Market Concentration, Labor Quality, and Efficiency: Evidence from Barriers in the Real Estate Industry

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Abstract

This paper studies the anticipatory effects of entry barrier policies. Exploiting a novel dataset of U.S. real estate licensees and quasi-exogenous variation in licensing costs for brokers, I show that broker entry increased 50% in anticipation of the increasing barrier, resulting in a net long-term increase in the stock of brokers. For consumers, the entry influx decreases market concentration but lowers service quality. For laborers, the policy decreases the share of minority entrants. The average broker shifts from performing listings to overseeing more agents, highlighting the importance of accounting for heterogeneity in worker role when analyzing labor market efficiency.

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1 Introduction

While economic theory posits that free entry into markets is efficient, there are certain market failures that barriers to entry may address, such as consumers having incomplete information about the quality of service providers. Occupational licensing is a common entry barrier that governments and trade associations deploy to protect consumers from untrained participants. These barriers come with a trade-off: while the increased training may lead to a better quality workforce, it can also lead to an increase in market concentration and potentially higher prices. Prior research has shown that licensing leads to welfare losses for both workers and consumers (Kleiner and Soltas, 2023). Policies such as licensing, education, or insurance requirements which create entry barriers are often announced in advance, which can trigger current and potential laborers to make employment decisions in anticipation. However, the effects of these anticipatory reactions remain understudied.

This paper studies the consumer and employment consequences of changes to entry barriers in the context of the U.S real estate industry. The impacts of occupational licensing are particularly important in this setting, where there are two types of licensees in the labor market: a "salesperson," the entry level, who must work under the employment of a "broker," the professional level. While either licensee can legally represent others in real estate transactions, brokers can, in addition, take a portion of the commission earned on the listings performed by the salespeople they oversee. Real estate represents both a massive consumer industry and a large labor market. Nearly 90% of home sellers and 90% of home buyers used a real estate agent in 2024, and there are over 3 million licensees in the U.S.[1] Further, real estate has been shown to be a context in which free entry is socially wasteful because the price of the service does not adjust (Hsieh and Moretti, 2003).[2]

Establishing connections between occupational licensing barriers and market outcomes is chal-

[1]Source: National Association of Realtors (NAR). See https://www.nar.realtor/research-and-statistics/quick-real-estate-statistics.

[2]This lack of price competition has been under legal scrutiny since the opening of the *Joshua Sitzer, et al. v. The National Association of Realtors, et al.* case, a class-action lawsuit which alleged that large brokerages along with the National Association of Realtors (NAR), the highly influential trade organization, enforced policies which inflated commission prices paid by home sellers.

lenging for two primary reasons. The first is data and measurement. Research into the effects of occupational licensing across industries has historically been limited due to the high cost and lack of availability of regulatory data (Kleiner and Timmons, 2020). Particularly when studying an apprenticeship industry such as real estate, the timing of entry and exit between the levels of employment *within* the industry, not just in and out of the industry, must be observed. It is also often difficult to measure productivity and performance in many service industries. To overcome this challenge, I compile a novel dataset of the universe of real estate licensees in five states, matched with productivity information in the form of listings data from multiple Multiple Listings Service (MLS) databases within those states. These new data allow me to identify licensees by type and connect licensees to their own output, which prior studies have been unable to leverage.

The second challenge to estimating the effects of entry barrier changes is identification; there are many factors which could explain worker entry into an industry and consumer outcomes in that industry. To isolate the effect of labor market entry on industry outcomes such as worker productivity, an exogenous change in the cost of entry is needed. I exploit a policy reform providing quasi-exogenous variation in an entry barrier. In 2012, the Texas Real Estate Commission (TREC) announced a significant increase in the eligibility requirements to upgrade to a broker license. Notably, this policy was announced a year before it went into effect, giving brokers time to enter under the old requirements.

To understand the potential anticipatory effect of such a reform, I provide a conceptual framework in which brokers have a dynamic wage equation and are forward looking. When there is an unexpected announcement of a future increase in the licensing costs, an anticipatory influx of brokers is predicted in the short term before a long-term decrease in entry. The framework predicts short-term decreases in market concentration, laborer quality, and efficiency. The long-term consequences depend on the magnitude of the short-term entry response to the policy and whether paying a higher entry cost correlates with performing at a higher quality.

To test these predictions, I compare counties in Texas with similar control counties in other states before and after the policy reform in a synthetic difference-in-difference framework (Arkhangelsky et al., 2021) that weights control counties and time periods based on their similarity to treated counties. I first establish that the policy generates a significant anticipatory influx of new brokers. This amounts to an increase of nearly 50% from the pre-announcement quarterly average. While entry is ultimately suppressed in the long term, the total stock of licensed brokers is still increased by about 7% in the average treated county, contrary to the policy's expected effect.

Using the policy as a quasi-exogenous shock to broker entry, I consider the effects of the entry barrier change on consumers and workers. On the consumer side, I find that the short-term influx leads to a persistent decrease in market concentration. I examine whether consumers benefit from this increased competition, because in the U.S. real estate industry, prices for real estate agent services (i.e., commissions) generally do not adjust. I find that the new brokers who rush to enter under the easier regime are of lower quality than prior cohorts of brokers, as measured by probability of sale and aggregate listing outcomes (i.e., sale price and days on the market). Further, the broker cohorts which enter in the long term after the policy are still of lower quality, likely due to requirements which incentivize converting a higher number of listings in a short time frame. Taken together, these results suggest that higher licensing costs induce more broker entry in the short term while providing minimal benefits to consumers in the long term.

On the employment side, I find that the higher entry cost has distributional consequences and leads to a 24% decrease in the share of entering female brokers and a decrease in Hispanic broker entry. Additionally, I consider the effects of the policy on labor market efficiency. Existing studies of the efficency effects of entry costs typically treat all laborers within an industry as equal. However, these traditional measures of efficiency may not work as well in a context in which there are managers and subordinates. For instance, this paper confirms prior evidence that increased entry leads to a decrease in labor market efficiency when defined as total listings per agent (Hsieh and Moretti, 2003). This is suggestive of inefficiency in the sense that, with the increased entry, brokers are no longer working at their capacity constraint. However, I provide evidence that brokers are in fact expanding their market presence in that the mean firm has fewer brokers performing listings and has a higher ratio of salespeople-to-brokers. This demonstrates that brokers are shifting to more managerial duties and suggests that analyses of labor market efficiency should directly account for heterogeneity in worker role.

This paper contributes to the literature on occupational licensing by providing evidence of the effects of anticipatory employment responses to entry barriers. The long-term effects of licensing stringency on quality and market concentration have been studied in a wide array of industries, beginning with the work of Friedman and Kuznets (1945), which showed that increasingly restrictive entry into medical school led to growth in doctors' wages.[3] While increased licensing costs are generally linked to long-term increases in market concentration, the literature provides mixed results regarding labor quality. Many studies find no evidence of increased quality of service after increased licensing. For instance, Farronato et al. (2024) use the setting of home improvement services to show that more stringent licensing leads to less competition with no increase in consumer satisfaction. On the contrary, Larsen et al. (2020) show that stricter academic qualifications for teachers increased the left tail of the quality distribution (as defined by the teacher's undergraduate institutions), and Anderson et al. (2020) show that midwifery licensing laws in the early 1900s led to a decrease in maternal and infant mortality. Studies which have focused on the real estate industry (Shilling and Sirmam (1988), Guntermann and Smith (1988), Johnson and Loucks (1986), Carroll and Gaston (1979), and Chung (2022)) have largely relied on cross-sectional variation in licensing requirements. Further, due to lack of listings data, few of these papers have linked occupational licensing to the housing outcomes obtained by agents, whereas my rich listings data linked to licensees allows me to more directly capture market concentration and quality.

This paper additionally contributes our understanding of the impact of real estate agents as intermediares in housing transactions. This is the first paper to directly consider the distinction between salespeople and brokers, and to use licensee data across multiple states, as opposed to just one, to do so. Using data from Virginia, Turnbull et al. (2022) find that, because brokers have stronger reputational concerns in that their income is dependent on the performance of their whole office, they are more likely to sell a client's home as they would their own. Using licensee

[3] See Angrist and Guryan (2008), Blair and Chung (2019), Zapletal (2019), Yelowitz and Ingram (2021), and Bowblis and Smith (2021) for additional analyses.

information from Nevada, Lopez (2021) finds that licensees and their family members sell their properties at higher prices. The author controls for whether the licensee holds a broker or salesperson license, though a difference in performance of the two is not the focus of the study. Turnbull and Waller (2018) similarly control for the type of license while studying the added value that "top-tier" agents, as defined by total market share, bring to transactions.[4]

Finally, this paper contributes to a growing literature on efficiency in the real estate industry by accounting for the different types of agents in the market. Hsieh and Moretti (2003) posit that free entry is inefficient in a setting such as real estate when the price of the service is generally fixed. This is because commission payments are dissipated amongst new agents, and the productivity of the average agent decreases, which suggests that agents are not operating at their capacity constraint.[5] Gilbukh and Goldsmith-Pinkham (2019) study the market effects of a high volume of these "inexperienced" agents. The authors show that more inexperienced agents have a lower probability of sale, even when controlling for the brokerage they work for.[6] They write a model estimating the effect of the experience distribution of agents on housing market liquidity, and show that increasing entry costs, which should in turn lead to better experienced agents, increases liquidity. However, similar to the results herein, the authors find that increased licensing alone would not be sufficient to reduce entry inefficiencies. I expand on both of these studies by considering how entry costs may affect salespeople and brokers differently, while also contributing to the broader literature on labor efficiency by studying a labor market in which there are both managerial and non-managerial roles.

[4]This complements earlier work by Levitt and Syverson (2008), which shows that agents (without accounting for license type) sell their own home at higher prices than those of their clients due to agency costs.

[5]The authors utilize a static setting to show that, when the price of land in a city increases, the number of real estate agents increases, the productivity of an average real estate agent decreases, and real wage of typical agent remains unchanged. This is further empirically supported by Ingram and Yelowitz (2019), which find that, while an increase in house prices leads to an influx of new agents, this effect is dampened by more stringent licensing.

[6]Similarly, Waller and Jubran (2012) find that "rookie" agents, i.e., those with a salesperson license for less than two years, sell for less and have longer market duration.

2 Institutional Context

2.1 Real Estate Agent Labor Market

All U.S. states require a license in order to represent others in the sale or purchase of real estate. A real estate agent will generally have one of two licenses: either a "salesperson" or a "broker" license.[7] Both salespeople and brokers can represent clients in buying and selling property. However, a salesperson must do this under the supervision and employment of a broker. A broker, on the other hand, is eligible to work independently and to hire other real estate agents to work for them. A key distinction between the two types of licensees is that only brokers can legally contract with clients. Thus, even if a salesperson obtains a listing on her own, the broker's name must be on the contract, and it is the broker who is paid and provides payment to the salesperson. Because of this, brokers typically share the commission on the sales of all salespeople they supervise.[8]

There are relatively low barriers to obtaining a salesperson license. An individual must take a certain number of credit-hours of education, either in person or via online instruction, focused on issues such as contract terminology, disclosure laws, and fair housing polices, and must then pass two exams.[9] One is focused on state-specific rules and regulations, and one is a broader national-focused exam. If the individual passes the exams, she may then officially apply for a license. For that license to be active and valid, the prospective salesperson must find a licensed broker who will sign the license. In other words, a salesperson cannot begin representing clients until they are employed by a broker. [10]

[7]This licensing process is overseen by a state real estate commission or board, traditionally made up of a number of local real estate professionals, who is charged with establishing the licensing requirements, monitoring real estate activity, and enforcing real estate rules and regulations.

[8]The most common payment scheme is the commission split model, in which the broker and salesperson split the gross commission from all transactions the salesperson completes. Another common, though less prevalent, scheme is office fee model, in which the salesperson pays the broker a regular fee but keeps all commissions.

[9]To be eligible, agents typically must also be at least 18 years old, be a U.S. citizen or permanent resident, have a high-school diploma or equivalent, and pass a background check.

[10]The total fees to become a salesperson can range from about \$400 to \$1,000. See this example from online education provider, VanEd: https://www.vaned.com/blog/cost-to-get-a-real-estate-license/. This includes the fee for the background check, a course registration fee, an exam fee, and an application fee. This is a relatively small entry cost: For context, a 3% commission to a listing agent on a listing sold for \$100,000 is \$3,000, and even if the agent splits 50% of that with the broker, they still make \$1,500.

The eligibility requirements to upgrade to a broker license are more restrictive than those for a salesperson license, though similarly low in direct financial costs. To be eligible to upgrade to a broker's license, an agent must be actively licensed as a salesperson for a given number of years, depending on the state.[11] Before applying, the agent must take additional broker-specific coursework and pass another set of exams. In certain states, the application must include a list of prior transactions facilitated by the agent, which is typically signed off by the current supervising broker. For instance, a requirement of precisely this type was added as part of the 2012 Texas policy change.[12]

One primary reason to upgrade to a broker's license is the ability to work for oneself and therefore not have to share any commission. Brokers can also continue to work under the supervision of a fellow broker - in this case, the agent would typically earn a better commission split with her supervising broker than if she were to remain a salesperson.[13] A second potential benefit of upgrading is that a broker can hire and supervise other agents and, in turn, earn money off of the transactions of those agents. Finally, one might upgrade to a broker's license in order to be a "managing" or "designated" broker for a brokerage firm, which may come with additional compensation for running the day-to-day operations.

