Telemedicine Competition, Pricing, and Technology Adoption: Evidence from Talk Therapists *

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Abstract

This paper examines how new telemedicine competitors affected incumbent health care providers during the first waves of COVID-19. Using data from the largest mental health provider search platform in Canada, I show that increased telemedicine competition in a market caused incumbent providers in that market to stop offering income-based discounts to patients. I isolate the causal effect of competition in a difference-in-differences framework, comparing providers before and after a supply shock on the platform that exogenously assigned some markets new telemedicine search results. I find that higher-quality providers are more likely to stop income-based discounts when facing new telemedicine entrants, while lower-quality providers are more likely to exit the platform, which is consistent with telemedicine providers competing for more price-sensitive patients. The results suggest that expanding telemedicine options had a heterogeneous effect on the affordability of care.

Keywords: Digitization, telemedicine, competition, price discrimination, mental health, COVID-19
JEL Classification: I11, L11, O33

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1 Introduction

Expenditures on healthcare worldwide are large and growing, and greater competition between healthcare providers has frequently been encouraged as a way to restrain prices.[1] Telemedicine—the provision of health care services virtually or by phone—has the potential to dramatically increase competition, similarly to retail with the rise of e-commerce, or banks with the advent of mobile banking. However, there is little empirical work on the competitive impact of telemedicine. Prior to the start of COVID-19, take-up of telemedicine was limited, while during and post COVID-19 the widespread adoption of telemedicine has occurred alongside quickly changing policy, economic, and health shocks, making it challenging to isolate the effect of competition alone.[2]

In this paper, I tackle the problem of identification of the competitive effect of telemedicine expansion during COVID-19. The main contribution of this work is to provide the first causal evidence of the effect of telemedicine competition on healthcare provider pricing. There is a need for empirical evidence in this new context, as past studies of healthcare competition have shown that incumbents may reduce prices when new competitors enter, as in hospital competition (Gaynor and Town, 2011), or raise them if new entrants skim price sensitive patients, as when generics enter in pharmaceutical markets (Ching, 2010; Frank and Salkever, 1997). The consequences of telemedicine competition for the affordability of care may thus range from purely positive to mixed.

Identifying the competitive effect of telemedicine entry during COVID-19 presents several empirical challenges. To illustrate, consider a panel dataset of market entry and exit of healthcare providers observed over time. First, a telemedicine provider may enter a market in response to unobserved COVID shocks that make the market more attractive to serve. If these shocks also affect incumbents' behaviour, then a classic endogeneity problem will arise (e.g. Orhun (2013).) Second, even if telemedicine entry is not directly in response to COVID-19 shocks, if it is systematically related to market features that are themselves correlated with COVID-19 shocks—for instance, if entry is predominantly into rural markets—then the effect of telemedicine competition will be conflated with these shocks. Finally, a new telemedicine entrant typically does not enter a single geographic market but enters many markets simultaneously, similarly to a new online retailer. Indeed, if there is no regulation limiting their scope of practice, a telemedicine entrant may compete country-wide, making it a challenge to find a control group of incumbents who are not exposed to their entry. The difficulty of finding an unexposed control group with virtual entrants is not unique to telemedicine: despite the huge competitive implications of new digital services and e-commerce,

[1] In the popular press, see: "The Bad Health of American Health Care," *The Economist*, May 31, 2006; Mankiw, N. Gregory, "The Pitfalls of the Public Option," *The New York Times*, June 27, 2009; Gaynor, Martin et al. "Health Care's Crushing Lack of Competition,", *Forbes*, June 28, 2017.

[2] Pre-COVID-19, 1% of U.S primary care visits were by phone (Tuckson *et al.*, 2017). Outpatient visits of all types increased 1700% from January to June 2020 (Patel *et al.*, 2021).

studies of the causal effect of new online entrants in almost any industry are rare.[3]

I address these challenges in the context of mental health care in Canada. I focus on the market for talk therapy provided by private therapists, which comprises over 80% of total consultations and which is not covered under Canada's single-payer system (Bartram and Chodos, 2018). This setting is ideal for performing a clean analysis of the effect of telemedicine competition on providers, since most private talk therapists in Canada operate independent practices, set their prices flexibly, and are paid either directly by patients or via insurance policies that do not negotiate rates.

To identify the effect of telemedicine competition, I gather data from the largest therapist search platform in Canada, and leverage a unique supply shock. The platform lists upwards of 65% of Canadian private-practice therapists, and allows patients to perform a search within their postal-code derived forward sortation area (FSA) for nearby talk therapists operating on the platform.[4] Starting in June 2020, FSAs with fewer than 20 therapist search results had their results padded to 20 by adding non-local providers who offered telemedicine. New telemedicine search results were explicitly labeled, and listed below existing providers. The shock generates cross-FSA variation over time in how easily patients could find a telemedicine provider, which incumbents on the platform would plausibly be aware of and which is orthogonal to time-varying unobserved shocks in each FSA. The shock boosted competition from teletherapists in some markets by making search for teletherapists less costly (Ghose and Yang, 2009; Agarwal *et al.*, 2011).

The supply shock motivates a difference-in-differences analysis, where treated therapists are those whose FSAs receive new telemedicine search results on the platform. Since an FSA is treated if it has only a few therapists operating in it, a key identification issue is that treated markets may be more rural or isolated on average, leading therapists operating there to face systematically different COVID-19 shocks. The arbitrariness of FSA boundaries helps alleviate this concern: most treated therapists operate in medium and large cities, but simply happen to be located in small FSAs within those cities that naturally capture fewer therapists within their geographic boundary, making them more likely to have new telemedicine competitors assigned. The baseline analysis uses propensity score matching to balance treated and control therapists on market-level observables, but the results are robust to (1) only using therapists around the portal's arbitrary padding threshold; and (2) including city-month fixed effects, which compares therapists across FSAs within the same city allowing for unobserved time-varying city-specific shocks.

I find that therapists exposed to the telemedicine supply shock (7 new telemedicine competitors on average) decrease their propensity to offer income discounts by 8.3% but do not change their posted price.

[3]Many papers examine the effect of internet expansion on incumbents but do not separate the effect of online competition from other roles the internet plays, see Orlov (2011); Chandra and Kaiser (2014); Ater and Orlov (2015); Chiou *et al.* (2020); Jiang *et al.* (2022). Two exceptions are Chandra and Kaiser (2014) who study Craigslist's effect on print newspaper classifieds, and Zervas *et al.* (2017) who study AirBnB's effect on hotels.

[4]FSAs contain approximately 20 000 residents on average, double that of a zipcode in the U.S. data.

Therapists facing new telemedicine competitors also do not adopt telemedicine themselves. This latter finding is intuitive, given that therapists who do not already offer a virtual option by June 2020 are a selected sample with high costs of adoption relative to the benefits. More intense telemedicine competition also leads to greater exit from the platform, suggesting that entrants divert profits from incumbents. Taken together, these estimates suggest that for searching patients, geographically-distant teletherapists and local providers are substitutes (Zhou *et al.*, 2021).

What explains why telemedicine competition leads incumbents to stop price discriminating? I analyze heterogeneous responses along the quality spectrum and find that higher quality therapists stop income discounting at higher rates, while lower quality therapists either continue discounting or exit from the platform. These results are consistent with telemedicine entrants attracting price sensitive patients—an empirical regularity for which there is increasing evidence (Martinez *et al.*, 2018; Ellegård *et al.*, 2021). Intuitively, in response to telemedicine competition, lower quality therapists either must either compete head on with these new entrants for price sensitive patients or exit, while higher quality therapists can focus on serving patients with a higher willingness-to-pay. To validate this intuition, I write a model of dynamic, capacity-constrained therapists that expands on the price discrimination framework of Stole (2007) and which can match both the baseline and quality heterogeneity results.

Given that the shock occurs a few months after the beginning of COVID-19, the magnitude of the estimated competition effect is likely affected by the unique environment of that time. However, the evidence for underlying mechanism is not COVID-specific, which suggests more general policy implications. For governments who wish to boost mental health care access by increasing telemedicine coverage, the results show that telemedicine entry causes a clear reduction in access to local, in-person options, and that protection for incumbents in less-served areas may be needed to preserve these in-person options.[5] Moreover, the finding that new online competitors do not lead offline incumbents to adopt telemedicine technology in the post-COVID environment is novel, and may help set expectations for the diffusion of virtual care moving forward.

This paper adds to several distinct literatures. First, within the empirical health care competition literature, it is the first to analyze the effect of pure telemedicine competition on local incumbents' price choices. Studies of pricing in healthcare competition typically use mergers to show that increased competition within a geographic market restrains pricing power (Capps and Dranove, 2004; Dafny, 2009; Gowrisankaran *et al.*, 2015; Chorniy *et al.*, 2020) or else use cross-sectional regressions that leverage variations in numbers of competitors across local markets (Johar *et al.*, 2014; Gravelle *et al.*, 2016). Related

[5]New telemedicine options are useful for some patients, but not all patients can make this transition: older patients, patients who are concerned about digital security of health details (Schiffer *et al.*, 2021), patients who have no reliable internet (Dorsey and Topol, 2016), and patients who cannot speak freely to their therapist while at home due to concerns in their domestic life (Usher *et al.*, 2020; Kofman and Garfin, 2020), may all benefit from retaining affordable and local in-person options.

to our study, Johar (2012) find that more local competition is correlated with less income-based price discrimination, as general practitioners differentially lower prices for high income patients. The finding in this paper is consistent with telemedicine entrants attracting more price-sensitive patients, which is intuitively aligned with the result that generic entrants cause branded pharmaceuticals to raise prices in Ching (2010). Although this paper is not the first to use a shock to choice sets to identify the effects of health care competition (see for instance Gaynor *et al.* (2013, 2016) and Yoo *et al.* (2021)) it is the first to show how this strategy can be leveraged to achieve identification in the telemedicine context.

