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Connected, but Qualified? Social Affiliations, Human Capital, and Service Professional Performance

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Abstract. While social capital has been found to play an important role in economic transactions when information is incomplete, it remains unclear how it interacts with human capital in transaction performance. This paper explores the complementarity between social affiliations and human capital in transaction performance, and how affiliations influence the match between qualified professionals and consumers. I argue that human capital is important to professional performance, but that social affiliations lead consumers to increasingly match with lower human capital professionals. Thus, while social and human capital function as complements in transaction performance, social capital can substitute for human capital in the selection process. I test my argument using a novel approach that pairs data from a primary real estate multiple listing service in Utah with hand-collected data on geographically assigned church congregation boundaries. This setting allows me to identify listings for which real estate agents and home sellers share a common church congregation, and to explore the impact of this affiliation, as well as human capital variables, on transaction outcomes. I find that agent performance improves when listing for affiliates, on average, and that gains increase with agent human capital. However, consistent with my theory, I find that sellers are more likely to use inexperienced and underqualified affiliated agents. Human capital deficiencies reduce benefits from social affiliations and lead to inferior transaction outcomes in extreme cases. This suggests a new underexplored dark side to social capital from human capital deficiencies, which is driven by the selection process under incomplete information.

Supplemental Material: The online appendix is available at <https://doi.org/10.1287/orsc.2018.1279>.

Keywords: social capital • social affiliation • human capital • agency theory • productivity • professional services • knowledge workers • panel data

Introduction

Human and social capital have each been found to significantly influence economic transactions. Human capital refers to an individual's knowledge, skills, and ability (e.g., Becker 1964, Ployhart and Moliterno 2011), and influences performance through competency (Rosen 1983, Coff 1997, Hitt et al. 2001, Kor and Leblebici 2005, Crook et al. 2011, Nyberg and Wright 2015). Social capital refers to the benefits an individual derives from membership in a social structure, and influences performance through trust, improved information flows, and motivational mechanisms (Granovetter 1985, Coleman 1990, Nahapiet and Ghoshal 1998, Portes 1998, Kale et al. 2000, Adler and Kwon 2002, Westlund and Adam 2010). Social capital has been shown to be particularly important to transactions when information is incomplete, and individuals in such cases often draw on social mechanisms to minimize agency problems (Geertz 1978, Ben-Porath 1980, Coleman 1990, Greif 1993, Podolny 1994, DiMaggio and Louch 1998, Hoetker 2005, Elfenbein and Zenger 2013). However, given incomplete information, it

remains unclear how social and human capital interact to influence transaction outcomes, and when social capital helps and hurts in transactions.

Human and social capital are of particular importance in human capital-intensive settings, such as professional services. In these settings consumers must rely on the knowledge and skills of professionals (Teece 2003), but information is often incomplete and asymmetric, leading to potential for agency problems. Even ex post, service professional performance is difficult for consumers to judge, resulting in high potential for opportunism (Darby and Karni 1973, Dulleck et al. 2011) and weak signals of professional quality, including through reputation (Gubler and Cooper 2019). Examples include healthcare, real estate, financial services, legal services, and consulting. In such cases consumers may choose to transact with socially connected professionals (DiMaggio and Louch 1998, Hoetker 2005) to avoid agency problems, minimize search costs, and to benefit from social norms and preferences. However, it remains unclear how the potential performance benefits from social

capital in the transaction are influenced by the level and applicability of professional human capital, and how social capital influences the match between qualified professionals and consumers. This paper seeks to understand these questions.

I argue that social and human capital function as complements in performance, but as substitutes in the selection process. In line with previous theory, I maintain that social capital will lead to improved transaction outcomes, on average, through solidarity, information, and motivation benefits. However, drawing on human capital theory, I assert that these performance benefits will only manifest when a professional has the necessary capability, which is influenced by the level and applicability of their human capital. Finally, I argue that with incomplete information, consumers increasingly rely on social capital instead of human capital in the selection process, which increases the use of human capital-deficient professionals. This reduces the benefits of social capital and even leads to inferior outcomes in some cases.

I test my theory and arguments by pairing rich transactional real estate data with novel data on religious congregation boundaries in Utah County, Utah, from 1998 to 2014. In Utah County, nearly 90% of the approximately half million residents report belonging to the Church of Jesus Christ of Latter-day Saints, also called the Mormon Church (ASARB 2010). This church geographically assigns each home to a congregation, which church-going members must attend. By collecting a panel of congregation boundaries, as well as home addresses for real estate listing agents and homes being sold, I identify listings for which agents and home sellers share a common social affiliation through the formal social structure of the church congregation. I then investigate the impact of affiliations on (1) agent performance in transactions, including final selling price, probability of sale, and time on market; (2) agent performance given agent human capital; and (3) agent human capital levels, measured by experience and expertise applicability.

My results suggest that sellers and agents benefit on average in transactions when social affiliations are present. Agents list and sell comparable homes for 2% (approximately \$4,015) more when listing for affiliates, sell homes 3.5 days quicker, and are more likely to complete sales. However, I find that the benefits of social affiliations depend on agent human capital, only manifesting after agents have been involved in about 20 transactions and when agents have applicable selling experience. Finally, I find that human capital deficiencies are more prevalent when social affiliations are present. Sellers use affiliated agents who have listed 35 fewer homes on average and are

about 8% more likely to use agents that specialize in buying (*not* selling) homes. Thus, while social affiliations provide performance benefits to consumers and professionals *on average*, these benefits depend on agent human capital, which can be lower with affiliations. When consumers choose highly inexperienced affiliated agents, transaction outcomes from affiliations can consequently turn negative.

Theoretically, this paper highlights an underexplored dark side to social capital through the selection process, as consumers rely on socially affiliated professionals and overlook professional knowledge and skill. While social capital provides increased access to resources (Burt 1997, Adler and Kwon 2002), assessing its value in transactions requires understanding the value of the resources to which it connects, such as human capital. Thus, social capital does not necessarily lead to better outcomes in transactions, and in some cases can lead to adverse outcomes through selection. This is an underexplored area in social capital research (Adler and Kwon 2002, Kwon and Adler 2014) as well as in the literatures on partner selection (e.g., Podolny 1994, Beckman et al. 2004, Hoetker 2005, Rogan and Sorenson 2014). While some studies have noted downsides of social ties from malfeasance or over embeddedness (Geertz 1963, Baker and Faulkner 2004, Portes 2014, Yenkey 2016), this study is the first to my knowledge to show downsides via the selection process and human capital deficiencies.¹ Thus, a more nuanced theory of social capital must explain how social connections impact who transacts together, as this provides added insight into when social capital helps and hurts in transactions.

This paper also contributes to literatures on human capital and answers recent calls from scholars to explore links between social and human capital (e.g., Adler and Kwon 2002, Wright et al. 2014, Nyberg and Wright 2015). The findings suggest that social capital provides the largest benefits to performance when professionals have high human capital, but that human capital influences the selection process less when information is incomplete. The United States economy is increasingly shifting toward industries that rely on service professionals and knowledge workers (Drucker 2007), and key to firms competing in these industries is overcoming information problems and utilizing valuable human and social capital embodied in employees who function as service professionals (Coff 1997, Hitt et al. 2001, Teece 2003, Huckman and Pisano 2006; e.g., Campbell et al. 2012). This study suggests that managers can best leverage both resources by understanding the complementarity between social and human capital in performance, but substitution in the selection process.

Theoretical Motivation

This study builds on literatures in social capital, human capital, and agency theory. I first briefly review the extant theorized performance benefits from social capital in transactions when information is incomplete. I then argue that these performance benefits will depend on partner capability, which is influenced by the level and applicability of their human capital. Finally, I argue that human capital can be paradoxically lower in transactions with affiliates as consumers rely on social mechanisms. My theory highlights a previously underdeveloped yet theoretically important tension: While social and human capital function as complements in performance, they may also substitute for each other in the selection process. Consequently, a more nuanced theory is needed to clarify when social capital helps and hurts in transactions.

My focus in this paper is on social affiliations, which are connections from common memberships in formal social institutions external to economic transactions. Examples of such institutions include religious groups, schools, alumni organizations, the military, clubs, corporations, charitable organizations, labor unions, cultural groups, and professional associations. Affiliations generate social capital (Portes 1998, Putnam 2001), which is broadly defined as “the ability of actors to secure benefits by virtue of membership in . . . social structures” (Portes 1998, p. 6). The literature on social capital has long argued that such connections influence individual behaviors (Ben-Porath 1980, Granovetter 1985, Coleman 1990, Greif 1993, Portes 1998, Putnam 2001, Adler and Kwon 2002), although there are many avenues through which connections may occur, including through social affiliations, and empirical work has lagged theory.

More precisely, social affiliations may lead to two types of social capital: structural social capital and relational capital. Structural social capital refers to benefits that flow from network connections (Nahapiet and Ghoshal 1998), while relational capital refers to mutual trust, respect, and friendship among individuals that is built from prior—typically economic—interactions (Kale et al. 2000). Thus, structural social capital relates more to network positions while relational capital relates to dyadic repeated interactions. Work in management has shown the importance both types of social capital to transactions and performance (e.g., Uzzi 1997; Adler and Kwon 2002; Moran 2005; Hoetker 2005; Elfenbein and Zenger 2013; Byun et al. 2018, 2019; Ody-Brasier 2018).

In my theory and setting, benefits are hypothesized to accrue from the presence of a social affiliation, and not from positions in a network or from prior interactions directly per se. However, I expect that social affiliations influence networks and lead to significant

interactions between individuals in noneconomic settings. Because I do not directly measure or theorize about network structures or prior interactions, but about the general presence of a social structure that engenders interactions, as well as social norms, in-group preferences, and social preferences, I have chosen to primarily use the general terms “social affiliation” and “social capital” in this paper.

Existing Theory: Affiliations Improve Professional Performance and Transaction Outcomes

In human capital-intensive settings, professionals often draw on their knowledge and expertise to deliver a service to consumers (Teece 2003). However, information problems can abound, stemming from knowledge and expertise differentials between consumers and professionals, as well as from difficulties monitoring and evaluating professional performance, even ex post (Darby and Karni 1973, Dulleck et al. 2011). Such information problems may lead to issues for consumers from opportunism and hidden action by professionals (moral hazard), as well as to issues from hidden information about product or service quality (adverse selection) (see Zenger and Gubler 2016).

In the face of such issues, there are three primary mechanisms argued in the literature through which social affiliations may positively impact transactions. First, social structures facilitate the flow of information (Coleman 1990, Uzzi 1997, Nahapiet and Ghoshal 1998, Reagans and McEvily 2003). This includes the quantity of information transferred, as well as its quality. Second, social affiliations create solidarity benefits between consumers and professionals. These benefits arise from common identity (Tajfel et al. 1971, Billig and Tajfel 1973, Ben-Porath 1980, Ashforth and Mael 1989); from shared expectations, norms, and obligations supported by the social structure (Granovetter 1985, Coleman 1990, Adler and Kwon 2002); or from previous interactions (Geertz 1963, Greif 1993, Podolny 1994, Kale et al. 2000). Such benefits include increased levels of trust, goodwill, and reciprocity. Finally, transacting with social affiliates leads to increased motivation. This stems from external social mechanisms, as each party seeks to fulfill obligations and avoid reputational losses or social punishments, as well as from internal pressures from social (e.g., Charness and Rabin 2002) and in-group preferences (Tajfel et al. 1971, Billig and Tajfel 1973).

