0}) > 0$. It captures how much of the initial counterparty's network capital becomes accessible to the new agent through the first match. A more central counterparty exposes the entrant to a larger set of potential trading opportunities, relationships, and information, so the amount of network capital internalized by the entrant increases with $c_{j,0}$.

[5] The timing is as follows. At $t = 0$, new agent e enters the market and completes the initial transaction with counterparty j in the established network G_0. From $t = 1$ onward, agent e is treated as an incumbent.

[6] In our empirical section, networks are constructed separately within each Metropolitan Statistical Area (MSA) and quarter. Percentile ranks therefore provide a comparable measure of an agent's relative position within each local network.

2.2 Early Deal Flow and Survival

Reflecting the real estate intermediary features, network capital acquired through the initial counterparty can translate into early deal flow, which provides both immediate commission income and opportunities to build future business. Let $V_{e,1}$ denote the number of transactions completed by entrant e in the post-entry period.[7] We assume

$$V_{e,1} \mid c_{j,0} \sim \text{Poisson}\big(\varphi(c_{j,0})\big)\,. \tag{2.2}$$

Let T_e denote the number of periods entrant e remains active. Because early deal flow generates future transaction opportunities, we model career continuation using a standard duration framework (Meyer, 1990). An entrant who is active in period τ continues into period $\tau+1$ with probability

$$\rho_\tau(V_{e,1}) = \rho + (1-\rho)\left[1 - e^{-\eta\delta^{\tau-1}V_{e,1}}\right] \tag{2.3}$$

where $\rho, \delta \in (0,1)$ and $\eta > 0$. The first term, ρ, represents the average baseline continuation probability.[8] The second term captures the incremental continuation advantage generated by early transaction volume. η governs the sensitivity of continuation to post-entry transaction volume, and δ represents the persistence of this effect.

Conditional on realized post-entry transaction volume, continuation probabilities are independent across periods. We therefore define the survival function conditional on the post-entry volume, $g_t(v)$, as the probability of surviving through horizon t given realized volume v. Because post-entry volume is random conditional on initial counterparty centrality, $S_e(t)$ averages this conditional survival probability over the distribution of post-entry volume:

$$g_t(v) \equiv \Pr(T_e \geq t+1 \mid V_{e,1} = v) = \prod_{\tau=1}^{t} \rho_\tau(v), \tag{2.4}$$

$$S_e(t) \equiv \Pr\big(T_e \geq t+1 \mid c_{j,0}\big) = \mathbb{E}\big[g_t(V_{e,1}) \mid c_{j,0}\big]\,. \tag{2.5}$$

[7] The post-entry is the period immediately following the agent's initial transaction.

[8] For parsimony, ρ is common across entrants. Entrants may differ in latent ability or persistence, but random matching makes the distribution of these attributes independent of initial counterparty centrality. Allowing for such heterogeneity does not alter the model's average survival comparison.

We derive the following proposition, which states how initial counterparty centrality affects post-entry deal flow.

Proposition 1 (Post-Entry Deal Flow)**.** *Transacting with a more central initial counterparty increases the entrant's expected post-entry transaction volume:*

$$\frac{\partial \mathbb{E}[V_{e,1} \mid c_{j,0}]}{\partial c_{j,0}} > 0. \tag{2.6}$$

Proof. *See Appendix A.*

A more central initial counterparty provides exposure to greater network capital and a broader set of trading opportunities. This exposure raises the arrival rate of post-entry transactions and therefore increases expected deal flow. Because transaction volume remains stochastic, entrants matched with more central counterparties face a post-entry volume distribution shifted toward higher values. We next establish how greater expected post-entry deal flow translates into a higher probability of career survival.

Proposition 2 (Career Survival)**.** *Greater realized post-entry transaction volume increases cumulative survival at every horizon. Consequently, transacting with a more central initial counterparty increases the entrant's survival probability and lengthens the expected career:*

$$g_t(v+1) > g_t(v), \qquad \frac{\partial S_e(t)}{\partial c_{j,0}} > 0, \qquad \frac{\partial \mathbb{E}[T_e \mid c_{j,0}]}{\partial c_{j,0}} > 0. \tag{2.7}$$

Proof. *See Appendix A.*

Each additional post-entry transaction raises the entrant's continuation probability in every subsequent period and therefore increases cumulative survival through any finite horizon. Proposition 1 shows that a more central initial counterparty shifts the distribution of post-entry volume toward higher values. Averaging over this distribution therefore yields a higher survival probability for entrants matched with more central counterparties.

2.3 Theoretical Hypotheses

We distill the model into two testable predictions about how a new agent's first network connection shapes early-career outcomes. The first concerns career survival, and the second concerns the channel through which that survival advantage arises.

Prediction 1. *New agents initially matched with highe centrality counterparties exhibit higher survival rates than those matched with lower centrality counterparties.*

This prediction follows from Proposition 2. A more central initial counterparty exposes the entrant to greater network capital, shifting post-entry deal flow toward higher values. Higher realized deal flow raises continuation in each subsequent period and therefore increases cumulative survival. Because the effect of early volume decays over time, the resulting survival advantage is strongest early in the entrant's career. Prior work shows that central network nodes facilitate access to information and deal flow (Rossi et al., 2018; Di Maggio et al., 2019; Han et al., 2024). Our empirical design tests this prediction at market entry, exploiting plausibly exogenous variation in the centrality of the entrant's initial counterparty.

Prediction 2. *An initial match with a higher-centrality counterparty increases post-entry transaction volume, and this additional deal flow contributes to the entrant's survival advantage.*

This prediction follows from the causal sequence established in Propositions 1 and 2. Proposition 1 shows that greater initial counterparty centrality shifts the distribution of post-entry volume upward, while Proposition 2 shows that greater realized volume increases cumulative survival. Post-entry transaction volume is therefore a primary channel through which initial-counterparty centrality affects career survival.

3 Data and Networks

Our analysis draws on MLS housing transaction data from Cotality for ten large Metropolitan Statistical Areas (MSAs), covering the period from January 2001 through June 2023. The data includes detailed information on the unit type (single-family detached, condominium, or townhouse), physical characteristics (e.g., bedrooms, bathrooms), location (e.g., zip code), and transaction details (e.g., sale date, sale

price). The data also contains fields (e.g., listing agent and buyer agent identifiers) that we use to construct the agent networks within each MSA. These networks are inherently MSA-specific because real estate agents almost always operate exclusively within their local markets. For example, agents active in Boston do not typically also work in Houston.[9]

We selected the ten MSAs using the following criteria. First, each MSA has continuous data available from 2001 to 2023. Second, the MSA has at least 200,000 transactions during the study period. Third, a single MLS operated in the MSA during the study period. This criterion facilitates the creation of within-MSA agent networks because agent membership and IDs differ across MLS platforms. To verify this condition, we measure the share of duplicate listings appearing across multiple MLS platforms. We set a threshold of less than 5%, but in most cases, fewer than 1% of listings appear on more than one MLS platform across the ten selected MSAs. Fourth, listing and buyer agent IDs must be reliably populated, as these fields are essential for network construction. Finally, we prioritize MSAs that offer geographic diversity and whose urban cores do not cross state lines. Based on these criteria, the selected MSAs are Boston, MA (BOS); Cleveland, OH (CLE); Charlotte, NC (CLT); Columbus, OH (COL); Detroit, MI (DET); Houston, TX (HOU); Jacksonville, FL (JAX); Minneapolis, MN (MIN); Oklahoma City, OK (OKC); and Tucson, AZ (TUC).

After selecting the ten MSAs, we filter the transaction data for each MSA to remove outliers (e.g., list or sale prices above $2 million), distressed transactions, and records missing key information, such as those without a listing agent ID. Appendix B.2 of the online appendix provides a detailed list of the filters. The 10-MSA combined filtered dataset contains over 6 million housing transactions involving 572,253 unique real estate agents. Panel A of Table 1 reports summary statistics for the filtered housing transaction dataset.

3.1 Network Construction

We construct an agent trading network for each of the ten MSAs separately. To capture the evolving structure of agent interactions, we construct a series of dynamic

[9]The online appendix provides evidence supporting this conjecture. Specifically, we show that there is no overlap in agent IDs and very little overlap in agent names and cell phone numbers across the ten MSAs.

networks over rolling time windows. We segment the full sample period into sequential three-month intervals (i.e., quarters), starting in January, April, July, and October of each calendar year. For each quarter t, we construct the network from all transactions completed in the three-year window $[t - 3\text{year}, t)$, which ends on the first day of quarter t. Intervals are half-open, so each transaction enters exactly one network window at each horizon. Finally, we stack these rolling windows into a network panel for each of the ten MSAs.

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. Dual-agency transactions, in which the same agent represents both sides, generate self-loops. We exclude them from the edge set – they carry no counterparty information and would mechanically inflate degree and eigenvector centrality – while retaining the agent as a node. The adjacency matrix therefore has a zero diagonal.

Figure 1 illustrates an example of an agent trading 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 interaction 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 in dollars (TP), and average transaction price (AP), summarizing the intensity and economic scale of the relationship. The transaction count (n) serves as the edge weight in the centrality calculations that follow. Figure 2 displays the reduced-form directed graph for Charlotte, NC in Q2 2006, illustrating what an actual agent trading network looks like at scale in our data.

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. 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 network capital in residential real estate brokerage markets.

3.2 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 (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 to which it is connected. This recursive structure is particularly relevant in the residential real estate brokerage setting, where indirect connections and the prominence of an agent's neighbors in the network can enhance visibility, information access, or deal flow.

We compute centrality on the reduced-form weighted directed graph defined above, in which each edge points from a listing agent to the buyer agent on the same transaction. The adjacency matrix is transaction-weighted: each entry records the number of transactions along that edge, so that repeated pairings enter the centrality calculation more heavily than one-off interactions. This captures not only whether two agents are connected but how often, which may proxy for the information channels, professional trust, or other ties that facilitate deal-making. Because centrality can be evaluated from either endpoint of these directed edges, we compute three measures of eigenvector centrality: in-centrality, out-centrality, and combined centrality.

In-centrality is computed 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 in-centrality of agent a is defined as:

$$C_a^{\text{in}} = \frac{1}{\lambda} \sum_{b \in \mathcal{N}^-(a)} A_{ba} \, C_b^{\text{in}}, \tag{3.1}$$

where $\mathcal{N}^-(a)$ denotes the set of agents with directed edges pointing to agent a (i.e., its in-neighbors), A_{ba} is the adjacency matrix entry giving the number of transactions from agent b to agent a, and λ is the largest eigenvalue of the adjacency matrix,

which coincides with that of its transpose. This formulation emphasizes that an agent's in-centrality is recursively determined by the centrality of the listing agents with whom it transacts as the buyer-side counterparty.

Out-centrality is computed based on outgoing edges. An agent is central if it frequently transacts as a listing agent with other highly central buyer agents. The out-centrality of agent a is defined as:

$$C_a^{\text{out}} = \frac{1}{\lambda} \sum_{b \in \mathcal{N}^+(a)} A_{ab}\, C_b^{\text{out}}, \tag{3.2}$$

where $\mathcal{N}^+(a)$ denotes the set of agents with directed edges originating from agent a (i.e., its out-neighbors), A_{ab} is the adjacency matrix entry giving the number of transactions from agent a to agent b, and λ is the largest eigenvalue defined above.

To make centrality comparable across MSAs and over time and to limit the influence of a small number of highly central agents, we transform each raw centrality measure into its percentile rank within each MSA-by-quarter cell. For agent a in MSA-quarter cell (c, t),

$$\tilde{C}_a^k = \frac{\text{rank}_{c,t}\big(C_a^k\big) - 0.5}{N_{c,t}}, \qquad k \in \{\text{in}, \text{out}\}, \tag{3.3}$$

where $\text{rank}_{c,t}(\cdot)$ is agent a's rank within cell (c, t) (ties broken by average rank) and $N_{c,t}$ is the number of agents active in the cell, so that $\tilde{C}_a^k \in (0, 1)$. All our empirical analyses use these standardized measures.

Combined centrality captures an agent's overall network centrality by averaging the standardized in- and out-centrality measures:

$$\tilde{C}_a^{\text{combined}} = \frac{\tilde{C}_a^{\text{in}} + \tilde{C}_a^{\text{out}}}{2}. \tag{3.4}$$

In-centrality reflects an agent's prominence as a buyer-side representative who transacts with more central listing agents, while out-centrality reflects prominence as a listing agent who transacts with more central buyer agents. Combined centrality summarizes an agent's influence across both sides of the residential brokerage market.

3.3 New Agents

We define a new agent as one with no prior transactions in the data. Although we have transaction data from January 2001 through June 2023, our empirical analysis uses only data between January 2004 and June 2021. This allows us to (i) identify new agents with no transactions from 2001 through 2003, (ii) construct the backward-looking three-year network centrality measures for the first counterparty agent that the new agents transact with, and (iii) determine whether the new agent survived one year. A new agent survives if they complete at least one additional transaction at least 365 days after their first transaction. Of the 572,253 unique agents in the filtered MLS data (see Panel A of Table 1), we identify 217,837 new agents who entered the real estate trading network between January 2004 and June 2021. After the trimming rules described below, our estimation sample comprises 151,896 new agents.

A challenge arises because a new agent's first transaction may not involve a "traditional" full-service counterparty agent. This issue is particularly relevant when the new agent represents the buyer, as the listing agent may instead be an entry-only or flat-fee listing service, a limited-service provider, or a team of agents. These "non-traditional" agents often generate spuriously high transaction volumes and, thus, high network centrality measures, but they do not correspond to individual, highly-central agents in the conventional network sense. Because the MLS data does not include a field that identifies these non-traditional agents, we mitigate this concern with two trimming rules. First, to remove non-traditional counterparty agents, we trim counterparty agent IDs by transaction volume during the backward-looking three-year observation period, removing the top 5% within each MSA for every rolling three-month window. Second, to remove non-traditional new agents, we drop new agents with more than 20 transactions in their first year, a volume that is unusually high for an individual new agent.[10]

Panel B of Table 1 presents summary statistics for 151,896 new agents after trimming the counterparty agent network data to remove non-traditional agent IDs. The first three rows of Panel B report summary statistics for the three counterparty network centrality

[10]The online appendix demonstrates that our results are robust to trimming the top 1% or 3% of counterparty agent IDs based on their transaction volume as well as the inclusion of new agents with more than 20 transactions. The online appendix also provides results showing that our findings are similarly unaffected when, instead of trimming, we flag the top 5% of non-traditional counterparty agent IDs with an indicator variable and include it as an additional control.

measures: in, out, and combined. These measures are expressed as percentile ranks within each MSA-quarter (see Section 3.2), so that they are comparable across the ten MSAs and over agents' varying entry times.

The next six rows of Panel B in Table 1 report summary statistics for a set of agent relationship variables that are mutually exclusive and collectively exhaustive. Each new agent's first transaction is assigned to the first applicable category in the following priority order: *Both Agents New*, *Dual Agent*, *In-house Agent*, *Listing Agent Non-member*, *Listing Agent Member*, *Buyer Agent Member*. Where a transaction satisfies more than one of these conditions, it is assigned to the higher-priority category. Accordingly, the definitions of the lower-priority indicators should be read as conditional on the transaction not belonging to a higher-priority category.

Both Agents New$_{i,j,t}$ is an indicator variable that equals 1 if agent i representing the seller and counterparty agent j representing the buyer in the transaction at time t are both new entrants to the network that quarter; otherwise, it equals 0. In transactions that lack a distinct MLS-member counterparty with an observed network centrality (i.e., *Both Agents New*, *Dual Agent*, and *Listing Agent Non-member*), no counterparty network centrality is observed. In these cases, we assign the neutral value of the percentile-rank scale, $\tilde{C}^{k}_{j,t} = 0.5$, which corresponds to the median of the counterparty centrality distribution. Because each of these cases is also flagged by its own indicator variable, the level effect of these imputed observations is absorbed by the corresponding indicator, so our estimates do not depend on the specific neutral value chosen. The summary statistics in Panel B of Table 1 indicate that 5% of new agents' first transactions are with another new agent.

Dual Agent$_{i,t}$ is an indicator variable that equals 1 if new agent i represents both the buyer and the seller in the transaction at time t; otherwise, it equals 0. *In-house Agent*$_{i,j,t}$ is an indicator variable that equals 1 if new agent i and counterparty agent j work for the same brokerage office; otherwise, it equals 0. Together, these two variables capture non-arm's-length relationships between the agents involved in the transaction. The summary statistics indicate that 8% of new agents' first transactions involve dual agency, and an additional 6% involve in-house agency, reflecting a nontrivial incidence of non-arm's-length relationships in initial market entry.

The next three control variables identify arm's-length relationships between the agents involved in the transaction. *Listing Agent Member*$_{i,j,t}$ is an indicator variable that equals

1 if new agent i represents the seller in an arm's-length transaction with buyer agent j who is an MLS member, and 0 otherwise. *Listing Agent Non-member*$_{i,j,t}$ is an indicator variable that equals 1 if new agent i represents the seller in an arm's-length transaction with buyer agent j who is not an MLS member, and 0 otherwise. The final relationship control variable, *Buyer Agent Member*$_{i,j,t}$, is an indicator variable that equals 1 if new agent i represents the buyer in an arm's-length transaction with listing agent j who is an MLS member, and 0 otherwise.[11] The summary statistics indicate that new agents are much more likely to provide buyer-side representation in their first transaction than seller-side representation.

