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RESEARCH ARTICLE



WILEY

Is the division of labor limited by the extent of the market? Opportunity cost theory with evidence from the real estate brokerage industry

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Abstract

Research Summary: The division of labor allows individuals to focus their time on a narrower band of activities and increase productivity through specialization, but this comes at a cost. When individuals divide labor, they divide value and split the “pie” they help create. In this article, I formally model this tradeoff and examine how it is affected by opportunity-cost considerations due to market characteristics. I then test the empirical predictions of the model in the residential real estate brokerage industry in Southeast Michigan. Consistent with the predictions, I find that the division of labor is more likely for properties in the midrange of the price distribution and in larger markets, but less likely at the tails and in markets where property prices exhibit substantial heterogeneity.

Managerial Summary: Today, with the diffusion of digital labor markets and the emergence of the gig economy, the organization of economic activity relies on an ever-finer division of labor. In this article, I examine

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how the division of labor is affected by the cost of dividing value, which emerges when middlemen take a cut of transaction revenues. Using data from real estate, I find the cost of dividing value can increase agents' incentives to cut out the middleman for high-value and low-value transactions, especially when the disparity between valuable transactions and the rest is large and when the availability of valuable transactions is limited. These findings shed light on the mechanisms aggregating individual endeavors into broader economic objectives, whether mediated by markets, online platforms, or organizations.

KEYWORDS

digital intermediaries, division of labor, market heterogeneity, opportunity cost, strategic human capital

1 | INTRODUCTION

The division of labor is the sine qua non of decentralized economic activity and a key driver of efficiency. This is as true today as it was in 1776, when Adam Smith began *The Wealth of Nations* with a discussion of the division of labor. Nowadays, the division of labor has reached an unprecedented level of granularity, with digital labor markets slicing up and transporting work anywhere in the world and individuals being hired for one-off assignments and gigs, even for complex intellectual projects. Various aspects of this phenomenon have continued to be a source of discussion among scholars. The initial contributions have pointed to the advantages of the division of labor, such as improved dexterity of workers and avoidance of setup costs (Babbage, 1833; Rae, 1834; Ricardo, 1817), as well as the connection between the division of labor and economic development (Marx, 1867; Young, 1928). The literature has subsequently examined the implications of the division of labor for human capital and organizations (Becker, 1981; Becker & Murphy, 1992; Garicano, 2000; Lucas, 1978; Rosen, 1982, 1983), firm performance (Bennett, 2013; Chatain & Meyer-Doyle, 2017; Lee & Puranam, 2017), and the basic processes in which objectives are divided into tasks (Raveendran, Puranam, & Warglien, 2016).

Most recently, the focus of research along these lines has been on the tradeoff between the returns to specialization and the costs of coordinating specialized labor (Garicano & Wu, 2012; Kretschmer & Puranam, 2008; Meier, Stephenson, & Perkowski, 2019). However, coordination costs have become increasingly less relevant due to the adoption of modern information technologies that facilitate monitoring and enhance transparency (Bloom, Garicano, Sadun, & Van Reenen, 2014; Liu, Brynjolfsson, & Dowlatabadi, 2018; Malone, Laubacher, & Johns, 2011). In this article, rather than focusing on coordination costs, I examine a different, understudied cost faced by individual workers when they divide labor: the opportunity cost of dividing value. This cost emerges when collaborating agents share the “pie” they jointly create, as in the cases of research scientists who share credit for joint publications (Bikard, Murray, & Gans, 2015), auto salespeople who split sales commissions (Bennett, 2013), or digital intermediaries who take

commissions on the transactions that occur on their platform (Agrawal, Horton, Lacetera, & Lyons, 2015; Zhu & Liu, 2018).

Because the opportunity cost of dividing value is influenced by market characteristics that determine the opportunities in the environment, I posit that understanding its role in the division of labor requires a return to Adam Smith's original theorem that "the division of labor is limited by the extent of the market." Specifically, I theorize that the opportunity cost of dividing value is low in large markets, where valuable opportunities are abundant. However, the opportunity cost of dividing value is high when some transactions are substantially more valuable than others, because the time and resources saved when dividing labor for valuable transactions may not have good alternative uses. These opportunity-cost considerations can reduce incentives to collaborate, especially when markets are heterogeneous, that is, the disparity between good transactions and other transactions is large.

To examine the influence of opportunity costs on the division of labor, I design a model that elucidates the assumptions of the theory and defines the effects that are difficult to characterize verbally. The model is a basic representation of the mechanisms at play, but it adds precision and provides a guiding framework for empirical analysis. I test the predictions of the theory using data from the residential real estate industry in Southeast Michigan, a setting in which the majority of transactions involves the division of labor between two types of agents: a seller agent, who helps the seller market the property, and a buyer agent, who assists the buyer by arranging visits. The two agents collaborate using online market-making platforms known as multiple listing services (MLSs), which significantly reduce search costs and information asymmetries that could hinder matching and coordination (Cheng & Yang, 2004; Yavas, 1994). On the MLSs, seller agents advertise properties for sale and offer a share of their commission on the property price to agents who find buyers. If a seller agent finds a buyer, that agent keeps the full commission.

My empirical findings show that agents are more likely to divide labor for properties in the midrange of the price distribution and in bigger markets than at the tails and in markets in which property prices exhibit substantial heterogeneity. These results are consistent with opportunity-cost logic advanced by the theory. When dealing with top-end properties, agents tend to focus their time and resources on capturing full commissions. Conversely, with low-end properties, agents often cannot find partners willing to spend time on such low-value transactions. As a result, the division of labor occurs in the midrange. This midrange grows larger in bigger markets where there is an abundance of properties for sale and agents divide labor to clear their inventories faster, but it shrinks in heterogeneous markets where the disparity between good properties and other properties is large. Supplemental analyses explore the mechanisms leading to these findings. They indicate that agents dealing with top-end and low-end properties tend to be at the opposite ends of a hierarchy: senior, more capable agents take on top-end properties to capture full commissions, while dividing labor for midrange properties of a lesser value; junior agents, on the other hand, collaborate with senior agents on midrange properties they could not otherwise access, while performing solo for low-end properties worth their time, but not that of their most senior colleagues. These dynamics are also reflected in the commission splits agents offer to potential collaborators. Commissions mirror the opportunity cost of dividing value. For low-end properties and in large markets, commissions are higher on average to induce collaboration. For top-end properties and in heterogeneous markets, commissions are lower to compensate for the higher opportunity cost of splitting the pie. As a further robustness check, the analyses rule out several alternative explanations,

demonstrating, *inter alia*, that the patterns in the data are unlikely to be driven by buyer heterogeneity or by the incentive schedules adopted by brokerages to keep transactions in-house.

The analyses and findings of this study contribute to the literature on the influence of markets on the division of labor (Baumgardner, 1988; Bresnahan & Gambardella, 1998; Duranton & Jayet, 2011; Garicano & Hubbard, 2009). Absent the coordination costs often cited as a limiting factor in the division of labor (and arguably made less relevant by modern information technologies), this study demonstrates that the choice of dividing labor is made in the shadow of the opportunity cost of dividing value—an inevitable element of collaborating via the market mechanism and in organizations. Because opportunity costs matter only when opportunities are heterogeneous, this study adds a novel dimension to Adam Smith's original theorem, namely, market heterogeneity. Market heterogeneity is likely to play an important role in collaborations and job outsourcing in settings where opportunities are unique and idiosyncratic, such as markets for ideas in creative and high-tech industries (Agrawal, Catalini, Goldfarb, & Luo, 2018; Arora & Gambardella, 2010; Luo, 2014).

This study also contributes to the growing literature on (dis)intermediation, which has attracted much scholarly attention in recent years due to the emergence of super-intermediaries in the digital economy (Gu & Zhu, 2020; Lobel, 2018; Parker, Van Alstyne, & Choudary, 2014). This study contrasts the uniform characterization of opportunities of prior work in this domain, which often assumes homogeneity in transaction values (Marx & Schummer, 2019), with a more granular depiction that can account for the vast heterogeneity of projects and opportunities in the digital economy. The approach taken in this study points to the prospect that intermediaries, including digital intermediaries, may not be well equipped to handle both high-value and low-value transactions—a novel insight that can emerge only if opportunities are assumed to be heterogeneous to begin with. Thus, it is perhaps no coincidence that managers of online platforms often fear disintermediation from valuable transactions and disengagement from unsalable ones (Agrawal et al., 2015; Hagiu & Rothman, 2016). Rather than imposing penalties to thwart attempts to take transactions off the platform or subsidizing low-value projects, this paper advises managers to recalibrate the business models of their platforms and focus instead on the midrange of the opportunity distribution, which is precisely the range amenable to the division of labor.

Finally, by drawing on insights from the corporate strategy literature on the fungible nature of resources as determinants of firm scope (Levinthal & Wu, 2010; Penrose, 1955, 1959; Teece, 1982), this study also adds to the literature on strategic human capital (Bennett, 2013; Byun, Frake, & Agarwal, 2018; Chatain & Meyer-Doyle, 2017). Specifically, my research demonstrates the implications of the interplay between fungible resources and market opportunities on a smaller scale, that of the individual, whose basic indivisibility drives opportunity-cost considerations. In this sense, the theory and findings of this paper provide the micro-foundations for characterizing individual workers as fungible and re-deployable resources (Levinthal & Wu, 2010; Sakhartov & Folta, 2014).

In the remainder of the manuscript, I adopt a narrative structure that places the context before the theory. This order has the advantage of integrating theory and empirics as well as concretizing concepts that might otherwise appear abstract or counterintuitive. I then discuss the assumptions of the model and their generalizability, conduct empirical analysis, and draw conclusions.

2 | INSTITUTIONAL BACKGROUND

The empirical setting of this study is the real estate industry in Southeast Michigan, United States. The real estate industry is of great importance to the U.S. economy. In 2018, brokerage commissions reached 155 billion USD, accounting for almost 1% of the U.S. gross domestic product (IBISWorld, 2018).

In the US, real estate agents are self-employed professionals who run their own independent brokerages or work as independent contractors for other brokers.¹ Agents act as intermediaries in the buying and selling of residential properties; they receive commissions on properties sold, typically 6% of the selling price. The majority of residential real estate transactions involve the division of labor between two agents: (a) a seller agent, who works with the property seller and performs various activities, such as setting the listing price and staging the property for open houses, and (b) a buyer agent, who works with the buyer, showing properties and offering advice on negotiations.² In approximately one-fifth of transactions, the same agent performs both the seller side and buyer side of the transaction, which is commonly referred to as dual agency. A commission, generally 6%, is paid to the seller agent by the property seller and, in cases in which a buyer agent is involved, is divided according to a commission split set in advance by the seller agent. Typically, the commission split is 50%, but can be more or less.³

At first glance, the interaction between the seller agent and the buyer agent may appear competitive and zero-sum, with the two agents taking opposing stances during the negotiations. In reality, however, their exchange is collaborative in nature. In industry jargon, the buyer agent is often referred to as the “cooperating agent” (Micelli, Pancak, & Sirmans, 2000). Indeed, the buyer agent does receive a commission on the selling price from the seller agent and the buyer agent's incentives are more aligned with those of the seller agent than with the buyer (Han & Hong, 2016).⁴

A salient feature of this industry is the division of labor, which is facilitated by the MLS platform where seller agents advertise properties and offer compensation (a percentage of the property price) to any agent who finds a buyer. As discussed by Yavas (1994: 176), “The MLS is probably the most significant feature of the brokerage industry... From a theoretical point of view, it can be considered as a mechanism that eliminates the trade frictions resulting from imperfect information.” Listing service platforms reduce coordination costs by disseminating information about properties for sale, thus lowering the information asymmetries and search costs that could hinder agents' ability to find partners. While today, MLSs are online, they have a long history and have evolved over time. According to the website of the U.S. National Association of Realtors (2014): “In the late 1800s, real estate brokers regularly gathered at the offices of their local associations to share information about properties they were trying to sell. They agreed to compensate other brokers who helped sell those properties, and the first MLS was born, based on a fundamental principle that is unique to organized real estate: Help me sell my inventory and I'll help you sell yours.”

¹From a legal standpoint, the relationship between brokers and agents is governed by an industry-specific federal statute designating agents as independent contractors (Burke, 2007). Working with an established brokerage is the norm at the beginning of real estate agents' careers (Dizik, 2014).