While the main financial cost of becoming licensed as a broker, e.g., the additional coursework, exam, and application fees, are similar to that at the salesperson level, there are additional non-monetary costs which may dissuade an agent from upgrading. In fact, only about 20% of all licensees ever upgrade to the broker level.[14] For instance, there are startup costs of setting up an office for brokers who choose to open their own brokerage firm. Similarly, brokers who manage other salespeople typically spend fewer hours working directly with clients and more time manag-

[11]The modal experience requirement across states is two years, according to the Association or Real Estate Licensing Law Officials (ARELLO).

[12]A license of either type typically has to be renewed every two to three years, depending on the state, to remain active. The renewal process requires an additional amount of continuing education coursework during the renewal period and a renewal fee to the state. Failure to comply with the renewal process will result in an inactive, and ultimately expired, license.

[13]These brokers are typically called an "associate broker" or a "broker-salesperson."

[14]Source: National Association of Realtors (see https://www.nar.realtor/research-and-statistics/quick-real-estate-statistics), and author's real estate licensee data.

ing and training their supervisees. A broker also assumes the liability of their employees; in other words, if a broker's salesperson behaves unethically or illegally, the broker could lose her license or suffer other disciplinary action.

2.2 Texas Real Estate Commission Policy Change

Prior to 2012 in Texas, an agent had to be licensed as a salesperson for at least two years to be eligible to apply to be a broker. Before applying, the agent was required to take 270 course-hours of broker-specific education and then pass another set of exams similar in structure to those for salespeople.

The Texas Real Estate Commission (TREC) Act was amended via Texas Senate Bill 747 to state that, effective January 1, 2012, an aspiring broker applicant would need to hold a salesperson's license for at least four years before applying, doubling the previous standard, and, if the applicant did not have a degree from an accredited university, take an additional 630 course-hours of education, tripling the previous standard. Additionally, the bill noted that TREC would have to write new rules instituting an experience requirement, as defined by a number of transactions completed, for prospective brokers.

These new rules were announced in October 2011, and were again effective on January 1, 2012. Future applicants would have to show evidence of completed transactions (i.e., representing either a seller or buyer in a completed sale) in order to be eligible for a broker's license. Before, broker applicants did not have to provide any proof of trtransactions and could essentially apply to be a broker after two years of holding a salesperson's license, even if the agent had never been involved in an actual transaction.[15]

Specifically, TREC introduced a point system which assigned various values to different types of transactions (e.g., residential vs. commercial, rentals vs. sales, etc.). The point system amounted

[15] The organization "Texas REALTORS" described the motivating force of the policy change as "focused on better preparing license holders to represent consumers in real estate transactions and ensuring education for applicants and license holders is targeted and of the highest quality." See https://www.texasrealestate.com/members/government-affairs/legislative-affairs/the-texas-real-estate-commission/.

to a salesperson having to show evidence that she had transacted at least one property in each of the four years prior to applying and a minimum of around twelve transactions total across those four years. This record of experience would have to be verified by the applicant's employing broker.

Any agent who was already licensed as a broker and had active status before the announced policy change was made effective was grandfathered in by the policy, but needed to meet the new education requirements by the next renewal.[16] An overview of the policy change is shown in Table 1. There were no similar changes made regarding the eligibility to obtain a salesperson's license.[17] To this day, Texas remains the most stringent state in terms of broker licensing.

Table 1: Broker Requirements in Texas Before and After TREC Change

	Before	After
Salesperson Wait Time	2 Years	4 Years
Total Transactions	0	12
Min. Transactions per Year*	0	1
Education No 4 Yr Degree**	270 Hrs	900 Hrs
Education w/ 4 Yr Degree	270 Hrs	270 Hrs
Exams	Yes	Yes

*Applicants needed at least one transaction in each of the preceding four years and about twelve transactions total across those four years

**Broker responsibility course now required; additional 630 hours of elective education needed if no college degree

3 Conceptual Framework

To understand the anticipatory reactions to future changes in entry barriers such as the TREC policy, I develop a conceptual framework which expands on the stylized setting of Hsieh and Moretti (2003). Suppose a pool of current and potential brokers which are forward-looking and face some entry cost.[18]

[16]Note that the policy referred to being eligible to *apply* to be have a broker's license. Applications can take up to a year to become official; thus, *entry* effects are delayed, and for empirical purposes I consider January 2013 to be the effective date of the policy. This gap in application and approval is why the data will show a run up of active brokers in late 2012 (as opposed to 2011), because these applications were likely submitted just before the policy went into effect in late 2011.

[17]The only change for salespeople in Texas at the same time was the removal of exemptions from course work for those who had college credit in a real estate-related field.

[18]In other words, this abstracts away from the choice to become a salesperson and from delineating the pool of salespeople who work part-time versus those who become a salesperson with the intention of one day considering an

3.0.1 Broker Employment with Static Entry Cost

Consider the case of the broker entry decision when facing a fixed entry cost, F, which is exogenously set by a policymaker or trade association. Let N_t be the total number of brokers in the labor market in period t.

Let the total number of listings in a market be denoted by X_t and the average price in the market by P_t. Assume that listings are randomly assigned to brokers, such that each broker performs $\frac{X_t}{N_t}$ listings. Further, in line with prior research which shows that commission prices in the real estate industry have historically been unchanging (Barwick and Wong (2019), Barwick and Pathak (2015), and Han and Hong (2011)), assume there is some fixed commission rate c.[19] Finally, assume that a share ρ of listings are sold. For now, we will assume this is constant across agents. Thus, each broker earns the same period-specific wage, denoted by w_t, where[20]:

$$w_t = \frac{\rho \cdot c \cdot P_t \cdot X_t}{N_t}.$$

Assuming a constant interest rate r and a constant exit rate δ, the discounted present value of working at the professional level in period t can be written as:

$$V_t = \int_t^\infty w_s e^{-r(s-t)} \cdot e^{-\delta(s-t)}\, ds,$$

which is equivalent to:

$$V_t = \rho \cdot c \int_t^\infty \frac{P_t X_t}{N_t} e^{-(r+\delta)(s-t)}\, ds. \tag{1}$$

Therefore, the value of being a professional is changing according to the schedule:

upgrade to the broker level.

[19]Some subset of these listings will be performed by that broker's salespeople, for which the broker will earn some share of the commission c. For simplicity, I assume this share of listings performed by salespeople is constant across brokers.

[20]Aside from notation changes, this wage equation is the same of that posited in Hsieh and Moretti (2003), with one exception. The authors theorize a fixed number of *sales*, denoted S, which is equivalent to $\rho \cdot X_t$ in my setting. I make this change so that I can still maintain that volume is fixed in a period, while relaxing an assumption that agents are homogeneous (here, I can vary ρ across agents).

$$\dot{V}_t = (r+\delta)V_t - g(N_t), \tag{2}$$

where $g'(N_t) < 0$. In a steady-state equilibrium, $\dot{V}_t = 0$ (i.e., the value is unchanging with respect to time). The $\dot{V}_t = 0$ schedule is downward sloping, because any rise in V_t would require the number of workers (N_t) to fall in order to preserve $\dot{V}_t = 0$. The dynamics of V_t are unstable. Holding N_t constant, if $\dot{V}_t > 0$, V_t will rise and if $\dot{V}_t < 0$, V_t will fall. This is depicted in Figure 1.

The flow of brokers in a given period, $\dot{N}_t$, will be determined by the share of exits, denoted by δ, and the number of entrants.[21] Assume the rate of broker entry (i.e., upgrading from a salesperson to a broker license) is proportional to the difference between V_t and the entry cost, F. In other words, if there is a larger gap, there will be more entry. Therefore, the number of brokers evolves as:

$$\dot{N}_t = -\delta N_t + \gamma(V_t - F) \tag{3}$$

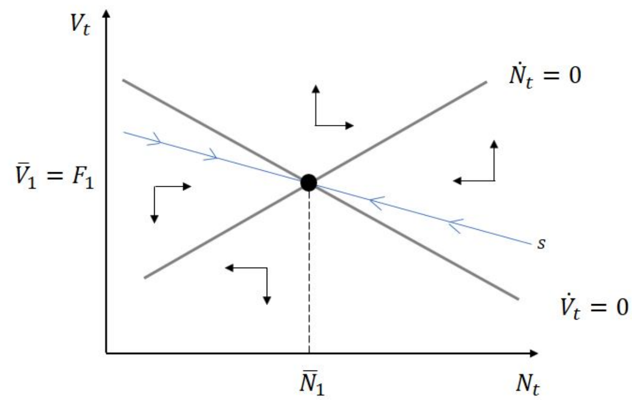
As illustrated in Figure 1, the $\dot{N}_t = 0$ schedule is upward sloping. When N_t is high, larger values of V_t will be needed to preserve zero entry. The steady-state equilibrium, where $\dot{V}_t = \dot{N}_t = 0$, occurs when at the point denoted $(\bar{V}, \bar{N})$ where $V_t = F$, and $N_t = f^{-1}((r+\delta)F)$. In other words, the value of being a broker is equal to the fixed cost, and the number of professionals is a function of the discounted fixed cost, following from equations 2 and 3. For any given number of brokers N_t, the corresponding equilibrium V_t is reached by the labor market adjusting along the saddle path s.

3.0.2 Broker Employment with Unanticipated Increased Entry Cost

Suppose that, to increase the qualifications and quality of the overall pool of brokers, a social planner announces unexpectedly that the entry cost will increase at a future period $t+k$. The lifetime value of being a professional immediately rises with the announcement due to the decreased

[21] In this setup, the assumption of a constant exit rate broadly means that a broker only exits the labor market when they retire die. This is generally supported by the data; in real estate, a license expires if an agent fails to complete the renewal process in a given time frame. While salespeople are more likely to do this, official broker exits are much more uncommon.

Figure 1: Fixed Entry Cost Dynamics



Note: Figure displays the relationship between the value of working as a broker, V_t, and the number of brokers in the market, N_t. F_1 denotes the fixed cost of entry into the broker profession. The light blue line labeled s denotes the saddle path for this dynamic equilibrium.

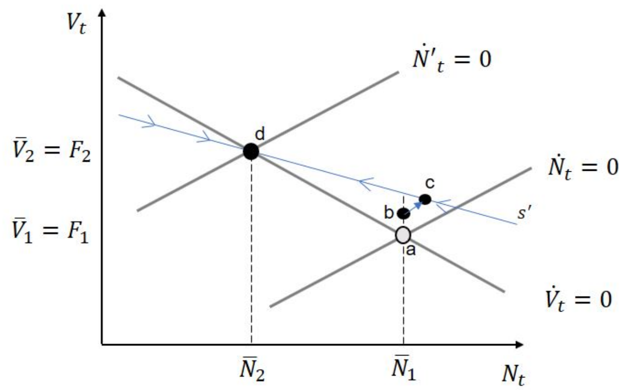
entry in the future. Since F has not yet increased, but V_t has immediately increased with the announcement, then by equation 3, there will be an immediate entry of professionals. Because F only increases later at $t+k$, there should be an initial increase in professional entry, followed by a decline at time $t+k$. Importantly, the specifics of these dynamics depend on the size of the immediate initial increase in V_t.[22] This new movement is depicted in Figure 2.

From the initial equilibrium a, when the entry cost is announced to eventually increase from F_1 to F_2, there is an immediate increase in the value of being a professional to some point b. At point b, the entry path is still governed by the original F_1, which corresponds to the $\dot{N}_t = 0$ schedule because F_1 is still in effect. At precisely period $t+k$, the dynamics will evolve along the new saddle path s' (point c), determined by the new entry cost F_2 and the corresponding $\dot{N'}_t = 0$ schedule. A new steady-state equilibrium, point d, will eventually be reached.

Figure 3 Panel A displays the flows of brokers under this setting, while Panel B displays the total stock of brokers. The solid red lines represent a market where the increased cost as described

[22]Two additional conditions must hold. The first is that V and N are governed by the initial system (F_1) through time $t+k$, and the new system (F_2) from $t+k$ onward. The second is that there are no other future increases in V that can be anticipated by the labor market participants (i.e., they do not expect any other future changes in requirements).

Figure 2: Unanticipated Increase in Entry Cost



Note: Figure displays the relationship between the value of working as a broker, V_t, and the number of brokers in the market, N_t under the case of a future increase in the fixed cost to enter the profession (F_t). The light blue line labeled s' denotes the saddle path for this dynamic equilibrium. The dynamic movement from the initial equilibrium *a* to the new steady state equilibrium *d* is described in Section 3.0.2.

occurs; the dashed gray lines represent a market which sees no change in entry cost. The strong increase in flows at t_1 translates to a relatively faster-growing stock between t_1 and t_{1+k}. The stock then grows relatively more slowly after t_{1+k}. Note that the way it has been drawn in Figure 3 Panel B assumes that the new equilibrium flow rate under the new licensing regime is greater than zero. Eventually the stock may be relatively lower at some point in the future determined by the new equilibrium flow rate $\dot{N}_t$ (which is dependent on δ and γ).