The next rows of Panel B in Table 1 report summary statistics for the additional controls included in our empirical analyses. The unit type shares are broadly consistent with the full transaction sample in Panel A: 84% of new agents' first transactions involve a single-family detached house, 14% a condominium, and 2% a townhome. The average sale price, however, is lower for the new agent sample than for the full sample ($240K vs. $278K), consistent with new agents transacting on lower-priced properties early in their careers. We control for sale price directly in Section 4.3. Roughly 43% of new agents work for a national brokerage firm, which we also control for and discuss in Section 4.3.

The final seven rows of Panel B report summary statistics for the outcome variables related to the new agents' survival rate and transaction volume. The survival rate summary statistics indicate that 67% of the new agents survive for more than one year, 58% for more than two years, and 48% for more than three years. The average survival length of new agents in the data is 1,679 days, or roughly four and a half years. Figure 3 highlights how new agents' survival varies over time with market conditions. Finally, the transaction volume summary statistics indicate that new agents in the data average 3.43 transactions in their first year and 22.91 total transactions.

[11] Only real estate agents who are members of the MLS can list properties on the MLS, so there are no *Buyer Agent Non-member* transactions in which new agent i represents the buyer in an arm's-length transaction with listing agent j who is not an MLS member.

4 Methodology and Results

4.1 Empirical Strategy

We exploit plausibly exogenous variation in the network centrality of the counterparty agent that a new agent is matched with in their first transaction to examine whether new agents who transact with more central counterparty agents have a higher survival rate than those who transact with less central counterparty agents. We estimate agent-level regressions of the following form:

$$Survive_{i,j,t} = \beta_1 Centrality_{j,t} + \beta_X X_{i,j,t} + \gamma_z + \delta_t + \varepsilon_{i,j,t} \tag{4.1}$$

The dependent variable in Equation (4.1), $Survive_{i,j,t}$, is a binary indicator identifying whether 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. Our baseline analyses focus on a one-year survival period, for which $Survive_{i,j,t} = 1$ if the new agent completes at least one additional transaction at least 365 days after their first transaction and 0 otherwise. We also examine longer survival periods, including a continuous measure of $Survive_{i,j,t}$ that denotes the new agent's survival length as one plus the number of days between their first and last transactions in the data.

In Equation (4.1), the primary variable of interest, $Centrality_{j,t} \in \{\tilde{C}^{\text{in}}_{j,t}, \tilde{C}^{\text{out}}_{j,t}, \tilde{C}^{\text{combined}}_{j,t}\}$, is one of the three standardized network centrality measures defined in Section 3.2, computed for the first counterparty agent j that new agent i transacts with, over the backward-looking three-year window ending at time t. We estimate Equation (4.1) with and without a set of mutually exclusive agent relationship and unit type controls, $X_{i,j,t}$. The six mutually exclusive agent relationship controls identify whether the agents involved in the transaction are both new entrants to the trading network that quarter or have an arm's-length relationship. The unit type controls indicate whether the new agent's first transaction involved a single-family detached house, a condominium, or a townhome. To avoid perfect multicollinearity, we omit one of the agent relationship (Buyer Agent Member) and unit type (Single-family Detached) controls. Finally, Equation (4.1) also includes additively (or multiplicatively) separable zip code and sale year fixed effects, $\gamma_z + \delta_t$, for the zip code z and sale year t of the new agent's first transaction. Including 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 enter the profession at the same time and work in the same location.

4.2 New Agent Survival

Table 2 reports the regression estimates from Equation (4.1), which assess the extent to which a new agent's initial network connection influences their early-career survival. Panel A reports estimates from our baseline estimation that does not include the agent representation and unit type controls, whereas Panel B displays estimates from a version that includes the additional controls. Columns 1 and 2 report estimates for the *Counterparty Centrality In* measure, columns 3 and 4 for the *Counterparty Centrality Out* measure, and columns 5 and 6 for the *Counterparty Centrality Combined* measure. The dependent variable in each column is an indicator variable identifying whether the new agent survived one year.

The counterparty network centrality coefficient estimates are positive and statistically significant in all six columns in Panel A of Table 2. The counterparty centrality coefficient estimates indicate that the probability of survival for new agents increases with the centrality of the first counterparty agent they transact with. Moving from the least- to the most-central counterparty agent (i.e., from the bottom to the top of the counterparty centrality distribution) increases new agents' one-year survival rate by 2.2 to 4.5 percentage points. This translates to approximately a 3 to 7 percent increase from the baseline one-year survival rate of 67 percent.

After including the additional agent relationship and unit type controls, the counterparty network centrality coefficient estimates remain positive and statistically significant at the 1 percent level in all six columns in Panel B of Table 2. Because the Counterparty Centrality Combined measure captures edges pointing in both directions, we consider it the most appropriate measure of the initial counterparty agent's network connectivity. We therefore focus on the Counterparty Centrality Combined measure and report results only for it going forward. In columns 5 and 6 of Panel B, moving from the least- to the most-central counterparty agent increases new agents' one-year survival rate by 2.8 to 2.9 percentage points, or roughly 4 percent relative to the baseline one-year survival rate. Consistent with Prediction 1, the results in Panels A and B of Table 2 indicate that new agents benefit from forming network connections with more central counterparty agents.

Panel B of Table 2 also reports the coefficient estimates for the unit type and agent relationship controls in Equation (4.1). The unit type controls are statistically insignificant in the even-numbered columns that include zip-by-sale-year fixed effects, indicating that new agents whose first transaction is a condominium or townhome are just as likely to survive as those whose first transaction is a single-family detached house. The rest of this section focuses on the agent relationship controls. As noted in Section 4, the buyer agent control is omitted from Equation (4.1), so the coefficient estimates discussed below are all relative to new agents who provide buyer-side representation in transactions involving counterparty agents from unaffiliated brokerage offices.

The first agent relationship control identifies transactions where both agents are new agents in the trading network that quarter. Neither the new agent nor the counterparty has prior transactions from which to construct a backward-looking centrality measure. Because we use a lagged three-year lookback window, neither agent has a network centrality. We therefore assign the counterparty agent the neutral percentile-rank value of 0.5 and flag the transaction with the *Both Agents New* indicator. Thus, the coefficient on this indicator captures the survival differential of beginning one's career opposite another new agent rather than a counterparty agent with an observed network centrality. In Panel B of Table 2, the estimates on *Both Agents New* are negative and statistically significant across all six specifications, ranging from -0.017 to -0.012. New agents whose first transaction pairs them with another new agent are thus roughly 1.2 to 1.7 percentage points less likely to survive one year than new buyer agents whose first transaction involves an MLS-member counterparty (the omitted *Buyer Agent Member* category). This finding reinforces our main result. The survival advantage conferred by a more central initial counterparty is absent when the counterparty is itself new to the network.

The 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 is the crux of this paper, the lack of network connectivity will decrease the new agent's probability of survival relative to new agents that transact with more central counterparty agents.

In Panel B of Table 2, the coefficient estimates on dual agent transactions are uniformly negative and statistically significant across all six specifications, ranging from -0.015 to -0.013. These estimates indicate that new agents whose first deal is a dual agent transaction, and thus involves no counterparty agent, are roughly 1.3 to 1.5 percentage points less likely to survive one year than new buyer agents whose first transaction involves an MLS-member counterparty. In terms of survival, the higher commission earned in the dual agency transaction does not offset the initial loss of network connectivity. Consistent with our main findings, this result indicates that new agents' survival probability increases with the network centrality of their initial counterparty.

One could argue that new agents already possess non-trading network ties within their brokerage office, which could influence their survival probability. Consequently, the brokerage office a new agent joins may shape their survival prospects. To partially address this issue, Equation (4.1) includes an *In-house Agent* indicator that captures within-office relationships. This variable also helps mitigate concerns that new agents may benefit from referrals from more experienced colleagues.

The coefficient estimates for *In-house Agent* transactions are positive but statistically insignificant across all six specifications in Panel B. This pattern indicates that new agents whose initial transaction involves a counterparty within the same brokerage office are no more likely to survive one year than new agents whose first transaction is a buyer-side, arm's-length deal with an MLS-member listing agent (the omitted *Buyer Agent Member* category). Taken together, the results suggest that new agent survival is primarily driven by the network centrality of the initial counterparty agent, rather than by shared brokerage affiliation. More broadly, although cross-office transactions may expose new agents to a wider segment of the trading network, the evidence is not consistent with the view that transacting across brokerage offices is itself a key determinant of early-career survival.

The coefficient estimates for *Listing Agent Member* transactions, in which the new agent represents the seller and initially transacts with an MLS-member buyer agent, are negative and statistically significant across all six specifications in Panel B of Table 2. This finding indicates that agents who begin their real estate career on the seller side are significantly less likely to survive for one year than those who first represent buyers. Specifically, we find that new listing agents have a one-year survival rate that is 2.3 to 2.7 percentage points lower than new buyer agents. A plausible interpretation is that early buyer-side work provides broader network exposure and more frequent interaction with

experienced, high-centrality counterparty agents that have direct control over local deal flow through their listings. The online appendix provides evidence consistent with this interpretation by plotting the average number of previous transactions, which serves as a rough proxy for experience and network connectivity, that listing agents have relative to buyer agents. The plot shows that listing agents typically have two to three times as many prior transactions as buyer agents.

Panel B of Table 2 also reports coefficient estimates for *Listing Agent Non-member* transactions, which are similar to *Listing Agent Member* transactions in that the new agent represents the seller but differ because the counterparty buyer agent is not an MLS member. By definition, these counterparties are not part of the MLS network. The coefficient estimates on the *Listing Agent Non-member* indicator are negative and statistically significant across all six specifications, and their magnitude is economically large. New listing agents whose first transaction involves a non-member counterparty have a one-year survival rate that is 9.8 to 10.6 percentage points lower than comparable new agents who begin on the buyer side. This finding is consistent with Prediction 1 in that initial transactions with unconnected non-member counterparty agents provide no direct opportunity for further network formation, thereby limiting subsequent deal flow and lowering short-run survival.

4.3 Transaction and Brokerage Controls

A natural concern is that the estimated survival benefit of transacting with a more central counterparty reflects something other than the counterparty agent's network centrality. We consider two alternative channels: the compensation a new agent earns on their first transaction, and the brokerage firm the new agent joins. Table 3 augments the combined-centrality specification from column 6 of Table 2 with controls for each channel. Every column retains the multiplicatively separable zip-code-by-sale-year fixed effects and the full set of agent relationship and unit type controls, so that identification continues to come from comparisons among new agents who enter the same local market in the same year.

Because real estate agents are compensated through commissions, how much a new agent earns on their first transaction scales directly with the sale price of the property. If more central counterparty agents systematically transact on higher-value properties, the centrality coefficient could partly capture a larger initial commission payout rather

than the value of the network connection itself. Column 1 adds the natural log of the sale price, and column 2 instead adds a rich set of house characteristics. We allow each characteristic to enter flexibly by including full sets of indicator variables for 100-square-foot-wide bins of living area ($SQFT_{500\text{-}599,it}$, $SQFT_{600\text{-}699,it}$, ...), 10-year-wide bins of house age ($AGE_{0\text{-}9,it}$, $AGE_{10\text{-}19,it}$, ...), lot-size bins measured in acres, the number of bedrooms, and the number of bathrooms.

In both specifications, the counterparty centrality combined coefficient is 0.029 and remains significant at the 1 percent level, unchanged from the baseline estimate. The log sale price enters negatively (-0.010), indicating that, conditional on network centrality, new agents whose first transaction involves a higher-priced property are less likely to survive their first year. This finding runs counter to the compensation channel discussed above. If a larger initial commission drove survival, higher sale prices would predict higher survival, not lower. That the centrality coefficient is unchanged once sale price and detailed house characteristics are included indicates that the survival benefit conferred by a more central counterparty does not operate through the size of the new agent's first commission, ruling out compensation as an explanation for the centrality result.

The second channel concerns cross-brokerage differences in training, mentorship, compensation structures, and resources. New agents who join large, well-resourced firms may receive more onboarding support and referral flow than those who join smaller, local firms. We identify new agents in national brokerages through a two-step procedure. First, we normalize each office name (lower-case conversion, standardizing punctuation so that, e.g., "RE/MAX" becomes "remax") and extract its leading one-, two-, and three-word prefixes. For each prefix, we count the number of distinct offices that share it and the number of distinct MSAs in which it appears, and we flag as a candidate national brand any prefix that spans at least five offices and at least three of the ten MSAs. The cross-MSA requirement is what distinguishes national brands from locally common names. For example, a name fragment such as "carolina" may appear in many offices but only within a single MSA (i.e., Charlotte), and is therefore not flagged. Each office is assigned its longest flagged prefix, so that "keller williams" is identified in preference to a bare "keller," while genuinely single-token brands such as "remax" are still captured. Second, we manually review the flagged prefixes and retain those corresponding to recognized national franchises (e.g., RE/MAX, Coldwell Banker, Keller Williams, and Century 21), confirming in each case that the firm operates across

several of our MSAs with substantial transaction volume. An office is coded as a national brokerage if its name maps to one of these reviewed brands, and as local otherwise.

We identify 27 unique national brokerages, which account for 43% of the new agents in the data. Column 3 of Table 3 adds an indicator for whether the new agent works for a national brokerage. Column 4 replaces the indicator with fixed effects for the 27 national brokerages, with all non-national brokerages grouped into a single local category. The counterparty centrality combined coefficient is again stable at 0.028 and significant at the 1 percent level. The national brokerage indicator is positive and statistically significant at the 1 percent level. New agents at national brokerages are about 1.4 percentage points more likely to survive their first year, indicating that organizational differences between larger, national and smaller, local firms provide a modest independent survival benefit. That said, accounting for this advantage does not reduce the role of the initial counterparty agent's network centrality.

Column 5 includes the natural log of sale price and the national brokerage indicator together, so that the counterparty centrality combined coefficient is identified net of both the compensation and brokerage-resource channels simultaneously. The estimate is 0.029 and remains significant at the 1 percent level, and both controls retain the sign, magnitude, and significance from earlier when they were included individually. This indicates that neither channel accounts for the survival advantage conferred by a more central initial counterparty. Taken together, the results in this section reinforce our central finding. The network centrality of a new agent's first counterparty is a key determinant of early-career survival, operating independently of the characteristics of their first transaction and the firm they join.

4.4 New Agent Transaction Volume

The preceding sections establish that the network centrality of a new agent's first counterparty is a key determinant of early-career survival. We now examine the channel through which this benefit operates. Because real estate agents earn income only when a transaction closes, transaction volume is the key determinant of whether a new agent is successful. If transacting with a more central counterparty improves survival, it should do so largely by raising the new agent's subsequent transaction volume, where more central counterparties expose new agents to greater deal flow through referrals and repeat-interaction opportunities that generate future business. This section first shows

that initial counterparty centrality is associated with higher subsequent transaction volume, and then shows that volume is the channel linking centrality to survival.

Table 4 examines the effect of counterparty agents' network centrality on new agents' transaction volume. Columns 1 to 5 regress the log of new agents' transaction volume over the specified time horizon on counterparty agents' network centrality, unit type controls, agent relationship controls, and zip-code-by-year fixed effects. Column 6 returns to the one-year survival outcome and is discussed at the end of this section. We initially focus on new agents' first-year transaction volume, then expand the analysis to the longer term. Column 1 uses the full new agent sample in Panel B of Table 1. The remaining columns restrict the sample to new agents that enter the trading network between 2004 and 2019. This restriction ensures a minimum 3.5-year post-entry window for evaluating longer-term transaction volumes.

The counterparty network centrality coefficient estimates are positive and statistically significant in columns 1 and 2 of Table 4. This finding indicates that new agents' transaction volume increases with the network centrality of the first counterparty agent they transact with. Moving from the least- to the most-central counterparty agent (i.e., from the bottom to the top of the counterparty centrality distribution) increases new agents' first-year transaction volume by 8.7 to 8.8 percent.

The short-term effect on new agents' transaction volume in columns 1 and 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 4 support this conjecture, showing that the magnitude of the network centrality coefficient estimate increases with the transaction window length. In column 3, moving from the least- to the most-central counterparty agent increases new agents' transaction count over their first three years by approximately 12.7 percent. Similarly, in column 4, moving from the least- to the most-central counterparty agent increases new agents' total transaction count by approximately 13.5 percent.

Column 5 in Table 4 adjusts for differences in new agents' survival length using the log of transactions per year as the dependent variable. As in the preceding columns, we find that new agents' average annual transaction volume increases with the network centrality of the first counterparty they transact with. Moving from the least- to the most-central counterparty agent increases new agents' average annual transaction

volume by approximately 7.7 percent, indicating that the higher transaction volume is not simply the product of a longer survival length.