²This advice may not necessarily be in the buyer's best interest (see discussion below).

³The commission split is advertised *ex ante* and is binding. The two agents do not negotiate the split *ex post*.

⁴The interested reader can refer to Marsh and Zumpano (1988), Miceli, Pancak, and Sirmans (2000), and Olazabal (2003) for a discussion on the conflicts that are intrinsic in the agency relationship between buyers and their agents.

Mediated by the MLS, the division of labor allows agents to clear their inventories faster and sell more, but at the cost of compensating agents who find buyers. In the following, I design a model that mirrors this trade-off. On the supply side, agents gain in efficiency when dividing labor via simple comparative advantage dynamics, but lose half of their commissions. On the demand side, market size and market heterogeneity influence this trade-off by varying the relative benefits of efficiency versus value capture.

3 | THEORY

To better integrate theory and empirics the model in this section is set within the real estate brokerage industry. Despite this focus, the basic premises and predictions of the model are more general and by no means specific to the setting. In fact, the model builds on the human capital literature in economics (Becker, 1981; Becker & Murphy, 1992; Rosen, 1983) and strategic management (Agrawal et al., 2018; Bennett, 2013; Bikard et al., 2015; Chatain & Meyer-Doyle, 2017; Kretschmer & Puranam, 2008), borrowing several elements from existing team-production models. However, the model departs from prior work on a few critical dimensions. First, contrary to prior work, which has often examined complex processes in large teams while treating opportunity costs as an outside option, this model considers an economy with only two (real estate) agents and a richer demand environment with a distribution of opportunities. Opportunities are linked to different types of real estate properties, but they can be more generally interpreted as ideas, innovations, or projects. Second, the model assumes away coordination costs. Coordination costs are intrinsic to the division of labor “in the sense that the specialized parts must eventually work together” (Kretschmer & Puranam, 2008), but they can be managed and reduced through standards, interfaces, and market-making intermediaries (Sanchez & Mahoney, 1996; Spulber, 1996). Therefore, implicit in the theory is the assumption that the exchange between the two agents is mediated by a platform, such as an MLS.

3.1 | Model

The market consists of a mass, $M \in \mathbb{R}_{>0}$, of properties for sale, the types of which, θ , are distributed continuously and uniformly on the bounded interval $[\underline{\theta}, \bar{\theta}] \subset \mathbb{R}_{>0}$ according to the p.d.f. $f(\theta)$ with c.d.f. $F(\theta)$; M measures market size, and θ represents the underlying value of the property being transacted, with bigger, more luxurious, properties having a higher θ . The upper and lower bounds of the distribution of transaction types determine the heterogeneity of the market. Specifically, as the difference $(\bar{\theta} - \underline{\theta})$ increases, heterogeneity increases. Market heterogeneity is thus proportional to the standard deviation of the distribution of types, that is, $\frac{1}{\sqrt{12}}(\bar{\theta} - \underline{\theta})$. This parametrization is in line with prior work and follows the constructs of *demand heterogeneity* in Adner and Levinthal (2001), *consumer heterogeneity* in Adner and Zemsky (2006) and Zegners and Kretschmer (2017), and *customer heterogeneity* in Makadok and Ross (2013).

The sale of a property involves two activities, $\{s, b\}$. Activity s corresponds to working with property sellers, and b to working with buyers. Two agents $\{1, 2\}$ in the economy must match one seller activity to one buyer activity, either internally via dual agency or externally by dividing labor. For every property sold, the agents earn a commission $\gamma \in (0, 1)$ under dual agency

and $\frac{\zeta}{2}$ under the division of labor.⁵ The number of sellers and buyers for agent $i \in \{1, 2\}$ is the output of the activity-specific production functions:

$$Q_{is} = \rho_{is} \tau_i. \quad (1)$$

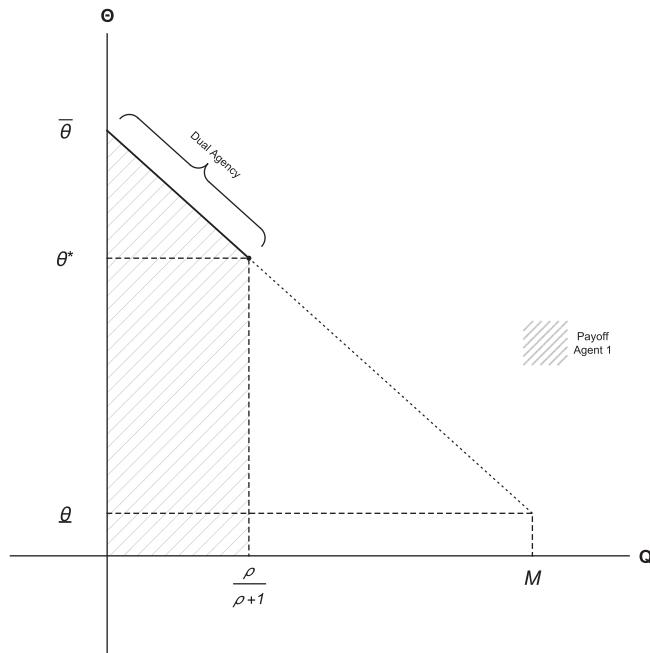
$$Q_{ib} = \rho_{ib} (1 - \tau_i). \quad (2)$$

The parameter $\tau_i \in [0, 1]$ indicates the percentage of time the agent allocates to s . The parameter τ_i captures the basic indivisibility of the individual, who has only a limited amount of time to allocate to alternatives (Rosen, 1983). This leads to “congestion” effects caused by multitasking (Chatain & Meyer-Doyle, 2017), making human assets “non-scale-free” (Levinthal & Wu, 2010) and thus subject to opportunity-cost considerations. The terms ρ_{is} and $\rho_{ib} \in \mathbb{R}_{>0}$ measure the efficiency with which the agent can perform activity s and b , respectively. I assume that $\rho_{1s} = \rho_{2b} = \rho > \rho_{1b} = \rho_{2s} = 1$. This assumption ensures comparative advantage dynamics in the model and drives the economies of the division of labor. With a 50% commission split, Agent 1 has a comparative advantage on the seller side of the market and Agent 2 has the advantage on the buyer side. This assumption implies that for all transactions for which the two agents divide labor, Agent 1 works with the seller and Agent 2 with the buyer. As a reflection of this, Agent 1 is at times referred to as the seller agent and Agent 2 as the buyer agent.

Before solving the model, it is worth considering briefly what would happen if one of the two agents, say, Agent 1, were left alone without the option of collaborating with a counterpart. In this case, she would have no choice but to sell all of the properties in her inventory as a dual agent. This would require matching sellers and buyers in a one-to-one proportion, which she can do by allocating time $\tau_1 = (\rho + 1)^{-1}$ to seller activities and $(1 - \tau_1) = \rho(\rho + 1)^{-1}$ to buyer activities. In total, she would deal with a quantity $\rho(\rho + 1)^{-1}$ of properties and attain a payoff equal to $M\gamma \int_{\theta^*}^{\theta} \theta_s f(\theta_s) d\theta_s$, where $\theta^* = F^{-1}(1 - M^{-1}\rho(\rho + 1)^{-1})$ is the lowest property type she would deal with as a dual agent (F^{-1} denotes the quantile function of F). Figure 1 illustrates these outcomes, providing a graphical representation of the quantity of properties handled by the agent (horizontal axis), types (vertical axis), and of her payoff (meshed area) when performing solo.

Returning to the two-player case, agents are assumed to observe an asynchronous move order. At Time 1, the seller agent, Agent 1, decides which properties to work on and, concurrently, whether to sell the property via dual agency or the division of labor. At Time 2, the buyer agent, Agent 2, decides whether to cooperate with the seller agent or sell other properties via dual agency. The asynchronous move order is a technical assumption that avoids coordination issues and ensures that, if advantageous, the division of labor will emerge in equilibrium. Although it can be dispensed with, as I later demonstrate, it prevents the logic of the arguments from being obscured by inessential details of a technical nature and is convenient to illustrate the results.

⁵I assume that agents have perfect control over which properties to sell via dual agency. In practice, only a portion of the properties for which agents want to capture the whole pie is sold via dual agency. This is because the agents' ability to strategically promote properties to buyers often depends on the type of buyer—who may exhibit substantial aversion to dual agency—or on the rules concerning the disclosure of dual agency (Han & Hong, 2016). As long as the probability of strategically promoting properties is non-zero and independent from (or increasing in) the time the agent spends performing both seller side and buyer side activities, the overall results still hold.

FIGURE 1 Solo agent

Lemma 1 (Polarization of Transactions). Denote the pair $\langle \tau_1^*, \tau_2^* \rangle$ as the subgame perfect equilibrium strategies of the agents in the economy, $\theta_t \in [\theta_1(\tau_1^*, \tau_2^*), \bar{\theta}]$ as the top-end properties, $\theta_m \in [\theta_2(\tau_1^*, \tau_2^*), \theta_1(\tau_1^*, \tau_2^*)]$ as the midrange properties, and $\theta_l \in [\theta_3(\tau_1^*, \tau_2^*), \theta_2(\tau_1^*, \tau_2^*)]$ as the low-end properties. If the division of labor and dual agency coexist in the subgame perfect equilibrium, then:

1. The top-end properties are sold via dual agency;
2. The midrange properties are sold via the division of labor;
3. The low-end properties are sold via dual agency.

(For proof, see Supporting Information Appendix A.)

Figure 2 illustrates the results of Lemma 1, representing the relationship between the cutoff types delineating the top-end, midrange, and low-end properties (vertical axis), equilibrium strategies (horizontal axis), and division of labor. The meshed area corresponds to the payoff of Agent 1, while the gray area to the payoff of Agent 2.⁶

The intuition behind the results of Lemma 1 is the following. Agent 1, who moves first, selects the properties to work on and decides whether to share listings with Agent 2. Agent 1 has limited time and cannot handle all properties in the market, and so has the option of

⁶The mass of properties for which agents divide labor is given by $\Delta(\tau_1^*, \tau_2^*) = Q_{1s}(\tau_1^*) - Q_{1b}(\tau_1^*) = Q_{2b}(\tau_2^*) - Q_{2s}(\tau_2^*)$, whereas $Q_{1b}(\tau_1^*) = \min[Q_{1s}(\tau_1^*), Q_{1b}(\tau_1^*)]$ and $Q_{2s}(\tau_2^*) = \min[Q_{2s}(\tau_2^*), Q_{2b}(\tau_2^*)]$ properties are dealt with via dual agency by Agent 1 and Agent 2, respectively. Using Equations (1) and (2) and the assumption $\theta \sim \text{unif}(\underline{\theta}, \bar{\theta})$, the cutoff types can be computed as $\theta_1(\tau_1^*, \tau_2^*) = \bar{\theta} - M^{-1}(\bar{\theta} - \underline{\theta})(1 - \tau_1^*)$, $\theta_2(\tau_1^*, \tau_2^*) = \bar{\theta} - M^{-1}(\bar{\theta} - \underline{\theta})\rho\tau_1^* = \bar{\theta} - M^{-1}(\bar{\theta} - \underline{\theta})(1 - \tau_1^* + \rho(1 - \tau_2^*) - \tau_2^*)$, and $\theta_3(\tau_1^*, \tau_2^*) = \bar{\theta} - M^{-1}(\bar{\theta} - \underline{\theta})(\rho\tau_1^* + \tau_2^*)$.

