The Price of Portability: How Interstate Licensing Transforms Mental Health Markets

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Abstract

Interstate occupational licensure compacts are an increasingly popular way of addressing provider shortages in mental healthcare markets. I study the effects of licensure compacts on the size and composition of the psychologist workforce. I develop an empirical model of entry for psychologists differentiated by whether they provide in-person or virtual care. Results show that the Psychologist Interjurisdictional Compact increased overall supply by 2.9 psychologists per market but decreased in-person supply by 0.59 psychologists. Fifty-three percent of this decline is attributable to increased competitive pressure from out-of-state therapists. While geographic license portability increases supply, it reduces access to in-person care.

Keywords: Occupational licensing, Interstate compact, Mental health, Labor supply
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1 Introduction

Markets for mental health care have evolved dramatically in recent years, and especially since the onset of the COVID-19 pandemic. Evidence suggests that the supply of mental health care providers is not sufficient to meet new levels of demand. As of 2024, over 120 million individuals reside in a mental health workforce shortage area (KFF, 2024). Shortages are especially acute for providers of psychotherapy, which is often referred to as talk therapy or colloquially as "therapy." The effects of this shortage are being felt by providers and patients: in 2023, 56% of psychologists reported having no openings for new patients, and among those who kept a waitlist, the average reported time spent on a waitlist for an initial appointment was over three months (APA, 2023). This is particularly concerning in light of research finding that longer wait times for mental health visits result in higher mortality rates among individuals experiencing mental health emergencies (Costantini, 2025).

There are several constraints on psychotherapy provider supply that may be contributing to the psychotherapist shortage. Some of the most pertinent barriers identified by stakeholders include low reimbursements for behavioral health services; burnout, particularly since the start of the pandemic; and the high costs of occupational licensure (GAO, 2022; Thom and Norris, 2023). In this paper, I examine how occupational licensure regulations affect the size and composition of the psychotherapist workforce.

To be licensed and practice independently, therapists must generally earn a graduate degree, complete a certain number of hours of supervised practice, pass required exams, and pay fees. The specifics of these licensure requirements vary across professions and states. Psychotherapists must also apply for and maintain licensure separately in each state in which they practice. Licensure costs may prevent therapists from seeking licensure in multiple states, which can disrupt continuity of care for patients who move to a state in which their therapist is not licensed. Low rates of cross-state licensure have become particularly constraining with the widespread adoption of teletherapy, use of which has stabilized to 10 times pre-pandemic levels, as well as with increases in state-to-state migration in the U.S. over the last decade (Cantor et al., 2023; Ismail, 2023).

In response to these trends, many states and professional associations have begun to form licensure compacts. These compacts facilitate the practice of psychotherapy across state lines by making it so that licensure in one compact member state implies licensure in all other compact member states. The Psychology Interjurisdictional Compact (PSYPACT), implemented in 2019, allows psychologists to practice teletherapy in any state that is a member of the compact (PSYPACT, 2025). The Counseling Compact, set to be implemented in 2025, does the same for licensed professional counselors (Counseling Compact, 2025). Licensure compacts such as these potentially increase the profitability of being a virtual therapist relative to an in-person one by dramatically reducing the costs of entering out-of-state markets, no matter their geographic proximity to the provider. To the extent that virtual and in-person therapy are substitutes for one another, increased entry of virtual therapists may put competitive pressure on in-person ones, resulting in a further decline in in-person provider supply.

I examine how occupational licensure requirements impact the structure of talk therapy markets, quantifying how licensure compacts differentially affect entry across differentiated providers. I focus on the entry decisions of psychologists, who diagnose and treat mental health conditions through psychological testing and talk therapy. I identify the practice locations and modalities of psychologists using the universe of therapist profiles maintained by Psychology Today, the leading online directory that mental health professionals use to advertise their services and connect with potential clients. Psychologists on Psychology Today can choose to advertise their services in a pre-specified number of markets. Entry in geographically distant markets is made possible by teletherapy and the ability to enter as an online-only provider.

I categorize psychologists into three types: those who practice in-person and are local to the markets they have entered; those who are local but choose to practice online; and those who are physically located in another state and provide only online therapy. I construct counts of the number of psychologists of each type practicing in each market and develop an empirical entry model that relates entry to own- and cross-type competition as well as to whether the market is in a PSYPACT member state. The model allows for correlation in unobserved profit shocks across types, using an affordability index that measures the cost of living born by in-person providers to separately identify the correlation in shocks from the cross-type competition effects. Because PSYPACT membership is likely correlated with unobservable determinants of profits, I employ a control function approach that uses state-level measures of licensure stringency across *all* licensed professions as an instrument for membership.

My estimates indicate that the entry of virtual therapists puts significant competitive pressure on in-person psychologists: the partial-equilibrium effect of the entry of one additional virtual therapist reduces in-person entry by 5.87% if that virtual therapist is local and by 15% if that entrant is out of state. I additionally find that PSYPACT membership results in a 27% increase in entry of out-of-state virtual psychologists, but no significant effect on entry by in-person or local virtual psychologist. I use the model estimates to compute entry thresholds in the style of Bresnahan and Reiss (1991). Entry threshold patterns vary across provider types, indicating that the nature of competition is itself differentiated according to provider modality.

Despite having a small direct effect on in-person entry, compact membership has the potential to negatively impact in-person entry by heightening competitive pressure from out-of-state therapists. I use the model estimates to compute the equilibrium effect of licensure compact membership taking into account this indirect competitive effect. I find that compact membership results in an increase in out-of-state entry of 3.47 psychologists on average. This indirect competitive effect accounts for 53% of the estimated decline in in-person psychologists of 0.56 providers per market. The compact therefore succeeds in expanding overall psychologist supply by 2.9 psychologists per market on average, but reduces access to in-person providers. Moreover, because the increase in provider supply is entirely driven by out-of-state providers, the policy reduces access to not just in-person but *local* providers.

These patterns have implications for how we think about standard measures of supply, which are usually geographically based, as well as for the likely effects of such licensure polices on patients. Given that recent research has found virtual talk therapy to be equally as effective as that provided in-person, the effects of compact membership on mental health are likely positive (Pescatello et al., 2021; Andrews et al., 2018). However, virtual therapy is likely not a close substitute for in-person care for individuals with serious mental illness or communication challenges. My results suggest that licensure compacts should be paired with policies to mitigate the effects of loss of in-person care for such individuals.

This paper contributes to a growing literature on the impacts of occupational licensure requirements for professionals who market their services via digital platforms (Blair and Fisher, 2022; Farronato et al., 2024; Deyo, 2022), which has found that higher occupational licensure requirements result in less competition and higher prices without improving consumer satisfaction. Using the static entry framework of Bresnahan and Reiss (1990, 1991), I likewise find that reductions in cross-state licensure requirements result in an overall increase in greater competition. I additionally show that these competitive effects have a meaningful impact on the composition of psychologist labor supply.

This paper also contributes to the literature investigating the determinants of entry into U.S. healthcare markets (Bresnahan and Reiss, 1991; Magnolfi et al., 2024; Abraham et al., 2007; Cohen et al., 2013). Goetz (2023) is the only other work to consider how the entry of virtual competitors impacts psychotherapy market outcomes. The author finds that price-elastic consumers substitute to virtual therapists following entry, resulting in higher post-entry prices for in-person incumbents. Relative to Goetz (2023), this paper endogenizes the therapist entry and modality decisions on the extensive margin, but is unable to assess intensive margin effects on price or utilization.

I proceed as follows: Section 2 describes the data; Section 3 presents the empirical entry model; Section 4 presents estimation results; Section 5 quantifies the equilibrium effects of licensure compacts on psychologist supply; and Section 6 concludes.

2 Setting and data

2.1 Data on number of psychologists

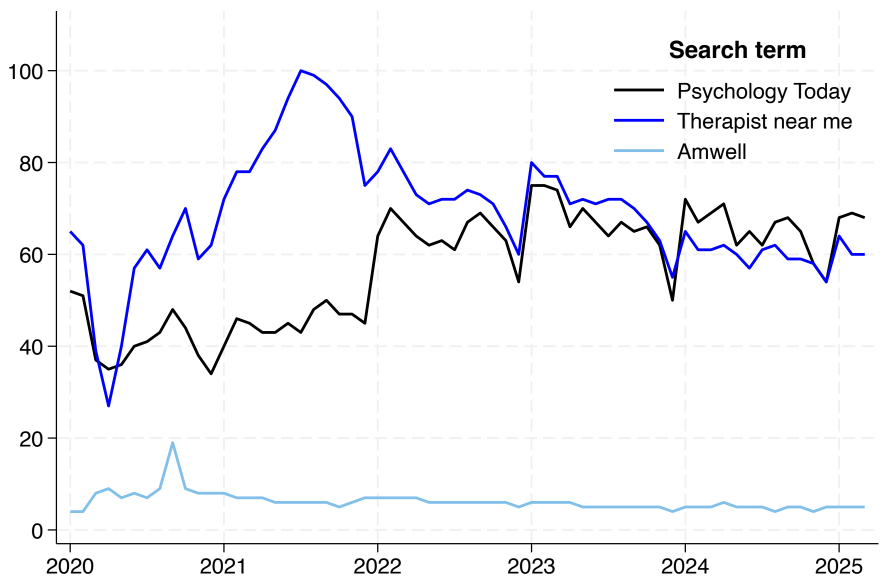
For information on the size and composition of the psychotherapy workforce, I use data from an online directory of therapists maintained by Psychology Today, the leading website that mental health professionals use to advertise their services and connect with potential clients. A Psychology Today therapist directory listing costs \$29.95 per month and includes an active listing, client messaging, and a telehealth platform. The directory allows for filtering by geography and professional type, the latter of which facilitates my focus on psychologists. This data was scraped in January 2025 and is a snapshot of the website at that time.