These mechanisms help resolve information problems in transactions when affiliations are present, leading to increased professional performance and improved transaction outcomes. Affiliations improve efficiency and coordination, as more trusting consumers increasingly rely on the expertise and advice

of professionals and information flows more easily between parties. Professionals are thus better able to draw on their knowledge and skills to improve performance while reducing transaction costs. Such flexibility allows access to value-creating strategies that otherwise are unavailable because of potential for opportunism and asymmetric information. Professionals also increase effort, given stronger incentives and greater returns to effort from the social structure, improving performance. My first hypothesis follows:

Hypothesis 1. *Social affiliations between professionals and consumers improve transaction outcomes.*

In my context—residential real estate—improved outcomes translate into higher selling prices, increased probability of home sale, and shorter time on market. As evidence toward the mechanisms, I expect agents to exert more effort marketing homes for affiliated sellers and to initially list homes at higher prices.

Extending Theory: Human Capital Complementarities and the Unexpected Downside of Affiliations
Professional Performance with Affiliates Depends on Appropriate Human Capital Profiles. While I expect social affiliations to lead to professional performance improvements on average, in line with prior theory, I argue that the magnitude of the improvement will depend on professional human capital. Human capital is conceptualized as the knowledge, skills, and abilities of individuals, and has been found to be positively related to performance (Becker 1964, Rosen 1983, Hitt et al. 2001, Crook et al. 2011). In service transactions, human capital is acquired over time through professional experience, as well as through formal training. However, knowledge and skills can be specific to a transaction type, and consequently human capital may not be broadly applicable across different types of transactions. *Ceteris paribus*, a high level of applicable human capital should be beneficial to professional performance.

Social capital is unique from other forms of capital. First, it resides in social connections between individuals (Burt 1997, Adler and Kwon 2002). Thus, while investments can be made to increase the value of social capital, it is more difficult to manage than other types of human capital. Second, the value of social capital is directly influenced by the value of the resources to which it provides access (Adler and Kwon 2002, Kwon and Adler 2014, Byun et al. 2019). While social affiliations may lead to increased trust, improved information, and higher levels of motivation, understanding the potential value of social capital to a given transaction consequently requires not only understanding the magnitude and nature of the access afforded by the social affiliation, but also the value of the resources to which the social affiliation

provides access. Thus, the value of a social affiliation that connects a consumer to a particularly skilled professional could be much higher than for a social affiliation that connects to an unskilled professional. This is driven by the value of the resource—in this case the service professional’s skill—to the transaction for which it connects, and not simply by the magnitude or nature of the connection itself.

In human capital-intensive settings, professional knowledge and skills are key resources to transaction performance. The value of a social affiliation between a professional and consumer is therefore directly influenced by the value of the affiliated professional’s human capital to the given transaction. Without the necessary knowledge and skills needed to succeed in the transaction, the professional will not be benefited significantly by solidarity benefits, improved information flows, or from increased effort stemming from higher levels of motivation. For instance, a real estate agent may be unsure how high they can price a particular home without having sold similar homes previously, or may struggle marketing and selling a home at a price premium without a professional network, even if affiliations provide transaction benefits.

Conversely, increased trust, improved information flows, and increased effort can lead to larger performance improvements when a professional has a high level of applicable human capital. In such cases, professionals have more expertise to draw on to generate transaction efficiencies. Increased consumer trust and information benefits lead consumers to trust professional advice more, resulting in less energy being spent on monitoring and verifying information (Dyer and Chu 2003), and instead allowing the professional to draw on their human capital more fully to improve performance. Increased experience also exposes professionals to different types of performance-improving strategies, which can be drawn on more given flexibility from increased trust and improved information flows. Finally, increased human capital may also create higher potential returns from professional effort, as the performance ceiling is raised in a transaction.

Thus, I expect social affiliations to lead to the largest benefits in transactions when professionals have the necessary knowledge and skills to succeed and improve performance. In cases where the level or applicability of human capital is low, the social affiliation benefits to performance will be small or disappear altogether. This leads to my second hypothesis:

Hypothesis 2. *Social affiliations and human capital function as complements in performance, such that social affiliations will lead to improved transaction outcomes as human capital increases.*

Relying on Social Affiliations Under Incomplete Information Can Lead to Lower Human Capital. The professional selection process in markets with incomplete information implies a new avenue through which social capital can have unexpected downsides. While scholars have investigated dangers from social connections (e.g., Geertz 1963, Portes 2014, Yenkey 2016), the downsides of social capital have received significantly less attention than the upsides (see Adler and Kwon 2002 for a review). This is striking, however, given increased potential for malfeasance from social connections (Granovetter 1985), lessened due diligence (Fairfax 2001, Baker and Faulkner 2004), and potential negatives inherent from social obligations and preferences (e.g., Uzzi 1997, Bandiera et al. 2005). While it is clear from previous work that social capital can lead to negative outcomes, such as through malfeasance or over-embeddedness, there remains limited work on the mechanisms through which downsides may occur.

I argue that the selection process underlying the consumer's decision to use a socially affiliated professional is important to transaction performance and hitherto underexplored. When service professionals can be monitored, or evaluated on performance, and performance information is readily available, consumers can rely on this information in selecting professionals (Hoetker 2005). As performance information becomes noisier, however, scholars have found that consumers increasingly rely on proxies, such as reputation (e.g., Shapiro 1983, Fombrun and Shanley 1990) or status (Podolny 1993, Benjamin and Podolny 1999). Consequently, professionals that have performed well in the past, or that have high reputation or status, are more likely to be chosen by consumers for future transactions.

When information is incomplete and professionals difficult to monitor and evaluate, however, reputation and status provide only noisy signals about service professional quality, and may not resolve consumer concerns about agency problems. For instance, professionals may have attained their high status through malfeasance (Balafoutas et al. 2013; e.g., Kerschbamer et al. 2016) or from association with a high-profile firm. Incomplete information makes it difficult for consumers to assess a professional's true quality, even *ex post*, as well as the extent to which they have behaved responsibly (Darby and Karni 1973, Dulleck et al. 2011) and will behave responsibly in the future.

In such cases, consumers may rely on social affiliations for a few reasons. First, the social structure places increased pressure on professionals to eschew opportunistic behaviors (DiMaggio and Louch 1998, Hoetker 2005) and increases professional liability in the transaction (Dulleck et al. 2011). This reduces

potential problems from opportunism and moral hazard. Moreover, improved information flows may aid consumers in monitoring and evaluating professional performance, while also providing important information about the professional's quality. Second, social affiliations reduce search costs (Rogan and Sorenson 2014). Incomplete information increases the difficulty in screening potential professionals. Given this difficulty, consumers may choose to reduce their cognitive and time efforts by transacting with affiliates, instead of engaging in an uncertain search. Social affiliations may provide more reliable added value than transacting with an unknown professional under incomplete information. Finally, social norms and preferences may push consumers to transact with affiliates. This follows from perceived social pressures and obligations by consumers as well as from a desire by consumers to "help out" an affiliate. Importantly, such norms and preferences may manifest even absent incomplete information.

While such a selection process—relying on affiliations and the social structure—may reduce agency problems and search costs, it can ultimately lead to consumers considering fewer professionals and ultimately transacting with human capital-deficient professionals. For instance, a consumer may rely on their inexperienced, though affiliated, financial-adviser neighbor to provide investment and retirement advice. Similarly, a consumer may only interview a couple of potential lawyers that are affiliates, instead of searching the broader market. In such cases, consumers place positive weight on the social affiliation in the selection process but consequently deemphasize human capital factors. Thus, socially affiliated professionals are chosen because of the affiliation, and not because of their knowledge, skill, and ability, or related proxies such as reputation or status. A stream of work in ethics and criminology supports this argument, finding that transacting with affiliates results in consumers doing less due diligence, including in selecting professionals (Fairfax 2001, NASAA 2001, Baker and Faulkner 2004, Yenkey 2016).

It is important to note that while social structures facilitate increased information transfer between consumers and professionals, ostensibly giving consumers advantages in identifying and choosing high-quality and trustworthy professionals, this does not necessarily result in superior matches. Because service professionals function as experts, each transaction is unique; consequently, previous performance is difficult for consumers to evaluate even with information. Thus, consumers may lack the expertise necessary to interpret information and objectively evaluate a professional's performance. Conversely, increased information from affiliations may lead to inferior matches if consumers fall into cognitive biases (e.g., Rogan and

Sorenson 2014, Weber 2017) or over weight a single piece of information. For instance, consumers may draw inferences about the professional's performance based on a single transaction with another affiliate, believing it to be highly representative of the professional's quality. Similarly, consumers may apply information gleaned from noneconomic interactions to make erroneous inferences about the professional's capability in economic transactions. Thus, even with increased access to information from the social structure, consumers may choose poorly equipped professionals.

Affiliations may thus result in consumers considering fewer professionals and ultimately selecting more human capital-deficient professionals. While human capital is typically valued by consumers when selecting professionals, affiliations substitute for human capital in the selection process, resulting in consumers choosing more randomly from the human capital distribution and from smaller choice sets of professionals. This increases the use of more underqualified professionals, as inexperienced affiliated professionals are preferred to unaffiliated highly qualified professionals. In the extreme, affiliations may even lead consumers to increasingly transact with highly underqualified professionals, or to push experienced affiliated professionals to engage in transactions outside of their knowledge and skills specialization (Rosen 1983), leading to inferior performance.

Social affiliations consequently dilute consideration of professional human capital in selection, leading to increased use of human capital-deficient professionals. Importantly, this negative selection process is exacerbated if the industry's professional experience distribution is skewed to the right (fat left tail, long right tail), as there are many more inexperienced professionals than experienced professionals. Such distributions may be likely to occur in service settings where the cost of entry/exit is low, there is a high failure/churn rate for professionals, and professionals often work part time. My final hypothesis follows:

Hypothesis 3. *Social affiliations and human capital function as substitutes in the selection process, such that consumers are more likely to choose human capital-deficient professionals when social affiliations are present.*

In my setting, I expect affiliations to lead sellers to use listing agents that are more inexperienced (lower total number of homes bought or sold) or that have low human capital applicability for the transaction (agents primarily have focused on the buying side in previous transactions, instead of the selling side).

Empirical Setting

The setting is the residential real estate industry, an economically significant and labor-intensive industry

that employs over one million service professionals in the United States. This industry is roughly equal in revenues to the brand name pharmaceutical industry, the hotel and motels industry, or the single-location full-service restaurants industry (IBISWorld 2014).

At the core of real estate is the real estate transaction, and this paper focuses on the selling side. Because of inexperience and lack of knowledge and skills, consumers rely on listing agents for their knowledge and expertise. Listing agent services include devising a selling strategy, posting the home on a listing service, marketing and finding buyers, staging and managing showings, negotiating offers, and completing contracts and other paperwork. Listing agents work and have fiduciary responsibility for the seller. Buyer agents, on the other hand, work and have fiduciary responsibility for the buyer. Listing and buyer agents engage in separate sets of activities for each transaction (see Online Appendix Figure A2 for an overview of activities). Consequently, the human capital acquired from one side of the transaction does not necessarily readily apply to the other side of the transaction. Many books and blogs in real estate highlight the different knowledge and skills needed to succeed as each type of agent.²

The primary tool used by agents to list and find homes is the locally owned and managed Multiple Listing Service (MLS). These databases are typically only available to agents and include a wealth of information on properties and transactions. To gain access to the MLS, agents pay a subscription fee. The MLS terms of use prohibit members from sharing logins. Consequently, access to the MLS provides agents significant information advantages over clients. Lack of access to data and limited expertise hinders consumers from gauging historic agent performance or from estimating the true value of homes.