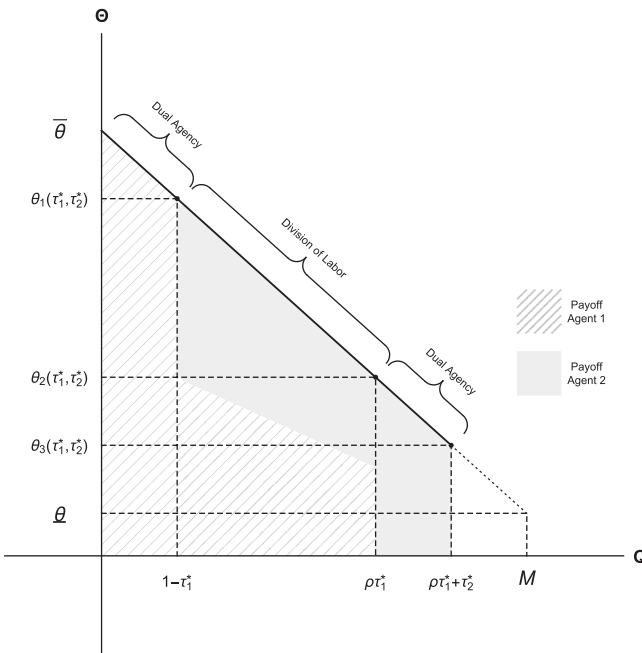


FIGURE 2 Transaction polarization

choosing between top-end and midrange properties; if the decision is to sell any property via dual agency, the agent keeps the top properties and shares the rest. Agent 2 will cooperate on the properties made available by Agent 1 and devote the remaining time to low-end properties. Because the opportunity cost of working on low-end properties is too high for Agent 1, Agent 2 will handle the low-end properties as a dual agent. The mechanisms leading to the polarization of transactions are likely to be replicated in the data. Dual agency should occur for different reasons at either end of the spectrum. For top-end properties, dual agency should be a choice: agents focus on capturing the whole pie for the most valuable transactions and outsource the rest. For low-end properties, dual agency should be an externality: agents perform both sides of the transactions because they have a harder time finding partners willing to divert their efforts from more remunerative opportunities. Thus:

Hypothesis 1 *The division of labor is less likely for top-end and low-end transactions than for midrange transactions.*

The specifics of the agents' strategies are derived by backward induction, starting at Time 2. At this stage, the strategy of the buyer agent, τ_2^* , solves the maximization problem:

$$\max_{\tau_2} \pi_2 = M \frac{\gamma}{2} \int_{\theta_2(\tau_1, \tau_2)}^{\theta_1(\tau_1, \tau_2)} \theta_m f(\theta_m) d\theta_m + M \gamma \int_{\theta_3(\tau_1, \tau_2)}^{\theta_2(\tau_1, \tau_2)} \theta f(\theta_l) d\theta_l, \quad (3)$$

subject to $\tau_2^*(\tau_1) \in [0, 1]$ and the market-clearing constraint $Q_{2b}(\tau_2^*) - Q_{2s}(\tau_2^*) \leq Q_{1s}(\tau_1) - Q_{1b}(\tau_1)$ ensuring that the number of buyer activities performed by Agent 2 is less than or equal to the number of seller activities made available by Agent 1 in the first stage. If the solution is interior,

$$\tau_2^*(\tau_1) = \frac{1+\rho}{(1+\rho)^2+2} \left(1+\rho - M \frac{\bar{\theta}}{\bar{\theta}-\underline{\theta}} \frac{\rho-1}{1+\rho} + \tau_1 \frac{1+3\rho}{1+\rho} \right). \quad (4)$$

Agent 1 anticipates $\tau_2^*(\tau_1)$ and her optimal strategy τ_1^* is derived from the maximization problem:

$$\max_{\tau_1} \pi_1 = M \gamma \int_{\theta_1(\tau_1, \tau_2^*(\tau_1))}^{\bar{\theta}} \theta_i f(\theta_i) d\theta_i + M \frac{\gamma}{2} \int_{\theta_2(\tau_1, \tau_2^*(\tau_1))}^{\theta_1(\tau_1, \tau_2^*(\tau_1))} \theta_m f(\theta_m) d\theta_m, \quad (5)$$

subject to $\tau_1^* \in [0, 1]$ and $Q_{1s}(\tau_1^*) - Q_{1b}(\tau_1^*) \leq Q_{2b}(\tau_2^*(\tau_1^*)) - Q_{2s}(\tau_2^*(\tau_1^*))$. If the solution is interior,

$$\tau_1^* = \frac{1}{1+\rho^2} + M \frac{\bar{\theta}}{\bar{\theta}-\underline{\theta}} \frac{\rho-1}{1+\rho^2}. \quad (6)$$

Proposition 1 (Market Effects on the Division of Labor). Denote the division of labor by $\Delta(\tau_1^*, \tau_2^*) = Q_{1s}(\tau_1^*) - Q_{1b}(\tau_1^*) = Q_{2b}(\tau_2^*) - Q_{2s}(\tau_2^*)$. If the division of labor and dual agency coexist in the subgame perfect equilibrium, then:

1. $\frac{\partial \Delta(\tau_1^*, \tau_2^*)}{\partial M} > 0$. The division of labor is increasing in market size.
2. $\frac{\partial \Delta(\tau_1^*, \tau_2^*)}{\partial \theta} < 0$ and $\frac{\partial \Delta(\tau_1^*, \tau_2^*)}{\partial (-\underline{\theta})} < 0$. The division of labor is decreasing in market heterogeneity.

(For proof, see Supporting Information Appendix A.)

The results of Proposition 1 derive from the signs of M and $(\bar{\theta}-\underline{\theta})$ affecting the agents' optimal strategies in Equations (4) and (6).⁷ The comparative statics of the market effects are illustrated in Figure 3, which provides a lens into the workings of Proposition 1. Panel (a) of Figure 3 demonstrates the first result of Proposition 1, which indicates that the extent to which agents divide labor is an increasing function of market size. This is because when market size increases ($+dM$ in Panel (a) of Figure 3), the economies of the division of labor gain scope. Agents can increase productivity through specialization, thereby compensating the revenues they forego when splitting commissions by selling more units. Furthermore, in larger markets, there are more transactions available for any given property type, and the opportunity cost of sharing commissions for valuable transactions is low because the next transactions at the margin are equally valuable. This result is likely to be replicated empirically. When market size increases, agents would likely face greater residual demands for their services and have several

⁷In Equation (4), M has a negative sign. This implies that, in larger markets, the buyer agent reduces the time allocated to the seller activities necessary to deal with transactions as a dual agent, specializing to a larger extent in the buyer side of the market. In Equation (6), M has the opposite sign, but a similar effect on the specialization of the seller agent. In larger markets, this agent focuses more on seller activities, reducing the number of buyer activities the agent would have performed as a dual agent. Market heterogeneity, $(\bar{\theta}-\underline{\theta})$, has the same sign as market size for both agents, but it enters the optimal strategies at the denominator. As a result, market heterogeneity has the opposite effect of market size on the division of labor.

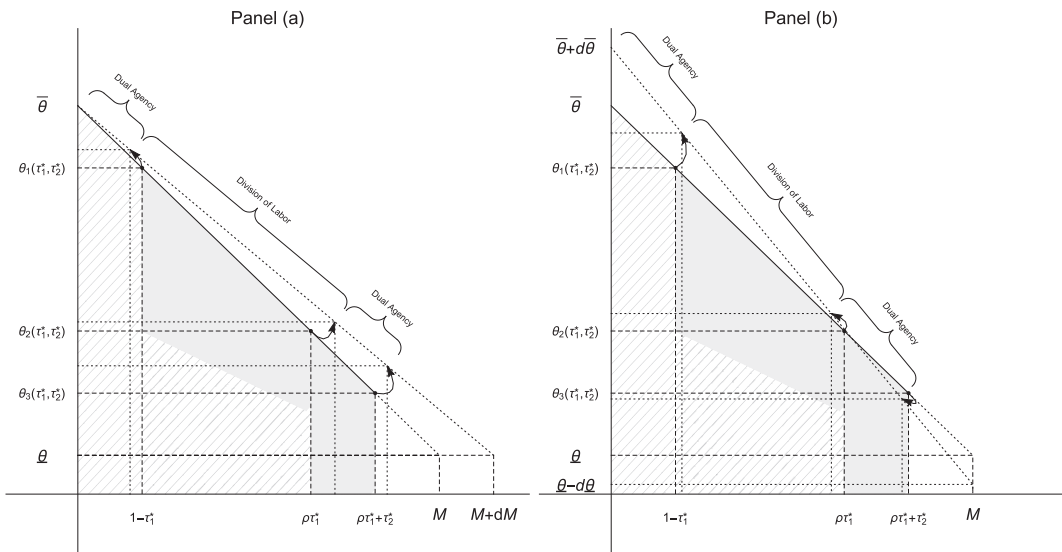


FIGURE 3 Market effects on the division of labor

comparable properties in their inventories. In this context, the division of labor would then become more advantageous, because it would allow them to clear their inventories faster at little opportunity cost. Therefore:

Hypothesis 2 *The division of labor is more likely in larger markets.*

The other result of Proposition 1 is that the division of labor is a decreasing function of market heterogeneity. As shown in Panel (b) of Figure 3, an increase in market heterogeneity ($+d\bar{\theta}$ and $-d\bar{\theta}$) widens the gap between top-end and low-end properties. This causes the economies of the division of labor to become less valuable, because they expand agents' inventories toward cheaper properties. At the same time, the opportunity cost of sharing commissions for top-end properties increases, because the alternative—handling more properties near the low-end—becomes less valuable in relative terms. Empirically, when market heterogeneity increases, agents should respond by exerting more effort to keep top-end transactions in-house, thus reducing their availability to work on other properties. This effect originating at the top should then trickle down to the low-end as an externality. Accordingly:

Hypothesis 3 *The division of labor is less likely in more heterogeneous markets.*

Proposition 1 also implies, as a corollary, that market effects originate near the cutoff types because they influence the allocation of the agents' time at the margin. The localized effects of market size and market heterogeneity can be observed in Figure 3, which reveals that small changes in market characteristics affect the agents' calculus only for the properties close to the cutoffs, while leaving unaffected the properties that are too valuable to be shared or too inexpensive to be worth two people's time. From an empirical standpoint, this should translate into

significant interaction effects between property types and market characteristics, with agents responding to changes in the market only for the properties near the cutoffs. However, because the exact location of the cutoffs on the property spectrum depends on the distribution of the variables of interest, several outcomes are equally likely a priori. Therefore, I offer no hypothesis regarding the interactions and sort out their merits as an empirical question.

3.2 | Discussion of the model assumptions and generalizability

The results of the model are conditional on several simplifying assumptions, which come at the expense of generality. In this regard, the assumption about the asynchronous move order is not without loss because it gives an advantage to the seller agent, the first mover, who can keep the most remunerative properties for herself and trap the buyer agent, the follower, in the corner of the opportunity distribution. Because first-mover advantages do not apply to all markets, there is a question as to whether the results of the model are robust to instances in which both agents can compete to access the most lucrative opportunities. In the last section of Supporting Information Appendix A, I endogenize the agents' move order by letting them develop the capability to attract property sellers at "Time 0." This creates a dynamic akin to strategic factor market competition (Asmussen, 2015; Barney, 1986), whereby ex ante heterogeneity gives the economic agent with the highest synergy the option to outbid a rival for a costly-to-acquire resource or capability. In the context of the model, this synergy is determined by the agents' comparative advantage, which gives the seller agent an edge over the buyer agent when it comes to investing in the ability to attract property sellers. Because of her superior capability, the seller agent can move first and enter a subgame that is qualitatively similar to the one examined in the model, thus leading to the results of Lemma 1 and Proposition 1.

The relationship between Agent 1 and Agent 2 can be interpreted as a hierarchy, a structure that enables Agent 1 to direct Agent 2's collaborative efforts. This result is arguably quite general. It is consistent with existing theories of organization (e.g., Chandler, 1977; Conner & Prahalad, 1996; Demsetz, 1988; Williamson, 1975), which demonstrate how the premise of heterogeneity inherent in the Ricardian model can lead to the emergence of coordinated hierarchical structures. In the context of the empirical setting, the above dynamics can be more specifically interpreted as follows. First-mover agents could be thought of as "more senior" agents. In any given market, senior agents might move first because they likely have an advantage in attracting property sellers vis-à-vis their less seasoned counterparts. Senior agents might have accumulated path-dependent investments in brand equity and reputation (Dierickx & Cool, 1989; Giustiziero, Kaul, & Wu, 2019; Lieberman & Montgomery, 1988) and thus be a seller's first choice in the majority of cases. If so, senior agents would typically operate on the seller side of the market, attract the most valuable properties, and for properties of a lesser value share the pie. Junior agents would operate on the buyer side of the market, collaborate with senior agents on the transactions they would not be able to otherwise access, and perform dual agency for any additional transaction worth their time, but not that of their most senior colleagues. Later in the paper, I verify that this interpretation is consistent with the patterns observed in the data, thus providing an empirical validation of the assumptions of the model.