The Psychology Today data provides multiple advantages over alternative datasets. First, many therapists are self-employed: survey data from the American Psychological Association indicates that 43% of psychologists engaged in individual solo practice in 2021 (APA, 2021). For this reason, many psychotherapists will be excluded from datasets that are limited to workers who are not self-employed or are based in physician offices, such as the employment estimates of the Bureau of Labor Statistics or the National Ambulatory Medical Care Survey. Second, over one-third of psychologists do not accept insurance and so will be excluded from claims databases (APA, 2024).

As an example, Figure A1 provides a comparison of psychologist counts in the Psychology Today data against those in the Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS). The light and dark blue dots correspond to natural logarithm of each state's number of psychologists as given by the Psychology Today data and OEWS, respectively. The difference in these log counts is positive for 40 of the 47 states represented in the OEWS, averaging 0.52. Given that the correlation in the level count of psychologists across the two data sources is 0.98, these patterns seem to suggest meaningful and widespread undercounting of psychologists in this alternative data source.

Psychology Today contains both a breadth and depth of information on providers, including information on their demographic characteristics, areas of specialization, accepted insurance plans, and educational background, making it superior to more limited directories, including the online provider tools of individual insurers. Figure 1 shows the trend in Google searches for terms one might use to find a psychologist over the five years preceding the sample period. As of mid-2025, searches for "Psychology Today" were higher than that for competing online directories of therapists as well as for the very general search term "therapist near me," providing confidence that provider counts constructed with the Psychology Today data are the best available approximation of psychologist supply.

Figure 1: Trend in Google search terms for psychologists



Notes: Data come from Google trends: trends.google.com/trends/.

I categorize psychologists on the platform into one of three types, which are determined by the modalities they offer, their physical location, and the geographies in which they choose to advertise their services. Psychologists can choose from one of three modality categorizations: online only, in-person only, or both in-person and online. Each psychologist's listing is automatically included in the search results for the area corresponding to their physical location, and they can additionally choose up to two additional geographic markets in which to have their listing advertised.[1] I define an in-person psychologist as one who offers in-person services and is physically located in the same state as the market in which their services are being advertised, so that in-person provision is actually possible. I define out-of-state therapists as those who are located in a different state from that in which their services are being advertised and so offer online services only. Lastly, I define local online therapists as those who are physically located in the same state as the market in which their services are being advertised but offer online services only. These categorizations are mutually exclusive and collectively exhaustive partitions of the directory listings.

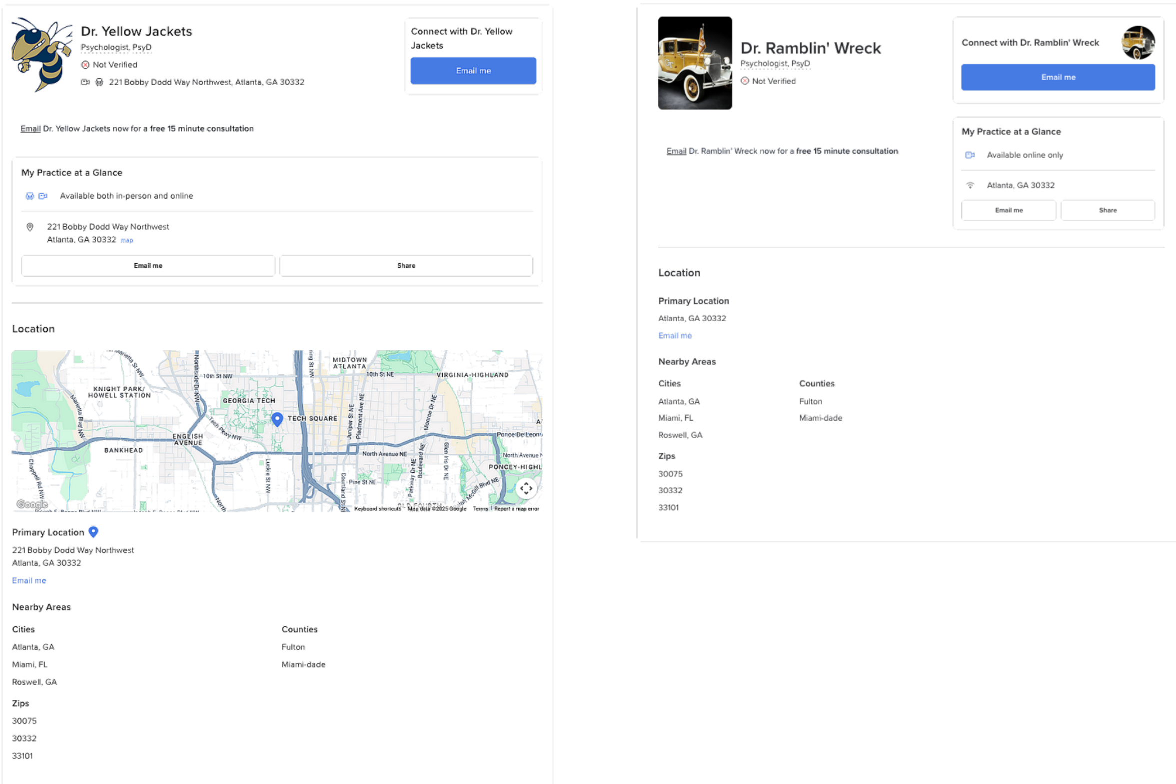
To fix ideas, Figure 2 provides example profiles for two psychologists who operate in the same markets but offer different modalities. Dr. Yellow Jackets will be categorized as an in-person provider for all of the Georgia markets that they choose to list on their profile, but as an out-of-state provider in Miami. Note that this categorization is based on the extensive margin of provider choice and reflects the fact that consumers in the Georgia markets *have the option* to receive in-person therapy from Dr. Yellow Jackets, while this is not possible for consumers located in Miami. Dr. Ramblin' Wreck will be categorized as a local online provider for all of their Georgia markets and as an out-of-state provider in Miami. The Psychology Today platform solicits and validates licensure information from all providers; in this example, we can therefore assume that both providers are licensed to practice psychology in both Georgia and Florida, or that Georgia and Florida are both members of an interstate licensure compact.

This psychologist-type categorization has two main advantages. First, licensure compacts reduce the barriers to across-state entry only. Although across-state entry necessarily implies

[1] Providers are required to provide a physical address, regardless of the modalities they offer.

Figure 2: Example Psychology Today profiles

(a) In-person and online | (b) Online only



Notes: Screenshots are of profiles made on Psychology Today for illustrative purposes only.

online provision, online provision does not necessarily imply out-of-state entry. Drawing this distinction between out-of-state and local providers allows me to empirically test whether licensure compacts differentially impact supply of these two types of providers. Second, the welfare implications of licensure compacts are likely very different depending on the extent to which they impact the geographic distribution of providers. The replacement of in-person psychologists with out-of-state ones reallocates providers across space in a way that the transition from in-person to local online provider does not, and the latter may have much more serious welfare implications for those for whom virtual care is inadequate.

Note that the platform prompts individuals to indicate their location to begin a search for both in-person and virtual providers. This means that while patients could technically choose any virtual provider regardless of the provider's location, they are presented a choice set of virtual (and in-person) providers who have chosen to have their services advertised in the patient's market. Other popular online directories of medical providers also offer location-based recommendations for virtual providers. A shared market definition for in-person and virtual therapists is therefore appropriate even if entry costs for geographically distant markets are lower for the latter.

I follow Magnolfi et al. (2024) in defining markets as primary care service areas (PCSAs), which are utilization-based catchment areas for the United States that reflect the travel of patients to primary care clinicians (Goodman et al., 2003). PCSAs are groupings of zip codes smaller than counties and are likely the closest approximation to the geographic area considered by individuals when constructing their psychologist choice set and searching on Psychology Today. There are 6,619 PCSAs with an average population of around 49 thousand individuals.

Table 1 provides summary statistics for all PCSAs using data from Psychology Today and area-level characteristics from a variety of sources. Over half of PCSAs have no in-person psychologists. The number of out-of-state psychologists trends non-monotonically with the number of in-person psychologists, which is potentially reflective of competitive pressures of the former on the latter. In-person psychologist counts are negatively correlated with measures of licensing stringency as measured by participation in the Psychology Interjurisdictional Compact as well as the license-to-work rank, which is a measure of the average licensing burden across all occupations in a state. In general, there are more in-person psychologists in areas that are more populous, higher income, more racially diverse, younger, less rural, more educated, and have greater rates of broadband internet adoption.