Incentives in Residential Real Estate

Incentives for home sellers and listing agents in transactions are largely aligned, although they diverge in important ways. Home sellers have strong incentives to sell their homes for the highest amount possible. However, they are also sensitive to time, as they may incur costs each day their home remains unsold. Listing agents similarly want homes to sell at high prices. However, because they are typically compensated a fixed percentage of the sale price, they have strong incentives to churn homes quickly. Listing agents typically receive 6% of the home selling price as commission, which is split with the buyer's agent and applicable brokerages. Thus, while a \$10,000 sale price drop is substantial for the seller, the fixed percentage may result in only a \$300 drop for the listing agent. Consequently, agents have strong incentives to complete sales and to sell homes quickly,

even at slightly lower prices (Rutherford et al. 2005, Levitt and Syverson 2008). Of course, agents also have strong incentives to maintain reputation, and selling a home too cheaply can damage reputation.

Agents and sellers have strong incentives to set the original sale price of the home correctly, and to adjust quickly if needed. If the sale price is too high the home will remain on the market too long, and buyers will consequently avoid it, believing it to have problems. Too low of a list price will result in the home selling quickly but too cheaply. While agents sometimes use low list prices to induce price wars, this practice is rare in most markets, including Utah.

Formal Social Structure in Utah: LDS Congregation Boundaries

I focus on the real estate market in Utah County, Utah, to take advantage of a setting where the social structure is significantly influenced by a single formal social institution. Of the 516,564 Utah County residents (114,350 families/148,350 housing units) reported in the 2010 U.S. Census (American FactFinder 2010), approximately 89% report being members of the LDS (Mormon) church (ASARB 2010). The LDS church assigns congregations geographically, and congregations significantly influence the social structure in Utah. Members attend weekly meetings and activities with a congregation, called a “ward.” Multiple geographically proximate wards are assigned to larger “stakes,” where members meet together less frequently. As of March 2014, there were 147 stakes in Utah County and 961 wards. The average ward has approximately 450 members, 118 families, and 154 housing units; the average stake has 7 wards.

Each house in Utah County is assigned to an LDS ward and stake based on its geographic location. With few exceptions, homes are assigned to a single ward and stake, and members are required to attend their assigned congregation.³ Indeed, to enter LDS temples, which play a significant role in LDS worship, members must regularly attend their assigned ward. In rare instances, church responsibilities cause members to temporarily attend different wards. Ward and stake boundaries are determined by church and stake leadership, based off of membership numbers, with little input from members.

Ward and stake boundaries are comprised of a set of houses in a geographic area. Online Appendix Figure A1 shows boundaries for a representative stake in Utah County with 7 wards. Because of the high density of LDS church members in Utah County, ward boundaries are small and typically do not line up with neighborhood boundaries. Stakes are similarly geographically small. For instance, the average stake in Orem, Utah, covers less than 3 square miles; each stake contains on average 7 wards. Consequently, it is

quite common for neighborhoods to be shared between multiple wards, and perhaps bridge stakes. Most homeowners in Utah County have many geographically proximate neighbors with similar homes and socio-demographic backgrounds, but who are members of different wards or stakes.

Friendships and social interactions in Utah are directly influenced by congregation boundaries (see Embry 2001). Online Appendix Table A1 contains a list of typical weekly and monthly activities. Given the large number of church events, church members often feel there is little time remaining for friendships outside congregation boundaries.⁴ The LDS Church employs a lay ministry, and each member is given a responsibility in the congregation. Examples include bishop, financial clerk, nursery teacher, sports director, and Scoutmaster. These jobs often require significant time and facilitate high levels of interaction between individuals. For instance, Scoutmasters take youth on monthly overnight campouts, hold weekly activities, and visit parents to discuss needs. Bishops and stake presidents assign ward and stake responsibilities, which may change at any time. Members typically do not request specific responsibilities.

The significance of congregation boundaries to social interactions is most keenly observed when they change. Boundaries occasionally change unexpectedly because of growth or to rebalance units. When boundaries shift, it is quite common for members to lament the “loss” of friendships. While individuals have not moved geographic location, the limited time church members have to maintain relationships outside of their congregation significantly affects future interactions. One member stated he barely knew his neighbors across the street, as they attend a different stake. Another noted that their neighbor three doors down “might as well be in another universe,” as they are in a different stake.

This setting has important benefits for addressing my research question. The experimental ideal is to have a setting where consumers and professionals are randomly assigned as social affiliates, and then are randomly assigned together in real estate transactions. It also would require variation in the strength of social affiliation as well as measures of human capital, transaction outcomes, and professional performance. My setting approaches this ideal. Sellers and listing agents are effectively randomized in church boundaries, as their decision of where to live is likely uncorrelated with future real estate transaction outcomes, should they choose to move. Affiliation strength varies between wards and stakes, and agent human capital and performance can be observed over a 16-year panel. The limitation of my setting, and indeed that of many field settings, is that transactions

are not randomly assigned. Because sellers chose agents, it is possible that they are selecting on some unobservable factors that also impact agent performance in transactions, limiting the generalizability of my findings. I discuss this limitation more thoroughly later in the paper.

Data

The data for this study originate from numerous sources. The core data set is from an MLS in Utah and contains data on all MLS-listed properties in Utah County from 1998 to 2014. This is the primary MLS operating in Utah County, and the largest MLS in the state. Most Utah agents rely on this service, and at any given time there are around 3,000 active listings in Utah County. Listing in the MLS is restricted to broker-subscribers, as well as their agents and assistants. Home listings are required to be entered into the MLS within 5 days of listing agreements, and information on sold houses, including sold price, is required to be updated within 10 days of closing. The MLS requires agents to do their due diligence when entering information, and incomplete or inaccurate information can result in fines or penalties.

The MLS database includes transaction-level data. Each listing contains data on housing characteristics (e.g., street address, square footage, number of bedrooms), important dates (e.g., listing date, sold date, under contract date), relevant brokerage and agent identities (listing agent, buyer agent, and brokerage identities), price information (e.g., original listing price, final listing price, final sales price), owner information (e.g., agent-owned, bank-owned), show instructions, listing contract terms (e.g., commission offered, short sale indicator), and sold terms (e.g., type of loan). The data also include public comments that describe the condition of the property. Following Levitt and Syverson (2008), I use the public comments text to construct 81 dummy variables that control for house quality and differences unobserved in other MLS variables.

I additionally collected data from other sources. First, I purchased license data from the Utah Division of Real Estate. These data contain agent license information, including home addresses. Second, I merged in property data from the County Assessor and Recorder offices. Finally, I added census geographic data using Google's API and the Census Bureau's geocoding service. This allowed me to record longitude and latitude for many homes in my data set, as well as census block and tract identifiers.

LDS Church Boundary Data

Because LDS congregation boundary data were unavailable continuously throughout my sample period, I obtained boundary data for every property in

Utah County at two points in time. This was done using publicly available congregation boundary records.⁵ I collected data for 2014 ward and stake assignments and paired these with 2008 data collected using a similar procedure (see Gathright 2010). While not continuous, these discrete snapshots allow me to identify church ward and stake assignments for the majority of homes in Utah County for 2007–2014. I link these data with hand-collected dates on stake creations and boundary changes to construct a panel of congregation boundaries for 1998–2014.

Real estate agent congregation boundaries were identified using home addresses. Each agent is required to provide a permanent mailing address to be licensed in Utah. When address changes occur, agents must update their address within 14 days. Interviews with license personnel suggested most agents provide home addresses, although some agents provide office addresses. To minimize problems of agents reporting office addresses, I exclude addresses from my analyses that include names of major roads that are zoned for commercial purposes (e.g., State Street, Main Street, Center Street) or that reference a suite number. However, including these addresses does not significantly impact my results.

Data Cleaning Process

I follow other major studies (e.g., Levitt and Syverson 2008) using real estate data in cleaning and preparing the data for analysis. First, I restrict my sample by excluding the top and bottom 1% of observations in terms of original list price.⁶ This removes homes that originally listed for more than \$1,149,000 or for less than \$60,000. I also restrict my analyses to homes that were on the market for less than 2 years, and more than 0 days. This dropped approximately 1,152 observations from my sample. Restricting my data in these ways removes outliers, such as luxury homes or uncommon short sales, that are difficult to sell and allows me to investigate common real estate transactions. Additionally, I excluded 63 homes that sold for greater than one and a half the original or final list price of the home, or that sold for less than a quarter of the original or final list price, as these appeared to be errors. Including these observations does not significantly impact my results. Finally, following Levitt and Syverson (2008), I also excluded homes that reported the total number of bedrooms, bathrooms, or kitchens as zero. This dropped a total of 5,577 observations from my sample. This cleaning procedure left me with a total of 80,774 home listings and 40,151 sold listings with social affiliation information.

It is important to note that while my data have unique strengths, they also have limitations. First, to match up the various datasets I had to rely on home addresses or tax ID numbers. In some cases, tax ID

numbers were not included in the listing, and addresses did not match up. Second, I do not observe when agents move residences. The license data only include current addresses. Consequently, I may be incorrectly specifying current congregation boundaries for agents that move. Third, the congregation boundary data only include two snapshots of boundaries for homes in Utah County, and not a full panel of boundary changes. These two snapshots, in conjunction with boundary change dates, allow me to identify congregation boundaries and boundary changes for many homes in the sample. However, if multiple boundary changes occurred between 2008 and 2014, or the stake split multiple times before 2008, it is impossible to reliably track boundaries. In such instances, boundaries had to be coded as missing. Finally, I am unable to identify church membership in my sample. While 90% of Utah County residents report being members of the church (ASARB 2010), my data do not include membership data.

While these data limitations exist, it is important to note that they all introduce noise in the data that should bias against me finding systematic results. Because I control for geographic distance, incorrectly classifying affiliations should reduce the theorized effects.

Methods

Dependent Variables

Transaction Performance. Final home sale price, time on market, and probability of sale are the primary metrics used to evaluate real estate transaction performance. The first dependent variable used is the natural log of final home sale price. After controlling for house and transaction characteristics, this variable reflects the price premium paid by the buyer to purchase the home, and higher values benefit sellers and agents. Agents influence price by advising sellers on the initial home listing price, effective marketing, and through negotiations with buyers. As an additional measure of price premium, I constructed a variable called *sale price to predicted sale price*, which compares the final home sale price to its predicted sale price. To predict each home's sale price, I regressed the log of sale price on home observables, quality controls, transaction controls, time controls, and geographic controls. The R^2 value for this regression was 0.87. I constructed the final variable by dividing the actual final sale price by the predicted selling price, winsorized to 2.58 standard deviations above and below the mean (top and bottom one half of 1%). A value of 1 implies that the sale price is equal to the predicted sale price; values above 1 indicate price premiums.

The second dependent variable captures time on market. There is typically a positive correlation between

days on market and the sold price premium, as it takes longer to sell a home if it is priced high. I measure time on market as the number of days between initial listing and closing. Fewer days on market significantly reduces agent costs and can benefit home sellers. I drop homes with days on market greater than two years to avoid uncommon situations, such as complex short sales.

Finally, I construct a dummy variable that takes the value of 1 if a home is sold. Sellers and agents typically enter into listing agreements, which give agents right to commissions if a home sells during a specific time period (typically 180 days). Listing agreements protect agent marketing investments and provide a reasonable period to sell the home. If sellers want to change agents, the home can be relisted after the listing agreement expires.

Independent Variables

Social Affiliation. To measure social capital, I define *affiliation* to take the value of one if a listing agent shares either the same ward or stake as the seller. For the robustness analyses that use affiliation strength as the independent variable, I construct affiliations separately: one variable for agents and sellers sharing the *same ward*, and one variable for agents and sellers sharing the *same stake* but not the same ward.

Human Capital Measures. I measure human capital continuously for each agent in two ways. First, I measure *total agent experience*, defined as the number of homes an agent has helped consumers sell or buy at the time of the transaction, with dual agency transactions counting as two.⁷ Experience is a standard human capital measure (see Crook et al. 2011). Second, I measure the applicability of an agent's previous experience to the current transaction. Applicability is measured by dividing the total number of seller agent transactions by the total number of transactions for each agent. Higher values reflect increased human capital applicability, as the majority of an agent's previous transactions have been selling instead of buying. To allow burn-in, I code these variables as missing until an agent has bought/sold five homes. Table 1 presents descriptive statistics for the dependent and independent variables. Table 2 presents correlations among the primary variables in the data set. As shown in this table, the two human capital measures are distinct, as they are only weakly correlated (correlation = 0.28).