The agent relationship controls in Table 4 broadly mirror the survival results in Table 2. Relative to new agents who enter as buyer agents, those who enter via Both Agents New, Dual Agent, and Listing Agent Member transactions generate lower subsequent transaction volume. These estimates are small and statistically insignificant over the first year (columns 1 and 2) but become negative and significant over the longer horizons (columns 3 through 5). New agents who enter via a Listing Agent Non-member transaction fare worst of all, with significantly lower transaction volumes at every horizon. This lower volume is consistent with, and likely contributes to, the weaker short-run survival of these agents documented earlier. The In-house Agent estimates, by contrast, are positive and statistically significant in every column, indicating that new agents whose first transaction involves a counterparty inside their own brokerage office go on to complete more transactions early in their careers. This volume advantage does not, however, translate into a detectable survival advantage. The In-house Agent coefficient is positive but statistically insignificant in Table 2, indicating that within-office first transactions raise early activity without materially improving one-year survival. Taken together, these patterns highlight how a new agent's relationship to their initial network connection shapes both the volume they generate and their survival.

Column 6 tests whether transaction volume mediates the survival effect by adding the new agent's first-year transaction count, and its interaction with counterparty centrality, to the one-year survival specification. A higher first-year transaction count should raise a new agent's survival prospects through greater commission earnings (holding transaction prices constant) and the additional client relationships and referrals that each closed transaction generates. Consistent with this intuition, first-year transaction volume is itself a powerful predictor of survival. In column 6, each additional first-year transaction raises the probability of surviving one year by roughly 5.4 percentage points. The interaction between counterparty centrality and first-year volume is negative (-0.008) and statistically significant at the 1 percent level, implying that the direct survival benefit of a high-centrality first counterparty diminishes as the new agent's own transaction volume rises. The marginal effect of counterparty centrality on survival is $0.040 - 0.008\,n$, where n is the new agent's first-year transaction count. It is largest for agents who close few deals in their first year and falls to roughly zero once n reaches about five.

This pattern is consistent with Prediction 2. Initial network connections are most valuable for agents who have yet to generate transaction volume of their own, and become less important once new agents begin producing enough endogenous deal flow to sustain themselves independent of their initial counterparty's network centrality. The declining direct effect does not, however, imply that counterparty centrality and transaction volume are competing determinants of survival. On the contrary, the network centrality of the initial counterparty is itself a source of the higher first-year transaction volume documented in columns 1 through 5. The attenuation therefore reflects the mediation anticipated by Prediction 2 rather than substitution between two competing determinants. A more central first counterparty raises survival largely by generating the early transaction volume that sustains the new agent, so that once we condition on realized first-year volume, part of which the connection itself produced, little independent role for counterparty centrality remains.

4.5 Long-Term Survival and Network Formation

Table 5 extends the survival analysis in the preceding sections by evaluating the extent to which the relatively short-term effect persists over the longer term. Once again, we restrict the sample to new agents that enter the trading network between 2004 and 2019 to provide a minimum 3.5-year post-entry window. Column 1 of Table 5 reports results from a regression using a modified version of Equation (4.1) where the dependent variable is the natural log of one plus the 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. Moving from the least- to the most-central counterparty agent increases new agents' survival length by approximately 22.2 percent, indicating that transacting with more central counterparty agents significantly increases new agents' career length.[12] On the surface, this finding suggests that the benefits of initial exposure to more central counterparty agents persist throughout the agent's career.

[12]Because survival length is measured as the span between an agent's first and last observed transaction, agents still active at the end of the sample are right-censored, and the OLS estimate in column 1 understates their career length. As censoring is most likely to affect the most productive (and often highest-centrality) new agents, this measurement error works against finding a positive centrality effect, so the column 1 estimate should be considered a lower bound. Section 5.1 addresses this concern using Cox and Weibull proportional hazards models that accommodate right-censoring.

Columns 2 and 3 of Table 5 examine this dynamic in more detail by re-estimating Equation (4.1) with a two-year survival indicator as the dependent variable. In column 2, the coefficient on counterparty centrality is positive and statistically significant, indicating that early exposure to a more central counterparty agent is associated with a higher probability of survival over two years. We then deliberately condition on a post-treatment outcome. Once the sample is conditioned on surviving the first year in column 3, the estimated effect declines in magnitude and becomes statistically insignificant. This exercise parallels column 6 of Table 4. There, conditioning on the new agent's realized first-year transaction volume absorbed the direct effect of counterparty centrality on survival. Here, conditioning on first-year survival does the same. In both columns, the conditioning is intentional. We close off the indirect path that runs through the new agent's realized early-career outcomes precisely so that any remaining coefficient would reflect a direct effect of the initial tie.

In both cases, the attenuation is not evidence that the initial network connection is unimportant, but instead is consistent with mediation. We condition on a realized early-career outcome that the initial connection itself helped produce, so little independent role for the initial network tie remains. The influence of counterparty centrality thus operates primarily through early-career dynamics, such as accelerated learning, faster integration into the local trading network, and improved access to deal flow, all of which are realized within the first year. After the first year, new agents become less reliant on their initial connection as they complete subsequent transactions and embed themselves more deeply in the network.

This pattern does not suggest that network connections no longer matter as agents advance in their careers. Instead, it suggests that the relative importance of the initial connection diminishes as agents gain more experience and expand their trading networks. The transactions a new agent closes early, documented in the previous section, are precisely how they build their own centrality in the trading network. Each additional counterparty is a new or strengthened tie, so the higher first-year volume generated by a more central initial counterparty is also the channel through which the new agent accumulates their own network centrality. First-year transaction volume and first-year network centrality are therefore not competing mechanisms but two aspects of the same one, both of which trace a single path that runs from the initial counterparty agent's centrality, through the new agent's early volume and own network formation, to longer-term survival.

Table 6 investigates this dynamic in more detail by examining how the initial counterparty agent's connectivity affects the new agents' network centrality at the end of their first year. In columns 1 and 2 of Table 6, the dependent variable is the new agent's end-of-year-one (EOY1) network centrality, which we regress on the network centrality of the first counterparty agent with whom they transact and the full set of unit type, agent relationship, and location-by-time controls. Column 1 uses the entire new agent sample, whereas column 2 restricts the sample to new agents that enter the profession between 2004 and 2019 and survive their first year. The counterparty centrality coefficient estimates are positive and statistically significant in both columns, indicating that new agents who begin their careers by transacting with more central counterparty agents tend to be more central themselves by the end of their first year. This pattern is consistent with persistence in early network advantages, where initial ties to more central established counterparty agents facilitate new agents' integration into the broader trading network.

Next, we investigate how a new agent's EOY1 network centrality affects their longer-term survival. In columns 3 and 4 of Table 6, the dependent variable is an indicator identifying whether the new agent survived the specified time horizon, which we regress on the new agents' EOY1 network centrality. Column 3 revisits the results in Table 5 by examining a two-year survival period, whereas column 4 examines a three-year survival period. In both cases, we use a subsample of new agents that survived the previous year. The coefficient estimates in columns 3 and 4 are both positive and significant at the 1 percent level, indicating that new agents' EOY1 network centrality is a key determinant of their probability of survival in subsequent years. Taken together, these results imply that new agents' initial network connection facilitates their early-career network formation, which, in turn, increases their probability of survival over the longer term.

4.6 Mechanism Tests

The preceding sections establish that new agents who transact with a more central first counterparty agent survive longer and complete more transactions, and that transaction volume is the channel through which counterparty centrality raises survival. This section identifies the mechanisms that generate that additional volume. A more central counterparty agent can raise a new agent's survival prospects in several distinct ways. First, the counterparty may provide referrals or direct repeat business to the new agent,

in which case we should observe the two transacting together again in the future. Second, the counterparty may provide direct access to their existing network, in which case the new agent should be more likely to transact with one of the counterparty agent's existing network connections. Third, the counterparty may act as a mentor, in which case the new agent should be more likely to co-locate with the counterparty in the same brokerage in order to work together more closely. We test each mechanism directly.

Identifying these mechanisms requires a baseline for what a new agent would experience absent any beneficial relationship with the first counterparty agent they transact with. For each new agent, we construct a placebo counterparty by drawing a random agent who transacted in the same zip code and year as the new agent's first transaction. This ensures that the placebo was active and part of the local trading network at the time of the new agent's entry. We then compare each outcome for the true first counterparty agent against the same outcome for the placebo. The difference, reported as the coefficient on *First Counterparty* in Panel A of Table 7, isolates the component of each mechanism that is specific to the true first counterparty, net of what common local market conditions and a randomly matched nearby agent would generate. Panel B reports the gradient of each outcome in the counterparty agent's network centrality. Both panels are estimated on new agents whose first transaction was with a distinct counterparty (i.e., we drop dual-agency transactions) in zip-by-year cells with at least five potential placebo agents. Columns 2 and 3 impose additional sample restrictions specific to each mechanism test, which we describe below.

The first mechanism we explore is repeat deal flow. A more central counterparty agent may direct future business to the new agent through referrals or preferential access to off-market pocket listings, resulting in repeat transactions that otherwise might not have occurred. In column 1 of Table 7, the dependent variable is an indicator equal to one if the new agent transacts again with the first counterparty agent, and zero otherwise. New agents transact again with their true first counterparty 1.1 percentage points more often than with a randomly matched placebo agent, significant at the 1 percent level. This is economically meaningful against a baseline repeat-transaction rate of 1.5 percent. Panel B shows that repeat business also rises with the counterparty agent's centrality, so more central counterparty agents are more likely to transact with the new agent again.

The second mechanism we explore is access to the counterparty agent's broader network. A more central counterparty can connect the new agent to the other agents with whom they are connected, thereby expanding the new agent's network reach and

preferential access to listing information. In column 2, the dependent variable is the share of the first counterparty agent's prior network (i.e., the agents the counterparty transacted with in the three years before the first transaction) that the new agent subsequently transacts with. Column 2 further restricts the sample to remove true counterparty agents (and their corresponding placebo agent) that do not have a prior network connection. This removes transactions where the true counterparty has no prior network (e.g., *Both Agents New* and *Listing Agent Non-member*), as well as pairs whose drawn placebo has no prior network.

By definition, a more central counterparty agent has a larger, more influential network. This raises a potential concern. If the new agent gains access to a more central counterparty agent's network, they have more agents available to transact with, so a raw count of transactions with the counterparty agent's existing connections would rise with centrality through opportunity alone. We address this by normalizing the overlap by the size of the counterparty agent's network, measuring the *share* of the counterparty agent's prior connections that the new agent transacts with.

In column 2 of Panel A, the share of the true counterparty agents's network that the new agent reaches is 0.2 percentage points higher than for a randomly matched agent, significant at the 1 percent level and economically meaningful against a baseline share of 1.2 percent. This finding implies that the access is privileged rather than incidental. However, this share does not rise with the counterparty's centrality. The coefficient on *Counterparty Centrality Combined* in Panel B is 0.0015 and statistically insignificant. New agents matched to more central counterparties therefore reach a larger number of the counterparty agent's connections because the network is larger, but not a larger fraction of it. These findings indicate that new agents benefit from a larger absolute set of connections when paired with central counterpart agents, but the relative share of the counterparty's network they reach does not expand.

The third mechanism we explore is mentorship through co-location. If a more central counterparty agent takes a new agent under their wing, the two should be more likely to work in the same brokerage office in the future. In column 3 of Table 7, the dependent variable is an indicator equal to one if the new agent and their first counterparty ever work in the same brokerage office after the initial transaction, and zero otherwise. For this test, we further restrict the sample to only include observations where the placebo agent does not already share the new agent's office at the time of the first transaction, so that the co-location baseline is not mechanically inflated. New agents end up working

in the same brokerage office as their true first counterparty 0.7 percentage points more often than as a randomly matched placebo agent, significant at the 1 percent level. This is economically meaningful against a baseline co-location rate of 6.7 percent. Panel B shows that co-location also rises with the counterparty's centrality. The coefficient on *Counterparty Centrality Combined* is 0.007 and significant at the 5 percent level, indicating that new agents who initially transact with more central counterparty agents are more likely to end up working with them in the same brokerage office.

Taken together, the results in Table 7 indicate that a more central first counterparty raises new agent survival primarily by expanding the new agent's deal flow and access to the counterparty agent's trading network. Across all three mechanisms, the true first counterparty agent provides significantly more of each of these benefits than a randomly matched agent. Repeat business and network access enlarge the new agent's pool of future transactions, which is precisely the mechanism through which initial counterparty centrality translates into the survival transaction volume documented in the preceding sections.

5 Robustness Tests

5.1 Survival Analysis

We assess the robustness of the main survival results by re-estimating the relationship between the network centrality of the first counterparty agent that a new agent transacts with and their career longevity within a formal survival analysis framework (Kaplan and Meier, 1958; Cox, 1972). This exercise addresses two concerns with the linear probability survival specifications. First, those specifications treat survival at fixed horizons as a series of binary outcomes, discarding information on when an agent exits, whereas the duration models we estimate here use the full timing of exit. Second, they do not explicitly account for right-censoring (i.e., agents still active at the end of the sample have not yet exited), which a hazard framework handles directly. We measure duration as the number of days between the new agent's first and last observed transactions and treat agents whose last observed transaction falls within 180 days of the sample end as

right-censored.[13] We estimate hazard models of the form

$$h_i(t) = h_0(t) \exp\left(\beta_1 \text{Centrality}_j + \beta' X_{i,j}\right), \tag{5.1}$$

where $h_i(t)$ is the exit hazard at duration t, $h_0(t)$ is the baseline hazard, Centrality_j is the combined network centrality measure for the first counterparty agent j that new agent i transacts with, and $X_{i,j}$ includes the same relationship and unit-type controls as in the baseline regressions. Our primary specification is a Cox proportional hazards model with zip-by-year stratification, which allows each zip-year to have its own baseline hazard and identifies the centrality effect from within-market, within-year variation. As a parametric robustness check, we estimate a Weibull proportional hazards model with MSA and year fixed effects. In both specifications, a negative coefficient implies a lower exit hazard and therefore longer survival.

Table 8 reports the results, which reinforce our main finding that initially transacting with a more central first counterparty agent lengthens a new agent's career. The coefficient on counterparty centrality combined is negative and significant at the 1 percent level in both specifications, indicating that new agents matched with more central first counterparty agents face a lower exit hazard. The Cox estimate of -0.065 in column 1 and the Weibull estimate of -0.094 in column 2 indicate a consistent negative effect. Because centrality is measured on a percentile-rank scale spanning zero to one, these coefficients imply that moving from the least- to the most-central counterparty agent reduces the exit hazard by roughly 6% to 9%.

The relationship controls display patterns consistent with our main results in Section 4.2. New agents whose first deal lacks an established counterparty (e.g., *Both Agents New*, *Dual Agent*) face a higher exit hazard in both specifications, consistent with these transactions offering less opportunity to form beneficial ties with established agents. This is especially true for new agents representing the seller whose first transaction is with a buyer agent that is an MLS non-member. These transactions raise the exit hazard substantially (coefficients of 0.308 and 0.300), consistent with non-member counterparty agents generating weaker network spillovers and fewer opportunities to build embeddedness in the MLS trading network. Similar to the main results, the in-house agent coefficient is small and statistically insignificant in both

[13] We add one day to all durations so that agents whose first and last transactions occur on the same day enter the parametric (Weibull) model, which requires strictly positive durations.

columns of Table 8. Taken together, the survival analysis aligns with both the new agent short-term survival results in Table 2 and the longer-term survival results in Table 5, reinforcing the robustness of our main findings.

6 Conclusion

We find that initial network connections play a critical role in shaping the early-career success of new real estate agents. By leveraging plausibly exogenous variation in the network centrality of the first counterparty agent with whom a new agent transacts, we identify its causal effect on early-career outcomes. Transacting with a more central counterparty in their first deal significantly raises a new agent's probability of survival and subsequent network centrality. These results corroborate the key predictions of our stochastic network-formation model: a more central first counterparty raises early-career survival, and this benefit operates largely through the higher transaction volume it generates. We identify three mechanisms through which this advantage operates: repeat business with the first counterparty, access to the counterparty's professional network, and co-location within the same brokerage. These findings show how seemingly minor differences at entry, such as which counterparty an agent happens to transact with first, can shape a career, underscoring the path-dependent nature of early-career success.

More broadly, the findings highlight the importance of network connections in professions where early-career success depends on information access, deal flow, and repeated interactions. The residential real estate brokerage setting we examine provides unusually clean identification, and the mechanisms we document may extend to other highly intermediated, relationship-driven labor markets. That a single, incidental first interaction can shape whether a new network entrant survives is, we suspect, not unique to real estate. It warrants attention from firms and policymakers in any market where early-career attrition is a concern.