Table 1: Primary care service area characteristics by number of in-person psychologists

	Number of in-person psychologists					
	0	1	2	3	4	≥ 5
Competitor counts						
Out-of-state	4.5 (3.8)	4.1 (4.4)	4.1 (4.5)	4.0 (4.8)	4.3 (6.4)	7.0 (12.0)
Local online	0.1 (0.4)	0.4 (0.9)	0.7 (1.2)	1.2 (1.6)	1.6 (1.9)	11.8 (28.0)
State policies						
PSYPACT	83.3%	83.5%	80.4%	77.4%	77.6%	69.3%
License-to-work rank	28.7 (13.7)	25.0 (14.5)	24.5 (14.7)	24.6 (14.8)	23.5 (14.9)	21.1 (15.4)
Socio-demographics						
Population (10k)	1.7 (1.9)	3.4 (2.8)	5.2 (3.9)	6.1 (4.8)	6.9 (4.9)	12.6 (12.0)
Median income ($10k)	6.7 (1.8)	7.7 (2.2)	8.2 (2.3)	8.5 (2.7)	8.7 (2.7)	10.3 (3.4)
Share insured	90.9 (5.7)	91.8 (5.3)	91.8 (5.2)	92.7 (4.4)	92.5 (5.5)	93.3 (4.5)
Share employed	95.1 (3.2)	95.2 (2.3)	95.2 (2.0)	95.2 (2.0)	95.4 (1.9)	95.2 (1.9)
Share Black	8.0 (15.1)	8.3 (14.0)	9.8 (13.3)	10.5 (15.3)	10.3 (12.8)	10.3 (13.0)
Share Hispanic	9.0 (14.2)	12.8 (16.0)	15.3 (18.5)	15.1 (17.3)	14.8 (17.3)	17.3 (16.0)
Share over 65	20.7 (5.9)	19.2 (6.2)	18.2 (5.8)	18.7 (6.6)	18.2 (6.8)	17.2 (5.9)
Share $\leq$ high school	36.1 (7.5)	31.8 (7.8)	29.1 (7.0)	27.0 (7.7)	26.3 (6.1)	20.8 (7.3)
Share rural	25.1 (38.9)	9.4 (24.4)	3.1 (14.0)	2.6 (13.0)	1.2 (5.1)	0.7 (6.2)
Share with broadband	32.7 (22.6)	49.8 (24.3)	61.7 (21.9)	63.0 (20.6)	65.5 (20.2)	72.9 (17.5)
Affordability index	100.4 (1.0)	100.0 (0.9)	99.8 (0.9)	99.7 (0.8)	99.6 (0.8)	99.3 (0.8)
Observations	3,619	715	383	234	174	1,494
Share of all observations	54.7	10.8	5.8	3.5	2.6	22.6

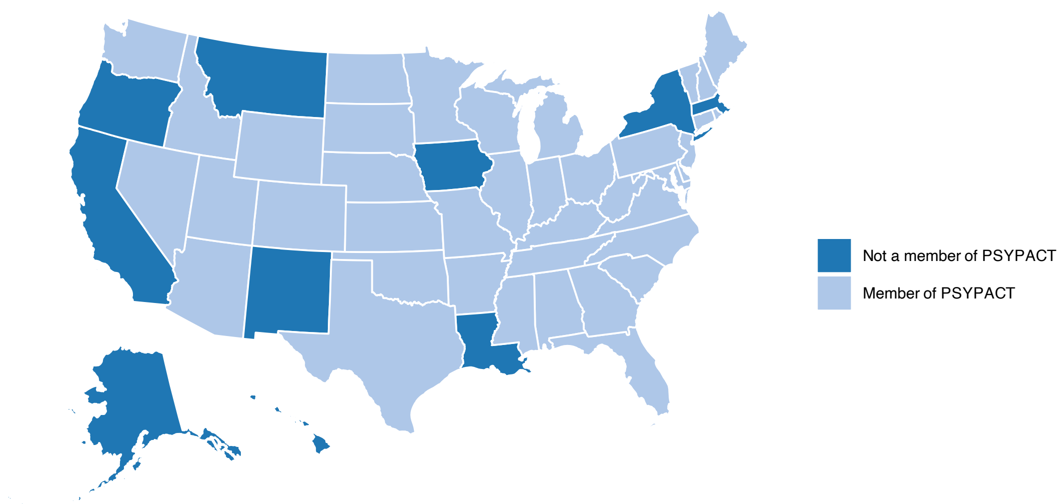
Notes: In-person psychologist and competitor counts come from Psychology Today. PSYPACT is a binary indicator for participation in the Psychology Interjurisdictional Compact. The affordability index is computed using price parity and income data from the Bureau of Economic Analysis (BEA, 2024). License-to-work rank is a ranking of states by the average burden for all licensed occupations (Institute for Justice, 2022). All socio-demographic characteristics come from the American Community Survey with the exception of broadband usage, which comes from the Microsoft United States Broadband Usage Percentages Dataset (Census Bureau, 2025; Kahan and Ferres, 2020).

2.2 The Psychology Interjurisdictional Compact

Interstate licensure compacts are agreements between states to broaden the geographic scope of licensure to include all compact member states. Licensure compacts are not new to healthcare: since its inception in 2000, 40 states have joined the Nursing Licensure Compact (NLC), which permits registered nurses living in member states to practice across state lines. Research has found that the NLC had little effect on the labor market supply or mobility of nurses (DePasquale and Stange, 2016). Research on the Interstate Medical Licensure Compact, implemented in 2017, finds that it resulted in a 3% increase in out-of-state practices for physicians whose home state participated in the compact (Deyo et al., 2016). The Psychology Interjurisdictional Compact (PSYPACT) is an interstate licensure compact for psychologists that was implemented in 2019. Unlike previous licensure compacts that sought to promote physical geographic mobility among healthcare providers, the explicit aim of PSYPACT was expand access to psychotherapy by "allow[ing] for the delivery of psychological services via telecommunications from providers to patients in separate states" (PSYPACT, 2023). It is the first licensure compact for mental health professionals. Figure 3 depicts the 40 U.S. states that have joined PSYPACT and the 10 that have not as of 2025.

To practice teletherapy under PSYPACT, psychologists must hold an active, unrestricted license in their home state that is a PSYPACT member. They must obtain both an E.Passport certificate from Association of State and Provincial Psychology Boards, which verifies their credentials and good standing, and an Authority to Practice Interjurisdictional Telepsychology from the PSYPACT Commission. The application therefore involves background checks and verification of existing licensure, but no additional licensure. In the absence of a compact, psychologists seeking to provide teletherapy in another state would have to become licensed in that state. The costs of additional licensure are non-trivial, as supervised hours requirements, fees, and renewal frequencies vary substantially across states. For example, the supervised hours requirement for psychologists varies from 1,500 to 4,000 hours, and initial licensure fees vary from \$50 in Idaho to \$600 in Nevada (NPTC, 2025; ASPPB, 2025). Licensure compacts may affect the profitability of entering the psychology profession, practicing virtually relative to in-person, and the level of competition between different types of providers. I model each of these effects in the following section.

Figure 3: Psychology Interjurisdictional Compact membership



Notes: Data on PSYPACT membership come from the commission's webpage: https://psypact.gov/

3 Entry model

I employ a static entry model of the simultaneous entry decisions of psychologists differentiated by modality and geographic proximity to the markets they serve in the style of Bresnahan and Reiss (1991). Let n_m^t denote the number of psychologists of type t in market m. All psychologists of a given type are identical and earn profits according to

$$\pi_m^t(\mathbf{N}_m, \mathbf{X}_m, \mathbf{W}_m^t) = S_m v^t(\mathbf{N}_m, \mathbf{X}_m) - F(n_m^t, \mathbf{W}_m^t).$$

Here, v^t corresponds to average variable profits, which are proportional to market population S_m and depend on the number of psychologists in the market $\mathbf{N}_m$ and market characteristics that determine demand and variable costs $\mathbf{X}_m$. Fixed costs F are a function of the number of firms of one's own type n_m^t as well as cost shifters $\mathbf{W}_m^t$. A cost shifter included in $\mathbf{W}_m^t$ for all psychologist types is a binary indicator for whether the market m is located in a state that participates in the Psychologist Interjurisdictional Compact. PSYPACT participation influences licensure costs associated with entry that do not scale with demand and so are an important element of the fixed cost of entry.

Entry thresholds are defined as the smallest market size that can sustain n^t. These thresholds are defined by the following breakeven condition:

$$\pi_m^t(\mathbf{N}_m, \mathbf{X}_m, \mathbf{W}_m^t) = 0 \implies S_{n^t}^t \geq \frac{F(n_m^t, \mathbf{W}_m^t)}{v^t(\mathbf{N}_m, \mathbf{X}_m)}. \tag{1}$$

Bresnahan and Reiss (1991) show that how entry thresholds change with n^t is reflective of both how the level of competition and entry costs evolve with the number of firms. If entry results in a meaningful decline in market power, then entry thresholds will fall with entry and entry threshold ratios, defined as $\frac{S_{n^t+1}^t}{S_{n^t}^t}$ will decline toward one as the number of entrants increases. Alternatively, if the fixed costs of entry fall with the number of entrants, then $\frac{S_{n^t+1}^t}{S_{n^t}^t}$ will be less than one.

3.1 Identification and estimation

I empirically specify the profit function of a psychologist of type t as

$$\pi_m^t(\mathbf{N}_m, \mathbf{X}_m, \mathbf{W}_m^t) = S_m\big(\alpha^t n_m^t - \mathbf{N}_m^{-t}\beta^t + \mathbf{X}_m\delta^t\big) - \mathbf{W}_m^t\theta^t - \sum_{n^t=1}^{N_t} \gamma_{n^t}^t + \varepsilon_m^t. \tag{2}$$

α^t and β^t capture how variable profits vary with the number of firms of one's own type and of other types, respectively. γ^t are components of fixed costs that depend on the number of firms of one's own type, and θ^t captures how fixed costs depend on the market's occupational licensure policy and other cost shifters. I impose the following assumptions on Equation (2):

(i) Markets are independent. This implies that psychologists do not take into account the cross-market effects of entry, nor are their regional-level unobservables that correlate the payoffs of entry across markets, such as insurance networks. I follow the literature and minimize the scope for correlation in payoffs across markets by estimating my model using only geographically isolated markets. I follow Magnolfi et al. (2024) and define geographically isolated PCSAs as those that are at least 35 miles away from all more populated PCSAs. Table A1 describes these 810 isolated PCSAs. I test the robustness to these assumptions in Section 4.