In addition to the asynchronous move order, it is useful to reflect on other assumptions. On the demand side of the market, agent compensation is assumed to be on a commission basis.

This assumption leads to the results of Lemma 1. If agents were to set undifferentiated prices for their services rather than earning commissions, the revenues produced by high-end, midrange, and low-end projects would be the same, thus muting the incentives that lead to the polarization of transactions. Even so, the results of Proposition 1 would be robust as long as agents exercised market power.⁸ On the supply side of the market, it is assumed that agents face time constraints and that they have the means to perform all the activities that are required to complete a project. These assumptions are two elemental drivers of the opportunity-cost logic behind Lemma 1 and Proposition 1. If agents were not constrained and had the capacity to perform multiple activities at the same time without penalty, they would not have to choose which to pursue. Similarly, if agents had the ability to perform only one activity, they would also not need to make choices. These reflections suggest that the results of this model cannot be generalized to large scale enterprises leveraging economies of scope or to professions in which mastering one activity requires substantial investments of time and effort that prevent other talents from being developed.

Another important assumption on the supply side is that the activities required to complete a project are complements of the type “*s* does not function without *b*.” This assumption affects the agents’ strategies via the market clearing constraint. If the constraint were eased by having another side that matched automatically, then both agents would behave like Agent 1, internalizing the most valuable opportunities and dividing labor for the remaining ones.⁹ Proposition 1, however, would still hold. Alternatively, if the constraint were assumed away by making complementarities between modules looser as, for instance, in the case of two components having largely independent values, then the model would transpose into a diversification framework, as in Baumgardner (1988), where specialization becomes a function of the competitive dynamics emerging when agents operate on the same side of the market. Such a significant change in outcomes underscores a subtle theoretical point regarding the distinction between the notions of specialization and division of labor, and their relation to complementarities. Whereas the division of labor builds on the premise of specialization, specialization alone is not sufficient because there would be no division of labor if individuals specialized in the same activity. For individuals to specialize in different activities, complementarities are necessary to ensure that mutual cooperation entails a total output greater than the agents’ separable outcomes (Alchian & Demsetz, 1972; Arrow, 1979; Yang & Ng, 1993).

In sum, these arguments suggest that the model is, in principle, applicable to contexts in which agents face heterogeneous opportunities, can price-discriminate or exercise market power, have the means to perform all the activities that are required to complete a project, but can also benefit from cooperation with other agents. Because these elements are present in the real estate industry, the model should apply to the empirical setting of this study.

⁸When setting a price, agents would face a trade-off similar to the one in the model. The economies of the division of labor would lead not only to more units sold but also to a reduction in price for all units. Market heterogeneity would have a negative impact on collaborations because, to sell more, agents would need to lower prices to a larger extent, given the greater disparity between top-end and low-end customers. In contrast, a higher demand would tilt the balance toward more collaborations by keeping prices high.

⁹Interestingly, this is what I find in the empirical analyses for “hot condos” (Model 4 of Table 5, graphed in Panel (b) of Figure 6). For hot condos, it is easier for seller agents to find buyer agents who are willing to collaborate.

4 | EMPIRICAL ANALYSIS

The dataset of this study comes from an MLS platform in Southeast Michigan and covers 562,855 sales of residential properties from 2000 to 2010. The data source reports information on virtually all properties for sale in the area during the observation period and covers a wide array of property characteristics (e.g., address, square footage, closing date, and price), agent characteristics (e.g., name of the seller agent, name of the buyer agent, agents' MLS identification codes), real estate agency office characteristics (e.g., MLS identification codes of the offices where the agents were employed), and characteristics of contracts between seller agents and buyer agents, including commissions offered by seller agents to buyer agents. The data source also provides information on "marketing areas" covering neighborhoods within cities and counties, which are designated by local real estate boards as MLS areas. In this study, MLS areas delineate geographic markets, which is consistent with the approach of Barwick, Pathak, and Wong (2017) and Han and Hong (2016).¹⁰ In total, the data cover 541 MLS areas, 15 counties, 27,919 agents, and 3,957 offices.¹¹

4.1 | Main variables

The goal of the econometric analysis presented in this paper is to provide a set of results consistent with the hypotheses, by testing the effects of property types, market size, and market heterogeneity on dual agency.

The independent variables identifying *property type* consist of a set of dummies corresponding to quintiles (20%) of the distribution of property prices in a given month and market. The first quintile (Q1) corresponds to low-end properties at the bottom of the distribution, whereas the fifth quintile (Q5) corresponds to top-end properties; *market size* measures number of listed properties for sale in a given month in a given market; and *market heterogeneity* corresponds to the standard deviation of the price of listed properties for sale in a given month in a given market.¹² The dependent variable, *dual agency*, is a dichotomous variable that takes the value of 1 if a property is sold by an agent performing both the seller and buyer side of the same transaction, and 0 otherwise.

¹⁰Because buyers use the MLS areas as a reference when searching for properties of interest and are unlikely to buy properties in other areas, MLS areas constrain the agents' ability to match buyers and sellers and should therefore delineate the scope of the market clearing constraint at the heart of trickledown effect of market heterogeneity. If geographic markets were identified by larger areas, such as counties (which, on average, cover 36 MLS areas), the trickledown effect connecting dual agency at the top and low ends of the property spectrum would be weaker and difficult to detect empirically. Alternatively, if markets were defined as the sets encompassing all the areas in which agents are active (29% of the agent-month dyads cover more than one MLS area), endogeneity would creep in because any unobserved shock affecting the agent's market scope, such as a productivity shock, would play a role in the identification of markets and in the measurement of market-level variables. In contrast, MLS areas are not affected by this type of endogeneity because they are exogenously assigned by the MLS itself.

¹¹In addition to the information provided by the MLS, I collected information on brokerages' ownership changes, name changes, mergers, acquisitions, and dissolutions from firms' websites. I also conducted interviews with practitioners and verified the names of offices and brokers with multiple listing IDs. I included only agents employed by real estate brokerages with more than five transactions during the observation period and excluded brokerages with small transaction volumes because of the impossibility of retrieving the histories of smaller firms.

¹²Property prices are corrected for inflation according to the Consumer Price Index, using 2010 as the base year.

TABLE 1 Summary statistics of main variables

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Dual agency	0.18	0.39	0	1	1																								
Market size	51.33	40.86	1	243	-0.021																								
Market heterogeneity	92,674	104,701.0		7,810,549	-0.03	-0.03	1																						
Agent experience in days	1,534	1,071	0	3,987	-0.05	0.04	-0.03	1																					
ln(agent cumulative listings + 1)	6.99	3.52	0	16.78	-0.07	0.06	-0.09	0.68	1																				
1(top decile of all agents)	0.58	0.49	0	1	-0.02	0.04	-0.07	0.30	0.65	1																			
1(above the median of all agents)	0.91	0.27	0	1	-0.03	0.02	-0.02	0.20	0.44	0.35	1																		
Ln(# of active agents in office + 1)	3.12	1.03	0	5.31	-0.12	0.11	0.13	-0.01	-0.06	-0.05	0.05	1																	
Office experience in days	1,522	1,036	0	3,987	-0.03	0.01	-0.01	0.67	0.41	0.12	0.06	0.14	1																
1(top 4 office in the market)	0.45	0.5	0	1	-0.01	-0.27	0.00	0.03	0.12	0.09	0.07	0.10	0.08	1															
Fraction of listings sold by office	0.23	0.19	0	1	0.05	0.01	-0.09	0.15	0.33	0.41	0.19	-0.28	0.05	0.08	1														
Fraction of agents in top 10 pct	0.17	-0.16	0	1	-0.03	0.12	-0.02	0.04	0.11	0.09	0.05	0.05	-0.02	-0.01	0.05	1													
Value added	0	0.20	-3.18	1.94	0.02	-0.07	0.16	-0.03	-0.03	-0.12	0.03	0.04	-0.07	-0.03	-0.02	-0.10	1												
Overall experience	3.93	1.55	0	8.75	0.05	0.06	-0.06	0.70	0.96	0.58	0.49	-0.03	0.39	0.22	0.10	0.28	-0.07	1											
Activity specialization	0.67	0.47	0	1	0.17	-0.04	0.00	0.06	0.32	0.29	0.31	-0.06	-0.04	0.06	0.04	0.14	0.03	0.24	1										
Type specialization	0.08	0.08	0	0.20	-0.35	-0.05	0.06	-0.14	-0.43	-0.40	-0.36	0.07	-0.02	-0.11	-0.08	-0.22	0.04	-0.46	-0.31	1									
Commission	3.14	0.53	2	6	-0.06	0.09	-0.12	0.14	0.20	0.21	0.01	-0.09	0.10	0.19	0.06	0.15	-0.23	0.23	-0.01	-0.10	1								
1 (condominium)	0.11	0.31	0	1	0.01	0.04	0.10	0.03	-0.03	-0.04	0.00	0.04	0.04	-0.02	-0.03	0.00	0.05	-0.01	0.00	0.02	-0.04	1							
1 (hot)	0.18	0.39	0	1	-0.04	0.02	-0.09	0.02	0.04	0.05	0.00	-0.04	0.01	0.03	0.04	0.04	-0.07	0.05	-0.01	-0.02	0.08	-0.05	1						

TABLE 1 (Continued)

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25			
Designated agency	0.12	0.32	0	1	-0.18	-0.03	0.01	-0.04	-0.05	-0.03	-0.02	0.07	-0.01	0.00	0.01	-0.03	0.05	-0.05	-0.05	0.07	-0.01	0.00	-0.01	0.00	-0.01	1						
Total square feet of the property	1,616	3,153	0	20,475	0.00	-0.02	0.09	0.01	-0.01	-0.01	0.00	0.02	0.01	0.01	-0.02	-0.01	0.03	0.00	0.00	0.01	-0.03	-0.03	-0.02	0.00	1							
Lot size in acres	0.16	1.88	0	59.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1							
House age in years	40.92	26.67	0	257	0.03	-0.07	-0.04	-0.02	-0.03	-0.02	-0.01	-0.02	-0.02	0.03	0.00	0.00	0.01	-0.02	0.01	0.00	0.00	-0.06	0.01	0.01	-0.01	0.00	1					
Number of bathrooms	1.61	0.74	1	13	-0.02	-0.09	0.29	0.05	-0.04	-0.04	0.00	0.07	0.05	0.03	-0.07	-0.05	0.13	-0.01	0.01	0.04	-0.15	0.05	-0.09	0.00	0.16	0.00	-0.09	1				
Number of bedrooms	3.08	0.85	1	25	-0.02	-0.04	0.12	0.02	0.00	0.00	0.01	0.03	0.01	0.01	-0.02	-0.01	0.05	0.00	0.00	0.01	-0.07	-0.37	-0.02	-0.01	0.13	0.00	-0.03	0.41	1			
List price in 2010 USD	190,044	180,527	1	14,865,971	-0.01	-0.07	0.51	-0.14	-0.18	-0.11	-0.03	0.15	-0.10	0.04	-0.14	-0.05	0.27	-0.13	0.02	0.07	-0.21	-0.05	-0.14	0.01	0.17	0.00	-0.07	0.56	0.34			

In addition to these variables, this study employs a wide array of controls to isolate confounding factors, such as general time trends and different baseline levels across agents, offices, and locations. These controls include market fixed effects, year fixed effects, office-level measures, agent-level measures, and agent fixed effects. It is important to control market fixed effects for time-invariant heterogeneity at the market level because, for example, buyers' aversion to dual agency may be stronger in markets in which buyers are better informed (e.g., university towns vs. rural areas). Year fixed effects control for time-variant trends that could affect the housing market, such as employment rates and demographics. Office-level and agent-level controls, including agent fixed effects, control for the varying propensities of different agents and offices to deal with properties as dual agents. These controls overlap with those in Barwick et al. (2017), with the exception of the variables that would be “bad controls” (Angrist & Pischke, 2009) for the purpose of the current study.¹³ These include commissions offered by seller agents to buyer agents, which I use as a dependent variable in the supplemental analyses, and property-level controls, which I discuss in the robustness tests. In the interest of brevity, I report the full list of variables in Supporting Information Appendix B. Table 1 reports summary statistics and pair-wise correlations for a subset of the variables.