Control Variables

As outlined in Table 3, I use a large number of variables to control for home physical characteristics, transaction characteristics, time effects, and geographic effects. I also use 81 dummy variables constructed

Table 1. Descriptive Statistics for Dependent and Independent Variables

Variable	N	Mean	Standard deviation	Minimum	Maximum
Sold	80,774	0.5	0.5	0	1
Original list price	40,151	212,112	119,937	60,000	1,149,000
Sale price	40,151	200,708	106,816	30,000	1,500,000
Sale price/predicted sale price	40,151	1.00	0.15	0.61	1.63
Days on market	40,151	112.45	87.98	1	728
Affiliation	40,151	0.09	0.29	0	1
Same ward agent/house	40,151	0.04	0.2	0	1
Same stake agent/house	38,678	0.05	0.21	0	1
Total agent experience to date	40,151	119.03	172.85	1	1,336
Seller agent (percent)	36,879	0.56	0.16	0.01	1
Key box used only	40,151	0.34	0.47	0	1
Call agent for appt.	40,151	0.56	0.50	0	1
Dual agency	40,151	0.25	0.43	0	1
Part time	40,151	0.214	0.41	0	1
Days since last sale	39,236	55.997	137.903	1	3,814
Mean # of transactions/year	40,151	22.902	34.555	0	322
# sold to date by agent	40,151	92.08	144.13	1	1,139
# years as agent	40,151	5.966	4.452	0	19

from the public comments to control for home quality (see Online Appendix Table A2). In addition to providing the descriptive statistics for the control variables, the final column of this table also presents a regression of the log of home sale price on the control variables.

Empirical Specification

To investigate the impact of social affiliations and agent human capital on real estate transaction outcomes, I use three primary specifications. The first is the following within-agent specification:

$$Y_{ijht} = \alpha_i + \beta_1 * X_{ht} + \beta_2 * Affiliation_{ijht} + \beta_3 * HC_{ijht} + \beta_4 * Affiliation_{ijht}x HC_{ijht} + \gamma_j + \eta_t + \varepsilon_{ijht},$$

where Y_{ijht} is the dependent variable, such as the log of sale price, for listing agent i selling house h while employed in brokerage j at time t . X_{ht} represents a vector of house characteristics, transaction characteristics, quality controls, and geographic controls. α_i are listing agent fixed effects, γ_j are brokerage fixed effects, and η_t are month and year time fixed effects. $Affiliation_{ijht}$ is a dummy variable capturing social

affiliations at time t ; HC_{ijht} is the continuous human capital variable capturing either agent selling percentage at time t , or agent experience at time t , and ε_{ijht} the error term. The unit of analysis for the within agent models is the agent/listing. All regressions are estimated using OLS with robust standard errors clustered at the agent level. For discrete choice models, I present OLS results to avoid bias from the incidental parameters problem, although logistic models provide similar results.

The second model is a between-agent specification. Whereas the first specification looks within agents to explore how affiliations and human capital applicability impact agent performance, the between-agent specifications investigate how transactions differ depending on affiliations and human capital, and how such differences impact transaction outcomes. The specification is as follows:

$$Y_{ht} = \alpha + \beta_1 * X_{ht} + \beta_2 * Affiliation_{ht} + \beta_3 * HC_{ht} + \beta_4 * Affiliation_{ht}x HC_{ht} + \eta_t + \varepsilon_{ht},$$

where Y_{ht} is the dependent variable for house h , at time t . X_{ht} represents a vector of house characteristics,

Table 2. Correlations for Main Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Original list price	1								
2. Sale price	0.97	1							
3. Sale price/predicted sale price	0.33	0.38	1						
4. Days on market	0.10	0.07	0.03	1					
5. Affiliation	0.13	0.14	0.04	−0.00	1				
6. Same ward agent/house	0.09	0.10	0.03	−0.01	0.67	1			
7. Same stake agent/house	0.09	0.09	0.03	0.01	0.71	−0.05	1		
8. Total agent experience to date	−0.01	−0.02	−0.03	0.04	−0.06	−0.05	−0.03	1	
9. Percentage seller agent	−0.02	−0.02	−0.05	0.00	−0.07	−0.07	−0.02	0.28	1

Table 3. Descriptive Statistics and Regression for Control Variables

Control variables	Explanation	N	Mean	Standard deviation	Minimum	Maximum	log(<i>Sold price</i>)
House controls							
<i>Total # bedrooms</i>	Number of bedrooms in home	40,151	3.79	1.22	1	16	0.005**
<i>Total # bathrooms</i>	Number of bathrooms in home	40,151	2.51	0.96	1	13	0.047***
<i>Total # kitchens</i>	Number of kitchens in home	40,151	1.07	0.26	1	4	0.014***
<i>Total # fireplaces</i>	Number of fireplaces in home	40,151	0.56	0.74	0	5	0.025***
<i>Total # laundry rooms</i>	Number of laundry rooms in home	40,151	1.00	0.34	0	5	0.021***
<i>Total # dining rooms</i>	Number of dining rooms in home	40,151	0.13	0.34	0	2	0.036***
<i>Total # family rooms</i>	Number of family rooms in home	40,151	1.15	0.71	0	5	0.0002
<i>% of basement finished</i>	% of basement that is finished	40,151	41.52	45.42	0	100	−0.0004***
<i>Garage capacity</i>	Number of parking spaces in garage	40,151	1.50	1.09	0	10	0.045***
<i>Pool</i>	Dummy for presence of a pool	40,151	0.68	0.25	0	1	0.008
<i>log(Square feet)</i>	Log of home square footage	40,151	7.69	0.47	6.21	9.82	0.418***
<i>log(Acres)</i>	Log of lot acreage	40,151	0.21	0.22	0	4.48	0.326***
<i>Year built</i>	Year home built	40,151	1,985	24.65	1,860	2,014	0.003***
<i>log(HOA fee)</i>	Log of home owner association fee	40,151	1.13	1.91	0	9.21	0.005***
<i>Zip code dummies</i>	Dummy for home zip code	40,151	Individual dummies				
<i>Property type</i>	Dummy for condo, mobile, single family, recreational, townhome, or twin home	40,151	Individual dummies				
<i>Quality dummies</i>	Quality dummies extracted from public comments (see online appendix)	40,151	Individual dummies				
Transaction controls							
<i>Short sale</i>	Dummy for short sale transaction	40,151	0.06	0.24	0	1	−0.099***
<i>Owner agent</i>	Dummy for owner agents	40,151	0.04	0.20	0	1	0.020***
<i>Coagent present</i>	Dummy for presence of a listing coagent	40,151	0.23	0.42	0	1	0.004
<i>Immediate possession</i>	Dummy for home ready for immediate possession	40,151	0.27	0.44	0	1	−0.040***
<i>Seller concessions %</i>	% of sale price offered as seller concessions	40,151	0.01	0.02	0	0.10	0.035
<i>Dual agent-agent</i>	Dummy for dual agency by single agent	40,151	0.25	0.43	0	1	0.009
<i>Dual agent-office</i>	Dummy for dual agency by single office	40,151	0.31	0.46	0	1	−0.002
<i>Distance: agent to house</i>	Distance in miles between listing agent home and listing	40,151	10.09	7.31	0	30	−0.001**
<i>Year</i>	Year house sold	40,151	Individual dummies				
<i>Month</i>	Month house sold	40,151	Individual dummies				
Experience controls							
<i>log(Total agent experience to date)</i>	Log of total number of homes listed or bought by agent to date	40,151	3.92	1.43	0.69	7.20	−0.003
<i>log(Buy agent experience to date)</i>	Log of total number of homes agents have helped buy to date	40,151	2.677	1.60	0	6.50	0.004***

Notes. The final column presents results from a regression of the log of home sale price on control variables, with dummies included for year, month, zip codes, property type, and home quality. The R^2 is 0.87, intercept 3.190***.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

transaction characteristics, quality controls, and geographic controls. Geographic controls include zip code dummies and a measure of linear distance between the agent and the listed home. Year and month time controls are represented by η_i . $Affiliation_{ht}$ is interacted with human capital variables HC_{ht} to test how agent experience and seller agent percentage influence outcomes between transactions. ε_{ht} is the error term. The unit of analysis for this model is the home listing. All regressions were estimated using OLS with robust standard errors clustered at the agent level.

The final model is a conditional logit specification, which estimates the probability of agent i being chosen from a list of alternative agents, J , to list a home based on agent observables X_{ij} , such as affiliation, experience, and applicability. These models are based

on McFadden’s consumer choice models (McFadden 1973) and have been used by scholars studying relational capital (e.g., Hoetker 2005, Elfenbein and Zenger 2013). This model investigates factors influencing the seller’s choice of an agent from a risk set, which I specify as any active agent who sold a home in the past year and lives in the same zip code as the seller (median = 49 agents). An agent is chosen by the consumer only if that agent offers the highest indirect utility to the consumer, compared with all other agents given agent observables. Errors are assumed to be IID and follow the extreme value distribution. The conditional logit specification is

$$P_{ij} = P(y_i = 1|X_i) = \frac{e^{X_{ij}\beta}}{\sum_{i=1}^J e^{X_{ij}\beta'}}$$

where P_{ij} is the probability of the observed choice y_i being chosen, given X_i . Conceptually, the model regresses a dummy variable *chosen*, which indicates the agent chosen for each listing, on variables for all alternatives in the choice set, including agent human capital and affiliation, as well as their interactions. The models are estimated as conditional logits, with robust standard errors clustered by listing.

Results

Descriptive statistics provide preliminary evidence in support of the hypotheses. Figure 1 presents the distribution of final home sale price divided by the predicted sale price. This figure suggests agents sell affiliate homes at price premiums, which extend to the entire price distribution. Figure 2 presents mean agent experience and expertise levels, broken out by affiliation. These figures suggest human capital levels are significantly lower when affiliations are present. Online Appendix Figure A3 shows the distributions of human capital by affiliate and nonaffiliate transactions, indicating a similar although shifted distribution for affiliated transactions. Taken together, these figures provide initial evidence that affiliations lead to higher prices in transactions, but to more inexperienced and underqualified agents being chosen.

The first hypothesis argues that affiliations result in improved transaction outcomes. The results for this hypothesis are presented in Table 4. Columns (1)–(4) present within-agent models for home sale price, sale price premium, time on market, and probability of sale. Columns (5) and (6) present between-agent

models. Because the “within models” include agent and brokerage fixed effects, as well as controls for home and transaction characteristics, as well as home quality, the results are interpreted as the within-agent performance change when an agent sells a comparable home for affiliates, compared with for non-affiliates. The results in columns (1) and (2) show agents sell comparable affiliated homes for approximately 2% (\$4,015) more ($\beta = 0.020$). Moreover, as shown in models 3 and 4, they sell such homes about 3.5 days quicker ($\beta = -3.470$) and are 3.2% more likely to complete the sale ($\beta = 0.016$). The “between models” in columns (5) and (6) provide similar results. Because selling homes at higher prices and quicker benefits both agents and sellers, this provides support for Hypothesis 1.