(ii) $\beta^t = 0$ for $t \in \{\text{out-of-state, local online}\}$. That is, out-of-state and local online psychologists have a competitive effect on in-person psychologists, but out-of-state and local online psychologists do not experience competitive pressure from psychologists of other types. This assumption is motivated by a literature documenting the competitive effects of online entry on offline firms (Zervas et al., 2017; Seamans and Zhu, 2014; Goetz, 2023). Additionally, substitution to the marginal in-person psychologist will be heterogeneous across consumers within a market and will likely be confined to the set of consumers who are physically proximate to them, resulting in a relatively small effect of in-person entry on virtual profits. The same cannot be said for the marginal virtual psychologist, substitution to which does not decline in distance.

(iii) Unobserved profit shocks are normally distributed and are assumed to be equal for local online and in-person psychologists in each market. Additionally, the covariance of shocks for online and in-person psychologists with shocks to the profits of out-of-state psychologists is given by ρ:

$$(\varepsilon_m^{in} = \varepsilon_m^{onl}, \varepsilon_m^{out}) \sim \mathcal{N}(0, \mathbf{\Sigma})$$
$$\mathbf{\Sigma} = \begin{bmatrix} 1 & 1 & \rho \\ 1 & 1 & \rho \\ \rho & \rho & 1 \end{bmatrix}$$

Profit shocks for in-person and local online providers are likely to be more tightly correlated with one another than with those faced by out-of-state psychologists because of their shared physical location: while shocks to demand are likely to generate correlation in the profits of all three types, local cost shocks will not affect the profitability of out-of-state psychologists, as their physical location is far removed from the market they have virtually entered.

Note that both ρ and β capture the correlation between n_m^{in} and n_m^{out}. Separate identification of these parameters requires the use of an instrument that shifts the profitability of one of these types of psychologists without directly influencing the profitability of the other. I use as a shifter of in-person psychologist profits a measure of market's cost-of-living, summarized in an "affordability index" that is computed as the ratio of price parities to median income. A higher affordability index value indicates that the cost of living is high relative to what people earn and is a less affordable place to live. Because out-of-state providers do not live in the markets in which they practice, the costs of living in those markets are not costs that they themselves incur. Given that income itself is already included in the variable profit functions of all provider types, this measure is likely to satisfy the exclusion restriction and affect only in-person providers' profits. I model the affordability index as influencing in-person providers' fixed costs. Descriptive evidence of the instrument's strength can be seen in Table 1 in which the affordability index falls monotonically with the number of providers.

Estimates of θ_m^t, the effect of PSYPACT participation, are likely biased by correlation of θ_m^t with ε_m^t: e.g., participation in PSYPACT may be just one of many ways that a market endeavors to lessen constraints on psychologist supply, the rest of which are unobservable. In order to be able to compute unbiased estimates of the equilibrium effects of licensure compacts, I must address the potential endogeneity from correlated entry and PSYPACT participation choices. I do this by leveraging a measure of the average licensing burden across all occupations in a state developed by the Institute for Justice (Institute for Justice, 2022). This measure takes the form of a state ranking based on the depth of requirements for specific occupations and the number of licensed occupations. A higher rank value implies greater licensure requirements. This "license-to-work" ranking is likely to be positively correlated with participation in licensure compacts such as PSYPACT, but not directly related to other policies that pertain to psychologist entry. Figure A2 depicts each state and its place in the licensure ranking.

Because the probability that a market has a given number of entrants is nonlinear in the endogenous variable, the standard instrumental variables approach of substituting predicted values of the endogenous regressor into the profit equations would induce bias (Terza et al., 2008). Instead, I employ a control function approach, in which the residuals from the first-stage regression are used to approximate the component of ε_m^t that is correlated with PSYPACT participation.[2] A flexible function of these residuals are then included the linear predictor of the second-stage ordered probit model (Petrin and Train, 2010; Wooldridge, 2010). In practice, I perform three separate first-stage regressions, one for each psychologist type, of an indicator for PSYPACT participation on the components of the variable profit functions and fixed effects for the number of firms of ones own type. I then include a fourth-degree polynomial expansion of the residuals from each of these regressions in the profit functions for their respective types. Table A2 provides results these first-stage regressions. For each, the effect of the license-to-work ranking is statistically significant at the 1% level and associated with a 0.7 p.p. increase in the likelihood of PSYPACT participation.

In estimation, I restrict the set of values that n^t can take to account for outliers and rare outcomes. In particular, I restrict $n^t = 0, 1, ..., 4, 5$ or more psychologists for those of the in-person or local online types. I restrict $n^{out} = 1, ..., 5, 6$ or more as less than 1% of markets have no out-of-state psychologists.

[2] Use of the control function approach to address discrete endogeneous explanatory variables requires that the first-stage residuals "act as a kind of sufficient statistic for capturing the endogeneity of [the discrete endogeneous explanatory variable]" (Wooldridge, 2010). However, (Wooldridge, 2010) also points out that this assumption is "no more or less general than the bivariate probit assumption" made in the alternative maximum likelihood approach.

4 Results

Table 2 provides parameter estimates for entry models estimated from a bivariate ordered probit that accounts for the endogeneity of out-of-state psychologist entry, while Table 3 reports parameter estimates for entry models estimated from univariate ordered probit models of psychologist entry, in which there is assumed to be no correlation in unobserved shocks to profits across provider types. Ordered probit model coefficients, standard errors, and marginal effects effects are reported for each covariate. Marginal effects are the partial equilibrium effect of a one standard deviation increase in the covariate.

In Table 2, we see that the estimated correlation between unobservables equals 0.04, and is both statistically and economically insignificant. This finding that out-of-state psychologist entry is seemingly exogenous conditional on observables differs from other findings in the literature. E.g., Magnolfi et al. (2024) find a strong positive association between the unobserved components of the profits of hospitals and urgent care centers. However, note that there are several reasons to expect a weaker correlation in this context, including the fact that out-of-state psychologists do not face same local cost shocks as in-person ones. Additionally, variation in the composition of insurance networks is likely to be driven by the addition and removal of local providers, generating changes in the profitability of in-person provision that do not affect out-of-state providers. I note that that the effect of the instrument—the affordability index—is large and statistically significant, a one standard deviation increase resulting in a 6.1% decline in the number of in-person psychologists.

Table 2: Bivariate entry model estimates

	In-person			Out-of-state			Local online		
	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Correlation with out-of-state shocks (ρ)	-0.039	(0.202)							
Variable profit parameters									
Number of in-person (α^{in})	0.180†	(0.023)							
Number of out-of-state (α^{out}, β^{in})	-0.064†	(0.019)	-12.18	0.161†	(0.042)				
Number of local online (α^{onl}, β^{in})	-0.049†	(0.018)	-9.38				0.092†	(0.018)	
Median income (δ)	-0.062	(0.036)	-11.70	0.012	(0.038)	0.31	0.001	(0.028)	0.18
Share insured (δ)	0.046	(0.026)	8.65	0.084	(0.054)	2.20	0.007	(0.028)	2.01
Share unemployed (δ)	-0.000	(0.015)	-0.02	-0.056†	(0.027)	-1.48	0.000	(0.016)	0.11
Share Black (δ)	-0.033	(0.020)	-6.29	-0.006	(0.035)	-0.14	-0.031†	(0.012)	-8.88
Share Hispanic (δ)	-0.032	(0.028)	-6.07	-0.001	(0.048)	-0.03	-0.046	(0.026)	-13.17
Share over 65 (δ)	0.029	(0.027)	5.42	0.002	(0.044)	0.04	0.024	(0.017)	6.95
Share $\leq$ high school (δ)	-0.066†	(0.033)	-12.62	0.100†	(0.041)	2.63	-0.052†	(0.020)	-14.86
Share rural (δ)	-0.043	(0.094)	-8.17	0.649†	(0.134)	17.02	-0.000	(0.089)	-0.10
Share with broadband (δ)	-0.008	(0.037)	-1.58	-0.127†	(0.043)	-3.33	0.025	(0.029)	7.09
Fixed cost parameters									
PSYPACT (θ_t)	-0.868	(2.458)	-17.63	9.446†	(4.422)	26.52	-1.935	(2.866)	-59.21
Affordability index (θ^{in})	-0.302†	(0.116)	-6.14						
γ_1^t	-0.741	(0.589)					1.407	(0.783)	
γ_2^t	0.476	(0.588)		-1.255	(1.319)		2.646†	(0.835)	
γ_3^t	1.863†	(0.612)		0.233	(0.918)		4.178†	(0.933)	
γ_4^t	2.937†	(0.638)		1.073	(0.879)		5.653†	(1.113)	
γ_5^t	4.191†	(0.829)		1.822	(0.863)		6.675†	(1.166)	
γ_6^t				2.593	(0.837)				
Number of observations	810								

Notes: Columns (1), (4), and (7) present coefficient estimates for the bivariate entry model. Columns (2), (5), and (8) provide standard errors for these coefficient estimates, calculated using 100 bootstrap replications. Columns (3), (6), and (9) provide the marginal effects for these estimates, which are the simulated % change in the mean number of psychologists given a one standard deviation in the row variable. † denotes statistical significance at the 5% level.