As such, a policy of this type is predicted to generate two phases: In the short term, entry and stock will increase from t_1 to t_{1+k}. In the long term, entry will decrease, and stock will potentially decrease from t_{1+k} onward depending on the parameters δ and γ.

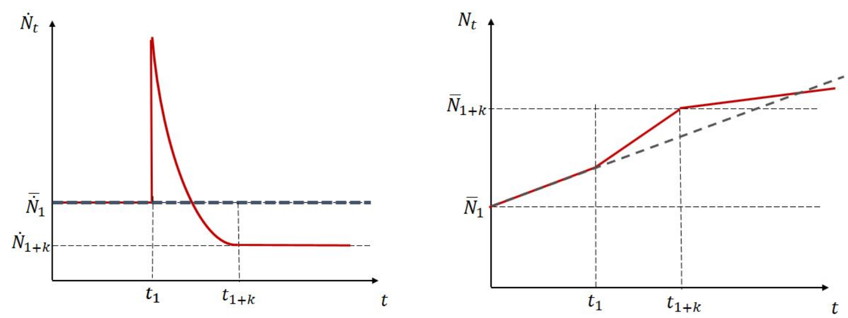
3.1 Concentration and Quality

3.1.1 Concentration

Let us measure the concentration in the market at a given time t using a Hirschman-Herfindahl Index (HHI) (see Rhoades (1993) for an overview of the development and applications of the

Figure 3: Flows and Stock of Brokers over Time

(a) Flows (b) Stock



Note: Figure illustrates the impact of an increase in entry cost on the flows, $\dot{N}_t$, (Panel A) and total stock, N_t, (Panel B) of brokers over time. The increase in entry cost is announced at time t_1 and effective at time t_{1+k}. The dashed line represents what would happen if no such policy occurred.

HHI). The index is calculated as:

$$h_t = \sum_{i=1}^{N_t} s_i^2,$$

where s_i is a broker i's share of the total listings. Note that smaller values of h_t represent a market that is *less* concentrated (i.e., exhibiting less market power). In this stylized setting where listings are randomly assigned, s_i is the same for all brokers and decreasing in N_t.

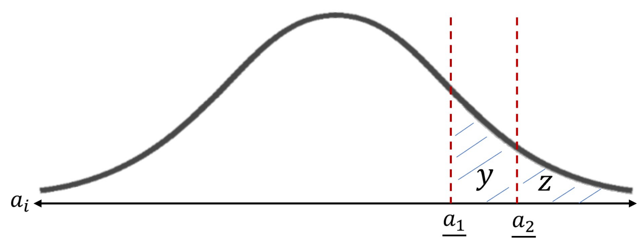
Thus, in the short term, when the policy induces entry and N_t is unambiguously increasing, h_t will decrease. In the long term, however, the dynamics of h_t will depend on δ and γ; in other words, only if the reduced entry in the long term leads to a stock of brokers which is lower than before the policy was announced will we expect to see a decrease in market concentration.

3.1.2 Quality

Now, let us assume that ρ, the share of listings that an agent sells, is a function of an agent's quality, a_i. In other words, higher quality agents sell a higher share of their listings. Recall that the social planner institutes a higher fixed cost F for the purpose of increasing the quality of new brokers. Therefore, assume that a fixed cost F correlates imperfectly to a quality cutoff $\underline{a}$ (such that any broker who pays F to enter should be of a quality greater than or equal to $\underline{a}$).

Let us denote this corresponding quality cutoff at the original fixed cost F_1 as $\underline{a_1}$, and the announced future fixed cost F_2 to be $\underline{a_2}$, where $\underline{a_2} \geq \underline{a_1}$. Assume some hypothetical distribution of a_i, as depicted in Figure 4.

Figure 4: Agent Quality Distribution



Note: Figure illustrates the distribution of the quality of individual brokers, a_i. When the cost of entry increases from F_1 to F_2, the quality threshold to be a broker (assuming that a higher entry cost correlates to higher quality labor) increases from $\underline{a_1}$ to $\underline{a_2}$.

Note that under the F_1 licensing regime, salespeople from both region y and region z are eligible to enter as a broker, whereas under the higher cost F_2 regime, salespeople from region y will be excluded.

As hypothesized above, the announcement will induce a certain number of salespeople to become brokers in the short run. Since salespeople from region y will be excluded once the cost increases, there will necessarily be relatively more entrants from y than from z in the short term, whereas there will only be entrants from z in the long term.

Therefore, in the short run, the average quality of entering brokers should decrease, while in the long run, quality of entering brokers should increase. Note, however, that this is dependent on the assumption that the higher entry cost correlates with higher underlying quality.

3.2 Efficiency

I define efficiency by the average productivity of real estate brokers, as in Hsieh and Moretti (2003). Decreasing average listings productivity points to social inefficiency because this suggests that agents are not producing at their capacity constraints; put differently, there are agents working in the real estate industry who could be engaged in profitable activities in other industries. Since there is no price competition, consumers cannot benefit from an increasing number of brokers.

In this setting, total listings (X_t) are exogenous and therefore fixed, while total sales ($\rho \cdot X_t$) are not.[23] Therefore, I can separate the concept of sales per broker from listings per broker. While listings per broker should unambiguously move inversely with the stock of brokers, it is not obvious in this setting how sales per broker (i.e., the preferred measure of broker productivity in this stylized setting) will move. This is because it is possible that higher quality brokers (i.e., those with a larger a_i) may close more sales.

3.3 Summary of Predictions

In summary, a future increase in the cost of entry for brokers should induce an influx of broker entry and therefore lead to and increase in stock in the short term. While broker entry will necessarily decrease in the long term, the effect on the overall stock is ambiguous and is an empirical fact which can be tested.

The announcement will decrease market concentration in the short term, and only if the stock of brokers ultimately decreases in the long term will market concentration increase. The announcement should induce brokers of lower average quality (relative to before the announcement) to enter the market in the short term. In the long term, assuming the stricter entry requirement improves the quality of brokers, entering cohorts will be of higher relative quality. Like market concentration, efficiency, as defined as the average broker listing productivity, is expected to decrease in the short term and move inversely to broker stock in the long term.

[23] In the Hsieh and Moretti (2003) framework, the total volume of sales is fixed. Social efficiency is defined by the productivity of the average agent, or $\frac{Sales}{N}$. Thus, anything that increases N decreases social efficiency.

Importantly, the effects for concentration and efficiency are tied primarily to the stock of brokers, N_t, not the flows $\dot{N}_t$. Thus, while an increased entry barrier may decrease entry as intended long term, the impacts of the policy will be dependent on the magnitude of the short-term reaction.

4 Data and Summary Statistics

4.1 Primary Data Sources

To study the effects of anticipatory reactions to entry barriers and to test the predictions of the above framework, this paper leverages two primary sources of data. The first source is licensing records for real estate agents in five states. Few papers have addressed the distinction between real estate brokers and salespeople because there is no central repository of licensees nationwide and no standardization across states in how licenses (and changes in license status) are recoded.[24] By compiling various public records, I collect a novel dataset of the license information for all real estate licensees, both current and inactive, in Texas, Florida, Louisiana, Ohio, and Connecticut dating back to at least 2000. This is the first paper to my knowledge to study salespeople and broker licensing combining multiple states' records. Having multiple states is beneficial because it is then possible to draw from many counties to create suitable controls for the counties in Texas, all of which were treated by this policy change.

Real estate license records generally identify an individual's type of license (e.g., broker or salesperson), when she received it, whether and when the license expired, and for whom she works if currently active. These records allow one to identify the type of license an agent and how long she has been licensed without relying on deducing tenure from observed listing activity. This also makes it possible to track entry and exit of both tiers of licensees over time.

The second data source is property listings from various Multiple Listing Service (MLS)

[24] In particular, there is significant heterogeneity across states in how to account for the transition from a salesperson to broker license. Many states append the broker license to the salesperson license without recording a date change, which makes it impossible to observe when the upgrade occurred. Other states completely replace a salesperson license in the records with the new broker license, making it impossible to observe when the individual was first licensed as a salesperson.

databases accessed via CoreLogic. An MLS is a database that agents in a given geographic area use to communicate their property listings with each other. MLS data includes any information that would show in a property listing such as list price, property characteristics, and crucially, the listing and buying agents' names. The MLS data, however, does not denote which type of license the seller or buyer's agent has, and thus in order to connect listing outcomes to agent type, both sources of data are necessary.

4.2 Sample Construction

The samples used in the following analysis include all counties from these five states which are present in the MLS listings from 2009-2019. Counties must have at least three listings per quarter for all quarters conditional on the following: listings must be a residential property for sale (as opposed to rental), have a list price within the 1st to 99th percentile for that county-quarter, and be on the market for less than two years. The sample retains only the counties which do not have missing covariate data for all quarters in the sample period as well. These data include county-by-quarter employment indicators from the Quarterly Census of Employment and Wages (QCEW) and Zillow's Home Value Index (ZHVI).

Aggregate Sample: The primary final analysis sample aggregates licensee information up to the county level, and matches this with listings information also aggregated to the county level. Table 2 compares the counties in Texas which are used for the aggregate sample against the remaining Texas counties which are not included due to data limitations. There are 250 counties in Texas in the licensee data (and, since both the Census and QCEW cover a universe, 250 counties in those as well). There are two channels through which a county may be excluded from the sample: the county does not appear in the MLS (either because it is not a database accessible through CoreLogic or there are not at least three listings in each quarter of analysis), or the county does not have Zillow ZHVI data. There are 40 counties which have all three sources populated. The biggest restriction is MLS access.

The data in the aggregate sample skew towards larger counties. The 88 counties without Zillow or MLS data have a mean population of less than 10,000 and are about 70% rural; thus, this study is more informative about larger, more urban areas. However, there is still a mix of rural areas in the sample; the average county in the sample is 36% rural. Additionally, housing dynamics such as the share of listings sold and the mean sale price are similar across counties with MLS coverage that are and are not in the final sample.

Table 2: Balance Table - Means of Key Variables for Texas Counties

Variable	**Source**	**In Final Sample**	**In all 3, Not Enough MLS**	**In MLS, no ZHVI**	**In ZHVI, No MLS**	**No ZHVI, No MLS**
Total Listings	MLS	1,016.75	40.95	84.25	.	.
Share Sold	MLS	0.54	0.43	0.49	.	.
Mean Sale Price	MLS	625.75	18.65	43.50	.	.
ZHVI	Zillow	123,515.70	86,929.59	.	95,762.18	.
Stock of Brokers	License	471.60	32.90	28.50	64.85	5.74
Stock of Salespeople	License	1,697.23	95.15	98.63	233.94	14.66
Earnings	QCEW	3,467.15	3,228.05	2,916.88	3,319.06	3,323.55
Employment	QCEW	152,294.10	14,026.80	8,157.38	22,452.57	2,090.69
Population	Census	469,554.20	66,823.90	42,985.63	83,985.64	8,860.09
Pct Rural	Census	36.46	63.13	73.82	46.36	69.49
N	**250**	**40**	**20**	**8**	**94**	**88**

Note: Data is shown for 2011Q4. There are 250 total counties in the public record licensee data (and, since QCEW and the Census cover a universe, all 250 of those counties have these variables as well). The column "In Final Sample" represents the 40 Texas counties used in my final sample of analysis (that have both MLS and Zillow ZHVI coverage). "In All 3, Not Enough MLS" refers to counties that have Licensee, MLS, and Zillow data but do not have enough MLS coverage either in terms of number of listings or times periods. "In MLS, No ZHVI" has MLS data but not Zillow ZHVI index, while "In ZHVI, no MLS" are the counties without MLS data. "No ZHVI, No MLS" has neither Zillow nor listing data. Note that for the "Mean Sale Price" row, all sale prices are winsorized to the 3rd and 97th percentile for a year-quarter across all states.

Matched Listings Sample: For analyses which require licensee-level information on both her type of license and her listing activity, the licensing records must first be matched to the listings data. There are many reasons to expect that not all of the licensed agents will be found in a record in the MLS. Primarily, the CoreLogic MLS data do not cover entire states.[25] Further, many agents

[25]For instance, the CoreLogic MLS data used herein contain six of the MLS systems in Texas. The two largest MLS'es in Texas, the Houston Association of Realtors (HAR) MLS, which covers the larger Houston area, and the North Texas Real Estate Info Systems (NTREIS) MLS, which covers the larger Dallas area, are both in my data. By way of comparison, I consider the CoreLogic MLS data in relation to the Texas A&M (TAMU) Real Estate Center Data, which provides county-level aggregate housing market measures for over 50 MLS systems in Texas. In Appendix A Figure A1 I compare the total number of sold listings according to the CoreLogic MLS data with the total number of sold listings in the TAMU data in the year 2017 by county. Bluer counties represent counties in which the CoreLogic data, which I use, have more listings. Of note, the CoreLogic data have better coverage in the Dallas and Houston areas, while coverage is lacking in the greater Austin area.