Second, the paper connects with a large literature on the effect of competition on price discrimination. Stole (2007) shows how competition can either increase or decrease the level of third-degree price discrimination: if there is one group of consumers who are brand-loyal and price inelastic, and another group who are not brand-loyal and are price elastic, then an increase in competition will drive prices for the second group down by relatively more, increasing discrimination. This is similar to the mechanism posed in my setting with brand-loyalty replaced by a preference for in-person care; however, with therapists, the capacity constraint will imply less discrimination since the option value of an open slot is preferred to receiving even lower prices from the price-elastic group. There are numerous papers that find competition can increase price discrimination (Busse and Rysman, 2005; Seim and Viard, 2011) and decrease price discrimination (Borzekowski *et al.*, 2009; Lin and Wang, 2015), as well as papers that explore how competition can increase some price differentials and decrease others (Dai *et al.*, 2014; Chandra and Lederman, 2018), although none consider the role of capacity constraints.

More broadly, the paper adds to an active research program on the effect of entry on pricing. The result that entry has small effects on posted incumbent prices is not uncommon: Ailawadi *et al.* (2010); Arcidiacono *et al.* (2020) show small or insignificant effects from the entry of Walmart on incumbent prices, while Busso and Galiani (2019) randomize entry of small retailers and find incumbents decrease prices on the order of 2%.

Third, this paper adds to the relatively sparse group of empirical studies of the effect of online competitor entry on incumbent firms' decisions. This sparsity likely stems from empirical difficulties in identification, since entry of an online competitor is typically not confined to just one market. There are numerous papers looking at the effect of the internet on incumbents (Orlov, 2011; Chandra and Kaiser, 2014; Ater and Orlov, 2015; Chiou *et al.*, 2020; Jiang *et al.*, 2022), but they typically do not separate the effect of new online competition from other roles the internet might play, such as a reduction in search costs or a substitute leisure activity. To observe actual cross-market and temporal variation in the presence of online competitors conditional on internet access is rare: two exceptions are Seamans and Zhu (2014), who study the staggered geographic rollout of Craigslist on the print newspaper industry and find a drop in classified advertising rates but an increase in subscriber prices, and Zervas *et al.* (2017), who study the rollout of AirBnB on the hotel industry. The current paper leverages the idea that even online, search is costly (Ghose and Yang, 2009; Agarwal *et al.*, 2011), and so a shock that makes some online options easier to find in some geographic markets can lead to meaningful variation in the number of relevant online competitors.

Finally, the paper provides novel supply-side evidence to a growing empirical literature on the substitutability of telemedicine and in-person care, and the determinants of telemedicine adoption. Cantor and Whaley (2021) find that in-person and virtual care are not very substitutable (elasticity of -0.2); their paper also documents a positive effect of social distancing policies on physicians' adoption of virtual care. Nord *et al.* (2019) and Martinez *et al.* (2018) use survey evidence to show more than 90% of telemedicine usage substitutes for an in-person visit, oftentimes replacing a relatively inexpensive or less-intensive form of care such as a nurse visit. Conversely, Ashwood *et al.* (2017) and Ellegård *et al.* (2021) find that only between 12 and 50% of telemedicine visits represent substitutions for in-person care, suggesting a large demand expansion effect due to the ease of accessing care through telemedicine. Rabideau and Eisenberg (2022) finds that teletherapy is a near-perfect substitute for in-person visits, leading to no new demand expansion. Zeltzer *et al.* (2021) use the large expansion in telehealth availability after the first wave of COVID-19 in Israel to show that patients with more access to telehealth increase usage but at a lower cost, leading to a net reduction in expenditure. Zhou *et al.* (2021) use a pre-COVID policy shock in the U.S. to show that rural hospitals lose revenue and patient volume to urban physicians who adopt telemedicine. This paper uses supply side data to show that telemedicine substitutes more closely with in-person care for lower willingness-to-pay patients, and find that the competitive effects of telemedicine can actually reduce in-person affordability.

2 Background

Almost 1 billion people worldwide are estimated to suffer from a mental health disorder, with lost productivity due to anxiety and depression alone estimated to cost the global economy US$1 trillion per year (Lancet, 2020).[6] Many mental illnesses can be treated effectively by psychotropic medications, a limited course of psychotherapy (talk therapy), or a combination of both (Cronin *et al.*, 2020). Recent recognition of the burden of mental illness and the availability of effective treatments has led to calls for mental health care to become a policy priority worldwide, as patient access remains low (Lancet, 2020).

2.1 Psychotherapy provision in Canada

Psychotherapy in Canada is provided mostly through the private healthcare system, with over 80% of consultations with therapists paid for out-of-pocket or using third-party health insurance from an employer

[6] See also Currie and Stabile (2006); Kessler *et al.* (2008); Jolivet and Postel-Vinay (2020) for detailed estimates of the labour market costs of mental illness. Costs of anxiety and depression in Canada are US$ 40 billion per year (Chodos, 2017).

(Bartram and Chodos, 2018).[7] Insurance plans typically take the form of a yearly spending allowance—insurers do not negotiate rates with therapists—and Canadians spend almost CAD$ 1 billion yearly on private consultations (Chodos, 2017). Most therapists serving patients in the private system operate an independent practice, and prices are unregulated although provincial professional associations suggest hourly rates. In addition to providing talk therapy, therapists may have other jobs—for instance, as school counsellors, social workers, or hospital psychiatrists.

2.2 The importance of provider portals for search

Most independently operating therapists do not advertise or maintain personal websites, making the patient's search process challenging. Instead, as with many medical practitioners, therapists rely on word-of-mouth referrals and/or pay a fee to list themselves on medical search platforms.[8] Given the sensitive nature of therapy and the still-present social stigma in seeking mental health care (Sandhu *et al.*, 2019), word-of-mouth referrals likely form a smaller share of new patients for therapists than for GPs. In 2013, over half of individuals in the U.S. used an online directory to search for medical providers (AOA, 2013).

In Canada, *PsychologyToday.com* is by far the largest privately-run search directory for therapists, with substantially more web traffic and an order of magnitude more licensed Canadian therapists listed compared to its next largest competitor.[9] It is also important relative to word-of-mouth referrals or other platforms: upwards of 65% of psychologists available for private practice in Canada (excluding Quebec) list on *PsychologyToday.com* (sources and provincial breakdowns are provided in Appendix A.3.) At time of data collection, therapists paid CAD$40/month to list on *PsychologyToday.com*, roughly comparable to the yearly fee for maintaining status in a professional association.

2.3 COVID-19 and mental health

COVID-19 presented a considerable shock to the demand for mental healthcare and the delivery of mental healthcare services in Canada and worldwide (APA, 2020; Liu *et al.*, 2020). In Canada, the first case of COVID-19 was confirmed on January 25, 2020; lockdowns were implemented at the provincial level beginning in late March, with phased re-opening beginning in late April.[10]

[7] Publicly funded coverage for one-on-one counselling with a trained psychiatrist or general practitioner is available, but highly restricted and typically associated with emergencies or severe psychiatric disorders that require medication.

[8] See https://www.prnewswire.com/news-releases/finding-dr-right-new-survey-reveals-word-of-mouth-the-most-used-resource-when-looking-for-a-physician-225798471.html

[9] As of April 2021, *Alexa.com* ranks *PsychologyToday.com* at #1277 in Canadian sites by traffic compared to #3077 for *BetterHelp.com*, roughly #18000 for *TalkSpace.com* and *MindBeacon.com*, and marginal rankings for the remainder of mentioned sites. There are over 10 000 Canadian therapists active on *PsychologyToday.com* compared to zero for *BetterHelp.com* (all therapists are U.S. based) and less than 1000 Canada-wide each for *Theravive.com* and *CounsellingBC.com*, and less than 500 for *GoodTherapy.com* (as of April 2021).

[10] Figure A.1 in Appendix A.1 replicates the analysis in Zeltzer *et al.* (2021) to illustrate aggregate patterns country-wide in 2020, with falling cases, falling test positivity rates, and increased mobility by June 2020.

Mental healthcare workers, including therapists, were legally permitted to continue practicing in-person for emergencies, and the first week in May saw full in-office accessibility restored.[11] Figure A.1 shows that COVID-19 induced substantial adoption of online care in my sample of private therapists, rising from roughly 50% of therapists offering an online option in January 2020 to over 80% of therapists in May 2020.

COVID-19 was also associated with an aggregate shock to the demand for mental healthcare in Canada, as in many other countries. Figure A.2 documents a broad reduction in individuals' self-reported mental health in Canada in 2020 compared to prior years, with 23% fewer respondents reporting excellent or very good mental health in April 2020 (54.0%) compared to June 2018 (69.4%.)

3 Data

The primary dataset comes from therapists' profile pages on *PsychologyToday.com*, collected at the end of each month from January 2020 through December 2020. In this section, I describe patients' search process on the platform during the sample period, what variables are observed, and the supply shock. I also explain how the final sample is selected.

3.1 Patient search on *PsychologyToday.com*

A Canadian user arriving at *PsychologyToday.com* is first prompted to search for therapists by either city or forward sortation area (FSA); an image of what this screen looked at at time of data collection is available in Appendix A.2. Forward sortation areas are geographically contiguous units with approximately 20 000 individuals on average (twice the size of a U.S. zipcode), and are identified using the first three digits of an individual's 6 digit postal code. Searchers do not create a profile, and no searcher-specific information is used to conduct the search other than the inputted geographic area.