Table 3: Univariate entry model estimates

	In-person			Out-of-state			Local online		
	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable profit parameters									
Number of in-person (α^{in})	0.132†	(0.021)							
Number of out-of-state (α^{out}, β^{in})	-0.059†	(0.016)	-15.01	0.114†	(0.032)				
Number of local online (α^{onl}, β^{in})	-0.023	(0.013)	-5.87				0.063†	(0.013)	
Median income (δ)	-0.053	(0.028)	-13.37	0.009	(0.026)	0.31	-0.001	(0.017)	-0.23
Share insured (δ)	0.039	(0.021)	9.90	0.060	(0.032)	2.22	-0.001	(0.019)	-0.27
Share unemployed (δ)	-0.001	(0.011)	-0.22	-0.040†	(0.018)	-1.49	0.003	(0.010)	1.27
Share Black (δ)	-0.026	(0.016)	-6.54	-0.004	(0.026)	-0.14	-0.022†	(0.008)	-8.84
Share Hispanic (δ)	-0.012	(0.019)	-3.01	-0.001	(0.026)	-0.02	-0.036†	(0.017)	-14.34
Share over 65 (δ)	0.019	(0.019)	4.91	0.001	(0.028)	0.05	0.015	(0.011)	6.06
Share $\leq$ high school (δ)	-0.042	(0.022)	-10.61	0.071†	(0.028)	2.65	-0.036†	(0.014)	-14.55
Share rural (δ)	-0.019	(0.071)	-4.80	0.459†	(0.126)	17.06	-0.007	(0.069)	-2.77
Share with broadband (δ)	-0.009	(0.026)	-2.34	-0.089†	(0.026)	-3.32	0.021	(0.016)	8.22
Fixed cost parameters									
PSYPACT (θ_t)	-0.426	(1.708)	-11.60	6.746†	(2.770)	26.8	-1.914	(1.919)	-81.97
Affordability index (θ^{in})	-0.275†	(0.093)	-7.49						
γ_1^t	-0.784	(0.519)					1.147†	(0.493)	
γ_2^t	0.091	(0.529)		-0.197†	(0.666)		2.004†	(0.521)	
γ_3^t	1.051	(0.574)		0.849†	(0.580)		3.053†	(0.580)	
γ_4^t	1.766†	(0.621)		1.449	(0.559)		4.015†	(0.693)	
γ_5^t	2.597†	(0.738)		1.979	(0.532)		4.706†	(0.805)	
γ_6^t				2.523	(0.517)				
Number of observations	810								

Notes: Columns (1), (4), and (7) present coefficient estimates for the univariate entry models. Columns (2), (5), and (8) provide standard errors for these coefficient estimates, calculated using 100 bootstrap replications. Columns (3), (6), and (9) provide the marginal effects for these estimates, which are the simulated % change in the mean number of psychologists given a one standard deviation in the row variable. † denotes statistical significance at the 5% level.

Because of the weak correlation in unobservables, the parameter estimates in Tables 2 and 3 of an additional out-of-state competitor on in-person psychologist profits are similar, equaling a decline of 12.18% for the bivariate model and of 15% for the univariate models. The competitive effect of local online psychologists on in-person profits is negative but weaker than that of out-of-state therapists, equaling 9.4% for the bivariate model and 5.87% for the univariate ones.

Major differences emerge across provider types in the effect of PSYPACT. In Table 3, we see that the presence of PSYPACT results in 26.8% more out-of-state psychologists, but that the effect of the compact is statistically insignificant for both other types of psychologists. That the direct effect of PSYPACT on in-person supply is negative is consistent with such compacts increasing the opportunity cost of in-person practice. In the next section, we will compare the magnitude of this direct effect on in-person supply to the indirect effect of increase out-of-state competition.

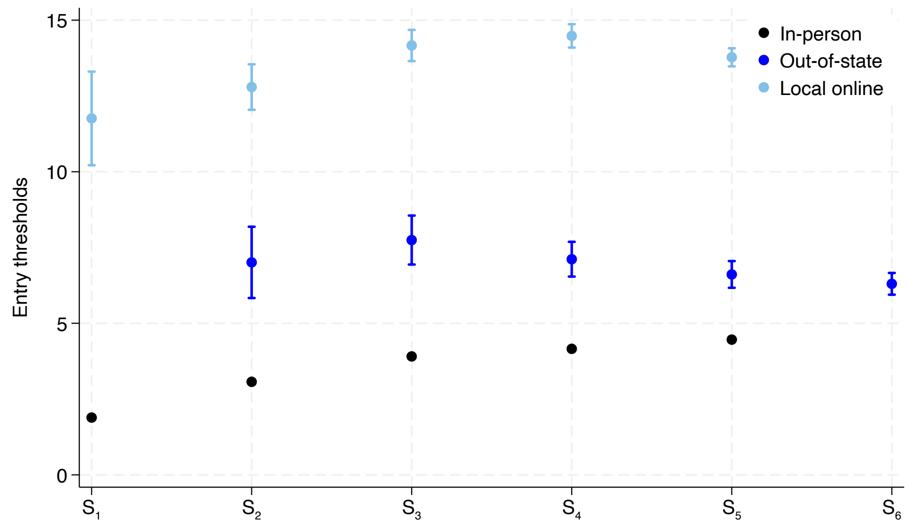
Several additional interesting differences emerge across outcomes in how demographics affect entry. For both the univariate and bivariate models, in-person and local online therapists are less likely to enter markets the more rural or less educated they are. The opposite is true for out-of-state therapists: a one standard deviation increase in the share of the market that is rural results in an increase in out-of-state entry of 2.65%, and an equivalent increase in the share of the market with less than a high school education results in an increase in out-of-state entry of 17.1%. These results suggest that out-of-state therapists may choose to locate in areas that policy makers traditionally classify as underserved.

4.1 Market power among psychologists

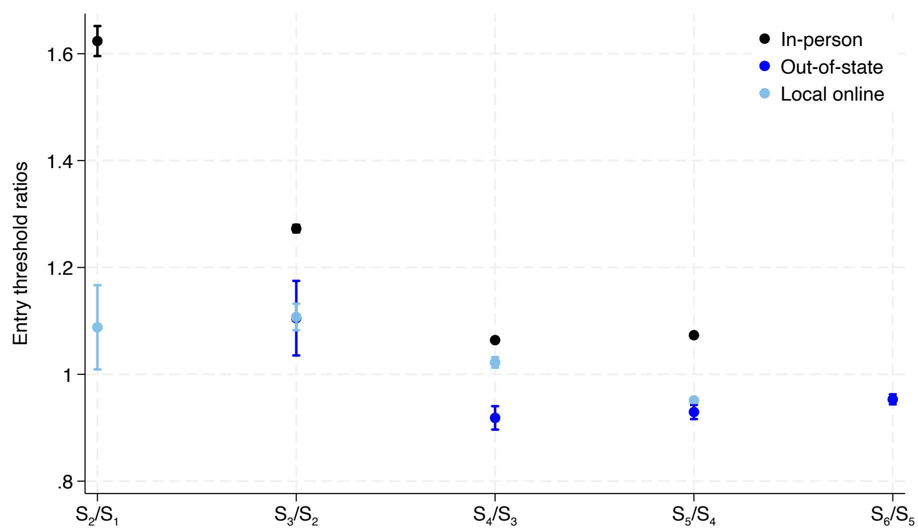
Using the model estimates, I compute entry thresholds as defined in Equation (1) and their ratios. Entry thresholds can be interpreted as the minimum market size, in ten thousand individuals, necessary to sustain a particular number of providers. Given the limited evidence of correlated unobservables, I compute these thresholds using estimates from univariate models.

Figure 4: Per-firm entry thresholds and ratios

(a) Entry thresholds



(b) Entry threshold ratios



Notes: Table reports entry thresholds and ratios from univariate ordered probit models. Entry thresholds are measured in 10,000 individuals per firm. Standard errors calculated using 100 bootstrap replications.

Figure 4 summarizes the results separately for each type of provider, Panel (a) plotting the entry thresholds and Panel (b) their ratios. The results indicate that the minimum market size necessary to sustain one in-person psychologist is approximately 19 thousand individuals. The same estimate for local online therapists is much larger, equaling approximately

117.5 thousand individuals.

Entry thresholds for in-person psychologists are increasing at a decreasing rate, suggesting that additional entry increases the level of competition among in-person providers. That entry threshold ratios appear to be declining gradually toward one suggests that oligopoly market power among in-person providers steadily declines with the number of firms. The same cannot be said for virtual therapists. Entry thresholds are constant for both out-of-state and local online therapists relative to in-person ones, and as a result their entry threshold ratios are clustered tightly around one.

These results are consistent with virtual provider markets being much more competitive than in-person ones at low levels of competition. One plausible explanation for this result is capacity constraints.: virtual providers are likely more able to optimize their availability to serve more patients and have higher capacity than in-person providers. Capacity constraints are one source of market power in models of homogeneous goods competition and will result in above marginal cost pricing if capacities are small relative to demand (Pepall et al., 2014).

4.2 Robustness

I check the robustness of these results to two important modeling assumptions. The first is that cross-competition effects are zero for virtual psychologists. Separate identification the full set of cross-competition effects for the bivariate model is difficult and would require profit shifters for each type of psychologists that do not affect the profits of either other type. Since there is little evidence of correlation in profit shocks across local and out-of-state providers, we focus on the univariate entry models and use them to test our assumptions on cross-competition effects. Table A3 provides univariate model estimates that include the full set of cross-competition effects, in which the number of providers of each type impacts the variable profits of all other types. Cross-competition effects for out-of-state providers are economically and statistically insignificant. Cross-competition effects are relatively more meaningful for local online psychologists, an additional in-person psychologist resulting in an 8.9% decline in the number of local online therapists, while an additional out-of-state psychologist results in a 15% decline. Since entry of local online therapists has minimal impact on in-person psychologist profitability in both our main estimates and when we include the full set of cross-competition effects, the assumption that cross-competition effects for local online therapists are zero is unlikely impact our results as to how PSYPACT affects access to in-person care.