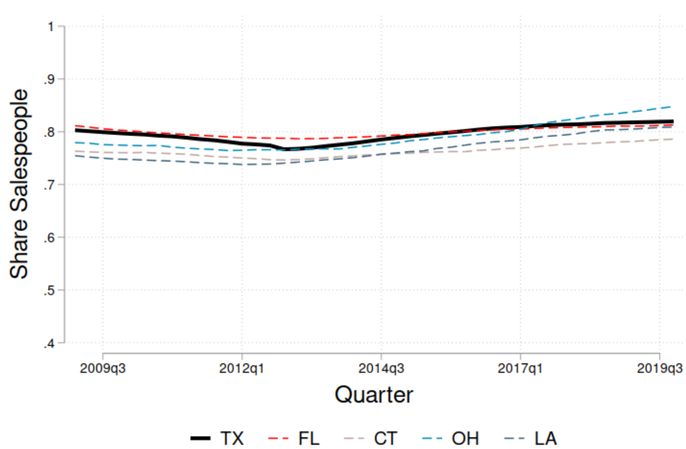
will obtain a license but then never actually perform a listing, while some agents work exclusively with rentals, commercial properties, timeshares, etc., which are all excluded from the sample. Appendix B Table 1 compares the number of listings in the MLS data in the aggregate sample to the listings which ultimately end up matched to agents licensed in those counties and are therefore in the matched listings sample.

4.3 Stylized Facts

4.3.1 Labor Market Structure for Real Estate Agents

These novel licensing data provide new information about the labor market structure in the real estate industry. Notably, the share of licensees that are salespeople is consistent both over time and geography at around 80% (see Figure 5). The thick black line represents the share of salespeople in Texas, while the remaining dashed lines represent the other states in the licensee data. Across the five states, the share is quite similar, ranging only from about 75% to 80%. In addition, this share has remained consistent across all states over the last decade.

Figure 5: Salesperson Share of Agents



Note: Figure reports the share of all licensed agents in each state who have a salesperson's license.

The composition of the labor market in this industry has remained constant across time and geography even though the absolute number of both types of agents varies across states. Table 3 reports the mean stock and entry of brokers and salespeople per 1,000 residents across counties in each of the states in the sample. Note that Florida has the largest real estate labor market with over seven salespeople and two brokers per 1,000 people, even though Texas has a larger population. The smallest of the states, Connecticut, falls in the middle with just over one broker and almost four salespeople per 1,000. In the empirical work, I will show that once controlling for various county and time trends, the stock of both brokers and salespeople is indistinguishable across states in the years before the TREC policy announcement, suggesting this heterogeneity in the number of workers is largely due to heterogeneity in housing markets. Despite these differences, the mean salesperson-to-broker ratio ranges only from 2.9 to 3.6.

Table 3: 2011Q4 Means per 1,000 Residents

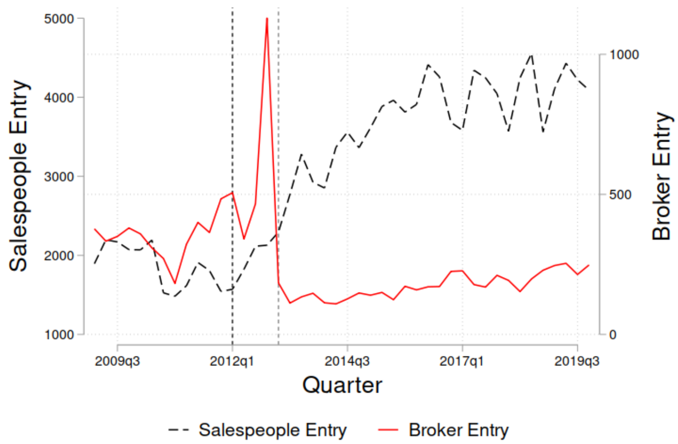
State	New Brokers	Stock Brokers	New Salespeople	Stock Salespeople	S:B Ratio	n
CT	0.005	1.269	0.042	3.719	2.933	8
FL	0.023	2.209	0.105	7.315	3.281	42
LA	0.000	0.777	0.035	2.514	3.221	3
OH	0.001	0.420	0.037	1.371	3.459	63
TX	0.013	0.881	0.051	3.120	3.599	40

Note: Means are for 2011Q4 for sample counties in all states. All numbers are per 1,000 county residents.

4.3.2 The TREC Policy Change

The TREC policy change was evidently salient to potential brokers when it was announced. Figure 6 plots the number of entering salespeople in the dashed black line (with the scale on the left-hand y-axis) and brokers in the solid red line (with the scale on the right-hand y-axis). While the entry of salespeople tracks a fairly smooth path over this time, there are three distinct phases of broker entry. First is a period of consistent entry of about 200-300 new brokers per quarter, then a sharp increase of about 800 new brokers in the quarter before the more stringent broker licensing is set to become effective, and then many quarters of depressed entry of less than 200 new entrants per quarter in the six-plus years following the policy change. Thus, while the policy does not appear to have an obvious or immediate effect on the decisions of potential salespeople, it is evidently quite relevant to potential brokers.[26]

Figure 6: TX Quarterly Entry



Note: Figure reports the number of newly licensed agents per year in Texas by agent type. The first black vertical line represents the policy announcement, and the second gray vertical line represents the policy effective date.

4.3.3 Broker and Salesperson Career Trajectory

Despite the fact that studies in the real estate literature typically treat salespeople and brokers as the same, the nature of the job is different between the two as described in Section 2. The licensing data matched with listings output shed light on how a broker's career trajectory differs from a salesperson's.

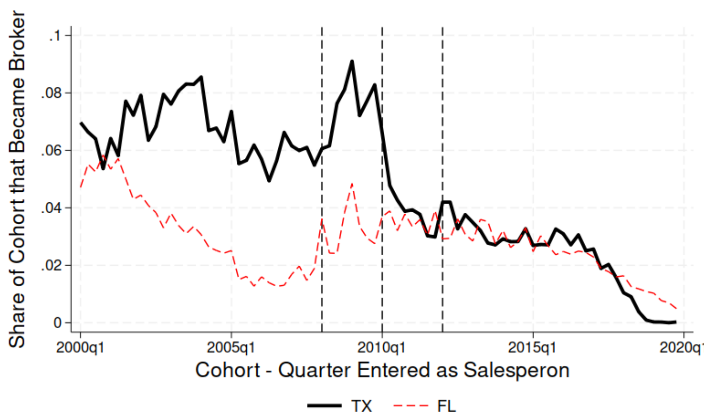
To establish a sense of whether upgrading to a broker is a necessary constraint in advancing an agent's career, I compare the cohorts of salespeople who could take advantage of "grandfathering" into the cheaper licensing (as described in Section 2.2) with those who could not. Recall that prior to the policy, a salesperson only needed to hold a salesperson's license for two years to be eligible to upgrade to a broker, while after the policy was effective the salesperson would need to wait four years. Thus, any agent with a salesperson's license for two to four years when the

[26] Although the number of salespeople is smoothly increasing over the period after the TREC policy announcement, event study evidence will show that the salesperson stock was similarly increasing in other states with no broker policy change around this time.

policy was announced was capable of quickly upgrading to a broker before the requirement became more stringent. Conversely, any salesperson with a license for zero to two years was unable to quickly upgrade, therefore needing to wait the full four years at minimum. I call the two-to-four years cohort the "grandfather-eligible" cohort, and the zero-to-two years cohort the "grandfather-ineligible" cohort.

Figure 7 plots the share of each entry cohort in Texas (where a cohort is defined as all of the agents being licensed as salespeople, i.e., beginning their real estate career, in a quarter) that eventually upgraded to a broker within six years of entering the industry. In the red dashed line, I also plot this for salesperson cohorts in Florida, where there is no change in policy, for comparison.

Figure 7: Share Broker within Six Years



Note: Figure displays the total share of each salesperson entry cohort that ever upgraded to a broker within six years of entry. A cohort is defined as all the agents in a given quarter who entered as a salesperson. The first vertical line represents cohorts who would have four years of salesperson experience when the TREC policy change would go effective. The second line represents cohorts who would have two years of experience. The third line is when the policy became effective.

There is a noticeably higher share of the grandfather-eligible cohort upgrading to brokers compared to the earlier cohorts, even though both groups faced the same similarly minimal requirements, suggesting that the policy did indeed encourage more people to become brokers than might have absent any change. Furthermore, while the share was constant between 4% to 8% for all cohorts prior to 2010, the share drops considerably for cohorts beginning in 2010, who would be grandfather-ineligible. This pattern suggests that the new policy, once binding, had the effect of preventing people who might have otherwise become brokers absent the change from doing so eventually.[27]

However, the trajectories of those who can take advantage of the grandfathering and those who cannot look quite similar. In Table 4, I compare the total listing productivity from 2009 to 2019 of agents who were in the grandfather eligible group with those who were not. I further break this up into those in each group who eventually became a broker (whether in that window or not) with those who never become a broker.

Two patterns emerge. First, there is selection by productivity into the broker career - agents who eventually become brokers perform more listings than agents who do not. Despite large heterogeneity in the experience of salespeople (Gilbukh and Goldsmith-Pinkham (2019)), at the median, those who become brokers are the more productive salespeople. Second, as evidenced, all agents who eventually become a broker, whether they are nudged to do so sooner or not, have similar productivities, while those who never become a broker also show similar trajectories. In other words, the extra two years of having a broker's license did not make the grandfather eligible cohort any more productive in terms of listings directly performed than those who did not.

5 Empirical Strategies

5.1 Event Study Specification

To link the dynamics of broker and salesperson entry illustrated in Figure 6 to the changing entry barrier put in place by TREC, I utilize an event study framework which compares counties in Texas with control counties in the other states before and after the announcement. The conceptual

[27] Those who are in the grandfather-eligible cohorts were also less likely to become a broker after the initial grandfathering period. Appendix A Figure A5 plots the density of the number of brokers entering by quarter. Panel A displays the quarter of entry for all brokers who entered the industry as a salesperson from 2008-2010, while Panel B represents those who entered as a salesperson from 2010-2012. The overwhelming majority of the grandfather-eligible cohort who eventually upgraded to a broker's license did so before 2012, with very few remaining becoming brokers after. In other words, most people in that cohort who became a broker either did it before the more stringent rules were in place or not at all. On the contrary, as shown in Panel B of Appendix A Figure A5, those who are grandfather-ineligible become a broker at a much smoother distribution. The largest mass occurs four years after the policy change, but overall there is a more equal distribution of years of experience before upgrading to a broker for this two-year cohort.

Table 4: Median Number of Listings Across Cohorts by Eligibility

	Total Listings
Eventual Broker, Grandfather Eligible	24
Eventual Broker, Grandfather Ineligible	27
Never Broker, Grandfather Eligible	7
Never Broker, Grandfather Ineligible	9
Overall	9

Note: Table displays the median number of listings by Texas agents who were initially licensed as salespeople between 2008 and 2012. These agents are divided into four groups. Row (1) is the group of agents who eventually became a broker and had at least2 years experience when the policy was announced (and therefore eligible to immediately apply to be a broker). Row (2) is the group who eventually become a broker but had less than 2 years experience and could not immediately upgrade. Row (3) is the group of agents who never became a broker but had at least 2 years experience when the policy was announced. Row (4) is the group who never became a broker and had less than 2 years experience.

framework described in Section 3 hypothesizes that when there is a future increase in the entry cost, there should be an anticipatory effect in which there is a large influx of entry of licensees in the short term. This is then followed by a decrease in entry of brokers once the higher barrier is in place. The event study approach is thus a useful starting point as it generates a point estimate for each quarter individually. I estimate the following equation:

$$Y_{jt} = \alpha + \sum \beta_{1t} Quarter_t * TEXAS_j + X_{jt} + \pi_{jt} + \lambda_j + \gamma_t + \varepsilon_{jt} \tag{4}$$

In this setting, Y_{jt} is an outcome in county j in quarter t. $Quarter_t$ represents dummy variables for year-quarters from 2009Q1 to 2019Q4. $TEXAS_j$ is an indicator equal to 1 if county j is in Texas, and was therefore treated by the policy announcement. λ_j are county fixed effects and γ_t are year-quarter fixed effects. To address seasonality most prevalent in specifications using listings data as outcomes, the specification includes state-by-quarter of year fixed effects (π_{jt}).[28]

X_{jt} represents a vector of county-by-quarter characteristics. These include controls for employment dynamics using the Quarterly Census of Employment and Wages (QCEW) from the Census.

[28]In order to leverage these fixed effects maximally, four $Quarter_t$ dummies are omitted from the specification, namely, quarters one through four of 2011 (the policy was announced in 2012Q1). Additionally, the γ_t fixed effect for quarter four of 2011 is omitted. Thus, coefficients can be thought of as relative to the average over the year before treatment.