In response to her search, the potential patient observes a list of therapists geographically proximate to the searched FSA distributed over multiple pages. Each page contains at most 20 therapists, with names, a photo, phone numbers, and credentials listed. Clicking a therapist then takes the searcher to a therapist detail page where substantial additional information is provided. There are no ratings on the website, patient-supplied or otherwise. Contacting a therapist can be done by phone or by an in-site email prompt.

[11]See https://www.publicsafety.gc.ca/cnt/ntnl-scrt/crtcl-nfrstrctr/esf-sfe-en.aspx for federal guidelines, and https://www.ontario.ca/laws/regulation/200082/v1 for Ontario guidelines

3.2 Observed data

For each of the 1620 FSAs in Canada in each month in 2020, I observe which therapists appear as results for that FSA, as well as all information provided on each therapist's detail page. There are 12 139 therapists on the site total.[12] I drop therapists based in Quebec from the panel due to their very different licensing and psychiatric-care environment compared to the rest of Canada, leaving 11 691 therapists in the sample.[13]

Each therapist is physically located in only one FSA, which I call their home market. They may also appear as a search result in multiple FSAs depending on which FSAs their location is geographically proximate to. A therapist's detail page is identical across searched FSAs they appear in within a month, but may change over time. I do not observe any patient-side information. My assumption is that each search FSA comprises a market for talk therapy services, and I will refer to FSAs as markets interchangeably.

I source market-level demographic information from the 2016 Statistics Canada Census, including information on FSA population, land area, average age, after tax income, average household size, labour force participation, share of individuals living in apartment complexes, share of the local labour force that works in retail trade or leisure and hospitality (NAICS 44-45 and 71-72), and share of the local labour force that works in health care. (NAICS 62.) Summary statistics for the therapist panel and the set of FSAs in the final data are available in Appendix A.6.

3.3 Supply shock

Beginning in June 2020, any FSA with fewer than 20 therapists listed as results had its first results page padded to 20 therapists. Padding was achieved by adding providers who were listed on *PsychologyToday.com* who offered virtual or telephone-based therapy but who were not local to that FSA. Results were displayed below the geographically local providers, under a text header labelled *Matching Counsellors providing teletherapy to clients in X*, where X is the province in which the searched FSA is located. For an FSA with 20 or more therapists listed ex ante, results were unchanged.

I visualize the shock in Figure 1. The x axis denotes the May 2020 number of search results in an FSA, the y axis denotes the June 2020 number of search results in the same FSA, and the size of each point denotes how many FSAs exhibit that precise number of therapists in May and June. While in May there are many FSAs with fewer than 20 therapists, by June there are almost none.

[12] In January 2021, the site changed their default settings for search, making the data unusable for this competition-focused study.

[13] Quebec has almost double the number of licensed psychologists compared to the largest province of Ontario despite having less than 60% the population (see Appendix A.3). Moreover, Quebec therapists are severely underrepresented on *PsychologyToday.com*, suggesting that it is not an important channel for referrals in Quebec.

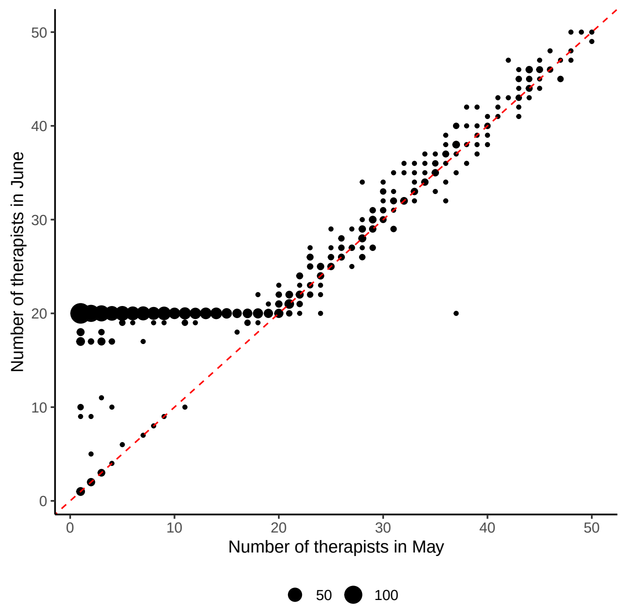


Figure 1: Supply shock to search results in June
Note: Each point corresponds to a number of displayed therapists for a searched FSA in May, and the number of displayed therapists for the same searched FSA in June, with point size capturing the number of FSAs with that combination of therapists displayed in May and June. Axes are truncated at 50 to better visualize the kink at 20 therapists.

3.4 Treatment and outcome variables

The outcome variables of interest are a therapist's posted price, whether they offer sliding-scale discounts based on income, whether they offer online care or not, and their decision to exit from the platform.

For prices, I observe a posted price range on a therapist's profile. I source data on transacted prices for a subset of therapists from one of Canada's largest private insurance companies and find that the minimum posted price most often agrees with the transacted price, see Appendix A.4 for details. Minimum posted price is thus my price measure.

Therapists can indicate on their profile page, in a standardized way, whether they offer a sliding-scale discount and whether they offer online care, so I code these variables as binary. The sliding-scale discount variable is available starting in April 2020 and exit in February 2020; prices and online care are available starting January 2020.

The analysis takes a difference-in-differences approach, with treated therapists defined as those who ex ante are more exposed to the supply shock, and the treatment period as months including and after June 2020. I define treatment at the therapist level, since a therapist may appear as a search result for multiple FSAs that are geographically close to her physical address. For a given therapist i at time t, in each FSA m where the therapist appears as a search result, let $N_{-i,mt}$ be the number of therapists appearing in the results page for that FSA excluding i and let $\mathcal{M}_{it}$ be the set of FSAs in which i appears as a result in time t. The treatment variable FewerThan19$_i$ equals 1 for therapists for whom $\frac{1}{|\mathcal{M}_{it}|}\sum_{m\in\mathcal{M}_{it}} N_{-i,mt} < 19$ for all t prior to June 2020. That is, a treated therapist will have, on average across the FSAs they appear as a search result in, fewer than 19 competitors in all of the pre-treatment months for which the therapist is present in the data. In Section 4.5 I consider multiple alternative treatment definitions, including (1) an alternative treatment indicator using the FSA population weights in the average of competitors and (2) continuous treatments based on the weighted average number of additional competitors in each FSA starting in June 2020.

3.5 Final sample construction and model-free evidence

In the baseline sample, I use propensity score matching to select a group of control therapists based on their similarity to treated therapists in May 2020.[14] Table 1 presents the pre-treatment sample means for outcome variables and matching variables, along with results from difference of means tests.

The supply shock assigns new telemedicine therapists to smaller markets; the purpose of matching is to ensure that while treated therapists' home markets may be geographically smaller, they are not different in ways that would affect their response to COVID-19 shocks. In particular, after matching, treated therapists' markets should not be any more rural, poorer, or any less well-served by therapists or healthcare workers, compared to control therapist' markets. I provide further discussion on sources of random variation in market size that can improve identification of the competition effect in Section 4.2.

In Figure 2, I verify that treatment status is associated with an increase in online competition. I plot the average number of competitors per capita (times 1000) in the local geographic market for both the treatment group and the matched control group. The treatment group experiences a jump in competition in June 2020 in panel (a) driven by a large addition of online therapists based in non-local FSAs, as seen in panel (b).[15] Some control therapists also experience a small increase in online competitors after the shock, since treatment coding is based on average exposure. Insofar as this affects the empirical results, estimates of the competition effect will be understated. I consider alternative treatment definitions in Section 4.5 that avoid this issue.

Figure 3 plots the average values of outcome variables for both the treatment and control groups over time. Exit from the platform visibly increases at the time of treatment for the treated group, and the propensity to offer sliding scale discounts drops sharply.

[14] Matching is one-to-one and done based on minimizing the distance between the predicted logit-based propensity for treatment.

[15] A therapist physically located in FSA m' is local to m if any therapist located in m' ever appeared as a search result for m prior to June 2020. For each i, I construct the numbers of local $\left(\tilde{N}_{-i,mt}\right)$ and non-local $\left(N_{-i,mt} - \tilde{N}_{-i,mt}\right)$ competitors appearing as search results in the local market, divide by the population of the local market, and multiply by 1000.