4.2 | Econometric methods

The relevant regression equation delineating the relationships between the variables of interest is:

$$\text{Dual agency} = \beta_1 \text{property type} + \beta_2 \ln(\text{market size} + 1) + \beta_3 \ln(\text{market heterogeneity} + 1) + \beta_4 X + u \quad (7)$$

Dual agency is a dichotomous 0–1 variable modeled as a linear function of a vector of *property type* dummies, the natural logarithm of *market size*, the natural logarithm of *market heterogeneity*, a vector of control variables and fixed effects, *X*, and *u*, a random disturbance. According to standard practice, I log-transform *market size* and *market heterogeneity* to correct for the skewness of their distribution.

In all models, I use standard ordinary least squares (OLS). Although non-linear models are often used when the dependent variable is dichotomous, linear (probability) models make the interpretation of the marginal effects more intuitive and their estimation more robust (Angrist & Pischke, 2009; Singh & Agrawal, 2011). Moreover, linear models avoid the computational complexity associated with the estimation of non-linear models when a large set of controls and fixed effects are included in the analyses. In all specifications, standard errors are clustered at the market-month level to account for the repetition of *market size* and *market heterogeneity* across observations at that level.

4.3 | Main findings

Table 2 reports the main findings. The first three models in the table explore the basic relationship between dual agency, property types, and market characteristics, with higher

¹³For a comprehensive discussion of “bad controls,” refer to Angrist and Pischke (2009: pp. 64–68).

numbered models having stricter specifications with additional controls. Specifically, Model 1 controls only for market fixed effects and year fixed effects; Model 2 adds the agent and office controls; Model 3 adds the agent fixed effects; and Model 4 examines the interactions among property types and the two indicator variables, taking the value of 1 when *market size* and *market heterogeneity* are above their respective yearly median in a given market. Whereas the first three models provide direct tests of the hypotheses, Model 4 examines whether the effects of *market size* and *market heterogeneity* are constant along the property spectrum or more concentrated toward certain property types. The latter case would be consistent with the workings of Proposition 1, which suggests that changes in market characteristics should affect some, but not all properties.

The results of the first three models in Table 2 are generally supportive of the hypotheses. The effect of the *property type* dummies is consistent with the U-shaped relationship of Hypothesis 1. The properties in the midrange (Q2, Q3, and Q4) are predicted to be less likely to be sold via dual agency than the low-end (Q1) and top-end (Q5) properties. The parameter estimates are statistically significant ($\alpha = .01$). In Model 3, the most restrictive of the first three models, a property in Q3 is 18% less likely than a low-end property to be sold via dual agency¹⁴ and 12% less likely than a top-end property.¹⁵ In all models, the effect of *market size* and *market heterogeneity* is consistent with Hypothesis 2 and Hypothesis 3, respectively. The effect of *market size* is negative, while the effect of *market heterogeneity* is positive. The parameter estimates are statistically significant ($\alpha = .01$) and stable across specifications. Using Model 3 as a reference, the economic magnitudes of the parameter estimates can be interpreted as follows. A one standard deviation increase in *market size* (41) above the mean (51) corresponds to a 3% increase in *dual agency* ($-0.0091 \times (\ln(41 + 51 + 1) - \ln(51 + 1))/0.18$). A one standard deviation increase in *market heterogeneity* (104701) above the mean (92674) corresponds to a 12% increase in *dual agency* ($-0.0030 \times (\ln(104701 + 92674 + 1) - \ln(92674 + 1))/0.18$).

Model 4 demonstrates how the effects of *market size* and *market heterogeneity* interact with *property types*. According to the results, also presented in Figure 4, an increase in *market size* (Panel (a), Figure 4) tends to affect mainly properties in the midrange. The interaction is significant for Q2 ($\alpha = .01$), Q3 ($\alpha = .01$), and Q4 ($\alpha = .05$). *Market heterogeneity* (Panel (b), Figure 4), in contrast, is associated with an increase in *dual agency* for the low-end and top-end properties, with the interaction being significant for Q1 ($\alpha = .05$), Q4 ($\alpha = .01$), and Q5 ($\alpha = .01$). These results corroborate the prediction that market effects are likely to have a localized impact along the property spectrum. According to the findings, the effect of *market size* tends to originate in the midrange of the price distribution, while that of *market heterogeneity* is more likely at the extremes. It is possible that an increase in *market size* does not affect the properties at the very top and the very bottom of the distribution because those are the properties for which dual agency is always more likely to occur. Conversely, the effect of *market heterogeneity* can affect these properties, because it originates at the top end, where the opportunity cost of sharing the pie increases and then trickles down to the low end as an externality.

¹⁴This quantity is the ratio between the coefficient of Q3 and the constant.

¹⁵This corresponds to the ratio between the coefficient of Q3 and the sum of the constant plus the coefficient of Q5.

TABLE 2 Main findings

Dependent variable	Dual agency			
	(1)	(2)	(3)	(4)
Q1 (<i>low-end</i>)	Baseline	Baseline	Baseline	Baseline
Q2 (<i>midrange</i>)	−0.0165 (0.0016) [<i>p</i> = .0000]	−0.0186 (0.0016) [<i>p</i> = .0000]	−0.0244 (0.0016) [<i>p</i> = .0000]	−0.0198 (0.0028) [<i>p</i> = .0000]
Q3 (<i>midrange</i>)	−0.0148 (0.0016) [<i>p</i> = .0000]	−0.0180 (0.0016) [<i>p</i> = .0000]	−0.0287 (0.0016) [<i>p</i> = .0000]	−0.0211 (0.0027) [<i>p</i> = .0000]
Q4 (<i>midrange</i>)	−0.0063 (0.0017) [<i>p</i> = .0001]	−0.0115 (0.0017) [<i>p</i> = .0000]	−0.0283 (0.0016) [<i>p</i> = .0000]	−0.0277 (0.0028) [<i>p</i> = .0000]
Q5 (<i>top-end</i>)	0.0286 (0.0018) [<i>p</i> = .0000]	0.0204 (0.0018) [<i>p</i> = .0000]	−0.0077 (0.0018) [<i>p</i> = .0000]	−0.0110 (0.0031) [<i>p</i> = .0003]
Ln(<i>market size</i> + 1)	−0.0111 (0.0017) [<i>p</i> = .0000]	−0.0078 (0.0017) [<i>p</i> = .0000]	−0.0096 (0.0016) [<i>p</i> = .0000]	
Ln(<i>market heterogeneity</i> + 1)	0.0033 (0.0005) [<i>p</i> = .0000]	0.0030 (0.0005) [<i>p</i> = .0000]	0.0030 (0.0005) [<i>p</i> = .0000]	
Q1 × 1 (<i>market size</i> > median)				−0.0017 (0.0022) [<i>p</i> = .4353]
Q2 × 1 (<i>market size</i> > median)				−0.0069 (0.0022) [<i>p</i> = .0021]
Q3 × 1 (<i>market size</i> > median)				−0.0090 (0.0022) [<i>p</i> = .0000]
Q4 × 1 (<i>market size</i> > median)				−0.0046 (0.0023) [<i>p</i> = .0434]
Q5 × 1 (<i>market size</i> > median)				−0.0017 (0.0026) [<i>p</i> = .5189]
Q1 × 1 (<i>market heterogeneity</i> > median)				0.0048 (0.0022) [<i>p</i> = .0265]
Q2 × 1 (<i>market heterogeneity</i> > median)				0.0033 (0.0022) [<i>p</i> = .1382]
Q3 × 1 (<i>market heterogeneity</i> > median)				0.0001 (0.0022) [<i>p</i> = .9816]
Q4 × 1 (<i>market heterogeneity</i> > median)				0.0080 (0.0022) [<i>p</i> = .0004]
Q5 × 1 (<i>market heterogeneity</i> > median)				0.0117 (0.0025) [<i>p</i> = .0000]
Constant	0.1789 (0.0075) [<i>p</i> = .0000]	0.3034 (0.0081) [<i>p</i> = .0000]	0.1717 (0.0142) [<i>p</i> = .0000]	0.1826 (0.0134) [<i>p</i> = .0000]
Observations	562,855	562,855	562,855	562,855
R-squared	0.0308	0.0501	0.1852	0.1852
Estimation	OLS	OLS	OLS	OLS
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

TABLE 2 (Continued)

Dependent variable	Dual agency			
	(1)	(2)	(3)	(4)
Seller agent controls	No	Yes	Yes	Yes
Seller office controls	No	Yes	Yes	Yes
Seller agent FE	No	No	Yes	Yes

Note: Cluster-robust standard errors in parentheses, *p*-values in brackets.

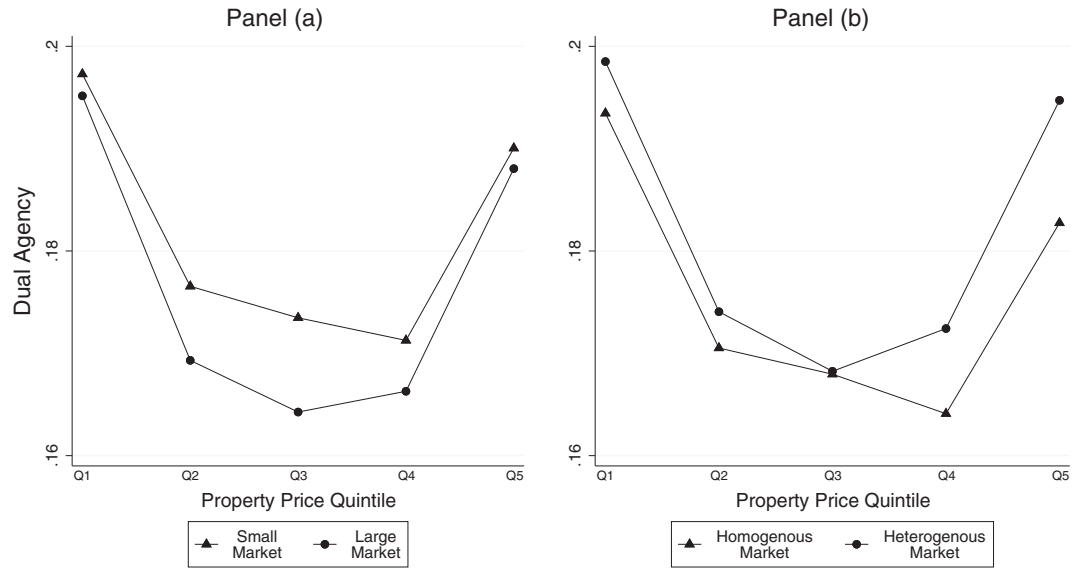


FIGURE 4 Dual agency by property type

4.4 | Supplemental analyses

To understand the mechanisms leading to the main findings, I perform a set of supplemental analyses. In Table 3, I explore the within-agent variation of *property types* and *dual agency* along four dimensions: (a) the value agents add to property prices, estimated as the agent's fixed effect in a hedonic model using property characteristics to predict the natural logarithm of property prices; (b) their overall experience, measured as the natural logarithm of the agent's cumulative sum of seller side and buyer side activities up to the month of the focal transaction; (c) the extent to which agents specialize on the seller side of the market, proxied by a dichotomous variable equal to 1 if agents devote at least 50% of their time to seller side activities in a given month; and (d) the extent to which agents specialize by property type, computed as the probability that the agents' inventory of types would occur if the types were chosen randomly with equal probability (higher values of the *type specialization* variable correspond to more uniform

TABLE 3 Supplemental analysis: Within-agent variation by property type and dual agency