These variables include quarterly hirings, separations, total employment, and total earnings at the county level. I also control for house price dynamics using the Zillow Home Value Index (ZHVI). Finally, I construct measures of housing market dynamics using the MLS data; these include the total listings sold in a county-quarter, the share of all listings sold, and the median days on the market for sold listings.[29] The specification includes one-quarter lagged values of these housing market variables in all specifications, unless noted. All specifications are weighted by a county's population in 2010 using the Census and standard errors are clustered at the state level. Appendix A Figure A2 displays data from the counties in each state separately for two employment variables and two of the controls.[30]

5.2 Synthetic Difference-in-Difference

While the event study approach is useful for establishing dynamic effects of entry barriers, a possible concern in this setting is that counties in the four control states are not suitable controls when given equal weighting. Thus, to estimate the short- and long-term consequences for market concentration, laborer quality, and efficiency, I employ a synthetic difference-in-difference design which allows me to compare counties in Texas against counties across the four untreated states while putting more weight on untreated counties which evolve most similarly to Texas counties.

The synthetic difference-in-difference approach, put forth by Arkhangelsky et al. (2021), combines tools from both difference-in-differences and synthetic controls to provide causal estimates in settings with multiple treated units but a potentially insufficient control group. The advantage of the synthetic difference-in-difference (herein SDiD) approach over a standard difference-in-difference (herein DiD) is that it is easier to restore the parallel trends assumption with this re-weighting. The advantage over synthetic controls is that the pre-trends do not need to match exactly; the estimation requires parallel (not matching) trends after the re-weighting of control units. Additionally, this

[29] Before calculating the median, the days on the market for all listings is winsorized to the 3rd and 97th percentile of a year-quarter across all counties in the sample.

[30] Panels A and B plot the mean earnings as reported by the QCEW across all counties per quarter, and the median ZHVI. Panels C and D plot the total (i.e., all counties added together) stock of brokers and salespeople, respectively, in the five sample states.

approach allows for multiple treated units, as opposed to just one as in synthetic controls. This is particularly helpful for leveraging variation in housing markets across counties.

The basic idea behind the SDiD design is to assign both unit and time period weights to non-treated units and pre-treatment time periods to better match the pre-treatment trend of the treated units. Therefore, more weight will be put in the control group on time periods in which the treated and non-treated counties are more similar and on the non-treated counties which are more similar to Texas counties along the dimensions of housing and employment dynamics. These weights are algorithmically selected based on the pre-treatment values of the outcome variable and selected inputs. I use the covariates described above in vector X_{jt} of Equation 4 to construct the weights.

The SDiD approach assumes a balanced panel with N units and T time periods. N_{co} control units are never treated, while N_{tr} units are treated after time T_{pre}. Let Y_{jt} be an outcome Y for county j in quarter t and W_{jt} denote the binary treatment exposure (in this case, the entry barrier policy announcement). Further, let α_j be a unit fixed effect and β_t be a time fixed effect. SDiD uses both unit weights to align pre-exposure trends in the outcome of untreated units with treated units (as in synthetic controls) and time weights to balance pre-exposure time periods with post-exposure time periods. Denote the unit weights $\omega^{\hat{sdid}}$ and time weights $\lambda_t^{\hat{sdid}}$.

The SDiD approach can be thought of as an alternative two-way fixed effect regression to estimate the causal effect of exposure to some treatment. Denoting this effect as τ, the estimator can be written as follows:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau,\mu,\alpha,\beta} \{ \sum_{j=1}^{N} \sum_{t=1}^{T} (Y_{jt} - \mu - \alpha_j - \beta_t - W_{jt}\tau)^2 \omega_j^{\hat{sdid}} \lambda_t^{\hat{sdid}} \}$$

By comparison, a standard DiD estimator is:

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau,\mu,\alpha,\beta} \{ \sum_{j=1}^{N} \sum_{t=1}^{T} (Y_{jt} - \mu - \alpha_j - \beta_t - W_{jt}\tau)^2 \}$$

These two estimators are similar, with the exception that the DiD implicitly uses unit and time weights equal to one. Finally, a synthetic controls estimator is:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\beta}) = \arg\min_{\tau,\mu,\beta} \{ \sum_{j=1}^{N} \sum_{t=1}^{T} (Y_{jt} - \mu - \beta_t - W_{jt}\tau)^2 \hat{\omega_j^{sc}} \}$$

While the synthetic controls approach does use the unit weights, it does not use unit fixed effects. The unit fixed effects allow for the flexibility of parallel trends in the pre-period, as opposed to identical matching. Further, the synthetic controls estimator does not utilize time weights either.[31]

To construct an estimate that is as comparable to the event study (and standard DiD) coefficients as possible, I first regress the outcome variables on all of the controls as above in Equation 4 and predict residuals, as following:

$$Y_{jt} = \alpha + X_{jt} + \pi_{jt} + \lambda_j + \gamma_t + \varepsilon_{jt}. \quad (5)$$

I then use the covariates in vector X_{jt} to construct the unit weights for the SDiD, with the residualized Y_{jt} (i.e., ε_{jt}) as the outcome variable.

A caveat to the SDiD approach is that, as noted, it requires a balanced panel. In this context, in areas where there may not be any broker entry or listing outcomes in a given quarter, that county would not be included at all in the estimation.

6 Anticipatory Effect of Changing Entry Barrier

The TREC entry barrier policy had large anticipatory effects on employment which were likely unintended but nevertheless persistent. Figure 8 displays event study coefficients by estimating Equation 4 with the number of new brokers per 1,000 county residents as the outcome in Panel A, and the total number of brokers per 1,000 county residents in Panel B. As the conceptual framework predicts, a future increase in entry cost induces a great deal of entry in the short term. The quarter which the higher entry cost was set to go into effect saw an increase of 0.02 brokers per 1,000 residents in Texas counties, which is double the mean entry in the year before the policy was

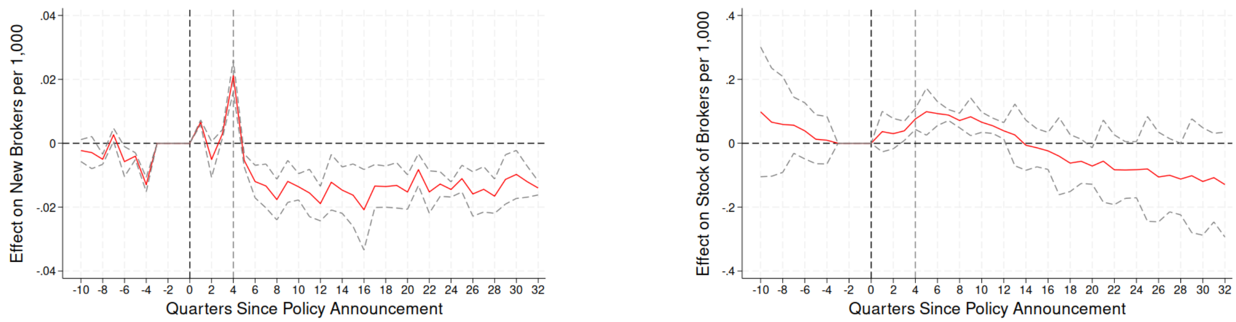
[31] See Appendix C for construction of the unit and time weights.

announced. Once the policy is effective, entry decreases relative to the pre-period, and still eight years later does not return to pre-period entry levels. This supply restriction is similarly about double the mean entry in Texas counties in the year before.

Figure 8: Broker Entry and Stock

(a) New Brokers per 1,000 Residents

(b) Stock Brokers per 1,000 Residents



TX Pre-Year Mean: 0.012
Long Run (t>4) DiD Coeff: -0.011***

TX Pre-Year Mean: 0.865
Long Run (t>4) DiD Coeff: -0.057

Note: Figure displays event study coefficients estimating Equation 4. The outcome variable is the total number of entering salespeople (Panel A) and the total stock of salespeople (Panel B) per 1,000 county residents. The red solid lines represent the coefficients, while the dashed gray lines represent the 95% confidence interval. The first black vertical lines represent the policy announcement, while the second gray vertical lines represent the policy effective date. This result uses licensee data in sample counties only.

While the expected effect of the policy was to restrict the supply of brokers, the initial inducement of entry leads to a larger stock of brokers in the short term. This effect lasts nearly three years. Starting about twelve quarters after the policy was announced, the effect seemingly levels out and the total stock of brokers on average in Texas counties is lower relative to the control counties, though not precisely estimated in this framework.[32] Appendix A Figure A3 displays event study

[32]These patterns are robust, though less precisely estimated, when considering the employment of *active* agents; i.e., salespeople and brokers who are identifiable in the MLS data. Appendix A Figure A4 utilizes the matched listings sample to consider the number of brokers and salespeople that are attached to a listing in a given quarter. There is a much smaller number of brokers used per 1,000 residents than there are brokers licensed. The mean in Texas counties the year before the policy was announced is 0.165 brokers per 1,000. The number of brokers identifiable in the MLS data does generally trend upwards in Texas counties relative to the control counties for about three years, decreasing by about double the pre-period mean four years out. Note that, as described in Section 4, this will be an under count of total brokers, as these represent only the brokers on listings who could be matched to their Texas licensing record. Further, this does not account for brokers who may be overseeing the listing process in a managerial sense while not actually being named in the listing itself.

coefficients for the employment dynamics of salespeople. While on average, entry, and therefore stock, is decreasing over time, we cannot reject that this decrease is significantly different relative to counties in the other states without a policy change. This result is different than what the raw data in Figure 6 might suggest, highlighting the importance of comparing Texas counties to counties without a policy change.

Due to the dynamic nature of reactions to entry barriers, it is important to appropriately define the time horizon over which the effects of such barriers are studied. Given the patterns elucidated by the event study, I define the short term as the first four quarters of the announcement window. I consider two different long-term periods: one beginning 4 quarters after the policy was announced and therefore effective (called "Long Run (t>4)"), and one beginning in quarter 12, when the stock of brokers ceases to increase (called "Long Run (t>12)"). The period "Long Run (t>4)" will be most relevant to outcomes directly related to the current pool of agents working in the market at the individual level, while "Long Run (t>12)" will be most relevant to issues related to the labor market structure.

Results from the preferred approach of the SDiD estimation further show that the policy decreases broker entry once it is effective by nearly 75% (Table 5, Column 1). The policy ultimately leads to more broker exits, likely due to the need to meet the higher education requirements by the next renewal cycle. However, the SDiD results also show that this short-term entry increase, and the related increase in stock, lead to a long-term stock that is still higher than the pre-policy level. In other words, the anticpatory effects of the entry barrier change are such that it ultimately leads to a long-term *increase* in broker stock which is non-trivial. The stock of brokers increases by about 0.06 per 1,000 residents in the long run (as defined by $t > 12$). This is an 7% increase over the pre-period quarterly mean across Texas counties of 0.865 brokers per 1,000 people. For context, the average Texas county in the sample has a population of 469,554 in 2010. This would mean an increase from about 406 brokers to 435 brokers in the average county. Finally, the stricter broker policy has a smaller but still significant effect on increasing broker exits and deterring salesperson entry in the long run.[33]

Table 5: Entry and Stock per 1,000 County Residents - SDiD

	(1) New Brokers per 1K	(2) Broker Exits per 1K	(3) Stock of Brokers per 1K	(4) News Salesppl per 1K
Short Run ($t\leq4$)	0.006***	-0.000	0.030***	0.000
	(0.001)	(0.001)	(0.006)	(0.004)
Log Run (t>4)	-0.009***	0.001*	0.075***	-0.008
	(0.001)	(0.001)	(0.023)	(0.009)
Long Run (t>12)	-0.009***	0.001**	0.061**	-0.018*
	(0.001)	(0.001)	(0.030)	(0.010)
TX Pre-Year Mean	0.012	0.001	0.865	0.054
Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample
N	156	156	156	156

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Note: Table displays results estimating an SDiD as described in Section 5.2. Note that the outcome variables are all measured per 1,000 county residents. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

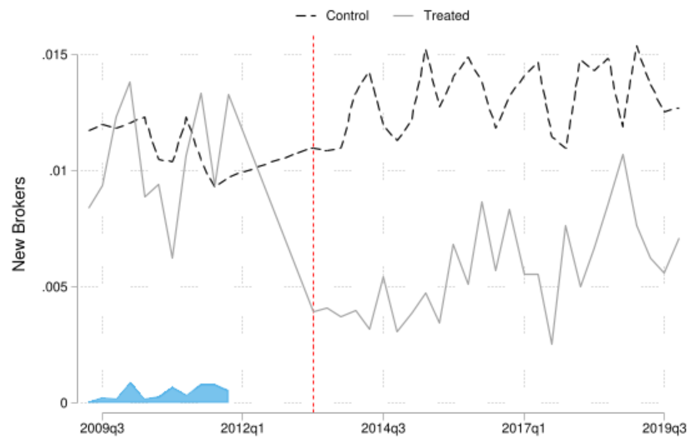
As described, the SDiD approach re-weights the counties in the control group such that the new weighted average of the outcome for the control counties is parallel to the average of the outcome across Texas counties. For illustration, I plot the re-weighted data trend for the outcome of new brokers per 1,000 residents in Figure 9.