Second, I test the robustness of my results to market definition. In particular, I reconstruct my analysis sample employing a more conservative definition of "geographically isolated," employing only PCSAs that are located no less than 40 miles from a more populous market, rather than 35 miles. There are 628 PCSAs that satisfy this criteria, a 23% decrease in sample size relative to the main analysis sample. It is highly unlikely that individuals substitute between providers located in these very geographically isolated markets and those located elsewhere for the provision of in-person care given that an individual located close to the former is located far from the latter. As discussed in Section 2, while choice sets for virtual therapists could theoretically contain all virtual providers regardless of location, online directories typically narrow them on the basis of physical proximity. Individuals wishing to expand their choice set of virtual providers would need to do so manually by, e.g., adding additional zip codes to their search criteria. If individuals seeking an online therapist incur search costs proportional to the number of additions they make to their search criteria, then this more conservative definition of isolated markets has the added benefit of including PCSAs that contain on average 1.24 more zip codes than the original definition, making it less likely that individuals are searching for providers outside their market. Table A4 presents results from the bivariate model using this subsample of PCSAs, where we see that our estimates for competition effects, PSYPACT, and correlation in shocks are all essentially unchanged relative to our main estimates.

5 Equilibrium effects of occupational licensure reform on provider supply

The results above suggest that there is scope for interstate licensure compacts like PSYPACT to substantially increase the competitive pressure placed on in-person psychologists from out-of-state practitioners. In this section, I decompose the total effect of PSYPACT on in-person psychologist supply into what I refer to as direct and indirect effects. The direct effect refers to PSYPACT's effect on profits holding fixed counts of competitors of other types. For in-person providers, the direct effect captures how the opportunity cost of being an in-person provider rises as the costs associated with out-of-state practice fall. The indirect effect refers to increased competitive pressure resulting from entry of competitors of other types.

I compute the effect of implementing PSYPACT for the subsample of markets where it has not been implemented. I further restrict this subsample to markets with no more than 10 in-person providers in order to exclude observations in the tails of this distribution. As with the entry threshold results, I use the univariate model estimates. To simplify the exposition, I focus on the indirect effect on in-person providers from out-of-state providers only, as the results for local online providers in Tables 2 and 3 suggested that PSYPACT has a small effect on local online entry. I proceed in the following steps:

(i) Compute the equilibrium effect of PSYPACT on out-of-state entry by setting the PSYPACT indicator equal to one, predicting the number of out-of-state providers, substituting this prediction in for n^{out}, and iterating until convergence at n^{*out}.

(ii) Compute the direct equilibrium effect of PSYPACT on in-person entry by setting the PSYPACT indicator equal to one, predicting the number of in-person providers, plugging this prediction in for n^{in}, and iterating until convergence at $n^{*direct}$.

(iii) Compute the total equilibrium effect of PSYPACT on in-person entry by setting the PSYPACT indicator equal to one and $n^{out} = n^{*}$, predicting the number of in-person providers, plugging this prediction in for n^{in}, and iterating until convergence at n^{*total}.

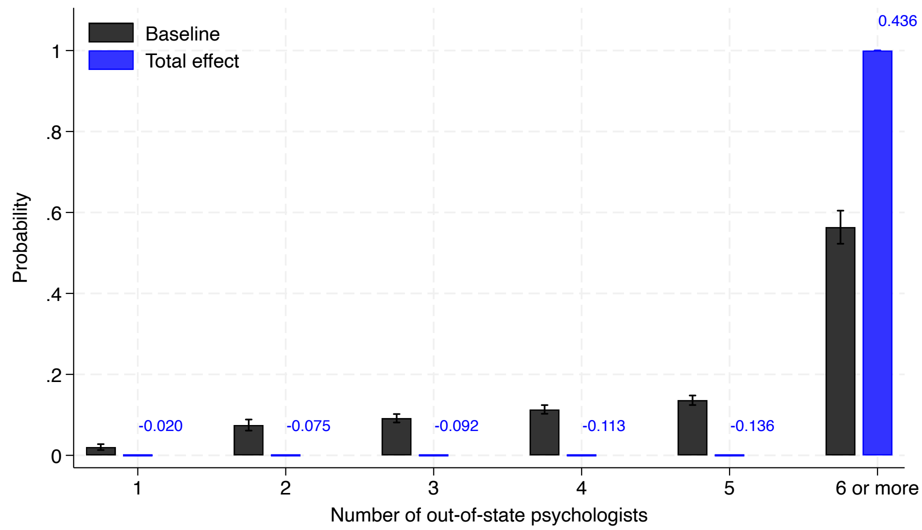
Figure 5 summarizes the results of this routine, showing the probability that the number of psychologists of a given type equals a given value. Panel (a) shows results for out-of-state psychologists, the black bars providing the model's predicted likelihood of observing each level of supply for the baseline sample in which PSYPACT is not active. Blue bar labels correspond to the difference between the counterfactual probability and the probability at baseline. The activation of PSYPACT results in a complete reallocation of probability weight from outcomes corresponding to between one and five out-of-state psychologists so that the model predicts that all markets will have at least six out-of-state psychologists. Table 4 translates these changes in outcome probabilities to changes in the expected number of psychologists. Given an average of 11.58 out-of-state psychologists in markets with six or more, these effects imply an increase in out-of-state supply of 3.47 providers on average, a 43% increase over baseline.

Panel (b) shows results for in-person psychologists. The direct effect of PSYPACT is to decrease in-person supply, increasing the probability of there being no in-person providers in a market by 13.8 p.p. and decreasing supply by 0.26 psychologists on average. The total effect, which takes into account the indirect effect of out-of-state entry, is larger: after accounting for the average increase in out-of-state entry of 3.47 providers, the probability of there being no in person providers in a market is 22.7 p.p. higher than baseline, and 8.9 p.p. higher than that estimated when considering the direct effect of PSYPACT alone. The estimated total effect of PSYPACT on in-person psychologist supply is a decline of 0.56 psychologists on average, a 52% decrease over baseline. The indirect effect amounts to a fall of 0.3 providers and accounts for 53% of the total decline in in-person supply.

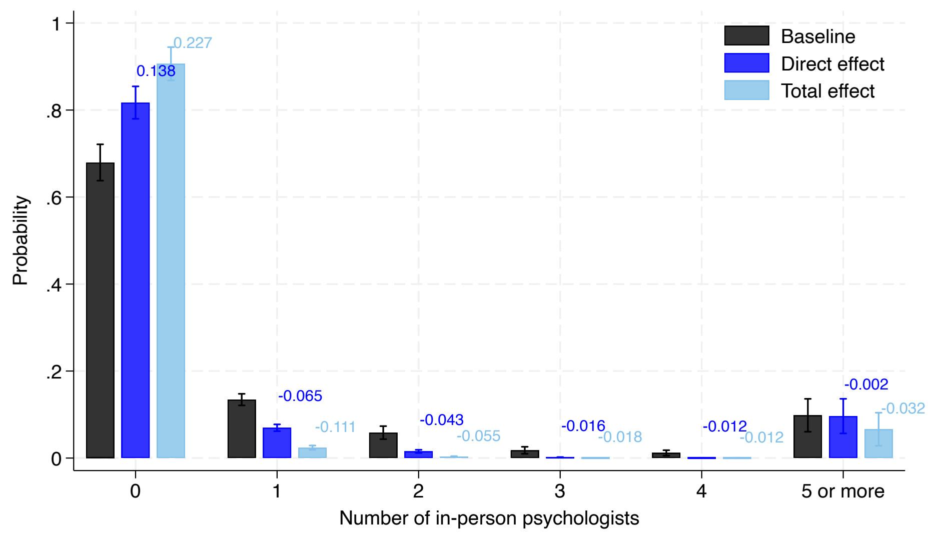
Note that without taking into account the modality or geographic locations of providers, PSYPACT is unambiguously successful in increasing the supply of psychotherapists, resulting in an average net increase of 2.92 providers per market. However, the benefits of the policy are meaningfully attenuated by competitive crowding out of in-person providers.

Figure 5: Decomposition of PSYPACT's effect on psychologist supply

(a) Out-of-state



(b) In-person



Notes: Figure illustrates counterfactual effect of implementing PSYPACT in subset of 166 PCSAs where it is not in place. Bars provide the predicted probability of a market having the number of psychologists indicated on the x-axis. Baseline predicted probabilities are those at observed values of covariates. Direct effect refers to predicted probabilities in equilibrium when PSYPACT is set to one. Total effect refers to predicted probabilities in equilibrium when PSYPACT is set to one and competitor counts are set to their predicted value in equilibrium. Standard errors calculated using 100 bootstrap replications.

Table 4: Decomposition of PSYPACT's effects on psychologist supply

	Number of in-person psychologists			Difference
	All	0	≥1	
In-person				
Baseline	1.08 (0.14)	0.19 (0.01)	3.07 (0.46)	2.87 (0.46)
Plus direct effect	0.82 (0.15)	0.10 (0.01)	2.43 (0.51)	2.32 (0.51)
Plus total effect	0.52 (0.16)	0.04 (0.004)	1.61 (0.54)	1.56 (0.54)
Out-of-state				
Baseline	8.11 (0.42)	7.69 (0.38)	9.04 (0.61)	1.35 (0.47)
Total effect	11.58 (0.67)	11.58 (0.67)	11.58 (0.67)	0 (0)
Total				
Baseline	9.82 (0.59)	7.89 (0.38)	14.18 (1.29)	6.28 (1.16)
Plus direct effect	13.04 (0.81)	11.69 (0.67)	16.08 (1.29)	4.38 (0.93)
Plus total effect	12.74 (0.76)	11.63 (0.66)	15.25 (1.20)	3.62 (0.91)
Number of observations	166	115	51	

Notes: Table counterfactual effect of implementing PSYPACT in subset of 166 PCSAs where it is not in place. Each cell contains the predicted number of psychologists of a given type. Baseline predictions are those at observed values of covariates. Direct effect refers to predictions in equilibrium when PSYPACT is set to one. Total effect refers to predictions in equilibrium when PSYPACT is set to one and competitor counts are set to their predicted value in equilibrium. Standard errors computed using 100 bootstrap replications.