Table 1: Pre-shock means and standard deviations for dependent and matching variables

Variable	Treated (N=1136)	Matched control (N=1136)	Unmatched control (N=7801)	Diff. of means p Matched	Diff. of means p Unmatched
Dependent variables					
Min. cost (\$/hr)	125	127	132		
	(38.85)	(38.26)	(41.81)		
Online therapy	0.76	0.77	0.78		
	(0.43)	(0.42)	(0.42)		
Sliding scale	0.47	0.47	0.49		
	(0.5)	(0.5)	(0.5)		
Matching variables					
No. specialities	2.71	2.71	2.8	0.98	0
	(0.85)	(0.84)	(0.71)		
No. therapy types	11.59	11.71	11.7	0.69	0.64
	(6.98)	(6.76)	(6.82)		
No. modality types	2.08	2.08	2.08	0.92	0.99
	(1.04)	(1)	(0.97)		
Insurance accepted	0.54	0.5	0.41	0.08	0
	(0.5)	(0.5)	(0.49)		
Title=Counsellor	0.29	0.26	0.23	0.11	0
	(0.45)	(0.44)	(0.42)		
Title=Other	0.05	0.04	0.05	0.38	0.33
	(0.22)	(0.21)	(0.21)		
Title=Psychologist	0.18	0.2	0.21	0.11	0.01
	(0.38)	(0.4)	(0.41)		
Title=Psychotherapist	0.17	0.19	0.26	0.21	0
	(0.38)	(0.39)	(0.44)		
Title=Social Worker	0.31	0.3	0.25	0.65	0
	(0.46)	(0.46)	(0.43)		
Region=Ontario	0.4	0.46	0.58	0.01	0
	(0.49)	(0.5)	(0.49)		
Region=British Columbia	0.15	0.18	0.22	0.03	0
	(0.36)	(0.39)	(0.42)		
Region=Atlantic provinces	0.15	0.06	0.02	0	0
	(0.35)	(0.24)	(0.13)		
Region=Prairie provinces	0.3	0.3	0.18	0.78	0
	(0.46)	(0.46)	(0.39)		
FSA Therapists per 1000	0.71	0.83	2.72	0.08	0
	(1.66)	(1.64)	(2.97)		
FSA retail/hospitality share	0.11	0.11	0.11	0.59	0.19
	(0.02)	(0.02)	(0.02)		
FSA health care share	0.06	0.06	0.06	0.57	0
	(0.01)	(0.01)	(0.01)		
FSA participation rate	0.65	0.65	0.68	0.39	0
	(0.06)	(0.07)	(0.06)		
FSA household size	2.41	2.43	2.29	0.14	0
	(0.35)	(0.32)	(0.46)		
FSA age	41.26	41.24	41.04	0.89	0.05
	(3.5)	(3.8)	(3.12)		
FSA after tax income	76911	79661	88039	0	0
	(24061)	(22487)	(31840)		
FSA density (pop/km2)	1183	1259	3708	0.23	0
	(1647)	(1367)	(4537)		
FSA apartment share	0.27	0.27	0.45	0.9	0
	(0.19)	(0.18)	(0.25)		

Note: The table presents averages and standard deviations for dependent and matching variables for all therapists present in May 2020 before the supply shock occurs, which is the group for which matching is performed. Dependent variables are their May 2020 values, exit is thus omitted since it is zero across groups. Standard deviations of each variable are presented in brackets below the means. Modalities are patient types, e.g. children, couples, elderly; specialities are the illnesses the therapist specializes in treating; therapy types include, e.g. cognitive behavioural therapy, hypnotherapy, etc.

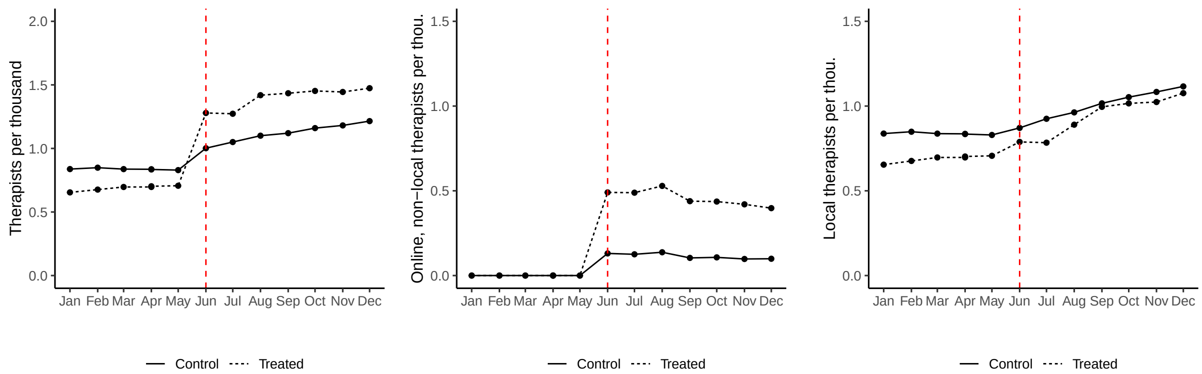


Figure 2: Average number of competitors per capita by treatment group, matched sample
Note: The left graph presents the average number of total competitors per capita $\times 1000$ *(competitors divided by local market population* $\times 1000$*) by treatment group, the middle graph is the average number of telemedicine competitors per capita by treatment group, and the right graph is the average number of local competitors per capita by treatment group.*

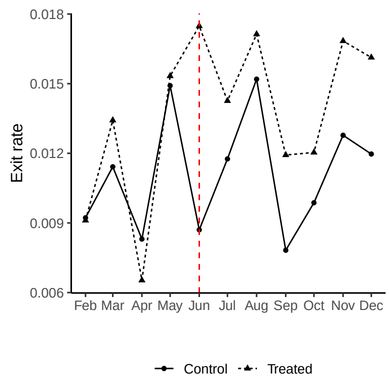
4 Empirical Analysis

4.1 Difference-in-differences model

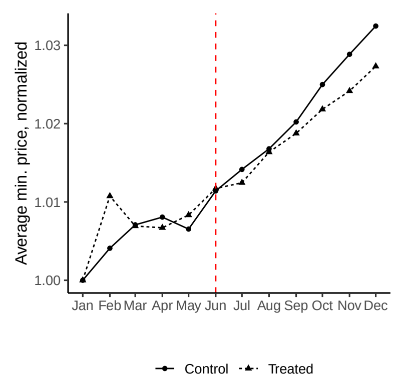
The baseline regression is a difference-in-differences using the propensity-score-matched sample:

$$y_{imt} = \beta \cdot \text{FewerThan19}_i \times \text{Post}_t + \alpha_i + \alpha_{rt} + \epsilon_{imt} \tag{1}$$

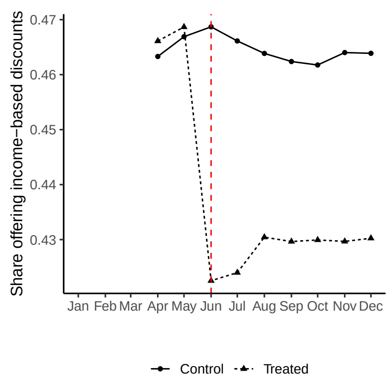
where i indexes a therapist, m is the FSA corresponding to a therapist's unique physical location, r is a region (Ontario, British Columbia, Prairies, or Maritimes) and t indexes the month. Recall that FewerThan19_i is the treatment variable, and equals one for therapists exposed to new telemedicine competitors by the algorithm shock, based on having fewer than 19 local competitors (on average across the search FSAs they appear in) prior to June 2020. Post_t equals 1 if the date is in June 2020 or later. I consider a range of outcome variables y_{imt}, including an indicator for exit from the platform; the hourly price; an indicator for whether i offers income discounting; and an indicator for whether i offers virtual care. Including a therapist-level fixed effect α_i and region-month-level fixed effect α_{rt} implies that comparisons are within therapists over time, allowing for flexible shocks that vary by month and region. Note that because the policy shock is not staggered over time, recent work showing that the two-way fixed effect estimator (TWFE) may be biased in the presence of heterogeneous treatment effects (e.g., (Goodman-Bacon, 2021)) does not apply, and a simple TWFE regression will consistently estimate the average treatment effect.



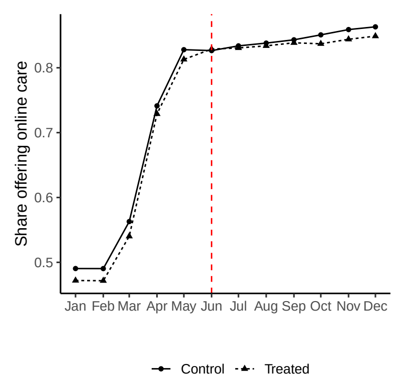
(a) Exit rate



(b) Normalized price



(c) Sliding scale



(d) Online offering

Figure 3: **Average outcomes, by treatment group**
Note: This graph plots the average outcome variables by treatment group, using the matched sample. Exit data starts in February since the first observed month is January; sliding scale data starts in April since sliding scale information was not collected in prior months. The vertical dashed line represents the month the supply shock occurred.

4.2 Identification

The typical identification concern when studying the effect of competition is endogenous entry and exit. Unobserved shocks that make a market more attractive induce entry, but also induce changes in outcomes among incumbents, confounding estimates of the competitive effect (Orhun, 2013). In our setting, telemedicine provider entry is assigned by the platform's search algorithm, which is orthogonal to transitory supply shocks that affect both entry and incumbents. The algorithm does assign entrants based on the number of therapists in a market pre-shock, which may be endogenous to time-invariant unobserved heterogeneity at the market level. However, the effects of this heterogeneity will be absorbed by the therapist fixed effects in Equation (1).

Contemporaneous COVID-19 shocks pose a key obstacle to separately identifying the effect of competition because of non-random assignment of treatment. The main concern is that since smaller markets receive new telemedicine providers, smaller markets are also different in ways that lead therapists operating there to respond differently to concurrent COVID-19 shocks.

Matching on the variables detailed in Table 1 rules out that observable differences in treated therapists' home markets lead to differential responses of treated therapists to COVID-19 shocks. First, treated and control therapists' home markets are similarly urbanized with the same population density, and so should be subject to the same supply shocks (e.g. availability of services, such as childcare) that manifested during COVID-19. Second, incomes are similar, as is the share of employees in the hard-hit retail and service sectors (Lemieux *et al.*, 2020), so any shocks to the ability to pay for mental health care should be equal on average across treated and control therapists. Third, there may have been localized shocks to mental health demand based on the health impact of COVID; however, age is the most important correlate of mortality in the first wave of the pandemic in Canada and I match successfully on this variable. Finally, aggregate shocks to mental health demand should affect treated and control therapists proportionately, as they operate in markets with similar numbers of therapists and health care workers per capita.