7 Consequences for Consumers and Workers

The evidence above illustrates that changing entry barriers generate strong anticpatory reactions which have dynamic implications for labor market entry and supply over time. More specifically, whether or intended or not, the TREC policy which increased the entry cost for brokers in practice acted as a positive shock to the stock of brokers. Therefore, the policy can be used as quasi-exogenous variation to investigate the impact of a larger pool of brokers, who are facing a stricter

[33] Appendix Table 2 displays the analogous naive DiD results, which suggest that the changing entry barrier had no significant effect on either the stock of brokers or salespeople employment in the long run. However, as discussed, the DiD estimation will put equal weights on the counties in the control states, which may be a concern in this setting primarily due to data limitations.Note that all effects that are estimated to be significant using the SDiD estimation are either of similar significance and magnitude when using the DiD or insignificant but in the same direction.

Figure 9: SDiD Weighted Data



Note: Figure displays trends in broker employment for counties in Texas ("Treated," solid line) and the weighted average of counties in the control states ("Control," dashed line). The vertical line represents the policy announcement. The weights used to average the pre-treatment time period are displayed in blue at the bottom of the graphs. See Arkhangelsky et al. (2021) and specifically their Figure 1 for more information.

licensing standard, on the real estate industry.

7.1 Consumer Effects: The Concentration-Quality Trade-off

Following from the conceptual framework in Section 3, the short-term anticipatory effect from the policy announcement should lead to a short-term decrease in market concentration. Given the empirical evidence reveals a long-term positive effect of the policy on the stock of brokers, market concentration is expected to continue to decrease in the long term. Further, the announcement of a higher entry cost is predicted to induce more entry from lower quality agents in the short term. If the stricter entry requirements correlate with higher quality performance, the average quality of entering brokers is expected to increase in the long term.

7.1.1 Market Concentration

To quantify the concentration of listings across brokerage offices, I calculate a Hirschman-Herfindahl Index (HHI), as described in Section 3. The HHI for a given county-quarter is calculated as follows:

$$HHI = \sum_i s_i^2,$$

where i indexes a listing agent or listing office as denoted in the MLS, and s_i represents that agent or office's share of the total listings in the county that quarter. Higher values of the HHI indicate a less concentrated, more monopolistic market.

The results suggest that, as a result of the anticipatory reaction to the increased licensing barrier, market concentration decreases. Table 6 displays SDiD estimation results using various HHI measures as the outcome. Columns 1 and 2 construct the HHI across all agents in a county using the aggregate sample and matched listings sample, respectively, whereas columns 3 and 4 construct the HHI across all listing offices.[34]

Of note, the brokerage market in Texas was already quite un-concentrated at the county level even before this policy was announced; an HHI below 0.15 is generally considered un-concentrated, and the mean HHI across Texas counties in 2011 at the agent level was 0.04 and at the brokerage level is 0.08. Results suggest that the policy did little to change the distribution of business across agents. At the brokerage office level, market concentration decreases persistently into the long run by 0.02, or about 25% relative to the mean HHI across Texas counties in 2011.[35]

7.1.2 Quality

The increased entry barrier counter-intuitively decreases market concentration in the long term due to the persistent short-term entry effect. However, as noted above, since the real estate industry

[34] Notably, though the matched listings sample is more restrictive, results are similar across samples.

[35] The unit in the HHI is a listing office across counties (for instance, two ReMax offices franchised by two different brokers in the same county would count as two separate business units), so this result does not rule out an explanation where more regional brand names are expanding by opening up multiple new offices within a county.

Table 6: Brokerage Market Concentration

	(1) HHI - Agents	(2) HHI - Agents	(3) HHI - Offices	(4) HHI - Offices
Short Run ($t \leq 4$)	-0.000	-0.023**	-0.000	-0.011
	(0.002)	(0.011)	(0.003)	(0.011)
Long Run ($t>4$)	-0.003	-0.023	-0.018***	-0.040**
	(0.003)	(0.014)	(0.006)	(0.016)
Long Run ($t>12$)	-0.004	-0.021	-0.020***	-0.041**
	(0.004)	(0.016)	(0.006)	(0.018)
TX Pre-Year Mean	0.037	0.113	0.080	0.169
Sample	Aggregate Sample	Matched Listings	Aggregate Sample	Matched Listings
N	156	147	156	147

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Table displays results estimating an SDiD as described in Section 5.2. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Before taking the residual as described in Equation 5, all outcome variables are first winsorized to the 97th and 3rd percentiles for the state-year-quarter. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

does not exhibit robust price competition, there is little way for consumers to benefit from the increased stock of brokers. Therefore, it is important to consider other dimensions along which agents and brokerages might be altering their behavior in response to changing competitive dynamics due to entry restrictions. One such potential dimension is the quality of service which they provide.

The TREC policy being studied is unique in that, unlike many licensing policies which aim to improve the quality of entry-level laborers, it instead focuses on the quality of managers. By increasing the entry barrier at the professional level, the policy potentially changes who is a desirable supervisor and trainer. Therefore, it is of interest whether brokers are better quality themselves, specifically at the time they become brokers and are eligible to manage, and whether they are better at training salespeople.

There is no consensus in the literature, however, regarding how to measure the "quality" of an agent.[36] Prior studies of licensing in real estate have used data on formally filed complaints against

[36] There is similarly little consensus in the literature over what specifically is the primary function of a real estate agent, broadly speaking, in a transaction. For a thorough review of the micro-structure of housing markets, including

agents in order to quantify the number of "bad" agents. However, because these complaints are filed by a presumably wronged client, they are quite subjective, highly selected, and likely to capture only extreme wrongdoing.[37]

To quantify quality in a way that is more objective than complaints and less subject to selection, I turn to the match of licensees to listings output, which prior papers could not leverage. A primary reason a home seller would hire an agent is to successfully sell the home, and sell it for a higher price and at a quicker pace. Therefore, I consider a number of measures to quantify both the listings experience of brokers and the returns to those listings in terms of price and time on the market. These measures capture broker quality to the extent that they capture a broker performing better on behalf of their client. Specifically, I calculate these measures over the four year window *prior* to entering as a broker, in order to capture the quality of brokers when they are immediately eligible to supervise and train salespeople.

To measure an entering broker's experience level, I calculate the overall number of sale-side listings, the number of sold transactions, and the share of all the listings that result in a sale in the four years prior to becoming a broker. I then take the mean of these measures across all brokers entering in a given entry cohort, such that results should capture whether upgrading brokers are better quality after the policy than cohorts who upgraded before.

To capture the ability of brokers to generate better returns on listings in terms of price and speed, I estimate a hedonic model for both price and time to sale by regressing the natural log of the sale price or the days on the market before the sale (DOM) for a given listing on a number of property characteristics, as well county and year-quarter fixed effects.[38] The residual of this regression can then be considered as the additional unexpected "return to the listing" (in terms of price or time). The residual is then averaged over all listings performed by a broker in the four

the role of the agent in transactions, see Han and Strange (2015). Empirically, Aiello et al. (2022) use exogenous variation in the likelihood of agent attention to show that the primary function of agents is to facilitate search (as opposed to provide information).

[37]These complaints are also rare. For instance, in all of Dallas in calendar year 2022, there were seven total complaints filed with TREC.

[38]Characteristics include the square footage of the property, total living area, the year the property was constructed, total number of bathrooms, total number of bedrooms, and indicators for whether the property has a fireplace, a pool, and a garage.

years prior to entry, and then this broker-level measure is averaged across all brokers in an entry cohort. This measure in turn captures whether listings performed by brokers from a given cohort are generating different returns from the listings performed by brokers who upgraded at a different time. More details about this process can be found in Appendix Section D.

Results are displayed in Table 7.[39] The policy changes are indeed binding in terms of broker experience. In the short term, when brokers could enter under the status-quo requirements, there is no difference between these cohorts and prior ones in the total number of listings and sales performed, as evidenced in Columns 1 and 2. In the long-term periods, however, these broker entry cohorts are performing more listings and sales as would be expected, given it is required of them in order to be a broker. Brokers in cohorts who begin after the policy is effective have on average 9 listings and 6 sales more per person. These short-term entry cohorts are worse at converting listings to sales, though (Column 3), and they take longer to sell listings than their prior cohorts (Column 5). Thus, not only does the policy announcement induce entry, but it induces inefficient entry in the sense of lower quality.

However, these cohorts of "better experienced" brokers in the long term are no better at converting listings into sales (Column 3), and generate smaller returns to price (Column 4). One dimension for which the results suggest the post-policy broker cohorts are higher quality is the speed of sale (Column 5, Long Term t>12). These broker cohorts see a decrease in the returns to time on the market on average, which is beneficial to the consumer (shorter sale times are generally seen as preferable, and thus a negative effect represents better quality). Thus, while brokers "improve" on one dimension in the long term (time on market), they look no different or worse on others (probability of getting a sale and the returns to the sale price). In other words, to the extent that consumers want to optimize successfully selling a home at a high price in a small amount of days, to gain on one dimension, they must sacrifice on at least one other. These results support an interpretation that the stricter policy requirements, name the transaction minimum, incentivizes

[39] As noted above, the SDiD approach requires a balanced panel. However, in many counties, there are a handful of quarters in which there are zero brokers entering, or none who have enough data over the prior four years. Thus, for this estimation in particular, too much information is lost by using the SDiD estimation, and I therefore report difference-in-difference estimates with the caveat that the sample panel is unbalanced.

prospective brokers to want to gather more listings and sell them quickly in order to hit the transactions required of them.

Table 7: Broker Quality

	(1) Total Listings	(2) Total Sold	(3) Share Sold	(4) Mean Return ln(Price)	(5) Mean Return ln(DOM)
Short Run ($t \leq 4$)	-3.570	-4.202	-0.068*	0.012	0.301**
	(5.680)	(4.821)	(0.028)	(0.056)	(0.085)
Long Run ($t>4$)	9.309***	6.684***	-0.005	-0.130***	-0.084
	(1.664)	(1.169)	(0.029)	(0.014)	(0.051)
Long Run ($t>12$)	4.095*	2.889*	0.009	-0.102***	-0.168**
	(1.654)	(1.122)	(0.029)	(0.016)	(0.055)
TX Pre-Year Mean	13.46	8.03	0.493	0.092	0.016
Sample	Matched Listings	Matched Listings	Matched Listings	Matched Listings	Matched Listings
N	61	61	52	44	44

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Note: Table displays results estimating a DiD using the time-invariant version of Equation 4. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. All outcome variables are first winsorized to the 97th and 3rd percentiles for the state-year-quarter.

The results provide no convincing evidence to suggest that a higher entry barrier leads to higher quality brokers. However, it may still be the case that they are better managers than before. To consider this effect, I consider the analogous quality measures for salespeople in their first four years *after* being licensed. This measure is intended to capture the early-career training newly licensed salespeople are receiving from their employing brokers who were licensed under the stricter regime. Results are displayed in Table 8.

Salespeople similarly acquire more experience under the post-policy broker cohorts, performing nearly 2 extra listings on average in the long term (Column 1); however, salespeople are also not any better at converting their share of listings to sales after the policy (Column 3). Further, the salespeople who enter under the post-policy brokers generate lower price returns (Column 4) and take longer to do so (Column 5). Thus, while brokers themselves are not meaningfully better at performing listings themselves when they upgrade, they additionally are not any better at training salespeople to generate higher-quality results for consumers.

Table 8: Salesperson Quality

	(1) Total Listings	(2) Total Sold	(3) Share Sold	(4) Mean Return ln(Price)	(5) Mean Return ln(DOM)
Short Run (t≤4)	1.288	0.692	0.039	0.027	-0.004
	(1.451)	(1.162)	(0.027)	(0.027)	(0.057)
Long Run (t>4)	1.669**	0.929*	-0.026	-0.100***	0.230**
	(0.717)	(0.559)	(0.029)	(0.038)	(0.097)
Long Run (t>12)	1.900***	1.080**	-0.028	-0.120***	0.244**
	(0.703)	(0.502)	(0.032)	(0.045)	(0.121)
TX Pre-Year Mean	6.67	4.35	0.621	0.043	-0.090
Sample	Matched Listings	Matched Listings	Matched Listings	Matched Listings	Matched Listings
N	50	50	44	31	31

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Note: Table displays results estimating an SDiD as described in Section 5.2. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Before taking the residual as described in Equation 5, all outcome variables are first winsorized to the 97th and 3rd percentiles for the state-year-quarter. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

7.2 Employment Effects: Heterogeneous Effects and Efficiency

7.2.1 Distributional Effects of Entry Barrier

The above results are consistent with the future entry barrier increase acting as a nudge to induce entry in the short term before ultimately decreasing entry in the long term. However, it has been established that licensing barriers could have differential effects for different types of potential entrants. For instance, Ingram and Yelowitz (2019) find that the impact of licensing is stronger for females. In Table 9, I consider how this policy affected female and minority entry into the broker labor market.[40]

Before the policy was announced, the majority (about 60%) of brokers are male. While real estate is often cited in the popular media as a female-majority industry, it is at the salespeople level where women make up the majority of agents (around 60%). It follows, then, that the mean share of female entrants is just 30% in Texas counties in the year before the policy announcement (Column 1). In the short term, the share of female entrants increases, suggesting that female brokers are

[40]To predict the gender of agents, I use the algorithm from genderize.io which uses a large number of social media profiles to predict gender based on first name. To predict race, I use the NamePrism algorithm, which utilized both first and last name. See Ye et al. (2017) and Ye and Skiena (2019) for more information.

forward-looking enough to take advantage of the lower entry cost. In the long term, the policy decreases this entry share by 7.2 percentage points, a decrease of nearly 24%.