The indirect effect of out-of-state entry on in-person provider supply has interesting implications not just for the average effect of PSYPACT, but also for the distribution of effects across markets. In particular, these indirect effects are likely to be most salient in markets that had a non-zero number of in-person psychologists ex ante, so that there is scope for out-of-state entry to induce in-person exit. In Table 4, I explore the potential for heterogeneity in the effect of PSYPACT according to each market's baseline number of in-person psychologists, stratifying markets based on whether their observed number of in-person psychologists equals zero. The baseline predicted difference in psychologist counts between the two groups of markets is 6.28. 45% of this difference is driven by differences in the number of in-person psychologists, the rest being driven by differences in the number of out-of-state and local online psychologists.

Turning to the effect of PSYPACT on these disparities, we first observe that PSYPACT completely eliminates the difference in out-of-state psychologist counts for the groups, reducing the difference in means from 1.35 to zero. This result stems from the fact that PSYPACT's large effect on out-of-state entry increases the likelihood of observing six or more out-of-state therapists in a market to one, as was observed in Figure 5. For in-person providers, we see that the direct effect of PSYPACT is to reduce in-person entry for both groups: the predicted number of in-person providers falls from 0.19 to 0.1 for markets with zero observed in-person psychologists, and from 3.07 to 2.43 for those with a non-zero observed count. With only the inclusion of the direct effect, the effect of PSYPACT on the difference in in-person psychologist counts between the two groups falls from 2.87 to 2.32, but this decline is not statistically significant.

The incorporation of the indirect competitive effect on in-person supply yields different results: among markets with zero observed in-person psychologists, the indirect effect is very small, reducing predicted in-person counts by 0.06. The effect is much larger among the other markets, for which the indirect effect results in an additional decline in in-person providers of 0.82. The indirect effect therefore accounts for 56% of the 1.46 decline in in-person psychologists generated by PSYPACT in this subgroup. The attenuation of PSYPACT's benefits among apriori high-supply areas implies that PSYPACT reduces disparities between the two groups, the mean difference in the number of in-person psychologists falling by 1.31 (46%) to 1.56. This decline in the disparity in in-person psychologist accounts accounts for 49% of the decline in disparities in total psychologist counts of 2.7.

This finding that PSYPACT is most beneficial for markets that would ex-ante be classified as most in need of treatment is not mechanical or a result of bias from endogeneous stratification (Abadie et al., 2018). Instead, it demonstrates that whether and how reductions in entry barriers affect provider supply depends on the presence of and intensity of competition with differentiated competitors.

6 Conclusion

Using a novel dataset on mental health provider supply, this paper demonstrates that interstate licensing compacts have the potential to affect the size and composition of mental healthcare markets. While PSYPACT successfully increases overall psychologist supply and expands access to virtual care, it simultaneously reduces access to in-person therapy by directly increasing the returns to virtual therapy and, more significantly, through intensified competition from out-of-state providers. As policymakers continue to pursue licensing compacts as a solution to healthcare workforce shortages, these results suggest the need for complementary policies to preserve access to in-person care for vulnerable populations who may not be well-served by virtual alternatives. This is particularly important given the impending implementation of the Counseling Compact, an interstate licensure compact for Licensed Professional Counselors set to go into effect in late 2025 (Counseling Compact, 2025). Future work documenting the effects of changes to the composition of mental health provider supply on utilization of talk therapy and mental health outcomes will be important for understanding the welfare effects of these licensure policies.

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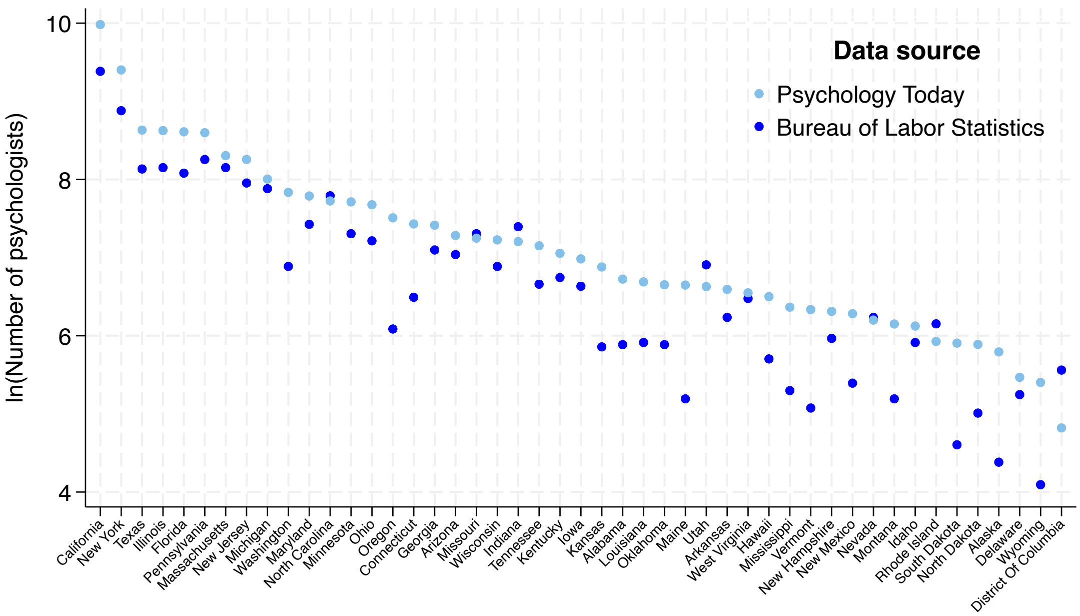
Appendix

Figure A1: Comparison of psychologist counts across data sources



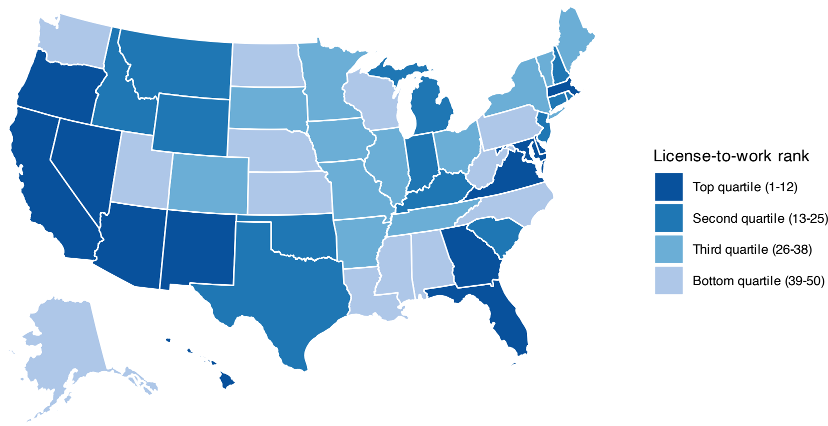
Notes: Data come from the Bureau of Labor Statistics Occupational Employment and Wage Statistics: https://data.bls.gov/oes.

Table A1: Isolated PCSA characteristics by number of in-person psychologists

	Number of in-person psychologists					
	0	1	2	3	4	≥ 5
Competitor counts						
Out-of-state	7.9 (5.9)	8.4 (5.8)	10.0 (5.4)	11.8 (8.7)	11.9 (13.4)	15.8 (14.3)
Local online	0.1 (0.5)	0.4 (0.8)	0.5 (0.7)	1.2 (1.4)	1.8 (2.3)	17.4 (41.2)
State policies						
PSYPACT	73.1%	75.6%	84.4%	95.2%	69.6%	72.0%
License-to-work rank	26.8 (14.4)	23.8 (15.0)	24.9 (14.5)	28.1 (13.1)	25.2 (16.9)	23.4 (15.8)
Socio-demographics						
Population (10k)	2.5 (2.9)	4.6 (3.9)	8.1 (5.5)	7.9 (6.1)	9.6 (5.6)	25.4 (18.4)
Median income ($10k)	6.3 (1.3)	6.7 (1.4)	6.9 (1.1)	6.9 (1.2)	7.3 (1.1)	8.2 (1.8)
Share insured	89.2 (5.5)	89.9 (5.0)	89.6 (5.3)	91.0 (2.9)	91.8 (3.7)	91.9 (4.0)
Share employed	95.2 (3.1)	95.3 (2.0)	95.2 (1.9)	95.3 (1.9)	95.2 (1.9)	95.2 (1.6)
Share Black	4.7 (11.0)	4.4 (8.4)	7.2 (10.3)	12.6 (19.1)	6.9 (8.0)	11.1 (11.9)
Share Hispanic	14.9 (19.7)	17.3 (19.2)	16.5 (21.7)	12.3 (17.8)	11.1 (11.8)	17.4 (17.4)
Share over 65	20.6 (6.0)	18.8 (4.9)	17.5 (4.9)	18.3 (6.3)	18.4 (4.0)	16.6 (4.4)
Share $\leq$ high school	33.1 (6.0)	31.8 (4.5)	29.9 (5.1)	26.5 (6.8)	29.2 (5.2)	24.3 (5.7)
Share rural	32.4 (39.3)	11.7 (21.9)	3.4 (6.0)	7.1 (21.7)	3.9 (9.5)	1.2 (4.0)
Share with broadband	37.2 (20.6)	47.9 (19.0)	55.9 (12.7)	57.2 (17.6)	58.2 (16.5)	65.6 (13.0)
Affordability index	100.4 (0.8)	100.3 (0.8)	100.1 (0.6)	100.1 (0.5)	100.0 (0.5)	99.7 (0.5)
Observations	428	82	45	21	23	211
Share of all observations	52.8	10.1	5.6	2.6	2.8	26.0

Notes: Isolated PCSAs are those with population-weighted controids that are more than 35 miles away from all more populated PCSAs. In-person psychologist and competitor counts come from Psychology Today. PSYPACT is a binary indicator for participation in the Psychology Interjurisdictional Compact. The affordability index is computed using price parity and income data from the Bureau of Economic Analysis (BEA, 2024). License-to-work rank is a ranking of states by the average burden for all licensed occupations (Institute for Justice, 2022). All socio-demographic characteristics come from the American Community Survey with the exception of broadband usage, which comes from the Microsoft United States Broadband Usage Percentages Dataset (Census Bureau, 2025; Kahan and Ferres, 2020).