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Tables

Table 1. Summary Statistics

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel A: MLS Transaction Data					
Sale Price (000s)	278.10	215.97	145.00	220.00	340.00
Single-family Detached	0.86	0.34	1	1	1
Condominium	0.12	0.32	0	0	0
Townhome	0.02	0.13	0	0	0
Age (Years)	37.39	30.43	13	31	55
Bedrooms	3.21	1.62	3	3	4
Bathrooms	2.41	1.07	2	2	3
Observations	6,055,235				
Unique Agents	572,253				
Panel B: New Agent Data					
Counterparty Centrality In	0.63	0.25	0.50	0.65	0.84
Counterparty Centrality Out	0.65	0.23	0.50	0.68	0.85
Counterparty Centrality Combined	0.64	0.20	0.50	0.64	0.82
Both Agents New	0.05	0.23	0	0	0
Dual Agent	0.08	0.27	0	0	0
In-house Agent	0.06	0.24	0	0	0
Listing Agent Member	0.25	0.43	0	0	0
Listing Agent Non-member	0.03	0.18	0	0	0
Buyer Agent Member	0.52	0.50	0	1	1
Single-family Detached	0.84	0.36	1	1	1
Condominium	0.14	0.35	0	0	0
Townhome	0.02	0.13	0	0	0
Sale Price (000s)	240.39	182.03	130.00	192.50	295.00
National Brokerage	0.43	0.49	0	0	1
Survive One Year	0.67	0.47	0	1	1
Survive Two Years	0.58	0.49	0	1	1
Survive Three Years	0.48	0.50	0	0	1
Survival Length (Days)	1,679.27	1,854.91	122	1,020	2,587
First Year Transactions	3.43	3.25	1	2	4
First Three Years Transactions	8.01	10.54	2	4	10
Total New Agent Transactions	22.91	60.71	2	6	20
New Agent Count	151,896				

Notes: Table 1 reports summary statistics for the data used in the empirical analysis. Panel A covers the MLS transaction data used to construct the agent trading networks, and Panel B covers the new agent data. Each variable is defined in the text and, in detail, in Table B.1 in the online appendix.

Table 2. New Agent Survival Rate

	Survive One Year					
	In		Out		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline estimation						
Counterparty Centrality	0.025***	0.022***	0.038***	0.040***	0.045***	0.044***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Observations	151,896	151,896	151,896	151,896	151,896	151,896
Adjusted R^2	0.023	0.030	0.023	0.031	0.023	0.031
Panel B: Baseline estimation with additional controls						
Counterparty Centrality	0.021***	0.018***	0.019***	0.020***	0.029***	0.028***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Both Agents New	−0.017***	−0.015**	−0.015**	−0.013*	−0.014**	−0.012*
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Dual Agent	−0.015***	−0.015***	−0.014***	−0.013**	−0.013**	−0.013**
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
In-house Agent	0.007	0.006	0.007	0.006	0.007	0.006
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Listing Agent Member	−0.026***	−0.027***	−0.023***	−0.024***	−0.024***	−0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Listing Agent Non-member	−0.101***	−0.106***	−0.099***	−0.103***	−0.098***	−0.103***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Condominium	−0.008*	−0.004	−0.008*	−0.005	−0.008*	−0.004
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Townhome	−0.012	−0.009	−0.012	−0.008	−0.012	−0.008
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Observations	151,896	151,896	151,896	151,896	151,896	151,896
Adjusted R^2	0.024	0.032	0.024	0.032	0.025	0.032
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓

Notes: Table 2 reports linear probability estimates from Equation (4.1) examining whether the network centrality of the first counterparty agent that a new agent transacts with affects the new agent's probability of surviving one year. The dependent variable in every column equals one if the new agent completes at least one additional transaction at least 365 days after their first transaction, and zero otherwise. Panel A reports estimates that exclude the agent relationship and unit type controls. Panel B reports the corresponding estimates with these controls included. Columns 1 and 2 use the *In* centrality measure, columns 3 and 4 the *Out* measure, and columns 5 and 6 the *Combined* measure. Odd-numbered specifications include additively separable zip code and sale year fixed effects. Even-numbered specifications include multiplicatively separable zip-code-by-sale-year fixed effects. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 3. Transaction and Brokerage Controls

	Survive One Year				
	(1)	(2)	(3)	(4)	(5)
Counterparty Centrality Combined	0.029***	0.029***	0.028***	0.028***	0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Both Agents New	−0.012*	−0.013*	−0.012*	−0.012*	−0.012*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Dual Agent	−0.013**	−0.012**	−0.012**	−0.012**	−0.012**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
In-house Agent	0.006	0.006	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Listing Agent Member	−0.025***	−0.025***	−0.025***	−0.024***	−0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Listing Agent Non-member	−0.103***	−0.103***	−0.103***	−0.103***	−0.103***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Condominium	−0.010**	−0.008	−0.005	−0.004	−0.010**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Townhome	−0.012	−0.011	−0.008	−0.008	−0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log(Sales Price)	−0.010***				−0.010***
	(0.003)				(0.003)
National Brokerage			0.014***		0.014***
			(0.003)		(0.003)
Observations	151,896	151,896	151,896	151,896	151,896
Adjusted R^2	0.032	0.032	0.032	0.033	0.032
Zip×Year FE	✓	✓	✓	✓	✓
House Controls		✓			
Brokerage FE				✓	

Notes: Table 3 reports linear probability estimates from Equation (4.1) examining whether the network centrality of the first counterparty agent that a new agent transacts with affects the new agent's probability of surviving one year. The dependent variable in every column equals one if the new agent completes at least one additional transaction at least 365 days after their first transaction, and zero otherwise. Every column uses the *Combined* centrality measure and includes the unit type and agent relationship controls as well as multiplicatively separable fixed effects for zip code and sale year. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 4. New Agent Transaction Volume

	Log(Number of Transactions)					Survive
	Year 1	Year 1	Years 1-3	Total	Per Year	One Year
	(1)	(2)	(3)	(4)	(5)	(6)
Counterparty Centrality Combined	0.088***	0.087***	0.127***	0.135***	0.077***	0.040***
	(0.014)	(0.014)	(0.020)	(0.027)	(0.015)	(0.012)
Both Agents New	−0.005	−0.004	−0.030**	−0.053**	−0.031***	−0.008
	(0.011)	(0.011)	(0.015)	(0.021)	(0.012)	(0.006)
Dual Agent	−0.007	−0.001	−0.043***	−0.093***	−0.068***	−0.008
	(0.010)	(0.010)	(0.014)	(0.019)	(0.010)	(0.005)
In-house Agent	0.070***	0.072***	0.094***	0.054***	0.055***	−0.003
	(0.010)	(0.010)	(0.015)	(0.021)	(0.011)	(0.006)
Listing Agent Member	−0.006	0.004	−0.038***	−0.094***	−0.046***	−0.019***
	(0.006)	(0.006)	(0.008)	(0.012)	(0.007)	(0.003)
Listing Agent Non-member	−0.187***	−0.186***	−0.345***	−0.496***	−0.264***	−0.073***
	(0.016)	(0.017)	(0.023)	(0.030)	(0.018)	(0.009)
Condominium	0.018**	0.015*	0.010	−0.010	0.003	−0.006
	(0.008)	(0.009)	(0.012)	(0.016)	(0.010)	(0.005)
Townhome	−0.009	−0.007	−0.005	0.001	0.019	−0.008
	(0.018)	(0.021)	(0.030)	(0.040)	(0.023)	(0.009)
Year 1 Transactions						0.054***
						(0.001)
Centrality × Year 1 Transactions						−0.008***
						(0.002)
Observations	151,896	136,939	136,939	136,939	136,939	136,939
Adjusted R^2	0.072	0.075	0.087	0.059	0.071	0.140
Zip×Year FE	✓	✓	✓	✓	✓	✓
Data Filter		2004-19	2004-19	2004-19	2004-19	2004-19

Notes: Columns 1 to 5 of Table 4 report regression estimates from a modified version of Equation (4.1) examining whether the network centrality of the first counterparty agent that a new agent transacts with affects their transaction volume. The dependent variable in the first five columns is the log of the new agent's transaction count over the specified time horizon. Columns 1 and 2 examine the number of transactions during the new agent's first year; column 3 examines the new agent's first three years; column 4 examines the new agent's total number of transactions; and column 5 examines the new agent's annual transaction volume adjusted for the length of their career. Column 6 reports linear probability estimates from Equation (4.1) examining whether the network centrality of the first counterparty agent that a new agent transacts with affects the new agent's probability of surviving one year. Column 1 uses the full new agent data sample from 2004 through June 2021, while columns 2 through 6 use new agents that enter the profession between 2004 and 2019. Every column uses the *Counterparty Centrality Combined* measure and includes the unit type and agent relationship controls, as well as multiplicatively separable fixed effects for zip code and sale year. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 5. New Agent Longer-Term Survival

		Survive Year Two	
	Survival Length	Unconditional on Surviving First Year	Conditional on Surviving First Year
	(1)	(2)	(3)
Counterparty Centrality Combined	0.222***	0.025***	0.002
	(0.055)	(0.009)	(0.007)
Both Agents New	−0.073	−0.012*	−0.003
	(0.045)	(0.007)	(0.006)
Dual Agent	−0.038	−0.015**	−0.010**
	(0.039)	(0.006)	(0.005)
In-house Agent	0.073*	−0.001	−0.009*
	(0.040)	(0.006)	(0.005)
Listing Agent Member	−0.138***	−0.026***	−0.012***
	(0.024)	(0.004)	(0.003)
Listing Agent Non-member	−0.776***	−0.100***	−0.020**
	(0.068)	(0.010)	(0.009)
Condominium	−0.012	−0.008	−0.008**
	(0.031)	(0.005)	(0.004)
Townhome	−0.075	−0.006	−0.002
	(0.071)	(0.012)	(0.009)
Observations	136,939	136,939	93,080
Adjusted R^2	0.047	0.035	0.012
Zip×Year FE	✓	✓	✓
Data Filter	2004-19	2004-19	2004-19

Notes: Table 5 reports regression estimates from modified versions of Equation (4.1) examining whether the network centrality of the first counterparty agent that a new agent transacts with affects their longer-term survival. The dependent variable in column 1 is the natural log of one plus the new agent's survival length, measured as the number of days between their first and last transactions in the data. The dependent variable in columns 2 and 3 is a two-year survival indicator. Column 2 examines whether the new agent survives two years, regardless of whether they survived the first year. Column 3 differs in that it examines whether the new agent survives two years using a subsample of new agents that survived their first year. Every column uses the *Counterparty Centrality Combined* measure and includes the unit type and agent relationship controls, as well as multiplicatively separable fixed effects for zip code and sale year. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 6. New Agent Network Formation

	New Agent EOY1 Centrality Combined		Survive Year Two Conditional on Previous Year	Survive Year Three Conditional on Previous Year
	(1)	(2)	(3)	(4)
Counterparty Centrality Combined	0.167***	0.155***		
	(0.003)	(0.003)		
Both Agents New	−0.013***	−0.009***		
	(0.002)	(0.003)		
Dual Agent	−0.066***	−0.061***		
	(0.002)	(0.002)		
In-house Agent	0.016***	0.015***		
	(0.002)	(0.002)		
Listing Agent Member	0.027***	0.032***		
	(0.001)	(0.001)		
Listing Agent Non-member	−0.045***	−0.038***		
	(0.003)	(0.005)		
Condominium	−0.001	−0.002		
	(0.001)	(0.002)		
Townhome	−0.003	−0.005		
	(0.003)	(0.004)		
New Agent EOY1 Centrality Combined			0.119***	0.132***
			(0.008)	(0.008)
Observations	151,896	93,080	93,080	81,324
Adjusted R^2	0.231	0.219	0.015	0.014
Zip×Year FE	✓	✓	✓	✓
Data Filter		2004-19	2004-19	2004-19

Notes: Columns 1 and 2 of Table 6 examine whether the network centrality of the first counterparty agent that a new agent transacts with affects their network centrality at the end of their first year. The dependent variable in columns 1 and 2 is the new agent's end-of-year one (EOY1) network centrality combined measure. Column 1 uses the full new agent sample, while column 2 uses a subsample of new agents who entered the profession between 2004 and 2019. Columns 3 and 4 examine whether the new agents' EOY1 network centrality (i.e., how central the new agent is at the end of their first year) affects their longer-term survival probability. Column 3 examines whether the new agent survives their second year using a subsample of new agents who entered the profession between 2004 and 2019 and survived their first year. Column 4 examines whether the new agent survives their third year using a subsample of new agents who entered the profession between 2004 and 2019 and survived their second year. Every column includes multiplicatively separable fixed effects for zip code and sale year. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 7. Mechanism Tests

	Repeat Transaction	Network Access	Shared Office
	(1)	(2)	(3)
Panel A: Access relative to a random match			
First Counterparty	0.0131***	0.0021***	0.0071***
	(0.0005)	(0.0003)	(0.0006)
Observations	278,534	237,690	232,880
Panel B: Gradient in counterparty centrality			
Counterparty Centrality Combined	0.0050**	0.0015	0.0068**
	(0.0023)	(0.0016)	(0.0027)
Observations	139,267	118,845	116,440
Zip×Year FE	✓	✓	✓
Agent Relationship Controls	✓	✓	✓
Unit Type Controls	✓	✓	✓

Notes: Table 7 examines the mechanisms through which the network centrality of the first counterparty agent contributes to the new agent's early-career success. Each column corresponds to a distinct mechanism test. In column 1, the dependent variable is an indicator equal to one if the new agent transacts again with the first counterparty. In column 2, the dependent variable is the share of the first counterparty agent's prior network (i.e., the agents the counterparty transacted with in the three years before the first transaction) that the new agent subsequently transacts with, restricted to counterparty agents with at least one prior transaction and normalized by network size. In column 3, the dependent variable is an indicator equal to one if the new agent and the first counterparty ever work in the same brokerage office after the first transaction, restricted to agent pairs that do not already work in the same brokerage office. Panel A reports the coefficient on *First Counterparty*, an indicator equal to one for the true first counterparty and zero for a placebo counterparty drawn at random from agents who transacted in the same zip code and year as the new agent's first transaction, with the two stacked. The coefficient measures the excess of each outcome for the true counterparty agent over a randomly matched placebo agent. Panel B reports the coefficient on the *Counterparty Centrality Combined* measure in a regression of the actual outcome on centrality. All specifications include the full set of agent relationship and unit type controls and multiplicatively separable zip code and sale year fixed effects. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 8. Survival Analysis

	Cox Proportional Hazards Model	Weibull Proportional Hazards Model
	(1)	(2)
Counterparty Centrality Combined	-0.065***	-0.094***
	(0.021)	(0.017)
Both Agents New	0.032*	0.052***
	(0.017)	(0.014)
Dual Agent	0.068***	0.052***
	(0.014)	(0.011)
In-house Agent	0.012	-0.002
	(0.015)	(0.011)
Listing Agent Member	0.093***	0.078***
	(0.008)	(0.007)
Listing Agent Non-member	0.308***	0.300***
	(0.023)	(0.020)
Condominium	0.016	-0.018**
	(0.012)	(0.008)
Townhome	0.019	0.008
	(0.027)	(0.021)
Observations	151,896	151,896
Zip×Year Strata	✓	
MSA+Year FE		✓

Notes: The dependent variable is survival duration (in days) from a new agent's first to last observed transaction in the data, plus one additional day to account for inclusive duration measurement. Column 1 reports a Cox proportional hazards model with zip code-by-year stratification. Column 2 reports a Weibull proportional hazards model with MSA and year fixed effects. All specifications include the same agent relationship and unit type controls as in the baseline regressions. The estimates are reported in log hazard scale. Standard errors, clustered at the zip code level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1 percent levels, respectively.