The policy also has a negative effect on the entry of Hispanic brokers (Column 2). Hispanic entrants make up the largest non-White category of entering brokers in Texas counties in the sample before the policy change despite coming in at less than 1% in 2011. There is no evidence of either Hispanic or Black (Column 3) entrants taking advantage of the nudge in the short term. In the long run, the higher barrier reduces entry by 0.001 percentage points, which is nearly half the pre-period entry share. The results suggest a smaller effect for Black brokers. Therefore, as the intended effect of the policy, to restrict broker entry, takes hold, fewer women and minorities enter the market.

Table 9: Broker Entry - Gender and Race

	(1) Share Female	(2) Share Hispanic	(3) Share Black
Short Run ($t \leq 4$)	0.070**	0.000	-0.000
	(0.035)	(0.000)	(0.000)
Long Run ($t<4$)	-0.065**	-0.001***	-0.000
	(0.031)	(0.000)	(0.000)
Long Run ($t>12$)	-0.072**	-0.001***	-0.000*
	(0.032)	(0.000)	(0.000)
TX Pre-Year Mean	0.306	0.002	0.0001
Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample
N	156	70	37

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Table displays results estimating an SDiD as described in Section 5.2. Note that the outcome variables are all measured per 1,000 county residents.Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

7.2.2 Efficiency

The analysis has thus far shown that, a future increase in the entry barrier induces an increase in broker entry while doing little to affect competitive dynamics and improve quality. The increased barrier had stronger effects for women and minorities. In this section, I revisit the idea of efficiency in the real estate labor market with a broader consideration of the distinction between the role of salespeople and brokers.

Building off of the work of Hsieh and Moretti (2003), I first define labor market efficiency by the productivity of the average agent. The conceptual framework described in Section 3 predicts that listings per broker should unambiguously decrease in the short and long term, while the effect on sales per broker is ambiguous in my setting. A decrease in this measure would imply that agents are not operating at their capacity constraint.[41] As a result of this quasi-exogenous shock to entry, brokers, in fact, have fewer listings and sales. Results are in Table 10; note that Column 1 corresponds to $(\frac{X_t}{N_t})$ and Column 2 to $(\frac{\rho \cdot X_t}{N_t})$. This would imply that the market is more inefficient because new entrants lead to less productivity as opposed to expanded market capability.

Table 10: Capacity Constraints

	(1) Listings per Broker	(2) Sales per Broker	(3) Mean Firm # Brokers	(4) Mean Firm S:B Ratio
Short Run (t≤4)	-0.130*	-0.081	0.051***	0.065
	(0.076)	(0.057)	(0.020)	(0.100)
Long Run (t>4)	-0.704***	-0.763***	-0.059*	0.296**
	(0.180)	(0.236)	(0.032)	(0.145)
Long Run (t>12)	-0.695***	-0.903***	-0.087**	0.381**
	(0.213)	(0.284)	(0.035)	(0.163)
TX Pre-Year Mean	3.68	1.89	0.804	1.43
Sample	Aggregate Sample	Aggregate Sample	Matched Listings	Matched Listings
N	156	156	148	142

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Note: Table displays results estimating an SDiD as described in Section 5.2. Note that the outcome variables are all measured per 1,000 county residents. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Before taking the residual as described in Equation 5, all outcome variables are first winsorized to the 97th and 3rd percentiles for the state-year-quarter. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

However, this measure of labor market efficiency does not account for the idea that the role of brokers and salespeople is inherently different. The ostensible purpose of the TREC policy is

[41] To test the assumptions of my updated framework, I first show that the policy does not change the housing market at large. Results are displayed in Appendix B Table 3. Columns 1 and 2 consider market quantities via the total number of listings and the total number of sales per 1,000 residents in a county. Note that Column 1 corresponds to X_t and Column 2 corresponds to $\rho \cdot X_t$. Column 3, which corresponds to P_t, estimates the effect of the policy on mean sale prices. The evidence suggests that, in the long term, listings, sales, and house prices are exogenous to broker entry.

to increase the managerial ability of brokers by requiring them to be better qualified to train and supervise salespeople. Thus, an alternative way to think about "efficiency" from broker entry is whether the larger pool of brokers are behaving more as managers and taking on more capacity as supervisors. Table 10 Columns 3 and 4 consider the mean firm structure after the policy, providing evidence that the higher barrier to entry leads brokers to shift to a more managerial role over time. These measures capture efficiency in the sense that the purpose of a broker is not to sell listings directly but rather to oversee salespeople.

Column 3 measures the mean number of brokers across firms in a county. As this uses the matched listings sample, I can only identify a firm's brokers if there is a broker at that firm performing listings. If a broker solely supervises, I would not be able to observe their existence at the firm via the MLS.[42] Therefore, this measure can be thought of as the number of brokers at a firm who remain transacting on listings directly. In the short term, the mean firm has more brokers than before the policy, which is necessarily mechanical because there was an increase in salespeople already existing at firms upgrading their license status. However, in the long term this effect entirely reverses. The mean firm has fewer brokers performing listings, suggesting that, brokers have pivoted to a more managerial role.

Column 4 measures the mean salesperson-to-broker ratio across firms in a county. This is the total number of salespeople performing listings for a firm in a given quarter divided by the total number of brokers observed at that firm. In the long term, this ratio is increasing by more than 25%. This further suggest that brokers are indeed working at a higher capacity after the policy as defined by salespeople they manage, as opposed to listings they perform. These results highlight the importance of considering the heterogeneity of duties across laborers within an industry when considering efficiency. This is particularly relevant for licensed industries where there are multiple licenses to progress through.

[42]This is why the mean firm has less than 1 broker pre-policy.

8 Conclusion

Policymakers and trade associations often use occupational licensing as a tool to correct for information asymmetries and ensure better service quality for consumers; however, this entry barrier comes with a trade-off between possibly increasing practitioner quality while also increasing market concentration. The effects of anticipatory responses to entry barriers are particularly understudied, even though they have important implications for the long-term labor pool in an industry. This paper uses the real estate industry as the setting to study the consumer and employment effects of changing entry barriers. It is important to understand these effects in the real estate industry, as it is both a consequential intermediary market for consumers, with financial implications at both the household and macro-level, and a massive labor market with a large number of participants across the US. This paper provides new evidence on the unintended consequences of licensing policy and its implications for efficiency in the real estate industry.

To estimate these effects, I construct a novel dataset of licensees and their productivity, while exploiting a policy change in Texas in 2012 that provides quasi-exogenous variation in the licensing cost for brokers. Using a synthetic difference-in-difference research design, I show that the policy reform causes an anticipatory influx of broker entry when the policy is announced, leading to a persistently higher stock of brokers even after the policy is in effect. The influx of brokers decreases market concentration; however, in an industry such as real estate which has uniquely little price competition, consumers cannot benefit as would typically be expected from increased competition. Further, the increased entry barrier does not lead to an increased quality of entering brokers, or the salespeople they supervise, in the long term. This suggests that restricting entry via higher licensing costs is not beneficial for consumers in this setting.

For workers, the evidence shows that the increased entry barrier has a stronger effect on women and minorities. Additionally, the induced entry is inefficient in that the laborers less productive as defined by the average listings volume. However, I provide evidence that brokers are becoming more managerial and supervising more entry-level licensees. This suggests that entry into the real estate labor market may not be as inefficient as previously believed and demonstrates the importance of accounting for heterogeneity in worker role when analyzing the efficiency effects of entry costs.

There are many fruitful directions for future research. The results highlight the long-term implications of strong anticipatory reactions to entry barrier announcements and serve as a caveat that our understanding of the long-term consequences of licensing policy may be a result of unintended and understudied short-term employment decisions. Specific to real estate, the results suggest that "efficiency" should be evaluated in the context of the role of each agent; namely, considering separately the non-managerial listing duties of salespeople as opposed to the managerial supervisory duties of brokers. These effects are particularly relevant in the wake of the changing regulatory landscape in real estate, in which the potential breakdown of the power of the NAR and large brokerages could increase the market influence individual brokers have both over the salespeople they supervise and the consumers they represent.

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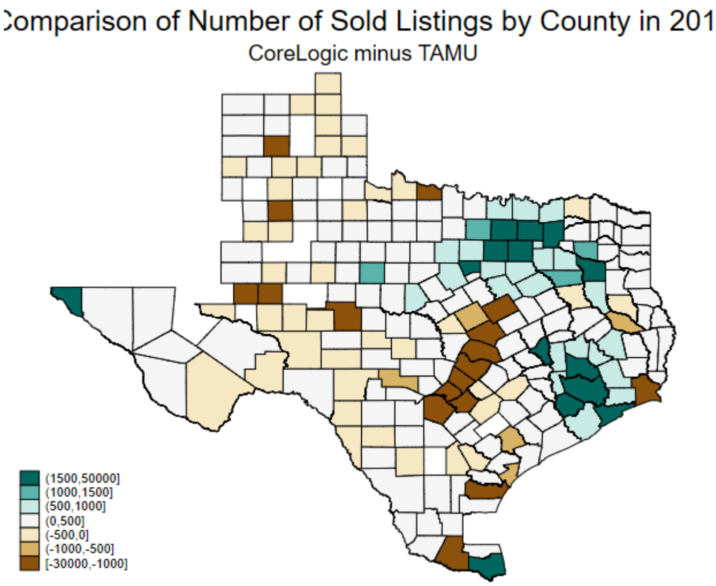
Appendix

A Figures

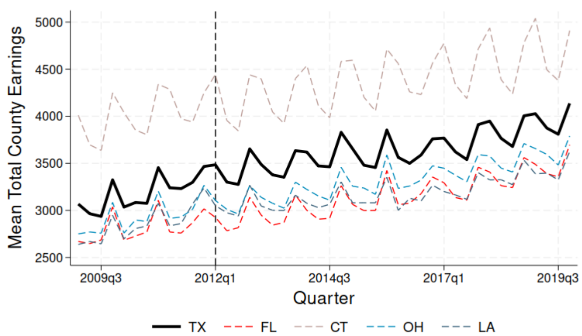
Figure A1: Comparing CoreLogic to TAMU Real Estate Center



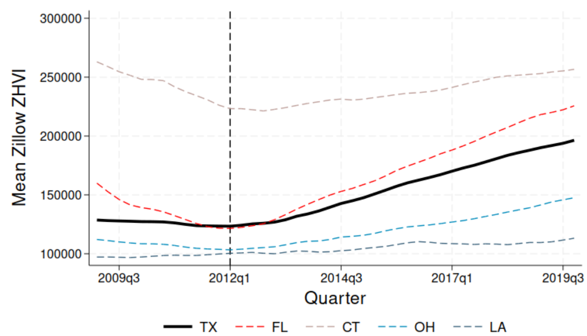
Note: Figure displays the number of total listings sold by county in 2017 in the CoreLogic data vs. the Texas A&M Real Estate Center data. Bluer shades reflect better coverage in CoreLogic, while orange shades represent better coverage by TAMU.

Figure A2: Raw Data Trends for All States

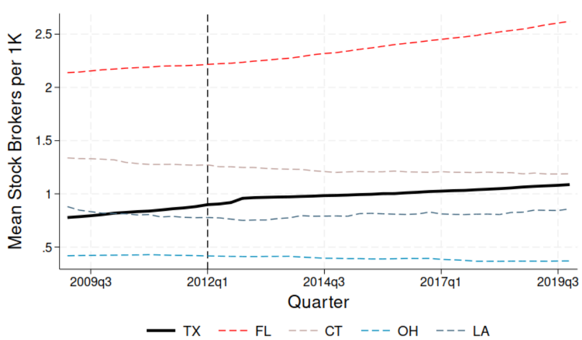
(a) Median Earnings



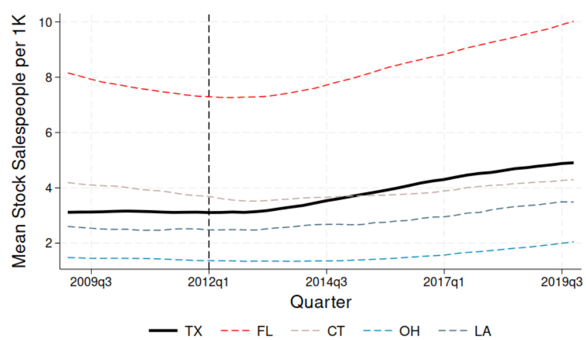
(b) Median ZHVI



(c) Total Stock of Brokers



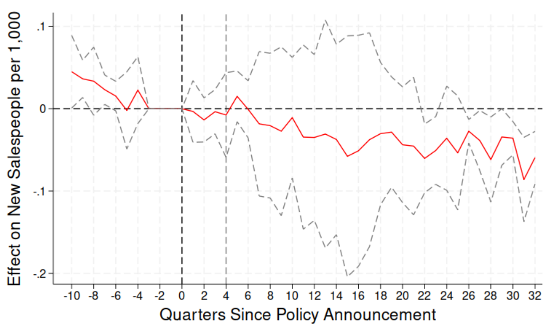
(d) Total Stock of Salespeople



Note: Figure displays raw data for counties in Texas (the blue solid line) and counties in my four control states. Panel A displays the Median Earnings across all counties is a given state over time using QCEW data. Panel B displays the median of Zillow's county-level ZVHI. Panel C displays total brokers added up across all counties, and Panel D displays total salespeople. The vertical line represents the policy announcement.