Even with similar observable characteristics, treated therapists' small home markets may be less connected or systematically different than untreated therapists' larger markets. I associate FSAs with cities using postal code data, and plot city populations against the cumulative share of treated therapists in June 2020 in Figure B.1. Only 22% of treated therapists operate in FSAs that are part of small cities (pop. less than 30 000.) Most treated markets are simply small subdivisions of larger cities, and so most treated therapists still operate in urban environments, with treatment driven by the arbitrary size of FSA boundaries.

To improve identification, I perform robustness checks that leverage cross-sectional exogeneity in treatment status the data. First, I use the arbitrariness of the 20 therapist padding threshold, and assume that unobserved COVID-19 shocks are similar for therapists just above and below this cutoff. Second, I use the fact that FSA sizes vary within cities, which generates variation in treatment status across therapists within a city depending on what FSA they are based in. I can then subsume any time-varying city-specific COVID-19 shocks by including city-by-month fixed effects for the approximately 550 cities in the data.

4.3 Baseline results

Results from Equation (1) using the full matched sample are presented in Table 2. With respect to pricing, I find that therapists who are exposed to additional telemedicine competitors by the supply shock ($\text{FewerThan19}_i = 1$) are not more likely to exit and do not change their prices, but do reduce their propensity to offer sliding scale pricing by 3.9 percentage points. This reflects a 8.3% reduction given the baseline propensity to offer a sliding scale of 0.47 among treated therapists in Table 1.

Since sliding scale prices are how therapists price discriminate between low and high income individuals, treated therapists become less willing to serve low income groups after the shock. I explore why therapists stop serving lower income patients at a lower price in a simple model in Section 6. These results are similar to findings in the pharmaceutical industry, where the entry of generic drugs leads branded incumbents to raise their prices (Frank and Salkever, 1997; Ching, 2010).

Therapists who are exposed to new telemedicine competitors by the supply shock exhibit no change in their propensity to add online care. Only the 19% of therapists who do not already offer online care at the time of the shock (see Table 1) can be positively affected by the treatment for this outcome variable, and whether or not a therapist already offers care is not random, but reflects market-level demand and therapist-level costs. Given that the initial onset of COVID-19 in March 2020 shifted preferences and delivery towards virtual care, therapists who were able to easily add the online channel likely already did so, and only those for whom the cost of adding an online channel was prohibitive remained offline by the time of the supply shock. For these therapists, new online competitors did not increase the marginal benefit of investing in virtual care.

Baseline results checks

I address whether unobserved COVID-19 shocks that are correlated with treatment status drive the results in Table 2 with three checks. First, to leverage the kink in the padding policy at 20 therapists, I run the difference-in-differences model in Equation (1) using therapists who have between 15 and 25 competitors. The identifying assumption is that in a small neighbourhood of having 20 competitors (on average), therapists face similar unobserved shocks, conditional on observables. Results reported in Table B.1 mirror those in Table 2.[16]

[16] The magnitude of the treatment effect is similar in Table 2 and Table B.1 despite fewer additional competitors being added for the latter results. This is due at least in part to the different control group for the trimmed sample regression; in Table B.2 I show that the Column (3) coefficient magnitude in the baseline regression is much larger when restricting the control group to have 25 competitors or fewer.

Table 2: Estimated effect of online competition

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	0.004	-0.0004	-0.039***	0.008
	(0.003)	(0.004)	(0.010)	(0.014)
Therapist FE	✓	✓	✓	✓
Region×Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.172	0.965	0.945	0.729

*Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. *p<0.1, **p<0.05, ***p<0.01.*

Second, even after balancing the sample on observables, the subset of treated therapists in rural areas may be driving the competition effect, potentially due to concurrent COVID-19 shocks. Moreover, it is also possible that the responses of treated therapists based in large cities like Toronto, which were hit especially hard economically by COVID-19, are contaminating the treatment effect. Results in Table B.3 restrict the sample to therapists based in FSAs that are part of cities of between 30 000 and 250 000 people. This subsample captures roughly half of treated and control therapists. The effect of competition on the propensity to offer income discounting remains negative and significant.

In the final check, I saturate Equation (1) with city-by-month fixed effects, to control for any unobserved COVID-19 shocks that manifest at the city-month level. While policy shocks typically occurred at the provincial level, business lockdowns were sub-provincial, and reported COVID-19 cases and labour market disruptions may have occurred at the city level. Including city-by-month fine fixed effects only compares outcomes of treated and untreated therapists within the same city, which eliminates identifying variation coming from therapists in any city comprised of a single FSA—i.e., most small cities and rural areas. Results reported in Table B.4 are consistent with the baseline findings.

4.4 Treatment intensity

In this setting, the entry of teletherapists could have acted as a competition shock, or as an information shock. In the former case, incumbents may perceive themselves as competing with the new options that have been introduced by the platform, so the intensity of new entry should matter for therapist responses.

Table 3: Estimated effect of online competition, with treatment intensity

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	0.001	0.004	-0.017*	0.016
	(0.003)	(0.004)	(0.009)	(0.015)
$\text{FewerThan9}_i \times \text{Post}_t$	0.012**	-0.013**	-0.077***	-0.027
	(0.005)	(0.006)	(0.021)	(0.023)
Therapist FE	✓	✓	✓	✓
Region×Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.173	0.965	0.946	0.729

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

Alternatively, from the presence of any new teletherapist result, incumbents may correctly infer that they are now competing with all telemedicine providers in their province of residence. In that case, any new teletherapist entrant is enough to signal the broader increase in competition, and the intensity of new entry should not matter for therapist responses.

To examine whether the number of new telemedicine entrants matters to incumbents, I estimate the following regression on the full propensity score matched sample:

$$y_{imt} = \beta_1 \cdot \text{FewerThan19}_i \times \text{Post}_t + \beta_2 \cdot \text{FewerThan9}_i \times \text{Post}_t + \alpha_i + \alpha_t + \epsilon_{imt} \tag{2}$$

where FewerThan9_i indicates a therapist i who had at most 9 competitors on average in the pre-treatment months, and thus would face at least a doubling of competition through the addition of the telemedicine providers. If therapists who face a greater increase in telemedicine competition have a stronger response, it will be reflected in the coefficient β_2 estimated significantly differently from zero.

Results from Equation (2) are reported in Table 3. Starting with Column 2, the more intensely treated group of therapists reduces posted prices slightly, by 1.3%. Much stronger is the reduction in the propensity to offer income discounts in Column 3, which falls by 9.4 percentage points (-1.7 - 7.7 in column 3), a 20% decrease relative to the baseline rate. The fact that intensity of competition matters implies that the supply change serves as more than an informational shock to treated therapists.

In Column 1, exit from the platform amongst the more intensely treated group of therapists increases by 1.21 percentage points (0.01 + 1.2 in column 1), an 89% increase over their baseline rate of exit of 1.50% per month in the pre-treatment period. Since listing on the platform requires paying a monthly fee, greater exit suggests that new competitors are diverting revenue from existing incumbents, who now no longer expect to earn enough revenue from platform referrals to make it worthwhile to stay and pay the fee.

An alternative story to explain exit is that therapists exposed to intense new competition operate in underserved markets and experience a COVID-19 demand shock. If this puts them at capacity, they may temporarily leave the platform to avoid paying the $40/month fee. This is unlikely to be the case: first, treated and control therapists operate in markets with very similar average therapists-per-capita, and so any aggregate demand shock for mental health care proportional to population should not disproportionately affect treated therapists. Second, most exit is permanent—only 13.3% of therapists who leave the platform end up relisting in a later month, implying that therapists who leave are not simply temporarily at capacity.

4.5 Robustness checks

In this section, I provide additional robustness checks on the baseline results.

Parallel trends assumption. I run a timing test to provide evidence for the assumption that treated therapists would have behaved similarly to control therapists in the absence of treatment. Results in Figure B.2 show no statistically significant difference between outcome variables for treated and control therapists until the website's change in search results displayed in June 2020, and no difference in pricing or the propensity to offer online care between treatment and control in any month. The lack of a pre-trend in outcomes suggests that the research design is controlling well for pandemic-related demand and policy shocks that manifest in months other than June 2020.

Population-weighted treatment. I consider an alternative treatment to check that the competitive response is not driven by search markets that generate very little demand. I construct a weighted average of the number of competitors in the searched FSAs a therapist appears in using FSA populations as weights, and code a therapist as treated if this weighted average number is less than 19 in all months prior to June 2020. Results reported in Table B.5 mirror the baseline findings in size and significance.

Continuous treatment. Since treatment status is based on a therapist's average exposure to new competitors, the control group contains some therapists who are still exposed to new online competitors, albeit fewer than the treatment group. While this should bias the DiD model against finding a significant effect, I consider two continuous treatment variables to test whether this is an issue. The first continuous treatment is the weighted average of an indicator function across the search FSAs a therapist appears as a result in, where weights correspond to FSA population, and the indicator equals one for an FSA if there are fewer than 19 competitors in that FSA prior to June 2020. Any therapist who experiences any increase in online competition due to the algorithm in June will have a positive value for this variable, with a maximum value of 1, and only therapists who experience absolutely no increase in competition will have a zero value. The second continuous treatment is the population-weighted average of the number of new online competitors starting in June 2020 in each FSA the therapist appears in. Results using both alternatives are presented in Table B.6 and B.7, and show a significant negative effect of treatment on the propensity to offer a sliding scale and a positive effect of exit for the second continuous treatment.