Table 9. Balance Tests

Panel A: Joint Test (Initial Counterparty Centrality & First Transaction Observables)	
Living Area	0.0029
Age	0.0006
Bedroom	0.2252
Bathroom	0.3567
Lot Size	0.0529
Property Type	0.1132
In-House Status	0.0000
Observations	158,500
Adjusted R^2	0.112

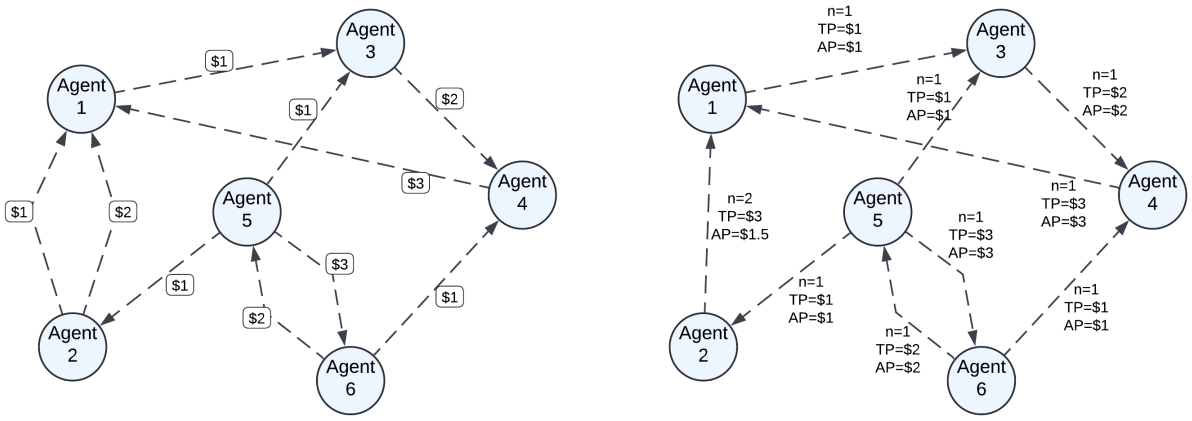
Panel B: Robustness to First Transaction Controls (z-score)			
	(1) Base	(2) Coarse	(3) Flexible
One-year Survival	0.004092***	0.004172***	0.004164***
	(0.001282)	(0.001283)	(0.001287)
Two-year Survival	0.003988***	0.004037***	0.004035***
	(0.001296)	(0.001296)	(0.001300)
Three-year Survival	0.002426*	0.002436*	0.002406*
	(0.001306)	(0.001305)	(0.001307)
Observations	158,500	158,500	158,500
Adjusted R^2 (1-year)	0.029	0.030	0.030
Adjusted R^2 (2-year)	0.046	0.046	0.046
Adjusted R^2 (3-year)	0.105	0.105	0.105
Zip-by-year FE	✓	✓	✓
Arm's Length MLS Member	✓	✓	✓
Coarse Controls		✓	
Flexible Controls			✓

*p<0.10; **p<0.05; ***p<0.01

Notes: Table 9 reports balance diagnostics for the new agent's first transaction sample and a robustness check for the main outcome regression. The sample includes one observation per new agent's first recorded transaction, restricted to arm's length MLS member transactions with an identified counterparty, excluding dual agency and non member counterparties. All specifications include zip-by-year fixed effects and zip clustered standard errors. Panel A reports family level joint test p values from a flexible nonlinear balance specification where the dependent variable is the z score of initial counterparty centrality. Regressors include indicators for living area bins (100 square feet), age bins (10 years), bedroom and bathroom categories, lot size bins, property type, and in house status. Panel B reports the coefficient on initial counterparty centrality from the main survival regressions (one, two, and three year survival) under progressively richer controls for first transaction observables. Column (1) is the baseline, Column (2) adds coarse controls (bedrooms, bathrooms, property type, in house status), and Column (3) adds the full flexible nonlinear controls used in Panel A.

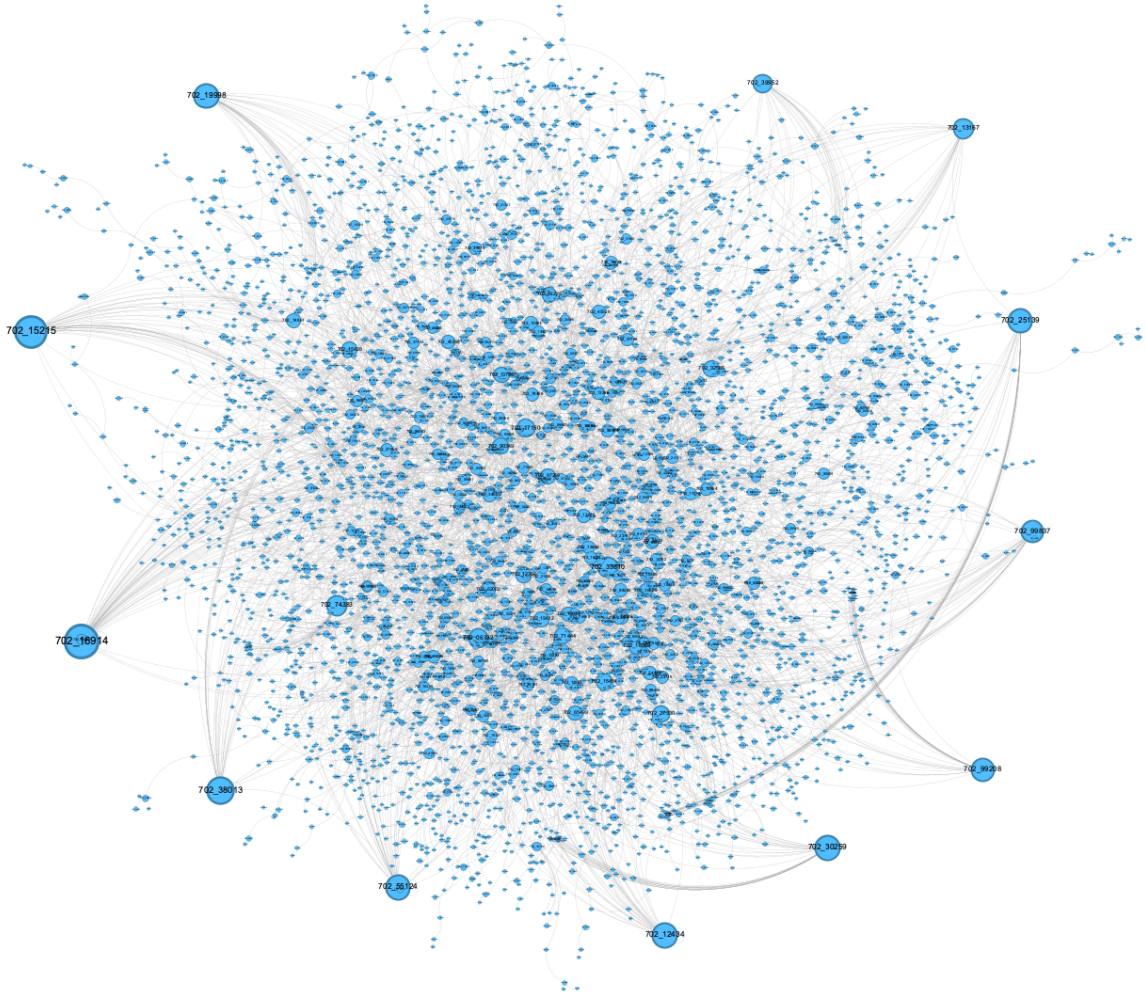
Figures

Figure 1. Raw Network Construction & Reduced-Form Graph



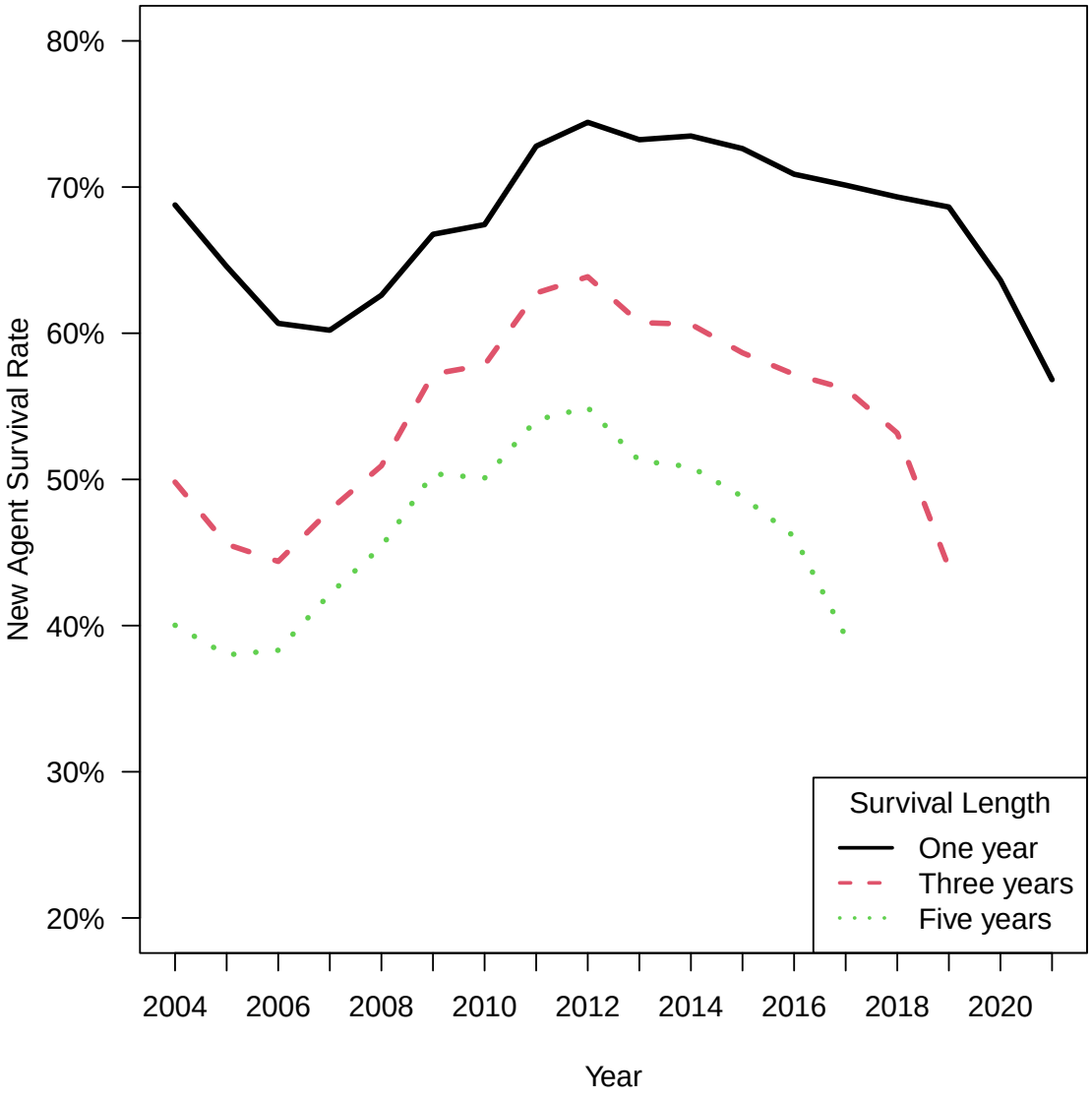
Note: Figure 1 plots an illustration of a real estate agent trading network. The left panel depicts a directed multigraph, where nodes represent agents, and each directed edge represents a single transaction from the listing agent to the buyer agent. Edges are labeled with transaction sale prices. The 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 volume in dollars (TP), and average transaction 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.

Figure 2. Reduced-Form Directed Graph of Charlotte for Q2 2006.



Note: Figure 2 displays the reduced-form directed graph of the real estate agent network for Charlotte, NC, constructed using transactions from Q2 2006. Each node represents an individual real estate agent, with node size scaled proportionally to the agent's degree (i.e., transaction volume). Directed edges represent aggregated transaction relationships from listing agents to buyer agents, where multiple transactions between the same agent pair are collapsed into a single weighted edge.

Figure 3. Fraction of New Agents that Survive Each Year



Note: Figure 3 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.

Online Appendix to

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

A Proofs

A.1 Proof of Proposition 1

Proof. By Equation 2.2,

$$\mathbb{E}[V_{e,1} \mid c_{j,0}] = \varphi(c_{j,0}).$$

Differentiating with respect to initial-counterparty centrality gives

$$\frac{\partial \mathbb{E}[V_{e,1} \mid c_{j,0}]}{\partial c_{j,0}} = \varphi'(c_{j,0}) > 0.$$

□

A.2 Proof of Proposition 2

Proof. For every $\tau \geq 1$, $\eta > 0$ and $\delta \in (0,1)$ imply $\rho_\tau(v+1) > \rho_\tau(v)$. Because all continuation probabilities are positive,

$$g_t(v+1) = \prod_{\tau=1}^{t} \rho_\tau(v+1) > \prod_{\tau=1}^{t} \rho_\tau(v) = g_t(v).$$

Let $\lambda(c) \equiv \varphi(c)$. Since $V_{e,1} \mid c_{j,0} = c \sim \text{Poisson}(\lambda(c))$, the Poisson derivative implies

$$\frac{\partial S_e(t)}{\partial c} = \varphi'(c)\, \mathbb{E}\big[g_t(V_{e,1}+1) - g_t(V_{e,1}) \mid c_{j,0} = c\big] > 0.$$

Finally, using the tail-sum formula,

$$\mathbb{E}[T_e \mid c] = 1 + \sum_{t=1}^{\infty} S_e(t).$$

Given $\rho, \delta \in (0,1)$, the sum converges and permit term-by-term differentiation. Therefore,

$$\frac{\partial \mathbb{E}[T_e \mid c]}{\partial c} = \sum_{t=1}^{\infty} \frac{\partial S_e(t)}{\partial c} > 0.$$

□

B Data Overview

B.1 Data Availability Statement

We purchased the Multiple Listing Service (MLS) data used in this study from Cotality. Our agreement with Cotality prohibits the posting or redistribution of the data. Researchers interested in replication can obtain the MLS data directly from Cotality. Additional information is available on the Cotality website.

B.2 Data Filters

Prior to running the empirical analysis, we apply several filters remove outliers and records with missing information in key fields. Below is a list of the filters we apply to the transaction data before creating the agent networks.

1. filter 1: unit type = single family detached | condo | townhome
2. filter 2: listing successfully sold
3. filter 3: 2001 $\leq$ sale year $\leq$ 2023
4. filter 4: \$20,000 $\leq$ sale price $\leq$ \$2,000,000
5. filter 5: \$20,000 $\leq$ list price $\leq$ \$2,000,000
6. filter 6: age $\geq$ 1
7. filter 7: remove duplicate listings
8. filter 8: number of sales in zip code $\geq$ 50
9. filter 9: remove if listing agent or buyer agent ID missing

Table B.1. Variable Definitions

Panel A: MLS Transaction Data	
Sale Price (000s)	Transaction price, in thousands of dollars
Single-family Detached	1 if the property is a single-family detached house
Condominium	1 if the property is a condominium
Townhome	1 if the property is a townhome
Age (Years)	Age of the property in years at the time of the transaction
Bedrooms	Number of bedrooms in the property
Bathrooms	Number of bathrooms in the property
Panel B: New Agent Data	
Counterparty Centrality In	Percentile rank of the first counterparty's weighted eigenvector in-centrality (buyer-side edges), computed over the previous 3 years
Counterparty Centrality Out	Percentile-rank of the first counterparty's weighted eigenvector out-centrality (listing-side edges), computed over the previous 3 years
Counterparty Centrality Combined	Average of the counterparty agent's in- and out-centrality percentile ranks; ranges from 0 (least central) to 1 (most central)
Both Agents New	1 if both the new agent and the counterparty are new to the trading network, so neither has a measured network centrality
Dual Agent	1 if the new agent represents both the buyer and the seller
In-house Agent	1 if the new agent and the counterparty work in the same brokerage office
Listing Agent Member	1 if the new agent is the listing agent and the counterparty is an MLS member
Listing Agent Non-member	1 if the new agent is the listing agent and the counterparty is not an MLS member
Buyer Agent Member	1 if the new agent is the buyer agent and the counterparty is an MLS member (the omitted category in the regressions)
National Brokerage	1 if the new agent's brokerage is a national franchise
Survive One Year	1 if the new agent completes at least one transaction more than 365 days after the first transaction
Survive Two Years	1 if the new agent completes at least one transaction more than 730 days after the first transaction
Survive Three Years	1 if the new agent completes at least one transaction more than 1,095 days after the first transaction
Survival Length (Days)	One plus the number of days between the new agent's first and last observed transactions
First Year Transactions	Number of transactions the agent completes within 365 days of the first transaction
First Three Years Transactions	Number of transactions the agent completes within 1,095 days of the first transaction
Total New Agent Transactions	Total number of transactions the agent completes over the observed sample window

Notes: Table B.1 defines the variables reported in Table 1, in the same order. The unit type indicators (Single-family Detached, Condominium, Townhome) and Sale Price appear in both panels but are only defined once in Panel A. All binary variables equal 1 if the stated condition holds and 0 otherwise.

C Robustness Checks

C.1 Additional Results

Table C.1. New Agent Survival Rate - Trim Top 3%

	Survive One Year					
	In		Out		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline estimation						
Counterparty Centrality	0.031***	0.030***	0.042**	0.027	0.061***	0.058***
	(0.005)	(0.006)	(0.019)	(0.021)	(0.010)	(0.011)
Observations	193,024	193,024	193,024	193,024	193,024	193,024
Adjusted R^2	0.023	0.029	0.023	0.029	0.023	0.029
Panel B: Baseline estimation with additional controls						
Counterparty Centrality	0.025***	0.023***	0.023	0.006	0.049***	0.043***
	(0.005)	(0.006)	(0.019)	(0.021)	(0.010)	(0.011)
Dual Agent	−0.015***	−0.017***	−0.018***	−0.020***	−0.015***	−0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
In-house Agent	0.012***	0.010**	0.012***	0.010**	0.012***	0.010**
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Listing Agent	−0.025***	−0.026***	−0.024***	−0.026***	−0.024***	−0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Counterparty Non-member	−0.101***	−0.106***	−0.103***	−0.108***	−0.101***	−0.106***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Condominium	−0.007	−0.005	−0.007	−0.006	−0.007	−0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Townhome	−0.007	−0.004	−0.007	−0.004	−0.007	−0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	193,024	193,024	193,024	193,024	193,024	193,024
Adjusted R^2	0.025	0.031	0.025	0.031	0.025	0.031
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓

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

Notes: The results in this table correspond to Table 2 except that we trim the top 3% of counterparty agent IDs instead of the top 5%.