The second hypothesis argues that the performance benefits of social affiliations in transactions will increase with professional human capital. Table 5 presents the results. The unit of analysis for columns (1)–(4) is the listing, so the results are between agents. Columns (1) and (3) show that the benefits of affiliations arise only when sellers use experienced agents (interaction $\beta = 0.015$) and agents with high human capital applicability (interaction $\beta = 0.139$). The base effect in each of these models is negative, suggesting that the benefits from social affiliations only manifest when agent human capital is moderately high. The results are shown more clearly in Figure 3. At the left-hand side of the graphs is shown the negative effect on sale price from affiliations at low levels of agent experience or applicability. The right-hand side shows the price premium increasing with

Figure 1. (Color online) Agents Sell Affiliate Homes Higher Above Predicted Selling Price

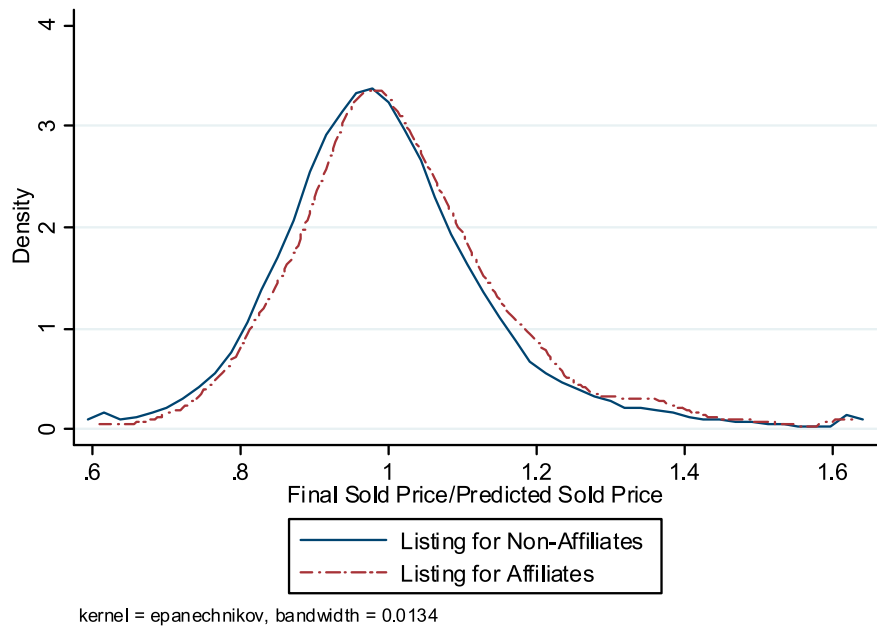
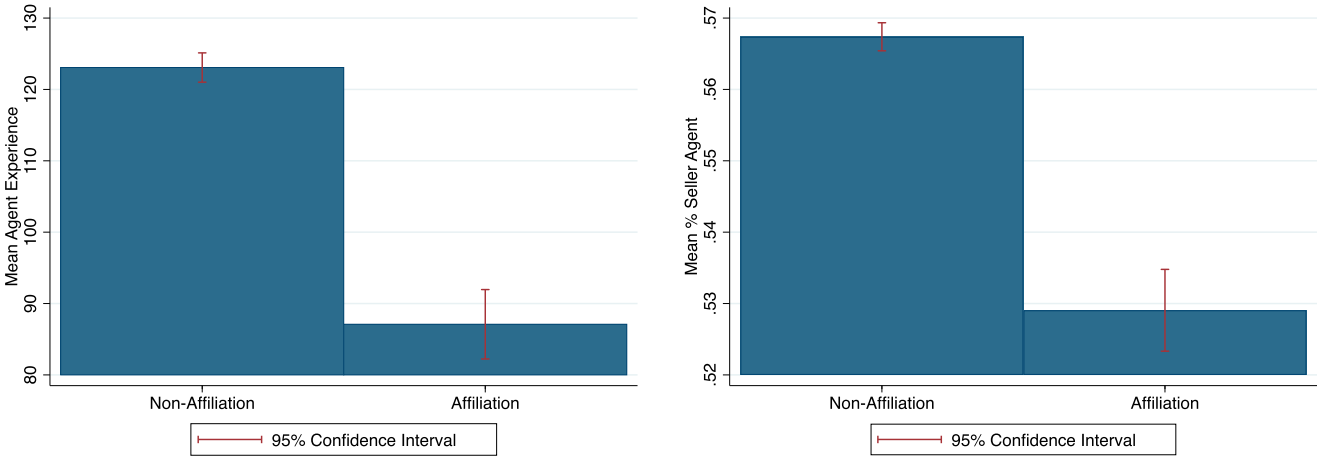


Figure 2. (Color online) Agent Experience and Seller Agent Expertise, by Affiliation



Notes. Means presented using the raw data. Experience median values are 57 homes for nonaffiliation and 43 for affiliation. Means for % seller agent are 0.575 and 0.54, respectively.

experience and expertise. Thus, at high levels of human capital, social affiliations result in transaction price premiums, compared with nonaffiliation transactions. Columns (5)–(8) of Table 6 provide the within-agent results. The unit of analysis for these models is the agent/listing, so the results are interpreted as the within-agent change in performance when agents list for affiliates, given agent human capital. Similar to the between-agent models, the results in columns (5) and (7) show that the sale price premium increases with agent experience (interaction $\beta = 0.009$) and human capital applicability (interaction $\beta = 0.092$). Figure 4 illustrates this more clearly. Figure 4(a)

shows that the sale price premium from affiliations only appears after agents have engaged in about 20 transactions. At low levels of agent experience, affiliations do not lead to increased performance. Figure 4(b) presents the results for human capital applicability. It similarly shows that the benefits of affiliations only manifest if the agent’s proportion of sold transactions to all transactions is approximately greater than 40%. Because time on market does not change significantly, as shown in columns (6) and (8), this suggests improved agent performance in transactions as human capital increases when social affiliations are present. This provides support for Hypothesis 2.

Table 4. Agent Performance and Transaction Outcomes from Affiliations

Dependent variable	Within models				Between models	
	(1) log(Sold price)	(2) Sale price to predicted sale price	(3) Days on market	(4) Pr(Sold)	(5) log(Sold price)	(6) Days on market
Affiliation	0.020*** (0.005)	0.019*** (0.005)	−3.470** (1.709)	0.016** (0.008)	0.019*** (0.005)	−3.567** (1.773)
Constant	3.611*** (0.183)	1.901*** (0.177)	−301.556*** (67.226)	3.835*** (0.264)	3.276*** (0.188)	−400.939*** (68.258)
House controls	Y	Y	Y	Y	Y	Y
Transaction controls	Y	Y	Y	Y	Y	Y
Time controls	Y	Y	Y	Y	Y	Y
Experience controls	Y	Y	Y	Y	Y	Y
Quality dummies	Y	Y	Y	Y	Y	Y
Geographic controls	Y	Y	Y	Y	Y	Y
Listing agent FE	Y	Y	Y	Y	N	N
Listing brokerage FE	Y	Y	Y	Y	N	N
R ²	0.898	0.217	0.311	0.223	0.874	0.158
Observations	40,151	40,151	40,151	80,774	40,151	40,151

Notes. Robust standard errors presented in parentheses are clustered by listing agent. House and transaction controls are noted in Table 3. Columns (3), (4), and (6) include a control for original list price. Time controls include year and month dummies, and their interaction, for when the house was sold for models 1, 2, and 5, and when it was listed for models 3, 4, and 6. Listing agent FE and Listing brokerage FE refer to listing agent and brokerage fixed effects, respectively.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5. Downsides of Affiliations from Human Capital Deficiencies

Dependent variable	Between models				Within models			
	(1) log(<i>Sold price</i>)	(2) <i>Days on market</i>	(3) log(<i>Sold price</i>)	(4) <i>Days on market</i>	(5) log(<i>Sold price</i>)	(6) <i>Days on market</i>	(7) log(<i>Sold price</i>)	(8) <i>Days on market</i>
<i>Affiliation</i>	−0.036*** (0.011)	−6.178 (4.868)	−0.054*** (0.016)	−6.071 (6.921)	−0.016 (0.010)	−7.529 (4.855)	−0.029** (0.014)	0.450 (6.711)
log(<i>Total experience</i>)	−0.004* (0.002)	3.119** (1.342)	−0.003 (0.002)	3.304** (1.641)	0.004 (0.003)	72.999*** (5.640)	0.006 (0.004)	58.879*** (4.313)
<i>Affiliation</i> × log(<i>Total experience</i>)	0.015*** (0.015)	0.776 (1.361)			0.009*** (0.003)	1.045 (1.239)		
% <i>Seller agent</i>			−0.043* (0.022)	−17.928** (7.576)			−0.034* (0.019)	−8.640 (14.464)
<i>Affiliation</i> × % <i>Seller agent</i>			0.139*** (0.034)	4.130 (12.936)			0.092*** (0.029)	−6.404 (12.428)
Constant	3.273*** (0.188)	−379.533*** (68.168)	3.183*** (0.199)	−361.590*** (72.997)	3.615*** (0.183)	−300.553*** (67.229)	3.551*** (0.191)	−303.236*** (70.617)
House controls	Y	Y	Y	Y	Y	Y	Y	Y
Transaction controls	Y	Y	Y	Y	Y	Y	Y	Y
Time controls	Y	Y	Y	Y	Y	Y	Y	Y
Quality dummies	Y	Y	Y	Y	Y	Y	Y	Y
Geographic controls	Y	Y	Y	Y	Y	Y	Y	Y
Listing agent FE	N	N	N	N	Y	Y	Y	Y
Listing brokerage FE	N	N	N	N	Y	Y	Y	Y
R ²	0.874	0.155	0.873	0.156	0.898	0.311	0.896	0.289
Observations	40,151	40,151	36,879	36,879	40,151	40,151	36,879	36,879

Notes. Robust standard errors presented in parentheses are clustered by listing agent. House and transaction controls are noted in Table 3, and models 2, 4, 6, and 8 include a control for original list price. Time controls include year and month dummies, as well as their interaction, for when the house was sold for models 1, 3, 5, and 7, and for when the house was listed for models 2, 4, 6, and 8. Listing agent FE and Listing brokerage FE refer to listing agent and brokerage fixed effects, respectively.