Dependent variable	Value added (1)	Overall experience (2)	Activity specialization (3)	Type specialization (4)
Q1 (<i>low-end</i>)	Baseline	Baseline	Baseline	Baseline
Q2 (<i>midrange</i>)	0.0158 (0.0008) [<i>p</i> = .0000]	0.0489 (0.0028) [<i>p</i> = .0000]	0.0092 (0.0011) [<i>p</i> = .0000]	0.0007 (0.0002) [<i>p</i> = .0042]
Q3 (<i>midrange</i>)	0.0288 (0.0008) [<i>p</i> = .0000]	0.0735 (0.0029) [<i>p</i> = .0000]	0.0167 (0.0012) [<i>p</i> = .0000]	0.0008 (0.0002) [<i>p</i> = .0012]
Q4 (<i>midrange</i>)	0.0467 (0.0010) [<i>p</i> = .0000]	0.0997 (0.0030) [<i>p</i> = .0000]	0.0222 (0.0012) [<i>p</i> = .0000]	0.0014 (0.0002) [<i>p</i> = .0000]
Q5 (<i>top-end</i>)	0.0792 (0.0012) [<i>p</i> = .0000]	0.1261 (0.0033) [<i>p</i> = .0000]	0.0264 (0.0014) [<i>p</i> = .0000]	0.0025 (0.0003) [<i>p</i> = .0000]
Q1 × 1 (<i>dual agency</i>)	−0.0087 (0.0014) [<i>p</i> = .0000]	−0.0408 (0.0065) [<i>p</i> = .0000]	0.1401 (0.0026) [<i>p</i> = .0000]	−0.0582 (0.0003) [<i>p</i> = .0000]
Q2 × 1 (<i>dual agency</i>)	−0.0005 (0.0015) [<i>p</i> = .7451]	−0.0404 (0.0071) [<i>p</i> = .0000]	0.1383 (0.0030) [<i>p</i> = .0000]	−0.0597 (0.0004) [<i>p</i> = .0000]
Q3 × 1 (<i>dual agency</i>)	0.0065 (0.0014) [<i>p</i> = .0000]	−0.0210 (0.0067) [<i>p</i> = .0017]	0.1366 (0.0029) [<i>p</i> = .0000]	−0.0614 (0.0003) [<i>p</i> = .0000]
Q4 × 1 (<i>dual agency</i>)	0.0156 (0.0015) [<i>p</i> = .0000]	−0.0044 (0.0065) [<i>p</i> = .4955]	0.1309 (0.0029) [<i>p</i> = .0000]	−0.0635 (0.0003) [<i>p</i> = .0000]
Q5 × 1 (<i>dual agency</i>)	0.0399 (0.0020) [<i>p</i> = .0000]	0.0144 (0.0067) [<i>p</i> = .0319]	0.1412 (0.0030) [<i>p</i> = .0000]	−0.0650 (0.0003) [<i>p</i> = .0000]
Constant	0.0157 (0.0017)	2.3679 (0.1200)	0.8441 (0.0379)	0.0924 (0.0046)
Observations	1,027,371	1,027,371	1,027,371	1,027,371
R-squared	0.3573	0.7283	0.3115	0.4465
Estimation	OLS	OLS	OLS	OLS
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
Seller agent controls	No	No	No	No
Seller office controls	No	No	No	No
Seller agent FE	No	Yes	Yes	Yes

Note: Cluster-robust standard errors in parentheses, *p* values in brackets.

distributions of types and, therefore, to less specialization by type).¹⁶ These four variables are regressed against the *property type* dummies and their interaction with *dual agency*, as well as agent fixed effects (with the exception of Model 1, where the dependent variable is a fixed effect

¹⁶In essence, the agents' portfolio is assumed to follow a multinomial distribution where each type has a 20% probability of success. By virtue of being a probability, the *type specialization* variable has the advantage of being scale free and can be used to compare agents having large inventories with agents having smaller inventories. It can also help reveal whether agents are unbiased or if they choose properties strategically.

TABLE 4 Supplemental analysis: Commissions

Dependent variable	Commissions			
	(1)	(2)	(3)	(4)
Q1 (<i>low-end</i>)	(baseline)	(baseline)	(baseline)	(baseline)
Q2 (<i>midrange</i>)	−0.1074 (0.0028) [<i>p</i> = .0000]	−0.0795 (0.0026) [<i>p</i> = .0000]	−0.0482 (0.0022) [<i>p</i> = .0000]	−0.0387 (0.0037) [<i>p</i> = .0000]
Q3 (<i>midrange</i>)	−0.1708 (0.0032) [<i>p</i> = .0000]	−0.1267 (0.0029) [<i>p</i> = .0000]	−0.0794 (0.0025) [<i>p</i> = .0000]	−0.0692 (0.0041) [<i>p</i> = .0000]
Q4 (<i>midrange</i>)	−0.2107 (0.0036) [<i>p</i> = .0000]	−0.1507 (0.0030) [<i>p</i> = .0000]	−0.0906 (0.0026) [<i>p</i> = .0000]	−0.0790 (0.0043) [<i>p</i> = .0000]
Q5 (<i>top-end</i>)	−0.2706 (0.0041) [<i>p</i> = .0000]	−0.1933 (0.0034) [<i>p</i> = .0000]	−0.1176 (0.0028) [<i>p</i> = .0000]	−0.1037 (0.0044) [<i>p</i> = .0000]
Ln(<i>market size</i> + 1)	0.0653 (0.0038) [<i>p</i> = .0000]	0.0507 (0.0035) [<i>p</i> = .0000]	0.0352 (0.0023) [<i>p</i> = .0000]	
Ln(<i>market heterogeneity</i> + 1)	−0.0066 (0.0009) [<i>p</i> = .0000]	−0.0069 (0.0008) [<i>p</i> = .0000]	−0.0037 (0.0005) [<i>p</i> = .0000]	
Q1 × 1 (<i>market size</i> > median)				0.0039 (0.0036) [<i>p</i> = .2692]
Q2 × 1 (<i>market size</i> > median)				0.0026 (0.0034) [<i>p</i> = .4416]
Q3 × 1 (<i>market size</i> > median)				0.0057 (0.0028) [<i>p</i> = .0412]
Q4 × 1 (<i>market size</i> > median)				0.0063 (0.0030) [<i>p</i> = .0349]
Q5 × 1 (<i>market size</i> > median)				0.0049 (0.0029) [<i>p</i> = .0862]
Q1 × 1 (<i>market heterogeneity</i> > median)				0.0173 (0.0036) [<i>p</i> = .0000]
Q2 × 1 (<i>market heterogeneity</i> > median)				−0.0001 (0.0033) [<i>p</i> = .9809]
Q3 × 1 (<i>market heterogeneity</i> > median)				−0.0056 (0.0028) [<i>p</i> = .0429]
Q4 × 1 (<i>market heterogeneity</i> > median)				−0.0077 (0.0030) [<i>p</i> = .0101]
Q5 × 1 (<i>market heterogeneity</i> > median)				−0.0088 (0.0028) [<i>p</i> = .0018]
Constant	3.0383 (0.0119) [<i>p</i> = .0000]	3.0420 (0.0117) [<i>p</i> = .0000]	3.2450 (0.0209) [<i>p</i> = .0000]	3.2615 (0.0211) [<i>p</i> = .0000]
Observations	562,855	562,855	562,855	562,855
R-squared	0.1795	0.2645	0.5725	0.5721
Estimation	OLS	OLS	OLS	OLS
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seller agent controls	No	Yes	Yes	Yes

TABLE 4 (Continued)

Dependent variable	Commissions			
	(1)	(2)	(3)	(4)
Seller office controls	No	Yes	Yes	Yes
Seller agent FE	No	No	Yes	Yes

Note: Cluster-robust standard errors in parentheses, *p*-values in brackets.

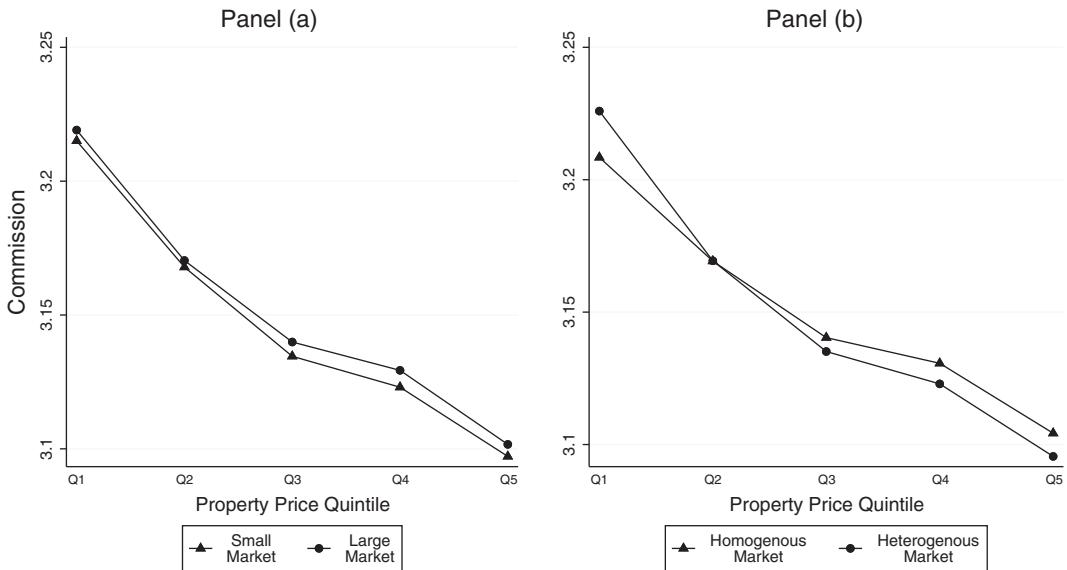


FIGURE 5 Commissions by property type

in and of itself), year fixed effects (with the exception of Model 2, where year dummies would capture the effect of experience), and market fixed effects.¹⁷ The purpose of these analyses is to validate the interpretation of the asynchronous move order assumption discussed in the theory section. The idea is that agents operating at the top end are “first movers” in the sense that they tend to be a seller’s first choice by virtue of their superior experience and capabilities. Models 1, 2, and 3 of Table 3 are consistent with this interpretation. They demonstrate that the agents at the top add 8% more value than in Q1 (with the difference being significant for $\alpha = .01$), are

¹⁷These analyses are based on a dataset consisting 1,027,371 observations, where the unit of analysis is the agent-transaction dyad for agents operating on either side of each transaction. Although the dataset should in principle consist of twice as many observations as the dataset used in the main analyses, it does not because the buyer agent is reported as not being a member of the MLS for 98,339 transactions. In these cases, no information on the buyer agent is available. Agent and office-level controls are not included in these analyses because they are deemed to be “bad controls” (Angrist & Pischke, 2009). In fact, agent and office-level characteristics are likely to be a function of the agents’ ability to source property types or perform dual agency. Therefore, controlling for these variables would soak up the within-agent heterogeneity the supplemental analyses aim to capture. The standard errors in Table 3 are clustered at the market-month level as before.