Figure A2: License-to-work state rank



Notes: Data come from the Institute for Justice (2022).

Table A2: First-stage regression results

	PSYPACT					
	In-person		Out-of-state		Online	
	(1)		(2)		(3)	
License-to-work rank	-0.007†	(0.001)	-0.007†	(0.001)	-0.007†	(0.001)
Affordabilty index	-0.013	(0.017)				
$\mathbb{1}\{n^t = 1\}$	-0.028	(0.050)			0.006	(0.049)
$\mathbb{1}\{n^t = 2\}$	-0.056	(0.067)	-0.026	(0.105)	0.019	(0.064)
$\mathbb{1}\{n^t = 3\}$	-0.167	(0.093)	-0.091	(0.105)	0.095	(0.088)
$\mathbb{1}\{n^t = 4\}$	0.037	(0.093	-0.061	(0.105)	0.068	(0.101)
$\mathbb{1}\{n^t \geq 5\}$	-0.011	(0.069)			0.066	(0.078)
$\mathbb{1}\{n^t = 5\}$			-0.050	(0.103)		
$\mathbb{1}\{n^t \geq 6\}$			-0.087	(0.098)		
Population $\times$						
n^{in}	0.002	(0.002)				
n^{out}	0.001	(0.001)	0.001	(0.001)		
n^{onl}	0.001	(0.001)			0.001	(0.001)
Median income	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Share insured	0.008†	(0.001)	0.008†	(0.001)	0.008†	(0.001)
Share unemployed	-0.004†	(0.001)	-0.004†	(0.001)	-0.004†	(0.001)
Share Black	-0.000	(0.001)	-0.000	(0.001)	-0.000	(0.001)
Share Hispanic	0.003†	(0.001)	0.004†	(0.001)	0.004†	(0.001)
Share over 65	-0.002	(0.002)	-0.001	(0.002)	-0.002	(0.002)
Share $\leq$ high school	0.001	(0.002)	0.000	(0.001)	0.001	(0.002)
Share rural	0.021	(0.013)	0.026	(0.014)	0.023	(0.013)
Share with broadband	-0.004	(0.002)	-0.003	(0.002)	-0.004†	(0.002)

Notes: Results are for first-stage regressions of control function correction for the endogeneity of PSYPACT. License-to-work rank is a ranking of states by the average burden for all licensed occupations Institute for Justice (2022). † denotes statistical significance at the 5 percent level.

Table A3: Univariate entry model estimates with full set of cross-type competition effects

	In-person			Out-of-state			Local online		
	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable profit parameters									
Number of in-person (α^{in}, β)	0.133†	(0.029)		-0.028	(0.015)	-0.86	-0.016†	(0.006)	-8.89
Number of out-of-state (α^{out}, β)	-0.066†	(0.017)	-12.95	0.118†	(0.039)		-0.027†	(0.012)	-14.92
Number of local online (α^{onl}, β)	-0.019	(0.015)	-3.69	0.013	(0.023)	0.40	0.073†	(0.015)	
Median income (δ)	-0.051	(0.033)	-9.96	0.015	(0.031)	0.47	-0.004	(0.015)	-1.91
Share insured (δ)	0.053†	(0.023)	10.35	0.092	(0.047)	2.86	0.020	(0.021)	10.75
Share unemployed (δ)	-0.008	(0.014)	-1.64	-0.055†	(0.025)	-1.72	0.000	(0.012)	0.17
Share Black (δ)	-0.026	(0.015)	-5.10	-0.002	(0.031)	-0.05	-0.018†	(0.009)	-9.97
Share Hispanic (δ)	-0.013	(0.031)	-2.56	0.041	(0.035)	1.28	-0.028	(0.018)	-14.99
Share over 65 (δ)	0.008	(0.026)	1.66	-0.003	(0.031)	-0.09	0.009	(0.012)	4.75
Share $\leq$ high school (δ)	-0.030	(0.027)	-5.92	0.055	(0.032)	1.70	-0.036†	(0.014)	-19.62
Share rural (δ)	-0.037	(0.102)	-7.29	0.604†	(0.176)	18.74	0.025	(0.084)	13.56
Share with broadband (δ)	-0.001	(0.026)	-0.12	-0.081†	(0.041)	-2.52	0.009	(0.021)	4.98
Fixed cost parameters									
PSYPACT (θ_t)	-0.076	(1.682)	-1.40	7.012†	(3.028)	20.57	-0.691	(2.169)	-35.61
Affordability index (θ^{in})	-0.255†	(0.114)	-4.71						
γ_1^t	-1.311†	(0.615)					1.038	(0.706)	
γ_2^t	-0.443	(0.638)		0.964	(1.502)		1.971†	(0.763)	
γ_3^t	0.682	(0.705)		0.495	(0.785)		3.043†	(0.839)	
γ_4^t	1.413	(0.818)		1.221	(0.739)		3.957†	(0.933)	
γ_5^t	2.190†	(0.978)		1.763	(0.716)		4.668†	(1.023)	
γ_6^t				2.363	(0.680)				
Number of observations	810								

Notes: Columns (1), (4), and (7) present coefficient estimates for the univariate entry models that include the full set of cross-type competition effects. Columns (2), (5), and (8) provide standard errors for these coefficient estimates, calculated using 100 bootstrap replications. Columns (3), (6), and (9) provide the marginal effects for these estimates, which are the simulated % change in the mean number of psychologists given a one standard deviation in the row variable. † denotes statistical significance at the 5% level.

Table A4: Bivariate entry model estimates with more conservative definition of geographically isolated markets

	In-person			Out-of-state			Local online		
	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.	Coef.	S.e.	M.e.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Correlation with out-of-state shocks (ρ)	-0.148	(0.186)							
Variable profit parameters									
Number of in-person (α^{in})	0.183†	(0.032)							
Number of out-of-state (α^{out}, β^{in})	-0.063†	(0.022)	-9.42	0.170†	(0.051)	3.85			
Number of local online (α^{onl}, β^{in})	-0.042†	(0.015)	-6.32				0.093†	(0.019)	29.95
Median income (δ)	-0.061	(0.039)	-9.21	0.027	(0.049)	0.60	-0.003	(0.021)	-0.89
Share insured (δ)	0.067†	(0.029)	10.02	0.132†	(0.059)	2.98	0.020	(0.034)	6.50
Share unemployed (δ)	-0.013	(0.016)	-1.94	-0.082†	(0.033)	-1.85	-0.006	(0.020)	-1.79
Share Black (δ)	-0.035	(0.020)	-5.20	-0.008	(0.041)	-0.17	-0.027	(0.014)	-8.60
Share Hispanic (δ)	-0.035	(0.041)	-5.28	0.051	(0.053)	1.15	-0.042	(0.032)	-13.38
Share over 65 (δ)	0.015	(0.033)	2.31	-0.009	(0.049)	-0.20	0.017	(0.019)	5.42
Share $\leq$ high school (δ)	-0.052	(0.028)	-7.86	0.084	(0.045)	1.91	-0.047†	(0.017)	-15.18
Share rural (δ)	-0.060	(0.131)	-9.06	0.818†	(0.210)	18.54	0.027	(0.122)	8.57
Share with broadband (δ)	0.001	(0.035)	0.18	-0.128†	(0.055)	-2.90	0.016	(0.026)	5.25
Fixed cost parameters									
PSYPACT (θ_t)	-0.233	(2.193)	-3.31	9.220†	(4.649)	19.76	-1.188	(3.215)	-36.19
Affordability index (θ^{in})	-0.284†	(0.128)	-4.03						
γ_1^t	-1.565†	(0.749)					1.172	(0.964)	
γ_2^t	-0.358	(0.735)		-2.308†	(1.956)		2.474†	(1.008)	
γ_3^t	1.296	(0.808)		-0.287†	(1.287)		3.990†	(1.071)	
γ_4^t	2.407†	(0.908		0.728	(1.257)		5.303†	(1.248)	
γ_5^t	3.575†	(1.051)		1.496	(1.213)		6.315†	(1.355)	
γ_6^t				2.336	(1.142)				
Number of observations	627								

Notes: Columns (1), (4), and (7) present coefficient estimates for the bivariate entry model estimated using a more conservatibe definition of geographically isolated markets that includes only primary care service areas (PCSA) no less than 40 miles from a more populous PCSA. Columns (2), (5), and (8) provide standard errors for these coefficient estimates, calculated using 100 bootstrap replications. Columns (3), (6), and (9) provide the marginal effects for these estimates, which are the simulated % change in the mean number of psychologists given a one standard deviation in the row variable. † denotes statistical significance at the 5% level.