Algorithm-induced demand shocks. The online therapists who were used to pad unserved search FSAs were exposed to new patients; if those therapists were themselves in the treatment group it may have incentivized them to stop serving lower income patients as they now had access to a greater pool of higher income patients. I trim the control and treatment groups to only include therapists who appeared as search results in at most 10 FSAs (the 90th percentile) in any month of the sample in which they appear. I show that there is no jump at treatment time in the average number of FSAs the therapists appear in, and then re-run the base specification. The competition effect remains negative and significant for the sliding scale indicator, see Appendix B.6 for details.

Intraprovincial movement. In 2020, policymakers were especially concerned about an exodus of households from the cities to their second homes in rural areas.[17] If treated therapists are concentrated in these areas, then an increase in local patients may have motivated changes in pricing, including ending income discounting. I incorporate auxiliary geographic data on second-homes and cottages into the baseline regression to rule out this channel in Appendix B.7.

5 Treatment effect heterogeneity

In this section, I evaluate how the effect of telemedicine competition on pricing depends on therapist quality. Recent empirical work in other healthcare domains suggests that telemedicine attracts price sensitive patients (Martinez *et al.*, 2018; Ellegård *et al.*, 2021). Since price sensitive patients would otherwise be served by lower quality local providers, this work suggests that these providers should be most strongly

[17] In the Canadian context, the Victoria Day holiday at the end of May typically marks the beginning of summer "cottage season", and policymakers were especially concerned about an exodus of households from the cities to their second homes in rural areas.

impacted by teletherapist entry.

I proxy for therapist quality with therapist titles. I trim the sample to include only psychologists, counsellors, social workers, or psychotherapists, which comprise 95% of the matched sample. The titles can be ordered in terms of credentials, with psychologists the most credentialled, followed by social workers and counsellors, and psychotherapists the least credentialled.[18] Summary information by credential is provided in Table B.11.

I run the following regression, where z indexes each title, and W_{iz} equals one if therapist i has title z:

$$y_{imt} = \sum_z \beta_z \cdot \text{FewerThan19}_i \times \text{Post}_t \times W_{iz} + \alpha_i + \alpha_{zrt} + \epsilon_{imt} \tag{3}$$

β_z captures whether therapists of type z exposed to the competition shock change their outcome variables, conditional on allowing average baseline outcomes for each therapist type z to change flexibly over time and across regions via the fixed effect α_{zrt}. Since titles are fixed, α_i absorbs the baseline time-invariant effect of different titles in different regions.

Column 1 of Table 4 shows that exit from the directory is driven exclusively by psychotherapists, with a large and significantly estimated coefficient. The large increases in psychotherapist exit suggest that telemedicine entrants reduce profits (on the portal) of lower quality therapists by the most, which is consistent with the previous literature. For posted prices in Column 2, as in the baseline there is no differential movement for treated therapists.

Results in Column 3 of Table 4 show that psychologists, counsellors, and social workers reduce their propensity to offer income discounts in response to competition, while psychotherapists maintain their income discounts. Psychologists' reduction in their propensity to offer a sliding scale is by far the largest, despite having the smallest initial propensity to offer a sliding scale in Table B.11. In Column 4, social workers have a marginally significant increase in their propensity to offer virtual care, but there is otherwise no significance or pattern of coefficients.

While teletherapist competition clearly has different effects along the quality spectrum, it remains to be seen whether the proposed mechanism—greater competition by teletherapists for price-sensitive patients—can explain the price discrimination results. I turn to this question with a simple applied theory model in Section 6.

Given that teletherapists are hypothesized to compete more with lower quality incumbents, in Table B.10 I verify that telemedicine entrants' prices tend to be lower than incumbents', and their income

[18] Psychologists require a Ph.D. or Psy.D. to practice and are members in professional associations nationwide. Counsellors and social workers typically require masters degrees (MA in Counselling Psychology and Masters of Social Work, respectively) and also have longstanding professional associations. The psychotherapist title is a relatively recent designation. Some provinces still did not have professional associations for psychotherapists at time of data collection and there are a broad range of practitioner types included under this designation in the data (e.g., art therapists, hypnotherapists, etc.)

Table 4: Heterogeneity by therapist title

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
FewerThan19$_i$ $\times$ Post$_t$ $\times$ Psychologist$_i$	0.006	0.001	-0.057**	-0.023
	(0.007)	(0.005)	(0.023)	(0.032)
FewerThan19$_i$ $\times$ Post$_t$ $\times$ Social Worker$_i$	-0.001	-0.003	-0.052***	0.050*
	(0.006)	(0.007)	(0.019)	(0.027)
FewerThan19$_i$ $\times$ Post$_t$ $\times$ Counsellor$_i$	-0.006	-0.002	-0.031*	0.005
	(0.005)	(0.007)	(0.017)	(0.024)
FewerThan19$_i$ $\times$ Post$_t$ $\times$ Psychotherapist$_i$	0.023***	0.005	-0.008	0.005
	(0.007)	(0.011)	(0.016)	(0.033)
Therapist FE	✓	✓	✓	✓
Title$\times$Region$\times$Month FE	✓	✓	✓	✓
Observations	22,371	20,873	18,605	24,364
R^2	0.182	0.967	0.947	0.734

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later, and further interacted with a therapist's title. This specification uses the full matched sample, minus therapists whose title could not be determined and was coded as "other." Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

discounting propensities higher than incumbents', in the markets that they enter. I also run Equation (3) using W_{iz} as discrete pricing categories. I code therapists into low, middle, and high hourly price bins based on their position in the price distribution in May 2020, and find that medium and high priced therapists reduce income discounting by more, but that there are no significant results for exit, see Table B.12.

6 Model of therapist behaviour

The pricing behaviour of therapists at first seems counterintuitive: basic models of price competition between differentiated firms imply that more entry leads to lower prices. Moreover, when price discrimination is modeled, theory predicts that discrimination may increase or decrease, but if it decreases, it is because all prices are being depressed—not that the lower prices are being eliminated as I find here. I discuss intuitively a model that can match the empirical results in this section, and formally develop the model in Appendix C.

My starting point is the model of price discrimination in Stole (2007). This model predicts that entry leads to more price discrimination by an incumbent firm under the condition that there are two groups of consumers, one of which is loyal to the incumbent firm and price inelastic, and one of which is not loyal and is price elastic. An entrant will compete strongly for the latter group of consumers and the prices this group pays will fall, while the former group of consumers continues to pay a high price.

I model therapists as serving two types of patient: price insensitive, high willingness-to-pay (WTP) types and price sensitive, low WTP types. Therapists are capacity constrained, and can match with at most one patient in each period. Their decision is whether to serve just the high WTP patients at their WTP, to serve both high and low WTP patients by offering the income discount (patient identities can be discerned costlessly), or to leave the platform to avoid paying the platform fee. Therapists are assumed to draw either a high WTP patient, low WTP patient, or no patient from a known distribution each period. The capacity constraint creates an option value for not serving the low WTP patients.

Motivated by the results in Stole (2007), I assume that telemedicine entry leads to a reduction in the price paid by the low WTP patients. As the price paid by low WTP patients falls after competitor entry, the relative attractiveness of the option value of an empty slot increases, and more therapists choose to stop serving the low WTP patients at a lower price via the income discount. Entry also decreases profits amongst therapists who previously found it optimal to price discriminate, leading to greater exit from the platform. This simple model can thus match the results in Tables 2 and 3.

The model can also match the results on quality heterogeneity. I assume that higher quality therapists draw high WTP patients more frequently and lower quality therapists draw low WTP patients more frequently. Before telemedicine entry, higher quality therapists can count on a steady flow of high WTP patients; since it is easy to fill their patient slot with a high type it is especially costly to take on a low type, and so they offer fewer income discounts as in Table B.11. After telemedicine entry taking on a low WTP type becomes even costlier, since the low type pays less. Meanwhile, lower quality therapists tend to serve both types already, but would receive few high WTP types if they discontinued income discounts, and so must either continue competing for low WTP types or exit.

The basic model requires two assumptions: telemedicine entrants compete for low WTP patients, and therapists face capacity constraints. The first assumption is argued for in Section 5. For the second assumption, note that it is not necessary that therapists are at capacity for the model's predictions to hold, only that these therapists' capacity is limited and that there is therefore an option value to keeping slots open for new patients. Reports from the popular press suggest that therapists were at capacity at points during the pandemic,[19] although survey evidence is mixed (Sammons *et al.*, 2020).

[19]See Caron, Christina, "'Nobody Has Openings': Mental Health Providers Struggle to Meet Demand," *The New York Times*, February 17, 2021; Budd, Ken, "Having Trouble Finding a Therapist? You're Not Alone," *AARP*, March 22, 2021; Leland, John, "How Loneliness is Damaging Our Health," *The New York Times*, April 20, 2022.

7 Additional discussion and limitations

7.1 Lack of price response

Posted baseline prices hardly move in response to telemedicine competition in this setting, even in the specification allowing for intensity of treatment. While I am unable to say exactly why that is, I can offer a few conjectures.

First, there may be behavioural frictions that keep therapists from adjusting prices. Recent papers spanning industries from chain supermarkets with thousands of products (Ailawadi *et al.*, 2010; DellaVigna and Gentzkow, 2019; Arcidiacono *et al.*, 2020) to small AirBnB operators setting prices for a single property (Huang, 2021) have found empirical evidence that a lack of price response to increased competition is widespread, with a variety of possible behavioural mechanisms at play. I do not advance any particular behavioural theory of why prices may not adjust in this setting, but merely highlight that frictions impeding flexible price setting are common.