Table C.2. New Agent Survival Rate - Trim Top 1%

	Survive One Year					
	In		Out		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline estimation						
Counterparty Centrality	0.028***	0.022***	0.044**	0.028	0.055***	0.041***
	(0.007)	(0.008)	(0.017)	(0.019)	(0.012)	(0.013)
Observations	206,408	206,408	206,408	206,408	206,408	206,408
Adjusted R^2	0.022	0.028	0.022	0.028	0.022	0.028
Panel B: Baseline estimation with additional controls						
Counterparty Centrality	0.024***	0.016**	0.026	0.010	0.044***	0.028**
	(0.007)	(0.008)	(0.017)	(0.019)	(0.012)	(0.013)
Dual Agent	−0.016***	−0.018***	−0.017***	−0.019***	−0.016***	−0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
In-house Agent	0.015***	0.014***	0.015***	0.014***	0.015***	0.014***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Listing Agent	−0.024***	−0.025***	−0.024***	−0.025***	−0.024***	−0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Counterparty Non-member	−0.105***	−0.108***	−0.105***	−0.109***	−0.105***	−0.108***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Condominium	−0.008**	−0.007*	−0.009**	−0.007*	−0.008**	−0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Townhome	−0.009	−0.007	−0.009	−0.007	−0.009	−0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	206,408	206,408	206,408	206,408	206,408	206,408
Adjusted R^2	0.024	0.030	0.024	0.030	0.024	0.030
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓

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

Notes: The results in this table correspond to Table 2 except that we trim the top 1% of counterparty agent IDs instead of the top 5%.

Table C.3. New Agent Survival Rate - Include Non-traditional Agent IDs

	Survive One Year					
	In		Out		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline estimation						
Counterparty Centrality	0.025***	0.019***	0.025***	0.026***	0.036***	0.033***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Non-traditional Counterparty	0.014***	0.010***	0.015***	0.015***	0.015***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	217,837	217,837	217,837	217,837	217,837	217,837
Adjusted R^2	0.022	0.028	0.022	0.028	0.022	0.029
Panel B: Baseline estimation with additional controls						
Counterparty Centrality	0.019***	0.012**	0.012**	0.012**	0.024***	0.020***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Non-traditional Counterparty	0.010***	0.006*	0.006**	0.005*	0.009***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Dual Agent	−0.013***	−0.015***	−0.014***	−0.014***	−0.011**	−0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
In-house Agent	0.014***	0.013***	0.014***	0.013***	0.014***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Listing Agent	−0.023***	−0.025***	−0.022***	−0.024***	−0.022***	−0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Counterparty Non-member	−0.101***	−0.105***	−0.102***	−0.104***	−0.099***	−0.102***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Condominium	−0.008**	−0.007*	−0.008**	−0.007*	−0.008**	−0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Townhome	−0.008	−0.006	−0.008	−0.006	−0.008	−0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	217,837	217,837	217,837	217,837	217,837	217,837
Adjusted R^2	0.023	0.030	0.023	0.030	0.023	0.030
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓

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

Notes: The results in this table correspond to Table 2 except that instead of trimming the top 5% of counterparty agent IDs to remove non-traditional agent IDs, we set their counterparty centrality equal to 0 and flag them with a Non-traditional Counterparty indicator variable.

Table C.4. Arm's Length and Brokerage Office Fixed Effects - In Measure

	Survive One Year					
	Members Only		Arm's Length			
	(1)	(2)	(3)	(4)	(5)	(6)
Counterparty Centrality In	0.022***	0.018***	0.020***	0.018***	0.012**	0.014**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Dual Agent	−0.014***	−0.016***				
	(0.005)	(0.005)				
In-house Agent	0.010**	0.007				
	(0.005)	(0.005)				
Listing Agent	−0.024***	−0.026***	−0.024***	−0.026***	−0.019***	−0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Condominium	−0.006	−0.004	−0.004	−0.002	−0.002	0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Townhome	−0.010	−0.008	−0.007	−0.006	−0.010	−0.009
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)	(0.010)
Observations	176,783	176,783	151,412	151,412	151,412	151,412
Adjusted R^2	0.022	0.030	0.023	0.032	0.080	0.088
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓
Office FE					✓	✓

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

Notes: The results in this table correspond to **??** except for the use of the Counterparty Centrality In measure instead of the Counterparty Centrality Combined measure.

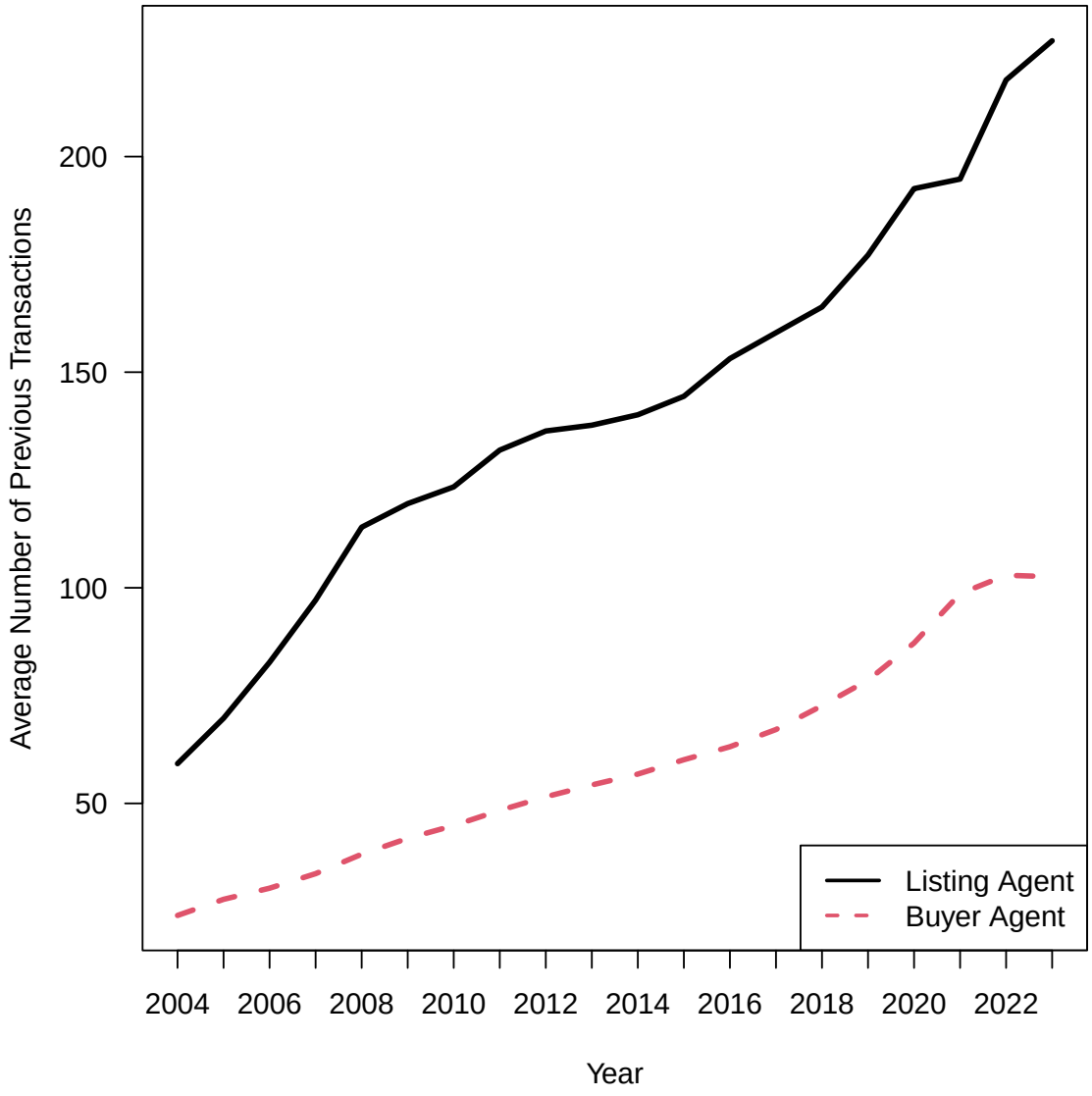
Table C.5. Arm's Length and Brokerage Office Fixed Effects - Out Measure

	Survive One Year					
	Members Only		Arm's Length			
	(1)	(2)	(3)	(4)	(5)	(6)
Counterparty Centrality Out	0.045**	0.032	0.037*	0.032	0.039*	0.045**
	(0.019)	(0.021)	(0.020)	(0.022)	(0.021)	(0.022)
Dual Agent	−0.017***	−0.018***				
	(0.005)	(0.005)				
In-house Agent	0.010**	0.007				
	(0.005)	(0.005)				
Listing Agent	−0.024***	−0.026***	−0.024***	−0.026***	−0.019***	−0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Condominium	−0.006	−0.005	−0.004	−0.002	−0.002	0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Townhome	−0.010	−0.008	−0.007	−0.006	−0.010	−0.009
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)	(0.010)
Observations	176,783	176,783	151,412	151,412	151,412	151,412
Adjusted R^2	0.022	0.030	0.023	0.032	0.080	0.088
Zip+Year FE	✓		✓		✓	
Zip×Year FE		✓		✓		✓
Office FE					✓	✓

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

Notes: The results in this table correspond to **??** except for the use of the Counterparty Centrality Out measure instead of the Counterparty Centrality Combined measure.

Figure C.1. Previous Transactions by Agent Type



Note: Figure C.1 plots the average number of previous transactions completed by listing and buyer agents over time. The figure provides evidence consistent with the conjecture that early buyer-side work provides broader network exposure and more frequent interaction with experienced, high-centrality counterparty agents. Specifically, the figure shows that counterparty listing agents typically have two to three times as many prior transactions as counterparty buyer agents.

C.2 Cross-Market ID & New Agent Classification

Our analyses inherently assumes that an agent's first transaction in a local MLS trading network represents their entry into the profession. A natural concern is that we may classify an agent with prior industry experience in a previous market as a new agent in their new market if they relocate across regions. Empirically, this is not a major concern because the new agent, with prior experience in a different market, will still be randomly assigned to a counterparty agent with unknown network centrality in the new market. Moreover, the new agent with prior experience will still need to build network connections to succeed in the new market, and the counterparty agent they first connect with will affect their probability of success.

Although we do not view this as a major concern, this section demonstrates that there is very little overlap among real estate agents across the ten MLS platforms in our study. Because the data are assembled from ten non-overlapping local MLS platforms, and we find no universally consistent identifier across them, we conduct a series of high-level diagnostic tests to assess the extent to which agents appear in more than one market. These diagnostics include comparing agent names across MLS platforms and examining the frequency with which identical agent identifiers (cell phone numbers) appear across them. Across all approaches, we find little evidence of cross-platform duplication. The incidence of potential duplication is extremely small, and the few cases that do arise are consistent with common names rather than true cross-market changes. Taken together, these tests reinforce that our classification of new agents is not meaningfully contaminated by agents with prior experience elsewhere, and that our empirical setting effectively captures new entrants into the real estate brokerage profession. The following subsections document the diagnostics we perform, their methodology, and key findings.

C.2.1 Agent IDs as National Realtors Database System

In Cotality MLS data, the agent identifier variable is defined as

> "Specific unique identifier provided by the Multiple Listing Service (MLS) to the buyer's agent. May be the same as the National Realtors Database System (NRDS) ID."

This naturally leads us to first examine whether the agent identifier in the MLS data behaves like an NRDS ID. We stack listing- and buyer-side agent records into an

agent-level file and flag IDs observed across multiple markets. Using the full set of agent records across the ten MLS platforms, we find no evidence of cross-market overlap in IDs: every agent ID appears in exactly one market (both in row-weighted counts and at the unique-ID level). This implies that either the MLS agent identifier is market-specific, or, if some are NRDS IDs, this subset is unique (i.e., there is no overlap).

C.2.2 Agent Names

Since IDs do not link across markets, we next assess name-based overlap. We standardize agent names by applying common cleaning operations (e.g., trimming whitespace, converting to uppercase, and removing punctuation/hyphens) to create a clean name variable. Using the agent-level file, we compute for each cleaned name the number of distinct markets in which it appears, and define an indicator variable to examine whether the cleaned name appears in two or more markets. We report both (i) row-weighted shares (treating each agent-record as an observation) and (ii) unique-name shares (treating each distinct as one observation).

Table C.6. Distribution of Cleaned Agent Names Across Markets

Markets per Name	Unique Names	Percent (%)	Cumulative (%)
1 Market	273,650	97.15	97.15
2 Markets	6,595	2.34	99.49
3 Markets	1,051	0.37	99.87
4 Markets	285	0.10	99.97
5+ Markets	94	0.03	100
Total	281,675	100	

The results in Table C.6 show that cross-market name ambiguity is uncommon in our sample: 97.15% of distinct cleaned names appear in only one market, and only 2.85% (8,025 out of 281,675) appear in two or more markets. Moreover, the small amount of overlap is concentrated in exactly two-market matches (2.34% of names), with three- or more-market overlaps extremely rare. Overall, this distribution suggests that potential misclassification of first appearance due to cross-market name duplications is unlikely to be a first-order driver of our results.

C.2.3 Agent Cell Phone Numbers

As an additional test, we examine the frequency with which agent cell phone numbers overlap across MLS platforms. In doing so, we assume that an agent's cell phone number is a stable personal identifier that does not change if they relocate or operate in more than one market, even when other identifiers - such as last names or agent IDs (see above) - may change. Because cell phone numbers are portable and rarely shared across unrelated individuals, they provide an additional way to detect whether the same person appears in multiple MLS systems. That said, it is important to note that the cell phone number field is not required (i.e., it can be blank) and is unpopulated for every agent in two of ten (Boston and Houston) MLS datasets.

Similar to the agent name analysis above, we standardize agent cell phone numbers by applying common cleaning operations (e.g., trimming whitespace and dropping non-numeric characters) to create a clean cell phone number variable. We also require the cell number to have ten digits, which has a minimal effect on the observation count. We then tabulate how many of the eight MLS platforms the cell phone number appears in.

Table C.7. Distribution of Agent Cell Phone Numbers Across Markets

Markets Per Cell #	Unique Cell #	Percent (%)	Cumulative (%)
1 Market	140,139	99.667	99.667
2 Markets	450	0.320	99.987
3 Markets	9	0.006	99.994
4 Markets	4	0.003	99.996
5+ Markets	5	0.004	100
Total	140,607	100	

If agents were routinely operating in multiple cities or relocating across cities, we would expect to observe nontrivial overlap in cell phone numbers across platforms. Instead, the results in Table C.7 show that the incidence of shared cell phone numbers is very rare (less than 0.5%), reinforcing our assertion in the paper that agents overwhelmingly operate within a single local market and that cross-platform agent mobility is minimal.

D Kaplan–Meier Survival Curves & Hazard Patterns

This appendix presents nonparametric survival evidence using Kaplan–Meier (KM) curves. These figures complement Section 5.1 by providing a model-free description of how new entrant survival evolves over time across economically relevant groups. In particular, the KM plots are useful for visualizing (i) the timing of attrition (e.g., whether separation occurs early or gradually), (ii) the magnitude of raw survival differences across groups, and (iii) whether the ordering of survival profiles is stable over the duration distribution.[1]

D.1 Specification

Let T_i denote the observed survival duration (in days) for new entrant i, measured as the number of days between the entrant's first and last observed transactions. Let C_i denote the censoring time implied by the administrative end of the sample (June 2023). The observed duration is $Y_i = \min\{T_i, C_i\}$, and the failure indicator is $\Delta_i = \mathbb{1}\{T_i \leq C_i\}$. As in Section 5.1, new entrants whose last observed transaction occurs within 180 days of June 2023 are treated as right-censored.

For the nonparametric analysis, we estimate the Kaplan–Meier survivor function,

$$\hat{S}(t) = \prod_{\tau \leq t} \left(1 - \frac{d(\tau)}{n(\tau)}\right) \tag{D.1}$$

where $d(\tau)$ is the number of exits at duration τ and $n(\tau)$ is the number of entrants still at risk immediately before τ. Intuitively, the survival function represents the probability that a new entrant remains active more than t days after entry, conditional the new agent belongs to a group (e.g., those with top 25% counterparty centrality, dual agent).

[1] Since the nonparametric estimator requires no functional-form assumptions on the baseline hazard, the KM figures are descriptive. They do not condition on first-transaction characteristics, relationship controls, or market-time controls, and are included to summarize raw survival patterns and motivate the multivariate hazard analysis in Section 5.1.

D.2 Results

D.2.1 Initial Counterparty Centrality

Figure D.1 plots KM survivor functions by whether the new entrant's first counterparty is in the top 25% of the centrality distribution (top quartile) or the bottom 75%. In the KM figures by centrality, entrants are grouped using a pooled (full-sample) cutoff for initial counterparty centrality, rather than market-time-cell-specific cutoffs. The two panels present the same comparison over short (0–60 day) and longer (0–500 day) horizons, which helps distinguish immediate attrition differences from gradual separation over time. The key descriptive pattern is that entrants matched to more central counterparties exhibit higher survival probabilities throughout most of the observed duration range. The level differences are modest but persistent in direction, which is consistent with the negative hazard-model coefficient estimates on initial counterparty centrality reported in Section 5.1.