TABLE 5 Supplemental analysis: Condominiums

Dependent variable	Dual agency			
	(1)	(2)	(3)	(4)
Q1 (<i>low-end</i>)	Baseline	Baseline	Baseline	Baseline
Q2 (<i>midrange</i>)	−0.0164 (0.0018) [<i>p</i> = .0000]	−0.0192 (0.0018) [<i>p</i> = .0000]	−0.0265 (0.0017) [<i>p</i> = .0000]	−0.0289 (0.0020) [<i>p</i> = .0000]
Q3 (<i>midrange</i>)	−0.0151 (0.0018) [<i>p</i> = .0000]	−0.0191 (0.0018) [<i>p</i> = .0000]	−0.0320 (0.0017) [<i>p</i> = .0000]	−0.0354 (0.0020) [<i>p</i> = .0000]
Q4 (<i>midrange</i>)	−0.0060 (0.0018) [<i>p</i> = .0009]	−0.0120 (0.0018) [<i>p</i> = .0000]	−0.0310 (0.0018) [<i>p</i> = .0000]	−0.0359 (0.0020) [<i>p</i> = .0000]
Q5 (<i>top-end</i>)	0.0305 (0.0019) [<i>p</i> = .0000]	0.0214 (0.0020) [<i>p</i> = .0000]	−0.0094 (0.0020) [<i>p</i> = .0000]	−0.0165 (0.0022) [<i>p</i> = .0000]
Ln(<i>market size</i> + 1)	−0.0112 (0.0017) [<i>p</i> = .0000]	−0.0080 (0.0017) [<i>p</i> = .0000]	−0.0096 (0.0016) [<i>p</i> = .0000]	−0.0096 (0.0016) [<i>p</i> = .0000]
Ln(<i>market heterogeneity</i> + 1)	0.0033 (0.0005) [<i>p</i> = .0000]	0.0030 (0.0005) [<i>p</i> = .0000]	0.0031 (0.0005) [<i>p</i> = .0000]	0.0032 (0.0005) [<i>p</i> = .0000]
Q1 × 1 (<i>condominium</i>)	0.0217 (0.0028) [<i>p</i> = .0000]	0.0154 (0.0028) [<i>p</i> = .0000]	−0.0014 (0.0027) [<i>p</i> = .6082]	−0.0073 (0.0030) [<i>p</i> = .0143]
Q2 × 1 (<i>condominium</i>)	0.0393 (0.0036) [<i>p</i> = .0000]	0.0335 (0.0036) [<i>p</i> = .0000]	0.0158 (0.0034) [<i>p</i> = .0000]	0.0064 (0.0036) [<i>p</i> = .0767]
Q3 × 1 (<i>condominium</i>)	0.0655 (0.0047) [<i>p</i> = .0000]	0.0586 (0.0046) [<i>p</i> = .0000]	0.0386 (0.0043) [<i>p</i> = .0000]	0.0293 (0.0045) [<i>p</i> = .0000]
Q4 × 1 (<i>condominium</i>)	0.0842 (0.0060) [<i>p</i> = .0000]	0.0773 (0.0058) [<i>p</i> = .0000]	0.0480 (0.0054) [<i>p</i> = .0000]	0.0410 (0.0056) [<i>p</i> = .0000]
Q5 × 1 (<i>condominium</i>)	0.0728 (0.0074) [<i>p</i> = .0000]	0.0636 (0.0072) [<i>p</i> = .0000]	0.0428 (0.0067) [<i>p</i> = .0000]	0.0332 (0.0070) [<i>p</i> = .0000]
Q1 × 1 (<i>condominium</i>) × 1 (<i>hot</i>)				−0.0317 (0.0057) [<i>p</i> = .0000]
Q2 × 1 (<i>condominium</i>) × 1 (<i>hot</i>)				0.0080 (0.0098) [<i>p</i> = .4147]
Q3 × 1 (<i>condominium</i>) × 1 (<i>hot</i>)				0.0187 (0.0135) [<i>p</i> = .1680]
Q4 × 1 (<i>condominium</i>) × 1 (<i>hot</i>)				0.0129 (0.0177) [<i>p</i> = .4658]
Q5 × 1 (<i>condominium</i>) × 1 (<i>hot</i>)				0.0651 (0.0227) [<i>p</i> = .0041]
Constant	0.1759 (0.0074) [<i>p</i> = .0000]	0.3005 (0.0081) [<i>p</i> = .0000]	0.1691 (0.0143) [<i>p</i> = .0000]	0.1778 (0.0141) [<i>p</i> = .0000]
Observations	562,855	562,855	562,855	562,855
R-squared	0.0322	0.0512	0.1855	0.1871
Estimation	OLS	OLS	OLS	OLS
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seller agent controls	No	Yes	Yes	Yes

TABLE 5 (Continued)

Dependent variable	Dual agency			
	(1)	(2)	(3)	(4)
Seller office controls	No	Yes	Yes	Yes
Seller agent FE	No	Yes	Yes	Yes
Interactions 1 (<i>hot</i>) \times Qs	No	No	No	Yes

Note: Cluster-robust standard errors in parentheses, *p*-values in brackets.

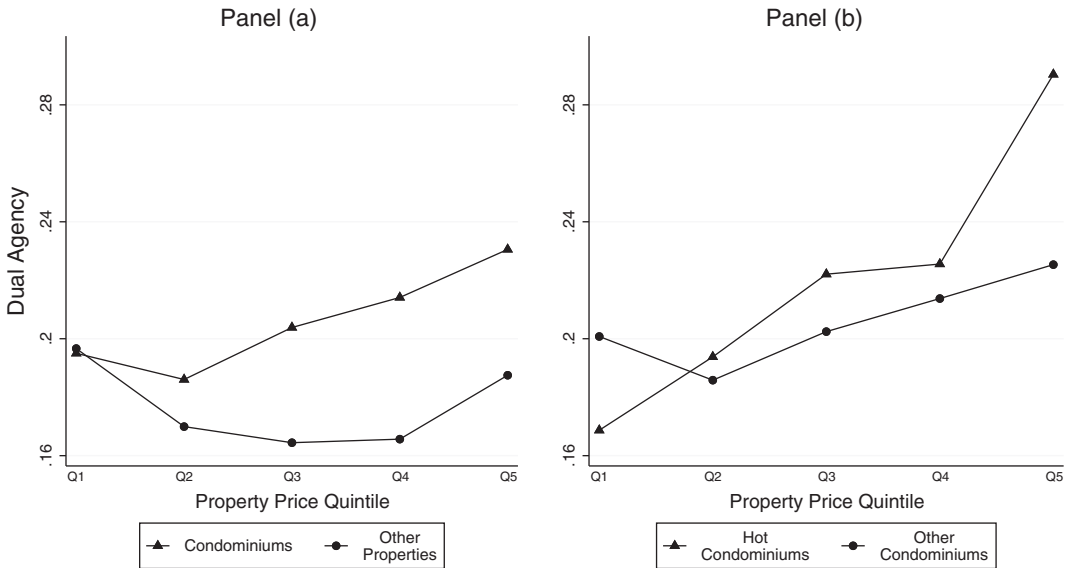


FIGURE 6 Dual agency by condominium type

13% more experienced ($\alpha = .01$), and are 2.6% more likely to operate on the seller side of the market ($\alpha = .01$).¹⁸ *Dual agency* magnifies this polarization. Specifically, agents performing dual agency in Q5 add 13% more value compared to those performing dual agency in Q1 ($\alpha = .01$), are 18% more experienced ($\alpha = .01$), and 2.8% more likely to operate on the seller side ($\alpha = .01$).¹⁹ Taken together, Models 1, 2, and 3 suggest that agents reach the top after having developed the ability to add value on the seller side of the market. To get there, they typically work their way up from the bottom of the price distribution where they start off as buyer agents. The results also indicate that *dual agency* at the tails of the property spectrum is performed by agents at the opposite ends of the real estate pecking order, consistent with the theory that casts dual agency at the top as a choice by the “first movers” (the most senior, capable

¹⁸The quantities correspond to the values of the coefficient of Q5. In Model 1 and 2, the dependent variable is log-transformed so that coefficients approximate percentage changes. In Model 3, coefficients are estimates of changes in probability.

¹⁹These quantities correspond to the coefficient of Q5, plus $Q5 \times 1$ (*dual agency*), minus $Q1 \times 1$ (*dual agency*).

TABLE 6 Supplemental analysis: Designated agency

Dependent variable	Designated agency			
	(1)	(2)	(3)	(4)
Q1 (<i>low-end</i>)	Baseline	Baseline	Baseline	Baseline
Q2 (<i>midrange</i>)	−0.0065 (0.0013) [<i>p</i> = .0000]	−0.0093 (0.0013) [<i>p</i> = .0000]	−0.0098 (0.0013) [<i>p</i> = .0000]	−0.0042 (0.0024) [<i>p</i> = .0777]
Q3 (<i>midrange</i>)	−0.0073 (0.0013) [<i>p</i> = .0000]	−0.0119 (0.0013) [<i>p</i> = .0000]	−0.0121 (0.0014) [<i>p</i> = .0000]	−0.0095 (0.0024) [<i>p</i> = .0001]
Q4 (<i>midrange</i>)	−0.0094 (0.0014) [<i>p</i> = .0000]	−0.0151 (0.0014) [<i>p</i> = .0000]	−0.0149 (0.0014) [<i>p</i> = .0000]	−0.0089 (0.0024) [<i>p</i> = .0002]
Q5 (<i>top-end</i>)	−0.0045 (0.0014) [<i>p</i> = .0014]	−0.0109 (0.0014) [<i>p</i> = .0000]	−0.0108 (0.0015) [<i>p</i> = .0000]	−0.0064 (0.0026) [<i>p</i> = .0126]
Ln(<i>market size</i> + 1)	0.0146 (0.0014) [<i>p</i> = .0000]	0.0135 (0.0014) [<i>p</i> = .0000]	0.0085 (0.0014) [<i>p</i> = .0000]	
Ln(<i>market heterogeneity</i> + 1)	0.0002 (0.0004) [<i>p</i> = .6841]	0.0005 (0.0004) [<i>p</i> = .1972]	0.0007 (0.0004) [<i>p</i> = .0921]	
Q1 × 1 (<i>market size</i> > median)				0.0021 (0.0019) [<i>p</i> = .2593]
Q2 × 1 (<i>market size</i> > median)				−0.0018 (0.0020) [<i>p</i> = .3697]
Q3 × 1 (<i>market size</i> > median)				−0.0002 (0.0019) [<i>p</i> = .8979]
Q4 × 1 (<i>market size</i> > median)				−0.0018 (0.0019) [<i>p</i> = .3537]
Q5 × 1 (<i>market size</i> > median)				−0.0013 (0.0021) [<i>p</i> = .5158]
Q1 × 1 (<i>market heterogeneity</i> > median)				0.0023 (0.0019) [<i>p</i> = .2281]
Q2 × 1 (<i>market heterogeneity</i> > median)				−0.0030 (0.0019) [<i>p</i> = .1245]
Q3 × 1 (<i>market heterogeneity</i> > median)				0.0011 (0.0019) [<i>p</i> = .5503]
Q4 × 1 (<i>market heterogeneity</i> > median)				−0.0035 (0.0019) [<i>p</i> = .0646]
Q5 × 1 (<i>market heterogeneity</i> > median)				−0.0006 (0.0020) [<i>p</i> = .7844]
Constant	0.0913 (0.0060) [<i>p</i> = .0000]	0.0096 (0.0062) [<i>p</i> = .1224]	0.1823 (0.0403) [<i>p</i> = .0000]	0.2035 (0.0403) [<i>p</i> = .0000]
Observations	562,855	562,855	562,855	562,855
R-squared	0.0227	0.0323	0.1008	0.1007
Estimation	OLS	OLS	OLS	OLS
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seller agent controls	No	Yes	Yes	Yes

TABLE 6 (Continued)

Dependent variable	Designated agency			
	(1)	(2)	(3)	(4)
Seller office controls	No	Yes	Yes	Yes
Seller agent FE	No	No	Yes	Yes

Note: Cluster-robust standard errors in parentheses, p -values in brackets.

agents) and dual agency at bottom as an externality suffered by the “followers” (the junior agents).

Also interesting are the results of Model 4, which show that the agents at the low end tend to be more specialized by property type ($\alpha = .01$) and that *dual agency* increases specialization across the property spectrum ($\alpha = .01$). These findings resonate with the notions that agents at the low end tend to have fewer options and that dual agency typically comes at the expense of market scope, consistent with the tradeoff between volume and value capture formalized in the theory section.

In the next set of supplemental analyses, I run the models leading to the main findings of Table 2 on a different dependent variable, that is, the *commission* offered by seller agents to buyer agents. In the majority of real estate transactions, the commission offered to the buyer agents is 3%, typically half of the total commission the property seller pays to the seller agent. However, seller agents can and do offer different “cuts,” depending on circumstances. In my sample, seller agents offer 3% commissions in 71% of the transactions, 3.5% in 8%, and 2.5% in 6%. In the remaining cases, the commission can be a different percentage or a lump sum (e.g., 1,000 USD). From a theoretical standpoint, the commission mirrors the opportunity cost of dividing value. When the cost of splitting the pie is low, commissions should increase and, vice versa. Therefore, I expect commissions to be higher for properties that are low-end and in large markets, but lower for properties that are top-end and in heterogeneous markets.

Table 4 reports multivariate regression models with *commission*, measured as a percentage of the sale price of a property, as a dependent variable. The results of the first three models are consistent with expectations and robust across specifications, with statistically significant parameter estimates ($\alpha = .01$). The highest commissions are typically offered for properties in Q1 (the baseline); they decline as the property type increases, that is, they are lowest for top-end properties in Q5. These findings suggest that agents are likely to incentivize collaborations on low-end properties in order to free up their time and focus on more remunerative opportunities, but offer lower commissions for top-end properties because alternative uses of their time would involve working on less valuable properties. As for the market effects, the variable of *market size* is positively correlated with *commission*, suggesting that when transaction volumes are high and seller agents need to clear their inventories fast, they incentivize the division of labor by offering bigger portions of the pie to potential collaborators. In contrast, *market heterogeneity* is negatively correlated with *commission*, arguably because when properties are heterogeneous, seller agents prefer to capture the whole pie for top-end properties.