Second, psychotherapy is an example of a credence good—a product whose qualities cannot be ascertained by consumers even after purchase. In experimental studies, high quality sellers setting prices for credence goods choose to set a "fair" price that captures the quality of the service (Dulleck *et al.*, 2012). It may be that if therapists lower posted prices in response to more competition, that may be seen as tantamount to an admission that initial prices were not "fair" to begin with given the offered quality, and thus that they are not engaged in fair pricing. In the price fairness literature, price changes that are not associated with cost shocks are typically perceived by consumers as unfair (Kahneman *et al.*, 1986; Xia *et al.*, 2004), and lead to substantial consumer pushback.

7.2 Limitations

First, I do not observe patient behaviour on the directory. While it is not uncommon to have no consumer data in studies of firm competition and pricing (Thomadsen, 2007; Shen and Xiao, 2014; Blevins *et al.*, 2018; Arcidiacono *et al.*, 2020), it means that the results can credibly speak only to the supply-side effects of telemedicine competition and not its total welfare implications. Secondly, the results are only directly valid in the context of talk therapy and independently operating practitioners. However, insofar as virtual care competes more for price sensitive patients in other healthcare contexts and incumbent providers are still capacity constrained, the results are likely to hold. Thirdly, although the sample is not representative as therapists self-select into participation on the directory, these therapists are the ones most actively soliciting new patients. New competition is not likely to affect the stability of ongoing patient-therapist relationships given the difficulty in finding a good match, so therapists searching for new patients are therefore the most relevant population when considering the effect of telemedicine competition.

7.3 External validity

The results in this paper cover only the short term response of therapists during the first and second waves of COVID-19, during a time period when no individuals were vaccinated in Canada, overall mobility was still below pre-COVID averages, and there were large shocks to mental health. While the competition effect may be well-identified, whether an effect of similar magnitude and direction would be observed during a time period with more regular movement patterns is impossible to say. However, the basic intuition that digital competition can raise some prices by attracting price-sensitive consumers is not COVID-specific. In addition to the previously mentioned Ching (2010) and Frank and Salkever (1997) studies on generic entry in pharmaceuticals, Jiang *et al.* (2022) find in the retail banking industry that proxies for increased digital competition in a market lead incumbent banks to raise prices on in-person services.

8 Conclusion

In this paper, I analyze the effect of new telemedicine entrants on incumbent healthcare providers during the first waves of COVID-19. The paper's main contribution is to provide the first estimates of the effect of telemedicine competition on incumbent providers' pricing and technology adoption. In particular, I show that telemedicine entry makes incumbent providers less willing to offer discounts for lower-income patients, and rationalize my findings with a simple model of capacity-constrained providers.

From the policymaker's perspective, this paper suggests that expanding telemedicine options may not make all households better off. Households who cannot access telemedicine options or who have a strong aversion to digital care do not benefit from the increased competition, and indeed may end up facing higher prices, especially if they seek the services of higher quality therapists. Policymakers should take steps to ensure that some local, in-person therapy options remain affordable in the face of expanding telemedicine options.

The paper raises a number of questions for future work. First, the analysis covers only the supply side of the policy change: while the expansion in online options may have led to exit of some therapists and increased local prices for some low-income patients who prefer in-person care, it may also have led to increased traffic on the patient side, better matches, and more accessibility in underserved areas. While demand stimulation is often seen as a cost-increasing side effect of telemedicine expansion, for underutilized services—such as mental health treatments—it may represent a net benefit (Ashwood *et al.*, 2017). Second, any negative welfare implications of this paper's findings stem from the assumption that there exist individuals who strongly prefer in-person care. While such individuals have been shown to exist (Schiffer *et al.*, 2021), the quantitative importance of this segment of patients is not yet well-known. Finally, the paper uses data after the first wave of COVID-19 in Canada, after preferences and delivery options for medical care have shifted dramatically. For mental health, these shifts have been substantial and long-lasting; further research should expand these findings to other types of medical care, where the shift may not be as large or lasting.

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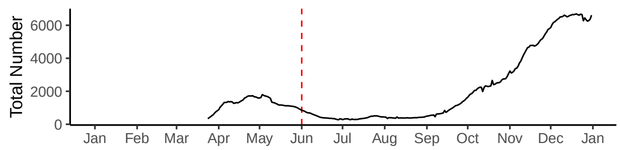
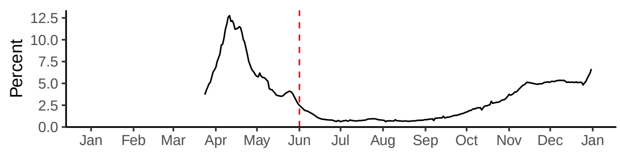
Web Appendix

A Background and Data

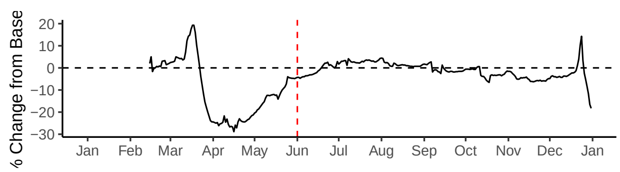
A.1 Covid trends in Canada in 2020



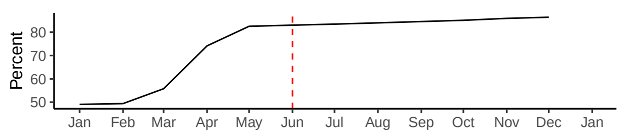
(a) New COVID-19 cases



(b) Positive COVID-19 tests



(c) Movement trends: visits to groceries and pharmacies



(d) Therapists offering online care

Figure A.1: **Canada-wide trends during the first wave of COVID-19**
COVID-19 case and percent positive data in Panels A and B is taken from the Government of Canada, movement data in Panel C is taken from Google's Global Mobility Reports and shows data for groceries and pharmacies. These data are seven-day moving averages. The percent of therapists offering online care uses data from PsychologyToday.com. Data periods correspond to when data is first and last available in each dataset. The red dashed line corresponds to the month (June, 2020) in which the supply shock happens.

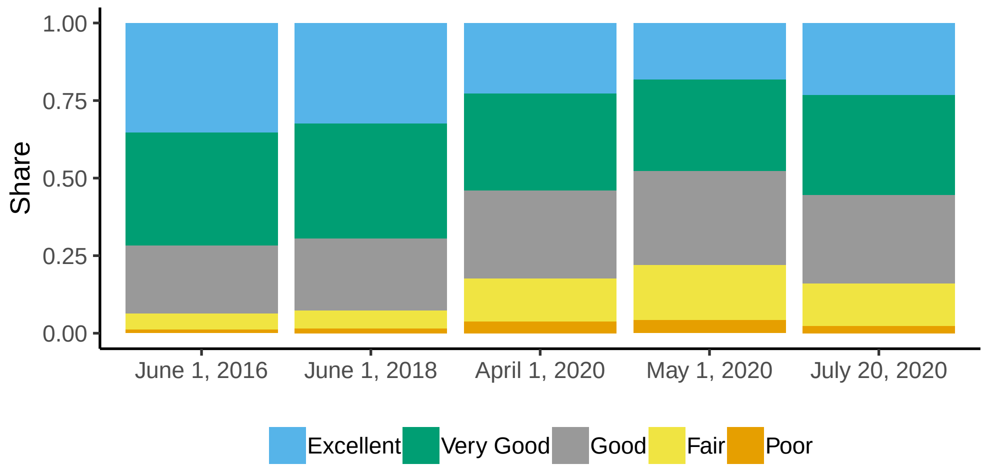


Figure A.2: **Self-reported mental health before and during COVID-19**
Data in 2016 and 2018 is sourced from the Canadian Community Health Survey. Data in 2020 is sourced from Waves 1, 2, and 4 of the Canadian perspectives Survey Series, each of which contains the exact mental health question from the 2016 and 2018 surveys. All surveys were administered by Statistics Canada.