D.2.2 Dual-Agent v. Non-Dual First Transactions

Figure D.2 compares KM survivor functions for entrants whose first transaction is a dual-agent deal versus a non-dual-agent deal. The short-horizon panel highlights a significantly lower survival probability implying early-career attrition, while the longer-horizon panel shows whether the survival paths continue to diverge over time. The descriptive pattern is consistent with the regression evidence in Table 2. New entrants whose first transaction is a dual-agent deal tend to exhibit lower survival probabilities, suggesting that dual-agency entry may provide fewer opportunities to establish durable inter-agent ties at the start of a career. The hazard regressions in Section 5.1 confirm this relationship after conditioning on first-transaction characteristics and market-time controls.

D.2.3 In-House v. Different-Brokerage First Counterparties

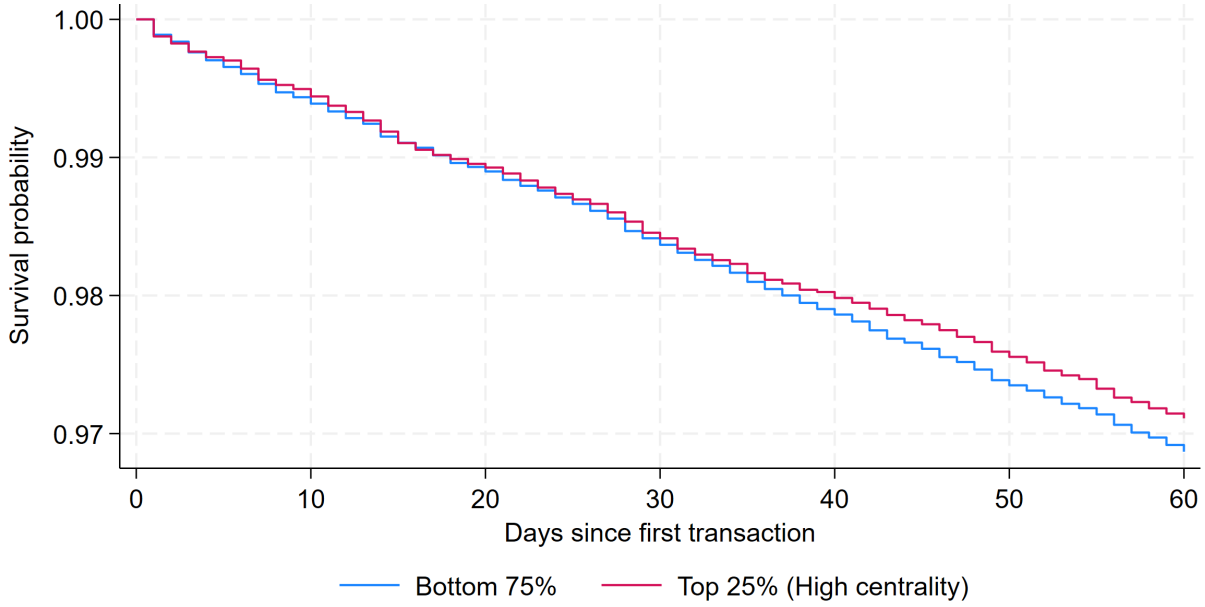
Figure D.3 reports KM survivor functions for entrants whose first counterparty is in the same brokerage office (in-house) versus a different office (different-brokerage). This comparison is restricted to non-dual first transactions so that a distinct counterparty is observed. In the 60-day horizon since the new entrant's first transaction, we do

not see strong evidence of diverging survival probability paths for two groups. This pattern is consistent with our finding in Section 4.2 that the new agent survival is not driven primarily by shared brokerage affiliation. In Panel (B), we document an interesting visual pattern. The new agent who transacts first with an in-house counterparty exhibits a meaningful lower survival probability than the one who transacts first with a counterparty at a different brokerage office. Intuitively, the first in-house counterparty transaction might limit that very initial external exposure a new entrant needs to reinforce its career longevity.

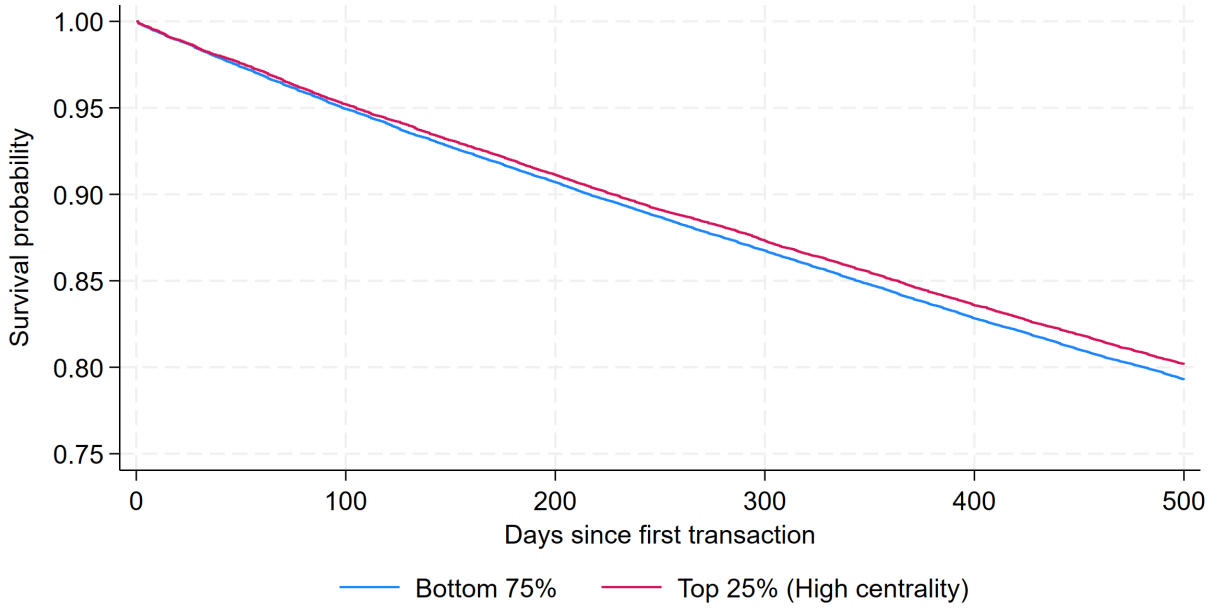
D.2.4 Entrant Role in the First Transaction

Figure D.4 compares KM survivor functions by entrant role in the first transaction, distinguishing entrants who first appear as buyer agents from those who first appear as listing agents. Consistent with Figure C.1 and our main regression analysis, we see a significantly lower survival probability for the new entrants who transact on their first deal as a listing agent. In Panel (B), we see this divergence to be persistent. This divergence confirms the intuition that buyer-side and listing-side entry may reflect different on-boarding pathways, opportunity sets, and relationship-formation margins.

Figure D.1. Kaplan–Meier Survival by Initial Counterparty Centrality



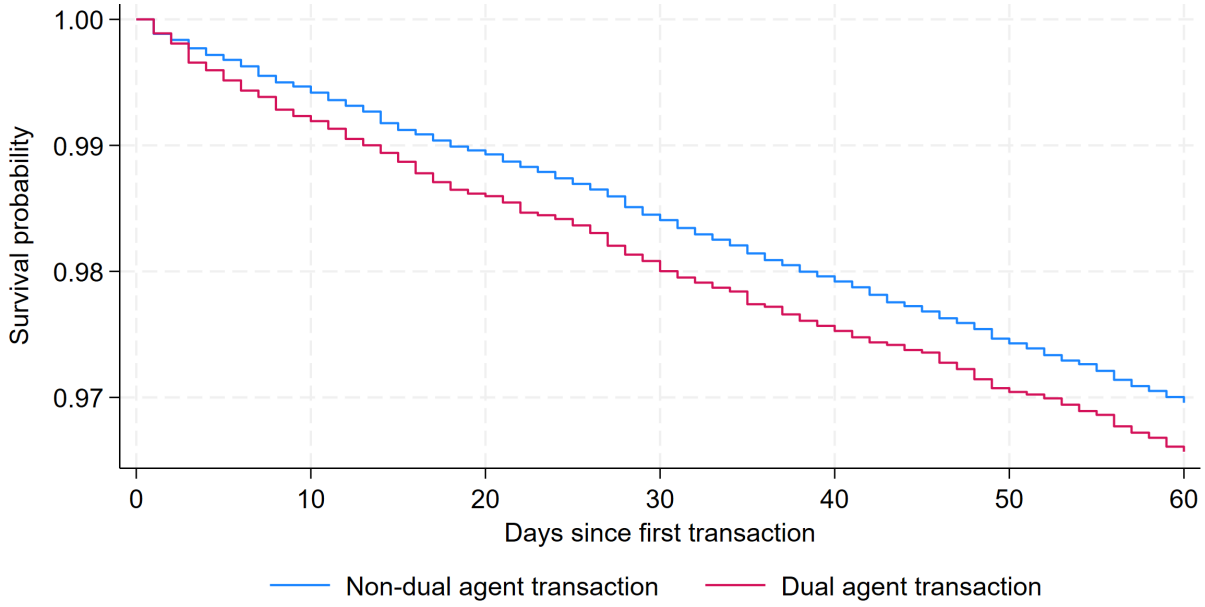
(A) 0–60 days



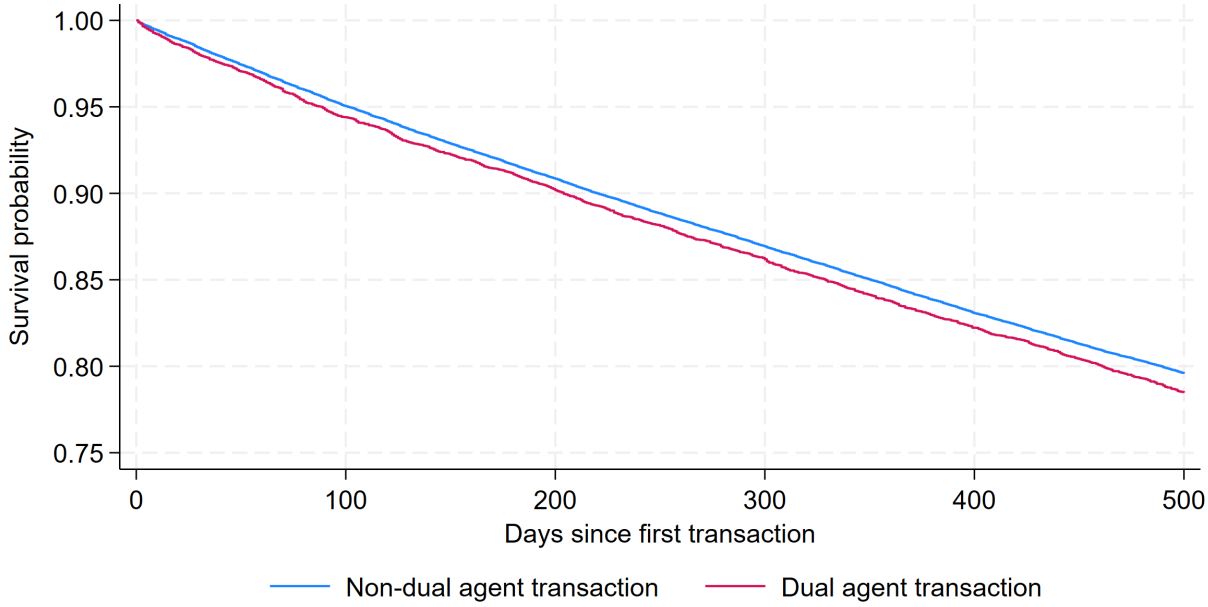
(B) 0–500 days

Notes: This figure plots Kaplan–Meier survivor functions based on the estimator in Equation (D.1) where the red line represents a group of counterparty agents with the top 25% centrality (pooled) and the blue line represents the rest. The horizontal axis measures days since the new entrant's first transaction, and the vertical axis reports the estimated survival probability. Panels (A) and (B) present the same comparison over the 0–60 day and 0–500 day horizons, respectively.

Figure D.2. Kaplan–Meier Survival by Dual-Agent Status of First Transaction



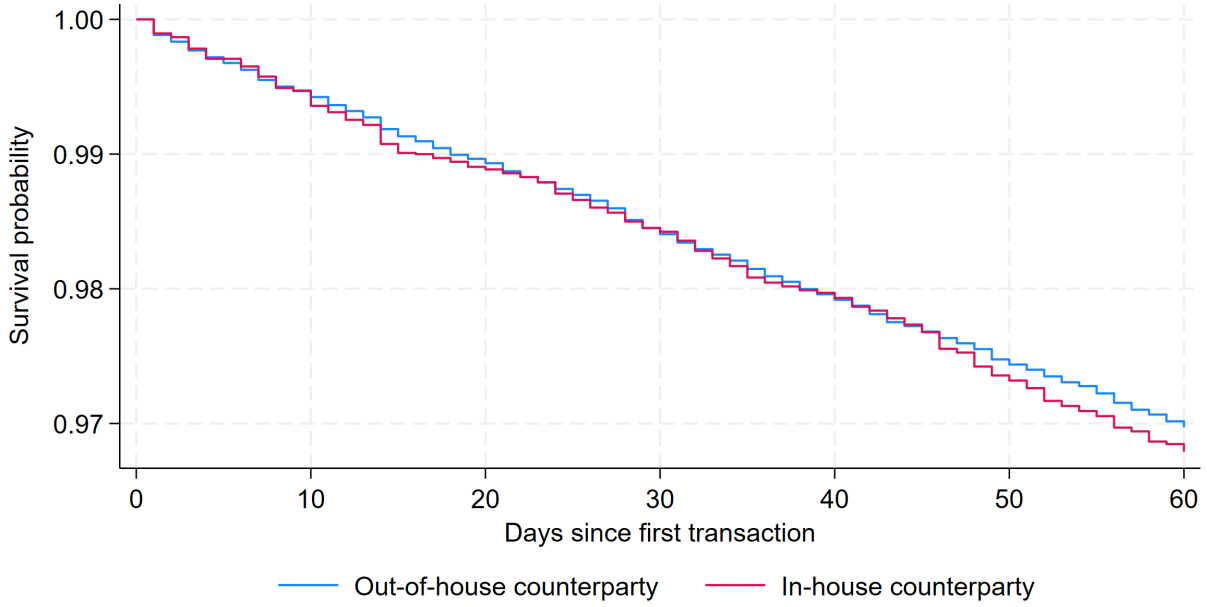
(A) 0–60 days



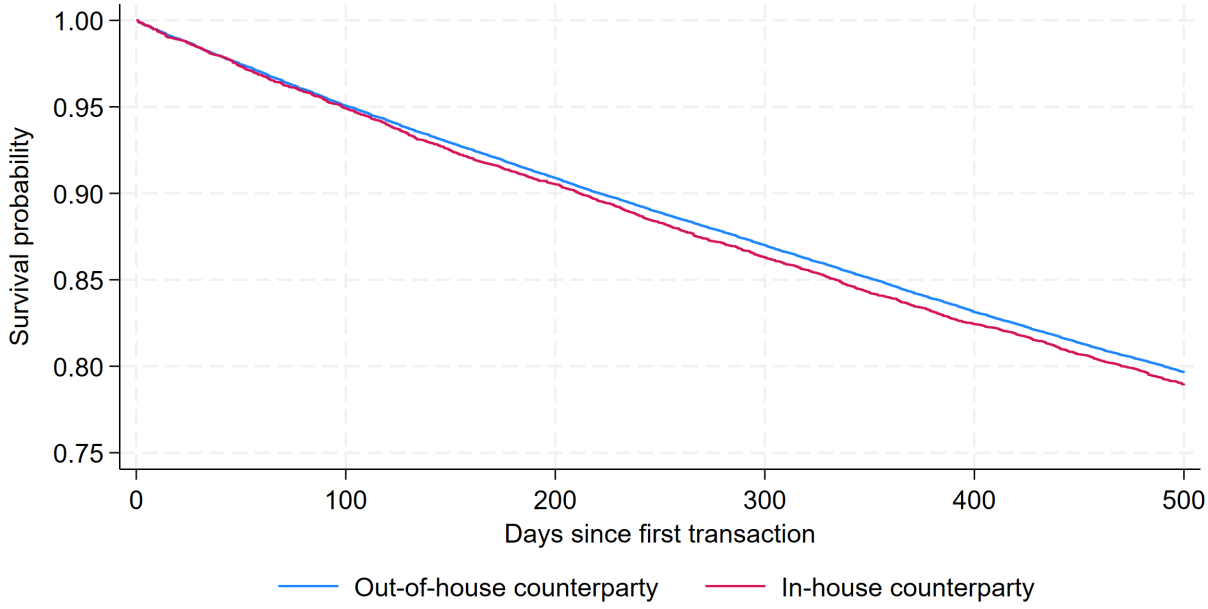
(B) 0–500 days

Notes: This figure plots Kaplan–Meier survivor functions based on the estimator in Equation (D.1) where the red line represents a group of new entrant agents whose first transactions are dual-agent deals and the blue line represents a group of new entrant agents whose first transactions are not dual-agent deals. The horizontal axis measures days since the new entrant's first transaction, and the vertical axis reports the estimated survival probability. Panels (A) and (B) present the same comparison over the 0–60 day and 0–500 day horizons, respectively.