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

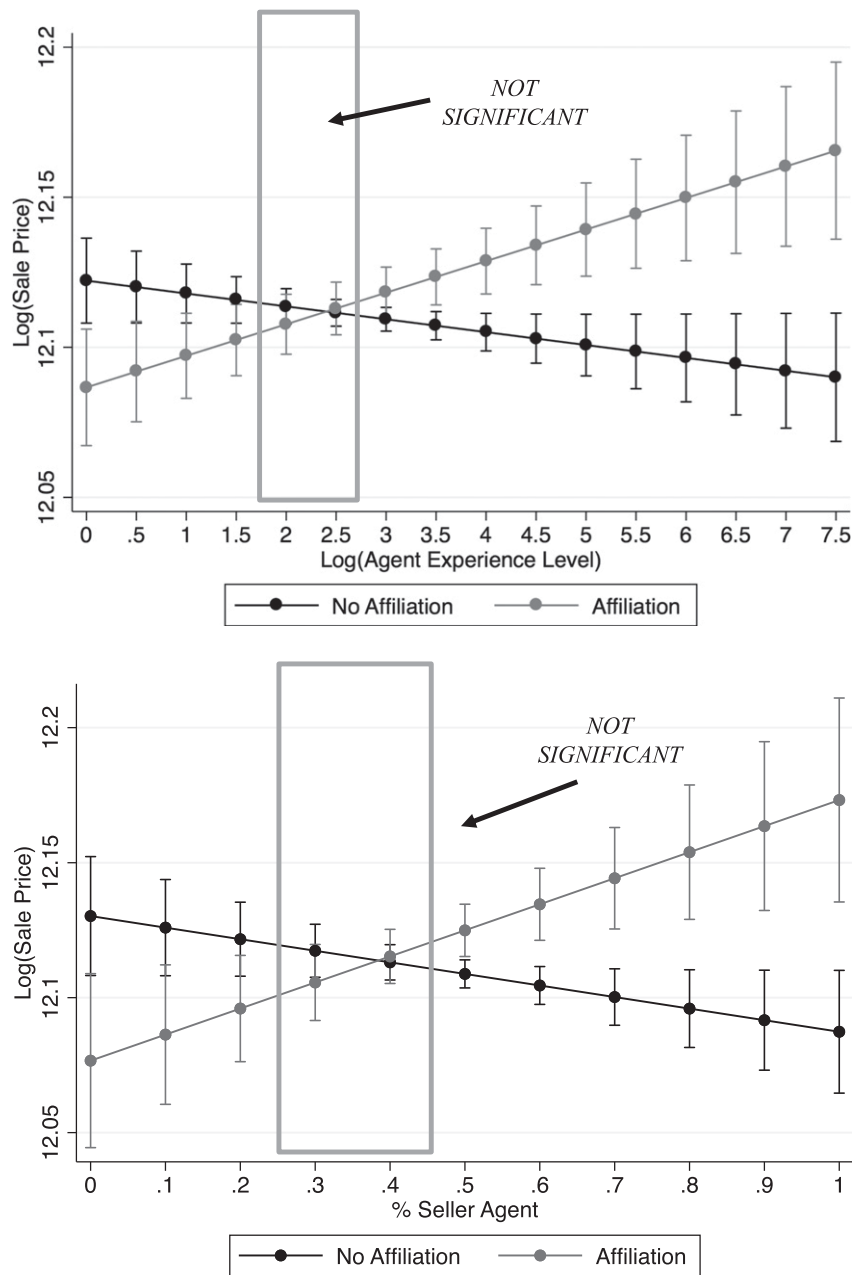
The final hypothesis argues that social affiliations and human capital will function as substitutes in the selection process. The raw data presented in Figure 2 and Online Appendix Figures A3 and A5 show that agent experience is much lower on average in transactions when affiliations are present, and agents have sold proportionately fewer homes than they have helped buy. Table 6 presents the results after including relevant controls. Columns (1) and (2) use OLS and logistic regression to predict the presence of an affiliation, based on agent human capital. After controlling for relevant house, transaction, and time variables, the results show a negative relationship between affiliations and agent human capital, measured as agent experience (OR = 0.849) and human capital applicability (OR = 0.318). The results from the conditional logit, presented in column (3), are similar. Absent affiliations, agent experience (OR = 1.735) and human capital applicability (OR = 8.947) are positively related to the agent’s odds of being chosen by a consumer. However, affiliations substitute for human capital in the selection process. Shown in column (3), affiliated agents are more likely to be chosen in general (OR = 1.268), but experienced affiliated agents (OR = 0.765) and affiliated agents with high human capital applicability (OR = 0.267) are less likely to be chosen.

The results from Table 5 provide additional evidence. The between models in Table 5, presented in Figure 3, show that at low levels of experience and human capital applicability, the performance results from affiliations are negative, compared with non-affiliations. However, as shown in Figure 4, there is no evidence that agents are changing performance behaviors listing for affiliates versus nonaffiliates at low levels of experience. The results in Figure 3 thus suggest that consumers are choosing lower-ability agents at low levels of agent experience and human capital applicability. The results in Figure 4(b) are similar and suggest that agents are more likely to be pulled out of their area of expertise when social affiliations are present, which results in reduced performance. Together, these results provide support for Hypothesis 3 and suggest that consumers are not selecting agents based on human capital to the same extent when choosing affiliates, compared with nonaffiliates. This results in less qualified agents being chosen.

Robustness Checks, Alternative Explanations, and Limitations

While my empirical identification strategy controls for many potential confounds, such as distance between

Figure 3. Impact of Experience and Expertise on Sold Price Premium, Between Models



Notes. These figures graphically present results from Table 7, columns (1) and (3). 95% confidence intervals are presented. Point estimates are statistically different everywhere at the 10% level, except where noted.

agents and sellers, type of listing, quality of homes, and other home characteristics, there still exist alternative explanations. In this section, I provide robustness checks to address these issues and to provide further evidence in support of my theorized mechanisms.

Strength of Social Affiliation

The first check draws on the variation in affiliation strength between wards and stakes. Social interaction and affiliations are much greater at the ward level than the stake level, as shown in Online Appendix Table A1. Thus, the theoretical mechanisms argued

should be stronger in wards than stakes. Online Appendix Table A3 presents the main models using these alternative affiliation measures. The results suggest that the benefits of affiliations are largest at the ward level, where affiliations are strongest, and smaller at the stake level. Homes sell for 2.5% more and 6.6 days quicker at the ward level, compared with nonaffiliate transactions. At the stake-level homes still sell for 1.5% more compared with unaffiliated transactions, although for less than the ward level ($p < 0.01$), and not any quicker than unaffiliated transactions ($p < 0.01$). The benefits for stakes are larger than for nonaffiliated

Table 6. Agent Selection Given Level of Experience and Expertise

Dependent variable	(1) Pr(Affiliation): OLS	(2) Pr(Affiliation): Logit	(3) Pr(Chosen): Conditional logit
% Seller agent	−0.082*** (0.009)	0.318*** (0.340)	8.947*** (0.373)
log(Total experience)	−0.012*** (0.001)	0.849*** (0.015)	1.735*** (0.011)
Distance	−0.017*** (0.001)	0.815*** (0.008)	1.080*** (0.003)
Distance squared	0.0001*** (0.000)	1.007*** (0.0003)	0.998*** (0.0001)
# Agents in brokerage	−0.0004*** (0.0001)	0.994*** (0.001)	1.001*** (0.0002)
Affiliation			1.268* (0.155)
Affiliation × % Seller agent			0.267*** (0.044)
Affiliation × log(Total experience)			0.765*** (0.018)
Constant	0.047 (0.163)	0.020 (0.049)	— —
House controls	Y	Y	N
Transaction controls	Y	Y	N
Time controls	Y	Y	N
Quality dummies	Y	Y	N
Geographic controls	Y	Y	N
R ²	0.073	0.119	0.109
Observations	36,879	36,848	1,061,353

Notes. Robust standard errors are presented in parentheses, with errors clustered by listing in column (3). Time controls include year and month dummies, as well as their interaction, for when the house was listed. Odds ratios reported for logit models.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

transactions, but smaller than for wards. This provides additional evidence that social affiliations, and the underlying mechanisms argued, are indeed driving the paper’s main results.

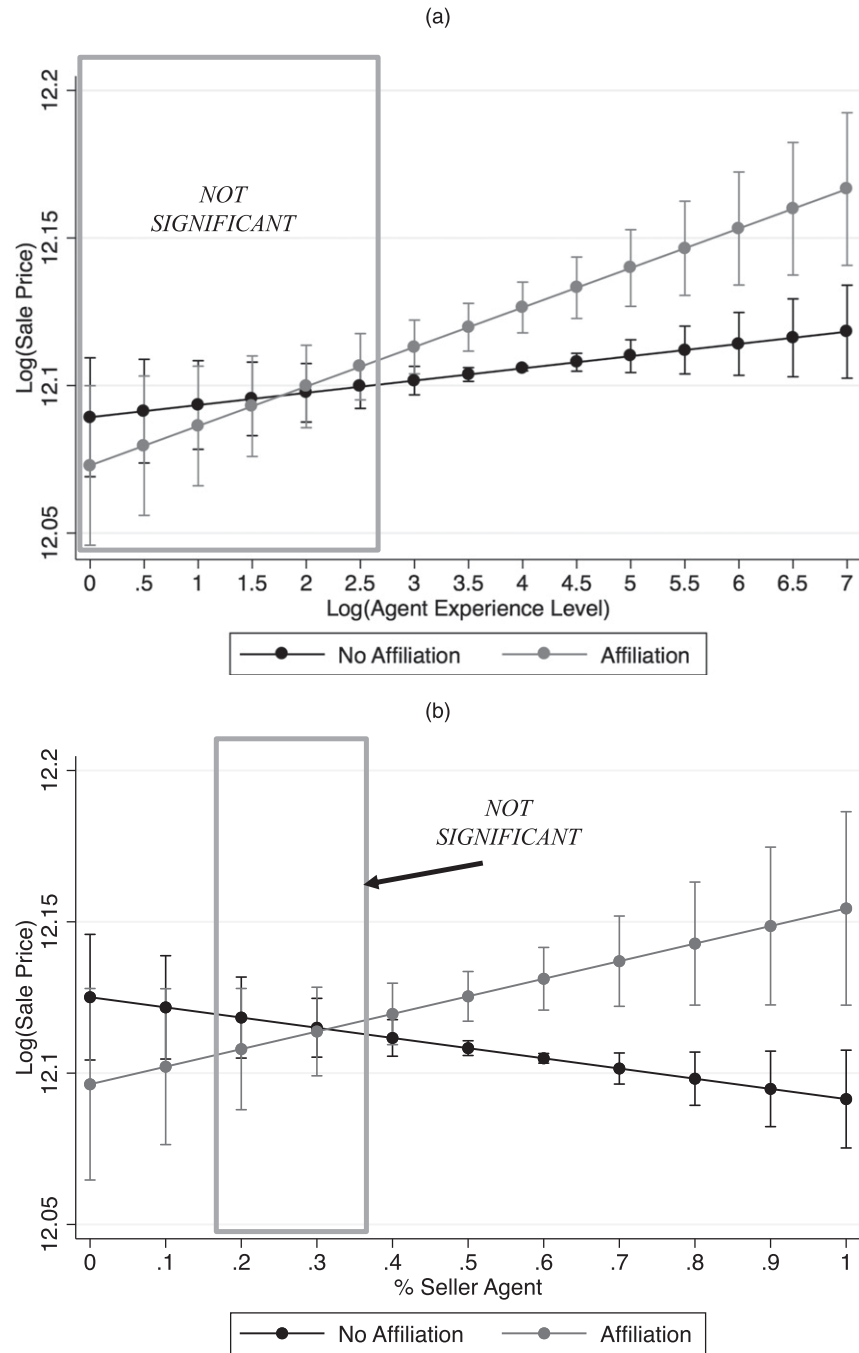
I next turn to the selection models. Online Appendix Figure A5 provides descriptive statistics for the human capital measures, broken out by same ward and same stake. These figures suggest that the least qualified agents are chosen when social affiliations are strongest. The conditional logit results in Online Appendix Table A4 support this story. The baseline effects of experience and applicability are similar to the results presented in Table 6. However, the odds of being chosen are much higher for same-ward affiliated agents at all levels of experience and human capital applicability (OR = 7.330), compared with stake-affiliated (OR = 0.421) or nonaffiliated agents. Moreover, the effect of agent expertise on the odds of being chosen are more attenuated at the ward level (OR = 0.743) compared with the stake level (OR = 0.822; p value on difference <0.05) and nonaffiliated agents. The results for agent expertise are similar, showing a larger attenuation at the ward level (OR = 0.183) than the stake level (OR = 0.441, p value on

difference <0.01) and nonaffiliated agents. Together, these results suggest that stronger affiliations result in even less qualified agents being chosen, supporting the theory arguing that social affiliations substitute for human capital in the selection process.

Evidence Toward Mechanisms

Next, I test for additional evidence consistent with the theorized mechanisms. I do this in in a few ways. First, I test for evidence of solidarity and information benefits that lead to increased flexibility and coordination in transactions with affiliates. For this test, I use incidence of dual agency transactions. Dual agency arises when a single agent represents both the buyer and seller in a transaction. Because of inherent conflicts of interest, dual agency requires trust and/or increased information. Agents have strong incentives to engage in dual agency as it allows them to capture both sides of the commission at lower costs. While dual agency may similarly lead to efficiency benefits for buyers and sellers by facilitating information exchange, decreasing time on market, and aiding the seller–buyer matching process, conflicts of interest may lead clients to refuse dual-agency deals. Most states,

Figure 4. Impact of Experience and Expertise on Sold Price Premium, Within Models



Notes. These figures graphically present results from Table 7, columns (5) and (7). 95% confidence intervals are presented. Point estimates are statistically different everywhere at the 10% level, except where noted.

including Utah, have laws requiring conflict of interest disclosures to consumers.