Model 4 interacts *property type* with market characteristics. The results, also represented in Figure 5, demonstrate that in larger markets (Panel (a), Figure 5) commissions tend to increase to induce collaborations, although the effect is small and statistically significant only for properties in Q3 ($\alpha = .05$), Q4 ($\alpha = .05$), and Q5 ($\alpha = .10$). When markets become more heterogeneous, however, the effect on dual agency is asymmetrical. Commissions increase for low-end

properties in Q5 ($\alpha = .01$), stay constant for properties in Q2 (no effect), and decrease for properties in Q3 ($\alpha = .05$), Q4 ($\alpha = .05$), and Q5 ($\alpha = .01$). This result reflects the various reasons for which *dual agency* occurs at the top and low end. When the price difference between the top end and the low end becomes large, the opportunity cost of sharing the pie for top-end properties also increases and, in response, seller agents offer lower commissions. Conversely, for properties at the bottom of the distribution, the opportunity cost of sharing decreases, because agents would rather spend their time on the much more remunerative properties at the top end. To compensate for this, seller agents respond by further increasing commissions.

In Table 5, I investigate whether the U-shaped relationship between *property type* dummies and *dual agency* is affected by the buyers' aversion to dual agency. Buyers might perceive dual agency to be against their best interest because dual agents have a fiduciary duty to sellers and could inflate property prices to increase their compensation. If buyer aversion to dual agency were stronger in the midrange, then the outcome of such unobserved heterogeneity would be a U shape. In Models 1, 2, and 3 of Table 5, I explore this possibility by running the same Models 1, 2, and 3 of Table 2, but with the addition of interactions between the *property type* dummies and the variable $1(\text{condominium})$, a dummy equal to 1 for condominiums (11% of transactions, see Table 1). Within the same MLS area, "condos" tend to be standard and similar to one another and thus should attract a homogenous set of buyers with comparable education, occupation, and income status. If the U shape were the result of unobserved heterogeneity among buyers, then it should flatten for condos because these are more likely to attract a uniform clientele.

The results, however, paint a different picture (see Panel (a) of Figure 6, which illustrates the findings of Model 3). *Dual agency* is on average more frequent for condos than for other types of properties, and more so in the midrange and top end of the price distribution. These results can be explained by the opportunity cost theory of this study. Given that condos are standard, they require less effort to sell and therefore allow agents to capture the whole pie at a low opportunity cost. This, in turn, increases the frequency of *dual agency*, especially for condos in the midrange and at the top end where the benefits of capturing the whole pie are more significant.

In Model 4 of Table 5, I find additional corroborating evidence for this explanation by interacting the *condominium* and *property type* dummies with the variable $1(\text{hot})$, a dummy equal to 1 if the closing price of the focal property is higher than its listing price, which indicates a "bidding war" (observed in 18% of transactions, see Table 1). From a mere probabilistic standpoint, one would expect a lower frequency of dual agency for "hot" condos because a larger availability of motivated buyers should reduce the chance of the highest bidder being among the seller agent's clients. However, as demonstrated in Panel (b) of Figure 6, the opposite is more likely. *Dual agency* tends to be more frequent for hot condos, with the exception of those at the low end of the price distribution. One possible explanation is that the agents' calculus for hot condos tilts toward dual agency because these properties are more valuable and easier to sell. At the low end, however, agents divide the labor in order to have a quick sale and move on to hotter condos. These dynamics are consistent with what the theory would predict for situations in which it is easier to find agents willing to cooperate (see the discussion of the model assumptions) and indicate that the externality that drives *dual agency* at the low end of the distribution does not apply to hot condos. This is reflected in Panel (b) of Figure 6, where the U-shaped relationship between *property type* dummies and *dual agency* morphs into an upward sloping curve.

Finally, in Table 6, I verify that the main findings are not the outcome of policies and incentives at the office level. Typically, an agent shares revenues (e.g., 50%) with the agent's office. However, because the majority of offices offer incentives to keep transactions in-house, if the agent collaborates with another agent within the same office (rather than dividing labor with an agent from a competing office), the originating agent can keep a higher split (e.g., 60%). It is then possible that *dual agency* is driven by an office policy of keeping transactions in-house rather than by the opportunity cost of dividing value. As a test for this alternative explanation, Table 6 shows the results of running the same models in Table 2 on the probability of observing *designated agency*, which occurs when seller agents and buyer agents work for the same office (but are not the same person). If *dual agency* and *designated agency* were driven by the same underlying mechanism, the results in Table 6 would be similar to those in the main analyses, but, in fact, they are rather different. *Designated agency* is on average more likely for low-end properties (Q1, the baseline) and less likely for any other type. Furthermore, the effect of *market size* is positive, rather than negative, and *market heterogeneity* has practically no effect. The interactions in Model 4 are not significant.²⁰ These results show that, when agents prefer to divide labor (for low-end properties and in bigger markets), office incentives steer them toward prioritizing collaborations within the same office, but they do not fundamentally alter individual preferences for dual agency.

In Supporting Information Appendix C, I conduct additional analyses to ensure that results are robust to controlling for property characteristics, to identifying geographic markets with counties rather than MLS areas, to the bursting of the housing bubble of 2007, and to the exclusion of outliers. Overall, the results are consistent.

5 | CONCLUSION

The division of labor is the fundamental mechanism that aggregates individual endeavors into broader economic objectives, whether mediated by market mechanisms, online platforms, or organizations. In this article, I examine an important, but understudied cost inherent in the division of labor: the opportunity cost of dividing value. By its very nature, the opportunity cost of dividing value is defined by market characteristics that delineate the opportunity set in the environment. In large markets, the opportunity cost of sharing value is low, because there is an abundance of opportunities and more scope for the efficiency gains of dividing labor. When markets are heterogeneous, however, and transactions have different valuations, the shadow cost of “splitting the pie” can reduce individual incentives to collaborate, because the time and resources saved by dividing labor may not have good alternative uses. In light of this, opportunity cost considerations can prompt agents to refrain from dividing labor for the most valuable transactions or for transactions at the opposite end of the spectrum. For the most valuable transactions, not dividing labor is a choice in which agents decide to focus their limited time on high-value transactions and to outsource the rest. For the least valuable transactions, not dividing labor is an externality. Agents may not divide labor because they cannot find partners willing to divert their time from more remunerative opportunities. I find support for the theory in the residential real estate industry, for which I demonstrate that the division of labor is more likely for properties in the midrange of the price distribution and in larger markets, but less

²⁰Except for the interaction between *market heterogeneity* and Q4, which is significant for $\alpha = .10$. Because there is no systematic pattern in the estimates, this could be the result of statistical noise.

likely at the tails and in markets where the disparity between the most valuable transactions and the rest is large. Supplemental analyses and robustness checks contribute to a consistent picture.

The theory and findings of this study make several contributions to the literature. First, this study extends the classic conversation on the influence of markets on the division of labor. This literature, largely influenced by Adam Smith's (1776) contributions, argues that the division of labor is limited by the extent of the market. Later works, most notably by Becker and Murphy (1992), have emphasized coordination costs—such as search costs associated with matching individuals to tasks—as an additional limiting factor, suggesting that decreases in coordination costs should lead to more division of labor, even when the market size is fixed (Cheng & Yang, 2004; Garicano & Wu, 2012; Meier et al., 2019). With digitalization and online labor markets matching jobs to contractors on the fly (Agrawal et al., 2015), the coordination costs emphasized by the existing literature may be becoming less relevant. This trend is exemplified by the online platforms used by real estate agents, the MLSs, which greatly reduce coordination costs, such as search costs and information asymmetries. Although a theory of coordination costs loses its theoretical bite in these settings, the explanation based on opportunity cost introduced by this study does not. Furthermore, because opportunity costs matter only when opportunities are heterogeneous, this explanation adds market heterogeneity as a new dimension to Adam Smith's original theory.

Second, this study offers the novel insight that intermediaries may not be well equipped to handle high-value and low-value transactions. This finding points to important managerial implications for all intermediaries facing the threat of disintermediation, which occurs when customers circumvent intermediaries to avoid fees (Gu & Zhu, 2020). Often, to deter disintermediation, managers resort to sticks and carrots by either imposing penalties or subsidizing participation (Agrawal et al., 2015; Hagiu & Rothman, 2016). These approaches, however, are merely palliative measures that do not deal with the underlying causes of the problem. According to the theory outlined in this study, managers are advised to reconsider their business model and redirect their services toward transactions in the midrange of the opportunity distribution. This range is the most favorable because these transaction types are valuable enough for intermediaries to earn good margins, but not so valuable as to make the commission fees seem unreasonable. These considerations can apply to numerous brokering industries in which intermediaries are remunerated on a commission basis, such as online platforms (e.g., Amazon) that charge a percentage of the transaction price to third-party sellers (Zhu & Liu, 2018), digital labor markets, such as Upwork, that charge a percentage of each transaction to workers (Agrawal et al., 2015), insurance agents who earn commissions on insurance premiums (Grossman & Hart, 1986), and salespeople in auto dealerships who split commissions when collaborating on car sales (Bennett, 2013). An interesting case in point is the famous La Place de Bordeaux, a complex web of intermediaries involved in the sale of Bordeaux wines. In recent years, inconsistent weather due to climate change has expanded variability and limited the stock of great wine (The Economist, 2020). This has led some of the priciest producers, including Sichel, Moueix, and Maitre d'Estroumel, to disintermediate (Pawtosky, 2015), making it harder for lesser chateaux to offload their inventory because “[w]hen intermediaries make a low margin, they’re not interested in distributing your wine” (The Economist, 2020). Although the costs and benefits of dividing labor must be contextualized to each setting, the polarization of transactions observed in the current study could explain some of these dynamics.

Third, this article contributes to the literature on strategic human capital, which often treats specialization as a long-term career choice and equates what individual workers know with what individual workers do (Byun et al., 2018). Although in some settings, the one-to-one mapping between individual knowledge and domain of practice is a useful approximation, individual workers may be adaptable (McKinsey, 2014; Wright & Snell, 1998) and know more than what they do at any given time (Teece, 1982). Therefore, at least in some contexts, specialization may not only be a function of expertise, but also a reflection of the opportunities in the environment. A generalist in a heterogeneous market could be a specialist in a large market, and vice versa. Because these adaptations require agents to reallocate their time and resources to different value-adding activities, the dynamics highlighted in this paper provide the micro-foundations for characterizing individual workers as resources that are fungible and redeployable (Levinthal & Wu, 2010; Sakhartov & Folta, 2014).

This study, of course, also has its limitations. Although the context of the real estate brokerage industry is advantageous for this study in that it provides rich transaction-level data and substantial variation in market size and market heterogeneity, a valid concern is whether the theory and findings generalize to other settings. As discussed in the theory section, the mechanisms examined in this study cannot apply, among others, to settings in which opportunity-cost considerations are immaterial. These include, on one side of the spectrum, professions in which agents have the capacity to master just one activity and, on the other side of the spectrum, industries in which large scale firms can leverage economies of scope. A second limitation of this study relates to the empirical analyses. Although I collected fine-grained data and ran several analyses and robustness checks, my ability to draw a causal inference from the results is limited, insofar as I analyzed a complex phenomenon without observing natural experiments or exogenous shocks in the data. Given these issues, I do not claim causality. Rather, my intent is to develop a coherent theoretical framework within certain boundary conditions and present a set of consistent results. In keeping with the exploratory intent of the analyses, my study invites further investigations based on complementary approaches with a view toward advancing our understanding of the mechanisms at work and laying the groundwork for cumulative theory building.

In conclusion, whereas strategy scholars have often treated the division of labor as an “external commonplace” (Houthakker, 1956: 182) and “developed some blind spots in understanding it” (Raveendran et al., 2016: 2110), this study takes a contrarian approach to the conventional wisdom and invites further analyses of this important topic. With the diffusion of digital labor markets and the emergence of the gig economy (Agrawal et al., 2015), this study of the division of labor can help scholars understand the transition of modern economies to the age of hyperspecialization (Malone et al., 2011).

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