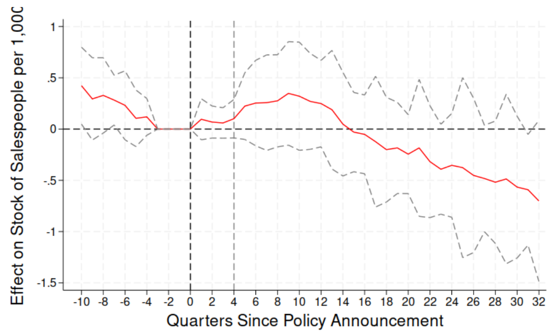
Figure A3: Salespeople Stock and Entry

(a) New Salespeople per 1,000 Residents



TX Pre-Year Mean: 0.054
DiD Long Run (t>4) Coeff: -0.053

(b) Stock Salespeople per 1,000 Residents



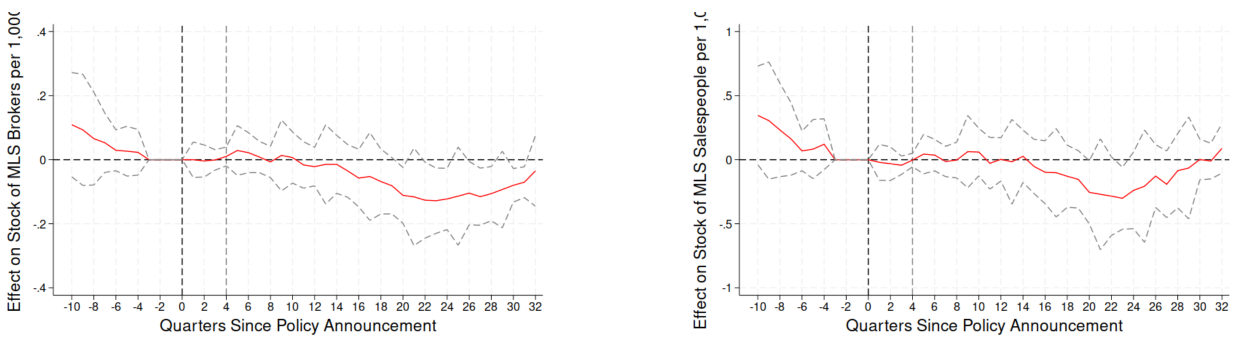
TX Pre-Year Mean: 3.118
DiD Long Run (t>4) Coeff: -0.238

Note: Figure displays event study coefficients estimating Equation 4. The outcome variable is the total number of entering salespeople (Panel A) and the total stock of salespeople (Panel B) per 1,000 county residents. The red solid lines represent the coefficients, while the dashed gray lines represent the 95% confidence interval. The first black vertical lines represent the policy announcement, while the second gray vertical lines represent the policy effective date. This result uses licensee data in sample counties only.

Figure A4: Active Brokers and Salespeople per 1,000 Residents

(a) Active Brokers

(b) Active Salespeople



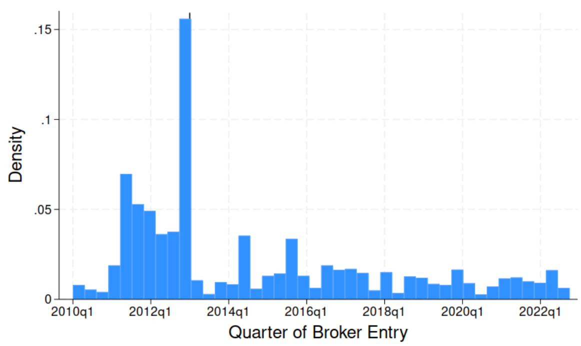
TX Pre-Year Mean: 0.165
DiD Long Run (t>4) Coeff: -0.072

TX Pre-Year Mean: 0.503
DiD Long Run (t>4) Coeff: -0.207

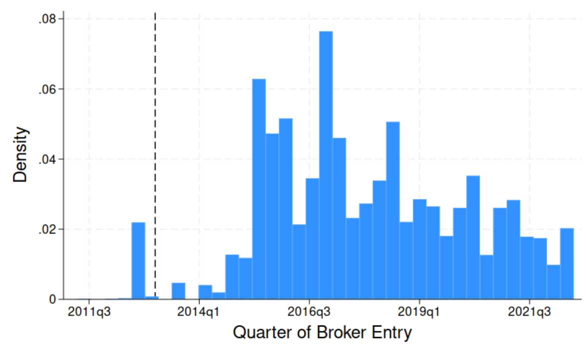
Note: Figure displays event study coefficients estimating Equation 4. The outcome variable is the total number of brokers (Panel A) and the total number of salespeople (Panel B) performing at least one listing in the MLS per 1,000 county residents. The red solid lines represent the coefficients, while the dashed gray lines represent the 95% confidence interval. The first black vertical lines represent the policy announcement, while the second gray vertical lines represent the policy effective date. This result uses the Matched Listings sample.

Figure A5: Entry Year by Group

(a) Grandfather Eligible



(b) Grandfather Ineligible



Note: Figure displays a distribution of the quarter in which an agent upgrades to a broker for two separate groups. In Panel A, I plot this distribution for the group of agents who were "Grandfather Eligible," i.e., those agents who became licensed as salespeople from 2008-2010, and had a least two years experience as a salesperson when the stricter licensing policy was announced. Panel B plots this for the "Grandfather Ineligible" group, i.e, the agents who were licensed from 2010-2012, and would not have two years experience when the impending stricter policy was announced.

B Tables

Table 1: Constructing the Matched Listings Sample

State	In Sample Counties	Matched to Listing Agent	Percent of Total
CT	726,011	382,246	52.65%
FL	4,556,778	2,095,535	45.99%
LA	64,618	29,911	46.29%
OH	1,662,350	866,567	52.13%
TX	2,639,873	1,096,759	41.55%
	9,649,630	4,471,018	46.33%

Note: Table reports number of MLS listings by state. "In Sample Counties" reports the total number of MLS listings in the sample counties by state. "Matched to a Listing Agent" reports the total number of listings remaining which can be matched to a licensee in my licensing records. "Percent of Total" reports the share of the total listings remaining.

Table 2: Entry and Stock per 1,000 County Residents - DiD

	(1) New Brokers per 1K	(2) Broker Exits per 1K	(3) Stock of Brokers per 1K	(4) New Salesppl per 1K
Short Run ($t \leq 4$)	0.005**	-0.000	0.036	-0.015
	(0.001)	(0.001)	(0.034)	(0.021)
Long Run ($t > 4$)	-0.011***	0.002	-0.057	-0.053
	(0.002)	(0.001)	(0.058)	(0.035)
Long Run ($t > 12$)	-0.011***	0.002	-0.104	-0.062
	(0.002)	(0.001)	(0.061)	(0.029)
TX Pre-Year Mean	0.012	0.001	0.865	0.054
Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample
N	156	156	156	156

Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Table displays results estimating a DiD using the time-invariant version of Equation 4. Note that the outcome variables are all measured per 1,000 county residents. Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Standard errors are bootstrapped.

Table 3: Housing Market Assumptions

	(1) Listings per 1K	(2) Sales per 1K	(3) ln(Sale Price)
Short Run (t≤4)	0.097*	0.067**	0.010
	(0.053)	(0.034)	(0.012)
Long Run (t>4)	-0.005	0.043	0.018
	(0.137)	(0.106)	(0.021)
Long Run (t>12)	0.095	0.084	0.010
	(0.159)	(0.118)	(0.025)
TX Pre-Year Mean	2.97	1.51	11.92
Sample	Aggregate Sample	Aggregate Sample	Aggregate Sample
N	156	156	156

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Note: Table displays results estimating an SDiD as described in Section 5.2. However, because these are housing outcomes, I do not want to include the MLS housing market controls in the specifications which residualizes the outcome variable, due to exogeneity concerns. Using Equation 5, I omit the MLS market-level controls (lagged total listings sold, share sold, and median days on the market). These variables are included, however, in the algorithm to choose how to weight control counties, as they still speak to pre-period similarity.Row (1) reports the coefficient on Texas*Post in the short term (the first 4 quarters after the policy was announced). Row (2) reports this for the long term as defined by quarters 4-32. Row (3) reports this for the long term as defined by quarters 13-32. *N* denotes the number of counties in the specification. Before taking the residual as described in Equation 5, all outcome variables are first winsorized to the 97th and 3rd percentiles for the state-year-quarter. Standard errors are bootstrapped. See Arkhangelsky et al. (2021) for more information.

C SDiD Weight Construction

C.0.1 Unit Weight Construction

Unit weights are chosen such that:

$$(\hat{\omega}_0, \hat{\omega^{sdid}}) = \arg \min_{\omega_0 \in \mathbb{R}, \omega \in \Omega} \ell_{unit}(\omega_0, \omega),$$

where:

$$\ell_{unit}(\omega_0, \omega) = \sum_{t=1}^{T_{pre}} (\omega_0 + \sum_{j=1}^{N_{co}} \omega_j Y_{jt} - \frac{1}{N_{tr}} \sum_{j=N_{co}+1}^{N} Y_{jt})^2 + \zeta^2 T_{pre} \|\omega\|_2^2$$

and:

$$\Omega = \{\omega \in \mathbb{R}_+^N : \sum_{j=1}^{N_{co}} \omega_j = 1, \, \omega_j = N_{tr}^{-1} \, for\, all \; j = N_{co}+1, ..., N\}$$

ζ is a "regularization parameter" chosen to match the size of a typical one-period outcome change (Δ_{jt}) for unreated units in the pre-period, and then scaled:

$$\zeta = (N_{tr} T_{post})^{\frac{1}{4}} \hat{\sigma},$$

where:

$$\hat{\sigma}^2 = \frac{1}{N_{co}(T_{pre}-1)} \sum_{j=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} (\Delta_{jt} - \bar{\Delta})^2$$

Note that there are two key differences from the synthetic controls unit weights. The first is the inclusion of the intercept term ω_0, which allows for the unexposed pre-trends to only need to be parallel. The second is this regularization parameter, which ensures the uniqueness of the weights.

C.0.2 Time Weight Construction

The time weights are constructed such that:

$$(\hat{\lambda}_0, \hat{\lambda^{sdid}}) = \arg \min_{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda} \ell_{time}(\lambda_0, \lambda),$$

where:

$$\ell_{time}(\lambda_0, \lambda) = \sum_{j=1}^{N_{co}} (\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{jt} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{jt})^2$$

and:

$$\Lambda = \{\lambda \in \mathbb{R}_+^T : \sum_{j=1}^{T_{pre}} \lambda_t = 1, \, \lambda_t = T_{post}^{-1} \, for\, all \, t = T_{pre}+1, ..., T\}$$

D Measuring Returns to Listings

To capture the ability of brokers to generate better returns on listings in terms of price and speed, I utilize the sample of listings matched to a licensee.

I begin by estimate a hedonic model for both price and time to sale by regressing the natural log of the sale price or the days on the market before the sale (DOM) for a given listing on a number of property characteristics, as well county and year-quarter fixed effects. I estimate the following equation using all of the listings in the matched listing sample:

$$Y_{it} = \alpha + X_i + \lambda_{it} + \gamma_t + \varepsilon_{it} \tag{6}$$

In Equation 6, Y_{it} is either the natural log of sale price or the natural log of days on the market (DOM) for listing i in quarter t. X_i is a vector of property characteristics whic includes the square footage of the property, total living area, the year the property was constructed, total number of bathrooms, total number of bedrooms, and indicators for whether the property has a fireplace, a pool, and a garage. Finally λ_i are county fixed effects, while γ_t are year-quarter fixed effects.

This estimation leaves each listings with a residual, ε_{it}. This can be though of as the “returns” to the listing, as they represent the portion of the price (or the time on the market) which cannot be explained by the property or market, and can therefore be attributed to the agent.

The residual is then averaged over all listings performed by an agent. Specifically, for brokers, I average this across only the listings performed by that broker in the four years before upgrading the license. For salespeople, this is averaged over only her listings in the first four years after becoming a salesperson. Thus, each salesperson or broker ends up with a single averaged residual for both price and time on market.

Finally, I average this broker- or salesperson-level returns measure over all brokers or salespeople by their entry cohort. For example, I would take this average over all brokers in a county which upgraded as brokers in 2011q4 as that county’s quality observation for that quarter.