My theorized mechanisms suggest that affiliations will lead to an increase in dual-agency deals, but that dual agency will not be detrimental to sellers. The results for these analyses are found in columns (1)–(3) of Online Appendix Table A5. I find that agents are over 15% more likely to engage in dual agency when listing for affiliates

($\beta = 0.038, p < 0.001$). Moreover, as shown in columns (2) and (3), the use of dual agency does not appear to significantly erode the sale price premium or increase time on market. Interacting agent experience with affiliation provides similar results, suggesting increased agent power is not driving the increase.

Second, I test for evidence of increased agent effort when selling homes for affiliated sellers. In this

setting, agents increase care and effort in transactions through marketing. I measure agent effort using the MLS instructions that listing agents leave for buyer agents about the procedure for showing a home. This may include instructions for accessing the home through a key box or electronic keypad, or instructions for scheduling an appointment. If the home is vacant, agents may place a key box and note the key box code in the confidential listing comments. While this allows buyer agents to easily show the home, it does not permit listing agents to actively manage and follow up on showings. Alternatively, agents may require calls to schedule appointments. This increases agent control over showings and provides opportunities for valuable feedback. If the home is occupied, appointments are required. In these cases, listing agents may instruct buyers to call the owner directly to set an appointment or to call the listing agent. When agents request buyers call them directly, they are able to actively manage the showing. Thus, using only a key box implies low agent effort, and requiring appointments through the agent implies higher effort.

Columns (4) and (5) of Online Appendix Table A5 show the change in agent marketing efforts when listing for affiliates, after controlling for home vacancy, distance, and original list price. I find that agents are 5% less likely ($\beta = -0.016$, base rate of 34%) to use a key box as the *only* method of showing the home, and request appointments approximately 4% more often ($\beta = 0.021$, base rate of 56%) when listing for affiliates. Results using seemingly unrelated regressions or seemingly unrelated bivariate probit regressions provide similar results. This suggests agents exert greater care and marketing effort when listing for affiliates.

Third, I test if market uncertainty in certain geographic areas is influencing agent selection. I measure market uncertainty in two ways: first, using the standard deviation of home sale prices divided by original list prices in each stake for each year, and second by using the standard deviation of days on market in each stake each year. As an additional test, I also ran the main models using stake fixed effects. The results for these models are found in Online Appendix Table A6, and in each case are similar to those presented in the paper. Affiliations do not appear to be correlated with market uncertainty. While this may provide some evidence against my theorized mechanism, it is important to note that uncertainty is generally high in this setting. Thus, even areas categorized as low uncertainty truly have a significant amount of market uncertainty for the seller. Moreover, other studies have found evidence of uncertainty leading to an increased reliance on social connections (e.g., DiMaggio and Louch 1998, Hoetker 2005).

Finally, in addition to quantitative tests, anecdotal evidence from unstructured interviews with real estate agents and consumers in Utah County provide additional support for the theorized mechanisms. These interviews included asking agents and consumers about their experiences selling real estate in Utah County, including within ward or stake boundaries. During the interviews, agents expressed feelings that, in general, they were able to be more productive when listing for congregation members. One agent attributed this to increased levels of trust. He noted that the “expectation is everyone is telling the truth, because [we are] all in the same ward. You don’t think, ‘Is this guy pulling my leg?’ You don’t get people always saying, ‘can you verify that?’” Another agent shared that information about the home and the financial situation of the seller is an important benefit to listing for affiliates.

My interviews also uncovered evidence of external and internal social pressures experienced by agents when listing for affiliates. One agent stated that he felt “more pressure to get the listing right” when working for congregation members. He remarked that, “You want to make sure you sell the home for the highest possible value . . . as this affects the social community, and you want to do it right.” He went on to express his frustration when one ward client accepted a low-ball offer, against his advice. He thought, “What do I do now? What will people think about this?” An agent also noted “you really want to do a good job for someone in your ward. Maybe less so than your best friend . . . but much more than for the normal client.”

One consumer who recently used an affiliated agent stated that

In retrospect, I think we overly trusted in [the professional with an affiliation], and then ended up getting something bad because of incompetence. If I would have gone online and looked for information, and ratings, maybe on Yelp looking for reviews, [professional] . . . would have done a better job. I would have relied on the Better Business Bureau, professional certifications, ratings and reviews, etc., not just on [the affiliation].

Evidence Against Alternative Explanations

There are multiple alternative explanations that could be influencing my results. First, while I argue that human capital is leading to inferior outcomes, it could be that agents with low human capital are simply acting opportunistically, perhaps because reputational concerns are weaker than for agents with higher human capital. Indeed, in Table 5 some of the insignificant point estimates suggest that agents may be selling homes cheaper *and* quicker when listing for affiliates. To test for agent opportunism, I use original and final list prices, and compare it to the results on final sale price in Figures 3 and 4. If agents are acting

opportunistically, they should be listing affiliate homes for less, or dropping list prices to sell homes quicker. The results for original list price are presented in Figure 5. Note that these are the controlled between models, with the listing as the unit of analysis. I find that in listings where low human capital agents are used, the original list price is lower, leading to a lower final sale price. The list price increases with agent experience. The results are similar for percentage of deals as a buyer agent (Online Appendix Figure A6). This seems at first glance to support the opportunism story. However, when looking at the controlled within models, where the agent/listing is the unit of analysis, the results clearly suggest that human capital deficiencies are driving the results. Shown in Figure 6, agents do not list affiliate homes for any less when human capital is low, compared with listing for nonaffiliates. Moreover, as shown in Online Appendix Figure A7, the final list price is not any lower for affiliate transactions than nonaffiliate transactions. This suggests that agents are not changing listing price behaviors for affiliate transactions unless they have significant experience, in which case they list and sell homes for more. However, home sellers are choosing agents that are inexperienced, and consequently list homes for less regardless of affiliation. This provides support for the theorized mechanisms in the paper.

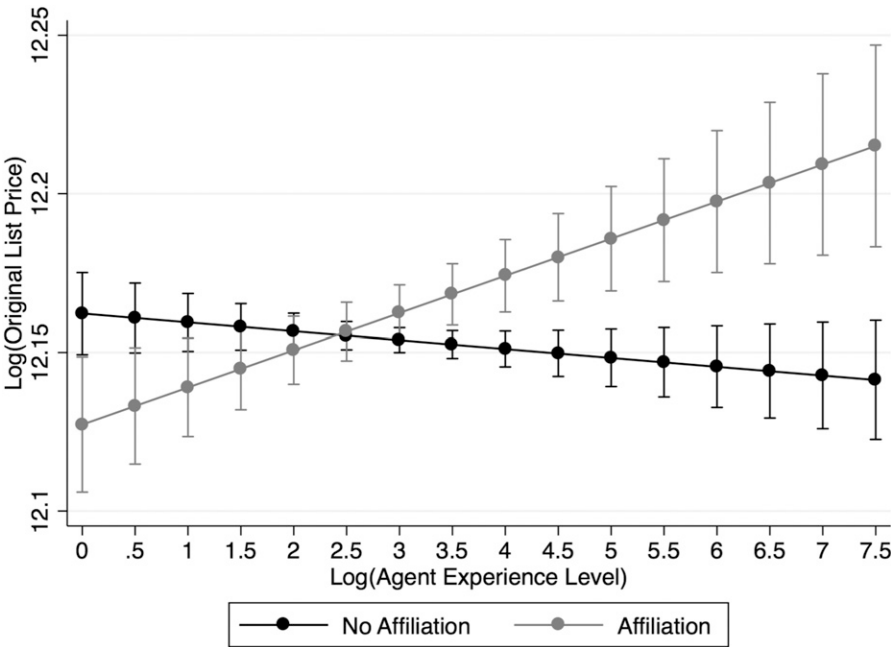
Related to this alternative explanation, it could be that home sellers know they are using human

capital-deficient agents, but they receive a commission discount from the agent to make up for their anticipated poor performance. Discussions with agents revealed that the maximum discount is usually 1% of sale price. While I do not have data on listing agent discounts, the negative impact of low human capital on sale price is more than 1%, suggesting that outcomes are still inferior for consumers even with a discount. My data show no significant difference in buyer agent commissions depending on affiliations.

Another concern is that I am not measuring human capital well. The baseline results for the human capital variables used in the paper are found in Online Appendix Table A7. While some of the evidence points to sale prices increasing with experience, time on market also seems to increase slightly. The results do not seem to show strong systematic improvements in performance with higher human capital. This is similar to the noninteracted human capital coefficients in Table 5. To add confidence to the main measures, I include additional measures of human capital and reproduce Table 5 using these measures. The results are found in Online Appendix Tables A7–A9. Additionally, I provide a robustness check that controls for agent tenure in column (1) of Online Appendix Tables A8 and A9.

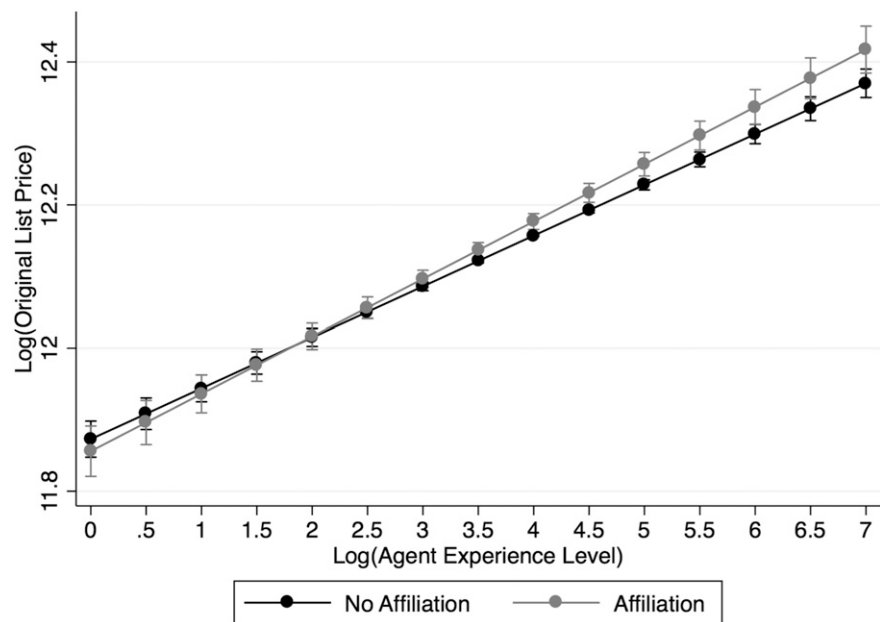
In all cases, the affiliate results are similar to those presented in the main paper. Low human capital corresponds to lower sale prices, and higher human capital to improved performance. This adds additional support

Figure 5. Between-Model Graphical Results for Original List Price by Affiliation



Notes. The figure graphically presents results from a model similar to those in Table 7, but with the log of original list price as the dependent variable. 95% confidence intervals are presented.

Figure 6. Within-Model Graphical Results for Original List Price by Affiliation



Notes. The figure graphically presents results from a model similar to those in Table 7, but with the log of original list price as the dependent variable. 95% confidence intervals are presented.

to the main measures. However, a puzzle remains concerning the baseline effects. In some cases, even with these alternative measures, higher human capital appears to lead to lower performance. While I cannot conclude what is driving this, it may be that increased human capital is used in different ways in real estate. Some agents may use it to sell homes quickly and cheaply (Levitt and Syverson 2008), while others use it to improve outcomes for sellers. Moreover, incentives may be too weak to motivate agents to perform well in transactions. Affiliations strengthen incentives, leading agents to draw on human capital to improve performance in these transactions. While I cannot conclusively pin down how human capital affects performance in all cases, it is clear that it leads to improvements in transactions with affiliates.