Figure D.3. Kaplan–Meier Survival by In-House Counterparty Status



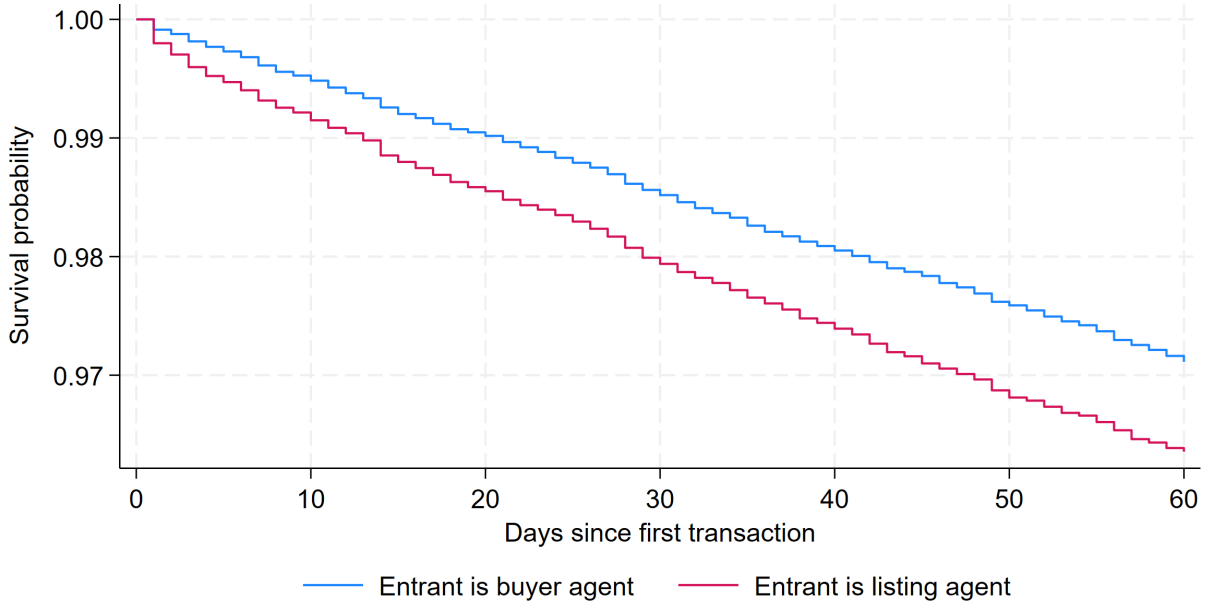
(A) 0–60 days



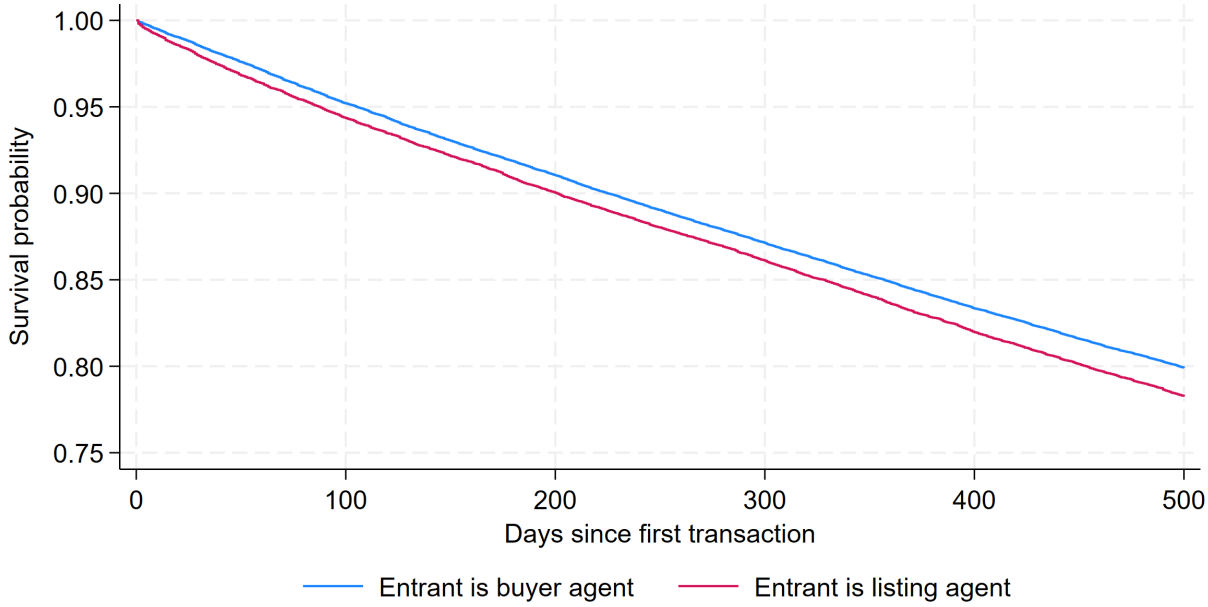
(B) 0–500 days

Notes: This figure plots Kaplan–Meier survivor functions based on the estimator in Equation (D.1). The horizontal axis measures days since the new entrant's first transaction, and the vertical axis reports the estimated survival probability. Panels (A) and (B) compare entrants with in-house versus (red) versus out-of-house (blue) first counterparties over the 0–60 day and 0–500 day horizons, respectively. Here, the out-of-house implies a different brokerage office. The comparison is restricted to non-dual first transactions so that a distinct counterparty is observed.

Figure D.4. Kaplan–Meier Survival by Entrant Role in First Transaction



(A) 0–60 days



(B) 0–500 days

Notes: This figure plots Kaplan–Meier survivor functions based on the estimator in Equation (D.1). The horizontal axis measures days since the new entrant's first transaction, and the vertical axis reports the estimated survival probability. Panels (A) and (B) compare entrants who first appear as buyer agents (blue) versus listing agents (red) over the 0–60 day and 0–500 day horizons, respectively.

E Testing for Upward Matching at Entry

The principal threat to the interpretation of β_1 in Equation 4.1 is *upward matching*: entrants with better unobserved prospects systematically obtaining more central first counterparties. If entrants who begin with well-connected counterparties differ in ways we do not observe, the estimated effect of initial counterparty centrality on survival would be overstated. Table 9 examines this concern on observable characteristics of the first transaction. This appendix examines the match itself.

The exercise compares the centrality of the counterparty each entrant actually transacted with against the centrality implied by how frequently incumbent agents transact in that market. Across every specification we consider, entrants obtain counterparties who are *less* central than transaction flow implies. We find no specification in which the match is tilted upward, which is the direction that would threaten our estimates.

E.1 Design

We ask a simple question. Among the agents a new entrant could have transacted with, how central was the one they actually transacted with, compared with how central we would expect the counterparty to be given how frequently each of those agents transacts?

We work with buyer-side entrants, for whom the counterparty on the first transaction is the listing agent. We drop dual-agency transactions, in which the entrant represents both sides and there is no distinct counterparty, and we drop entrants whose counterparty is itself a new agent, since such a counterparty has no measured network. This leaves 78,255 entrants spread over 180 market-years (ten MSAs, 2004–2021).

For each entrant we assemble an *opportunity set*: the listing agents working in the same MSA around the time the entrant's first transaction closed. Section E.2 describes how that set is built. We then locate the entrant's actual counterparty within it by percentile rank. A counterparty at the 50th percentile is more central than half of the agents available to that entrant; one at the 90th percentile is more central than nine in ten of them. Agents are ranked individually, so an agent counts once regardless of how many transactions they closed. Working in percentiles rather than in levels of centrality keeps the comparison meaningful across markets and quarters whose opportunity sets differ greatly in size. Our summary measure is the average percentile across entrants.

The question is what that average should be compared against. We build the comparison by simulation. In each of 50,000 replications we give every entrant a hypothetical counterparty taken from that entrant's own opportunity set, where an agent's chance of being selected is proportional to the number of listing transactions they completed; Section E.2 explains why. Averaging across entrants within a replication, and then across replications, gives the benchmark: the centrality an entrant would typically end up with if counterparties arrived simply in proportion to how often each incumbent transacts. The comparison is then a difference. We report the observed average percentile, the benchmark, and the gap between them.

E.2 Constructing the Opportunity Set

The opportunity set embodies two distinct claims. The first is a claim about *presence*: which incumbents were working the market when the entrant arrived. The second is a claim about *encounter rates*: how likely each of those incumbents was to be on the other side of any particular transaction. We specify them separately.

An agent belongs to an entrant's opportunity set (i.e. *roster*) if they completed at least one arm's-length listing transaction anywhere in the MSA during a window around the quarter in which the entrant's first transaction closed. We consider three kinds of window. A *backward* window covers a fixed number of quarters immediately before the entry quarter, and so uses only information predating the match. A *sandwich* window extends the same number of quarters on either side of the entry quarter, treating a transaction shortly after entry as evidence that the agent was working the market at the time of entry rather than as information available to the entrant. A *cumulative* window includes every agent who had transacted in the MSA at any point up to and including the entry quarter. The sandwich window is motivated by the distinction between presence and closing: an agent active in the market but without a closing inside a narrow backward window is absent from a strictly backward roster even though the entrant could have transacted with them. We report windows of one, two, four and eight quarters.

We measure volume either inside the roster window or cumulatively through the end of that window. The cumulative measure treats an agent's full record as the proxy for how often they are encountered, so that an agent who was briefly inactive still carries the encounter probability their career implies. We report both.

E.3 Results

Table E.1 reports the baseline specification: a sandwich roster of ± 4 quarters with cumulative volume weights. The counterparties entrants actually transacted with sit at the 56.1st percentile of the centrality distribution of available agents, against a benchmark of 64.2. The difference is -8.1 percentile points, $z = -6.01$, negative in 179 of 180 market-years and significant at the 10% level in 97.2% of them.

The same pattern holds, more strongly, for the counterparty's transaction volume itself: entrants transact with counterparties at the 62.4th percentile of the volume distribution against a benchmark of 73.8, a difference of -11.4 points and negative in all 180 market-years. Entrants are not matching up on either margin.

Table E.1. Counterparty Characteristics Relative to the Transaction-Flow Benchmark

Counterparty characteristic	Observed percentile	Benchmark	Difference	z	Market-years with negative difference
Eigenvector centrality	0.561	0.642	-0.081	-6.01	179/180
Transaction volume	0.624	0.738	-0.114	-9.84	180/180

Notes: The table reports the mean within-opportunity-set percentile of the counterparty on the new agent's first transaction, against the benchmark implied by transaction flow. The opportunity set is the set of listing agents with at least one arm's-length listing transaction in the MSA within four quarters either side of the entrant's first-transaction quarter; benchmark selection probabilities are proportional to cumulative listing transactions through the end of that window. Eigenvector centrality is constructed as described in Table B.1. Each row pools 180 market-years (ten MSAs, 2004–2021) covering 78,255 entrants, with 50,000 simulation replications per market-year. A negative difference indicates counterparties less central, or less active, than transaction flow implies; a positive difference would indicate upward matching.

E.4 Sensitivity and Coverage

Table E.2 reports the same statistic across roster windows and both volume measures. The difference is negative in all seventeen specifications, ranging from -2.49 to -8.23. The corresponding exercise for transaction volume is negative in all nine specifications we estimate, from -6.92 to -13.49. Pooling individual market-years, 98.9% of the centrality specifications and 99.9% of the volume specifications are negative. The absence of upward matching is not an artifact of a particular window.

Widening the roster raises the observed percentile, from 0.488 under a one-quarter backward window to 0.601 under a cumulative roster, because a wider window admits

agents who were present in the market but transacted infrequently. The benchmark rises in step, however, and the difference between them remains negative throughout. Cumulative volume weights strengthen the result where the roster is narrow—the one-quarter sandwich window moves from $z = -5.74$ to -8.23—and leave it essentially unchanged where the roster is wide.

Table E.2. Sensitivity to the Specification of the Opportunity Set

	Mean pool	Observed	In-window volume		Cumulative volume	
Roster window	size	percentile	Benchmark	z	Benchmark	z
Panel A: Backward windows						
1 quarter	2,507	0.488	0.542	−2.49	0.598	−5.66
2 quarters	3,667	0.509	0.567	−3.22	0.608	−5.92
4 quarters	4,910	0.529	0.599	−4.40	0.622	−6.13
8 quarters	6,221	0.549	0.630	−5.52	0.638	−6.22
Panel B: Sandwich windows						
±1 quarter	4,467	0.503	0.587	−5.74	0.616	−8.23
±2 quarters	5,460	0.528	0.610	−5.69	0.627	−7.23
±4 quarters	6,729	0.561	0.637	−5.49	0.642	−6.01
±8 quarters	8,515	0.597	0.665	−5.07	0.660	−4.81
Panel C: Cumulative window						
Through entry quarter	12,463	0.601	0.691	−6.83	0.691	−6.83

Notes: Each row reports a separate set of 180 market-year simulations for counterparty eigenvector centrality, varying the window used to construct the opportunity set. Backward windows use only quarters preceding the entrant's first transaction; sandwich windows extend the same number of quarters on either side; the cumulative window includes all agents active in the MSA through the entrant's first-transaction quarter. Mean pool size is the average number of distinct listing agents in an entrant's opportunity set. In-window volume sets benchmark selection probabilities proportional to listing transactions inside the window; cumulative volume uses all listing transactions through the end of the window. The two coincide for the cumulative roster. Row "±4 quarters" under cumulative volume is the baseline reported in Table E.1.

A backward roster excludes counterparties who were working the market but had no closing in the preceding quarters, and the entrants who transacted with them drop out of the exercise. Table E.3 reports the share of entrants whose realized counterparty appears in the opportunity set. The share is 81.6% under a four-quarter backward roster and 100% under the sandwich and cumulative rosters. The latter figure is mechanical in part, since the entry quarter contains the entrant's own transaction and therefore places that counterparty in the roster by construction. Removing the entry quarter isolates genuine coverage, which is 92.8% for the sandwich roster and 91.3% for the

cumulative roster—close to the 92.7% of counterparties observed to be active somewhere in the MSA in the prior year—and leaves the conclusion unchanged. The wider roster therefore recovers entrants who are untestable under a backward window rather than merely absorbing them.

Table E.3. Opportunity-Set Coverage

Roster window	Match rate	Observed percentile	Benchmark	z
Backward, 4 quarters	0.816	0.529	0.599	−4.40
Sandwich, ±4 quarters	1.000	0.561	0.637	−5.49
excluding the entry quarter	0.928	0.574	0.634	−4.09
Cumulative through entry quarter	1.000	0.601	0.691	−6.83
excluding the entry quarter	0.913	0.613	0.695	−5.83

Notes: The match rate is the share of entrants whose realized counterparty appears in the constructed opportunity set; entrants whose counterparty does not appear cannot be included in the exercise. All rows use in-window volume weights so that they are comparable to one another. The two rows excluding the entry quarter are estimated on a six-year subsample (2006, 2009, 2012, 2015, 2018, and 2021) covering 60 market-years; all other rows pool the full 180 market-years.

E.5 Results by Market

Table E.4 reports the baseline specification separately by MSA. The difference from the transaction-flow benchmark is negative in all ten markets, for both counterparty centrality and counterparty transaction volume. The magnitude varies with market size—it is largest in Houston, Detroit and Boston, and smallest in Oklahoma City and Tucson—but its sign does not.

Table E.4. Results by MSA

MSA	Observed percentile	Benchmark	z, centrality	z, volume
Boston (BOS)	0.532	0.602	−7.5	−12.9
Charlotte (CLT)	0.560	0.639	−5.6	−9.3
Cleveland (CLE)	0.550	0.633	−5.0	−7.7
Columbus (COL)	0.593	0.682	−5.0	−7.1
Detroit (DET)	0.523	0.625	−8.6	−17.2
Houston (HOU)	0.566	0.657	−10.2	−16.8
Jacksonville (JAX)	0.538	0.622	−4.7	−7.0
Minneapolis (MIN)	0.585	0.653	−6.4	−9.7
Oklahoma City (OKC)	0.600	0.653	−2.8	−4.9
Tucson (TUC)	0.560	0.649	−4.4	−5.8

Notes: Baseline specification of Table E.1: sandwich roster of ± 4 quarters with cumulative volume weights. The observed percentile, the benchmark and the z-statistics are averaged over the 18 entry years within each MSA. The observed percentile and benchmark columns refer to counterparty eigenvector centrality; the final column reports the z-statistic from the corresponding exercise for counterparty transaction volume.