Finally, while the main models include controls for geographic distance between agents and the home being sold, as an additional robustness check I ran within-agent models that include a dummy for proximate nonaffiliated homes. Previous studies have found that proximity reduces search and coordination costs, which can influence interactions and transactions (Boudreau et al. 2017, Catalini 2017). While the distance control and results from splitting affiliations into wards and stakes should reduce concerns about proximity, this robustness check increases confidence in affiliations, instead of simply proximity. The results, found in Online Appendix Table A10, show that proximity, defined multiple ways, does not

influence agent performance. Affiliations drive the changes in performance.

Sample Issues and Remaining Limitations

To check for issues that may have arisen from sample construction, including limitations noted earlier regarding matching the datasets, I reran all models on two subsets of data. The first omitted any agents whose first listing was before 1999. The second omitted all data from before year 2010. These subsamples should have the most accurate information on human capital and social affiliations. In both cases, the results are highly similar to those presented the paper. I additionally ran models controlling for competition (i.e., number of agents) within wards and stakes, and the results are similar. Finally, because church boundaries change occasionally, I also include an analysis that explores how these changes influence agent performance and transaction outcomes. The results, shown in Online Appendix Table A11, suggest that agents still perform better in transactions with previously affiliated sellers, compared with unaffiliated transactions. The between results are similar. The limited sample size (224 changes) should lead to caution in interpreting these results.

While this setting possesses unique benefits, limitations remain. The largest limitation is that affiliations may not be truly exogenous to the agent–seller relationship. Agents and sellers may be sorting into wards or stakes that have unobserved characteristics that lead homes to sell for price premiums. Or agents may be sorting

Table 7. Summary of Alternative Explanations and Robustness Checks

Concern	Test	Result
Are social affiliations driving the results?	Use difference in affiliation strength between church ward and stakes. Mechanisms should be stronger at the ward level than the stake level.	Find that ward performance benefits are larger for agents than stake benefits. However, the human capital substitution in selection is larger at the ward level than the stake.
Mechanisms not directly tested.	Run models with two new sets of dependent variables: (1) Dual agency, which requires increased solidarity and/or information; (2) agent marketing effort.	Find dual agency increases 15% with affiliations. Agents also exert more effort marketing homes when listing for affiliated sellers.
Is market uncertainty driving seller decisions?	Devise stake-level measures of uncertainty and include in selection model. Also include stake fixed effects in various models.	Uncertainty measures found to be insignificant. However, market as a whole is highly uncertain. Results robust to including stake fixed effects.
Is agent opportunism driving results, instead of low human capital?	Run models using original and final list prices as dependent variables. Opportunistic agents should list homes for less initially, and reduce prices of homes quicker after listing.	No evidence that agents list homes for less for affiliates. Results suggest sellers are instead choosing agents who list all homes for less.
Are agents providing discounts, and affiliated sellers simply accepting a lower quality agent for the discount?	Anecdotal evidence.	Interviews suggest this is not the case. Typical max agent discount is 1%, although loss from underqualified agents exceeds 1% in many cases.
Is human capital measured accurately?	Reran models using multiple alternative measures of agent human capital.	Results are highly similar.
Is geographic proximity driving the effects?	Reran models that include a dummy variable for geographically proximate homes, defined as either <0.25 miles, <0.5 miles, or <1.0 miles.	Results are highly similar, suggesting affiliations are driving the results and not simply proximity.
Are sample issues driving the results, stemming from time issues or agent addresses?	Reran all models on smaller subsets of the data: (1) First agent listings post 1998; (2) only observations for the year 2010 onward.	Results are highly similar. Coefficient estimates even larger on this less noisy sample.
How do number of agents per stake impact results?	Reran all models using (1) a dummy for stakes with zero agents, (2) the log of the number of active agents per stake, or (3) stake fixed effects.	Results are highly similar.
What are the effects of church boundary changes?	Include previous affiliations in model. Very few observations: 224.	Performance results similar.

into wards or stakes based on human capital. My discussions with agents suggested this is unlikely. Moreover, my data suggest that wards and stakes are similar to those located nearby, making it unlikely that certain wards or stakes enjoy significant advantages not captured in my controls. Regression results including stake and ward fixed effects are also highly similar to those presented in the paper. Thus, while agents decide where to live, it is unlikely that this significantly increases their probability of gaining access to transactions for which they can perform unusually well.

More concerning to some of my analyses, however, is that sellers choose agents. Thus, they may be choosing agents based on some unobservable in the data, which is correlated with performance. For instance, sellers may use underqualified affiliated agents in an effort to “help” them, even if it results in inferior monetary outcomes for the seller. Similarly, certain types of sellers could be choosing high/low

human capital agents, with unobserved seller characteristics correlated with performance. Random assignment of transactions alleviates these concerns, although my data, similar to many archival studies, do not include random assignment. If this type of selection is occurring, however, it is unclear why I find downsides from human capital-deficient agents, which in some cases also lead to inferior outcomes for agents, compared with listing for nonaffiliates. Thus, even if this is occurring, the results suggest that affiliated sellers are overlooking agent human capital, albeit for a different reason than I argue. Because of this issue, however, it is unclear if all affiliations will lead to the same effects. This provides an opportunity for future research.

Discussion and Conclusion

In this paper, I have argued and found evidence that social and human capital function as complements

in transaction performance. Agents sell comparable homes for 2% more without significantly increasing costs when social affiliations are present. Interestingly, and in line with my theory, I find that these positive affiliation benefits only manifest when agents have a moderately high level of applicable human capital. These results imply significant performance improvements for agents and brokerages: A regression at the brokerage/year level shows that the within-brokerage effect of increasing the yearly percentage of sales to affiliates by 10% is approximately 2% of brokerage revenue ($p < 0.01$). Home sellers also benefit significantly from using an affiliated agent, but these benefits depend on agents having the necessary human capital. When human capital is high, social affiliations lead to large benefits; When human capital is low, these benefits disappear entirely.

More strikingly, I have found that social capital substitutes for human capital in the selection process when information is incomplete. Given potential agency problems, search costs, and social norms and preferences, I find that sellers are more likely to select professionals based on affiliations, and not on their knowledge, skills, or ability. Positively weighting affiliations in the selection process dilutes consumer consideration of human capital or its correlates. This results in consumers transacting more with affiliated professionals that are ill equipped to succeed in the transaction, which in turn erodes benefits from affiliations and even leads to negative outcomes in some cases. Interestingly, while I find that performance benefits from affiliations are largest when affiliations are strong, my results show that consumers are also most likely to choose underqualified agents when affiliations are strong.

These results expose an unanticipated and previously underexplored downside to social affiliations that stems from the selection process and human capital deficiencies. While social capital provides access to resources (Burt 1997, Adler and Kwon 2002), understanding its value in transactions requires examining the value of the resources to which it connects. Previous work has shown downsides to social capital through malfeasance (e.g., Geertz 1963, Baker and Faulkner 2004, Yenkey 2016) and over-embeddedness (Uzzi 1997, Rogan 2014). However, this is the first study, to my knowledge, to theorize and empirically show social capital downsides from human capital deficiencies driven by the selection process. These results suggest a more nuanced theory is needed that incorporates partner selection with social capital. Such a theory will better inform when social capital is likely to help and hurt in transactions.

These findings similarly suggest a more socialized view of human capital, and contribute to calls to

investigate the links between human and social capital (e.g., Adler and Kwon 2002, Kwon and Adler 2014, Wright et al. 2014, Nyberg and Wright 2015). Human capital-intensive industries are becoming increasingly important. One estimate suggests that service industries now comprise 68% of U.S. GDP (Office of the United States Trade Representative 2014). When information is incomplete, the results suggest that firms should not only consider hiring and retaining individuals with high human capital, but should also consider social capital and complementarity between the two. I find that professionals are better able to draw on their human capital to improve performance in such settings when social affiliations are present. However, social capital has to be managed carefully, as it can reduce the benefits of human capital and reputation in the selection process and lead professionals to be drawn out of their area of expertise, which hurts performance. Thus, managers need to carefully manage human and social capital together in markets with incomplete information to improve performance in transactions.

While I have focused narrowly on social affiliations between professionals and consumers in transactions where information is incomplete, the results of this paper likely generalize more broadly. In many ways, the real estate setting may be a conservative one, as human capital is not typically seen as tremendously important to performance, and information is more readily available than in many other cases. I expect the theory and results to extend to other settings where individuals or firms select transaction partners, information is incomplete, and partner capability is important to transaction outcomes. For instance, Rogan and Sorenson (2014) found related effects at a different unit of analysis in the advertising industry with mergers and acquisitions. They find that common clients increase the probability of mergers and acquisitions, but lead to lower subsequent performance. Future work should continue to explore additional settings to unpack how social capital influences the selection process and transaction outcomes, including the underlying mechanisms driving the effects.

Moving forward, there is potential for expanding and extending this work. First, future work should focus on understanding and directly measuring mechanisms leading to the observed effects. Second, future studies should replicate the results in other settings, including with nonchurch affiliations. This might include professional or social affiliations, as well as their interaction. Third, future work should continue to explore selection issues surrounding which professionals are most likely to secure transactions with affiliates. Such an investigation could yield valuable insights into successful firm entry and inform hiring and staffing decisions. Finally, future

work should seek to understand which factors lead individuals to rely more on social capital instead of human capital in the selection process. This paper suggests that additional studies on the intersection of social and human capital are a fruitful area for additional research.

Overall, this paper suggests a more nuanced view of social and human capital is needed that incorporates characteristics of the actors involved and the potential for social capital to blind actors from considering partner human capital. While human and social capital can create significant benefits, as has been shown in prior work, it can also lead to unexpected downsides when information is incomplete. Given the increased importance of knowledge workers to productivity in many firms (Teece 2003), this work promises important future insights into firm management and strategy.

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Endnotes

¹ A related paper by Obukhova (2012) studies job referrals and social ties, and shows that family and close friends may be highly motivated to help job seekers find a job, but not the best qualified to help. Rogan and Sorenson (2014) use advertising data to study how indirect ties influence merger and acquisition decisions. They find that the probability of being acquired rose with the number of common clients, but that performance of the merged entities declined by losing clients and selling less to the clients retained.

² For instance, Mike Ferry, who founded a leading real estate coaching and training company, stated the following: “I believe the skill set of an agent who works with buyers is completely different than the skill set of an agent who works on listings. Yes, they both have fundamental skills that all salespeople need. ... The skill set of a listing agent and buyer’s agent are different from that point forward, meaning the ability to present in a fashion that causes a buyer or seller to sign a contract. ... I (have thought) for years that when an agent gets their license they should have to actually declare, ‘I want to work with buyers’ or ‘I want to work with sellers.’ The majority of agents do not have the total package of skill sets to do both and, in most cases, aren’t willing to learn them because they are so vast” (Mike Ferry, August 2014, as quoted by Buyers Trust Real Estate and Investment, <https://www.inman.com/2014/09/22/listing-specialists-and-buyers-agents-are-not-created-equal/>, accessed August 2017).

³ In some cases, homes are assigned to multiple wards. Examples include wards designed for single individuals (“singles wards”), newly married student couples (“student married wards”), or specific ethnic groups (e.g., “Spanish wards”).

⁴ The observations in this section are based on informal interviews and discussions between the author and church members.

⁵ These data for each home address can be accessed individually through the meetinghouse locator on <http://www.lds.org>.

⁶ Results are similar when dropping the top and bottom 1% of sold price.

⁷ The results are robust to counting dual-agency deals as one transaction or to excluding them altogether.

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