A.2 Platform screenshot

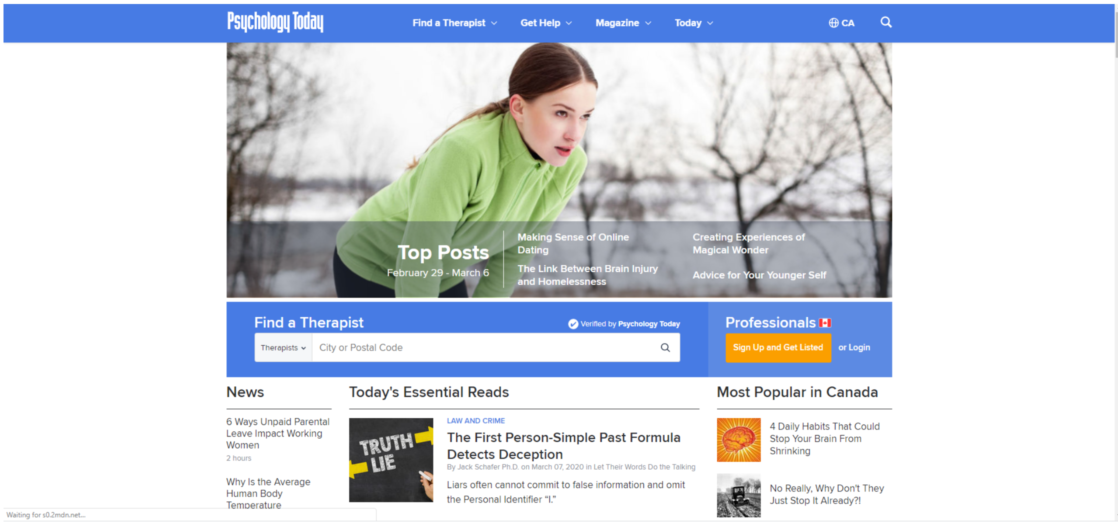


Figure A.3: platform frontpage screenshot, March 2020

A.3 Therapist counts

Table A.1: Therapist counts

Province	Pop. (m)	Type	*PT.com*	Total count	*PT.com*/Total	Private count	*PT.com*/Private
AB	4.402	Social Worker	220	7,705	0.029	62	3.548
AB		Psychologist	997	4,094	0.244	191	5.220
AB		Other	250				
BC	5.132	Social Worker	215	4,456	0.048	47	4.574
BC		Psychologist	160	1,271	0.126	248	0.645
BC		Other	1,534				
MB	1.377	Social Worker	99	2,630	0.038		
MB		Psychologist	19	292	0.065	178	0.107
MB		Other	103				
NB	0.780	Social Worker	21	2,207	0.010	123	0.171
NB		Psychologist	7	360	0.019	364	0.019
NB		Other	28				
NL	0.524	Social Worker	3	1,596	0.002	51	0.059
NL		Psychologist	3	282	0.011	70	0.043
NL		Other	20				
NS	0.976	Social Worker	36	2,328	0.015	300	0.120
NS		Psychologist	70	649	0.108	178	0.393
NS		Other	101				
ON	14.689	Social Worker	1,693	19,593	0.086	839	2.018
ON		Psychologist	603	4,074	0.148	692	0.871
ON		Other	2,665				
PE	0.159	Social Worker	3	346	0.009		
PE		Psychologist	1	56	0.018	19	0.053
PE		Other	8				
QC	8.557	Social Worker	60	15,121	0.004		
QC		Psychologist	209	7,694	0.027		
QC		Other	116				
SK	1.179	Social Worker	22	2,186	0.010	182	0.121
SK		Psychologist	29	504	0.058	54	0.537
SK		Other	44				
YT	0.042	Other	3				
YT		Psychologist	1				
YT		Social Worker	2				

Note: the "Type" column refers to type of therapist where Other includes registered psychotherapists, psychiatrists, counsellors, etc. "PT.com" is the count of each type in each province from PsychologyToday.com in May 2020. "Total count" is the total number of each type of therapist from official statistics, linearly imputed using 2015-2019 data to 2020. "Private count" is the total number of each type of therapist that lists themselves as available for private practice from professional association directories accessed in 2021; empty values indicate missing data for that province. Sources for all data are provided in Table A.2

Table A.2: Sources for social worker (SW) and psychologist counts

Province	Type	Count	Source	Link	Date Accessed
All	SWs, psychologists	Total	Canadian Institute for Health Information	https://www.cihi.ca/en	April 1, 2021
AB	SW	Private	Alberta College of Social Workers	https://acsw.ab.ca/	April 15, 2021
AB	Psychologist	Private	Psychologists' Association of Alberta	https://psychologistsassociation.ab.ca	April 15, 2021
BC	SW	Private	BC Association of Social Workers	http://www.findasocialworker.ca	April 15, 2021
BC	Psychologist	Private	British Columbia Psychological Association	https://www.psychologists.bc.ca/find$_psychologist$	April 15, 2021
MB	Psychologist	Private	Manitoba Psychological Society	https://mps1.wildapricot.org/	April 15, 2021
NB	SW	Private	New Brunswick Association of Social Workers	https://www.nbasw-atsnb.ca/	April 15, 2021
NB	Psychologist	Private	College of Psychologists of New Brunswick	https://cpnb.ca/en/psychologists/	April 15, 2021
NL	SW	Private	Newfoundland & Labrador College of Social Workers	https://nlcsw.ca/	April 15, 2021
NL	Psychologist	Private	Association of Psychology Newfoundland & Labrador	http://www.apnl.ca/	April 15, 2021
NS	SW	Private	Nova Scotia College of Social Workers	https://onlineservice.nscsw.org/	April 15, 2021
NS	Psychologist	Private	Association of Psychologists of Nova Scotia	https://apns.ca/	April 15, 2021
ON	SW	Private	Ontario Association of Social Workers	http://www.findasocialworker.ca	April 15, 2021
ON	Psychologist	Private	Ontario Psychological Association	https://www.psych.on.ca/	April 15, 2021
PE	Psychologist	Private	Psychological Association of Prince Edward Island	https://www.papei.org/	April 15, 2021
SK	SW	Private	Saskatchewan Association of Social Workers	https://www.sasw.ca/	April 15, 2021
SK	Psychologist	Private	Psychology Association of Saskatchewan	https://www.psychsask.ca/	April 15, 2021

Note:

A.4 Posted price verification

The dataset contains information only on posted prices, so I verify that these posted prices reflect transacted prices using an additional dataset.

The large insurer SunLife, at time of data collection, provided a public price range for each therapist based on recent insurance claims for therapists that signed on for direct billing on its own search platform. SunLife has since discontinued providing price range information. Within an FSA, therapists were divided into three price tiers based on local claims. For example, therapists in H3P—a neighborhood in Montréal—were divided into less than 120 CAD, $120 - 150$ CAD, and greater than 150 CAD ranges.

I gather this data from the SunLife platform for March and April 2020, match therapists across datasets using full names and the physical FSA they are located in, and compute the share of therapists whose posted prices fall in the range provided by SunLife. I match 1085 unique therapists across datasets, and find that minimum posted prices fall in the SunLife range 82.6% and 80.4% of the time for March and April, respectively, and maximum posted prices fall in the range approximately 66.0% and 66.2% of the time in March and April, respectively. The high rate of agreement for minimum posted prices justifies using this quantity as the price measure in the analysis.

A.5 Representativeness of sub-provincial geographic distribution of therapists

I verify that the therapists on PsychologyToday are distributed in a representative manner at the sub-provincial level. Administrative data collected by provinces tracks the number of psychiatrists employed by the government in different jurisdictions; I source data for the largest province, Ontario, from Kurdyak *et al.* (2017) at the sub-provincial local health integration network level, and find a similar distribution of government-employed psychiatrists, private psychologists, and all private therapists across space, see Figure A.4.

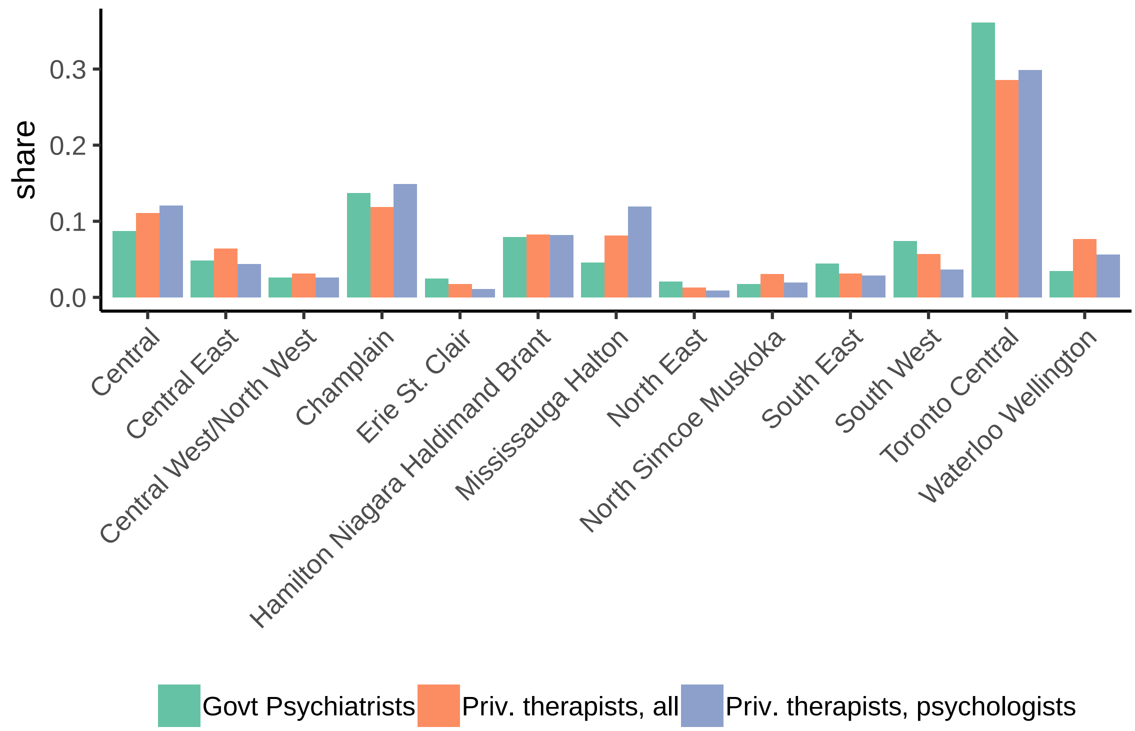


Figure A.4: Geographic distribution of practitioners in Ontario

Note: The sub-provincial geographic entity is the local health integration network (LHIN). There are 14 LHINs in Ontario; Central West and North West were combined as in Kurdyak et al. (2017). Shares are computed within-Ontario, within category (Govt Psychiatrists, Priv. therapists, all and Priv. Therapists, psychologists.)

A.6 Summary statistics

Table A.3: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Therapist-level variables							
Exit	111,715	0.01	0.10	0	0	0	1
Min. cost ($ per hour)	94,117	131.11	45.42	5.00	100.00	150.00	1,600.00
Max. cost ($ per hour)	79,567	162.00	67.66	20.00	130.00	190.00	10,000.00
Sliding scale	86,263	0.48	0.50	0.00	0.00	1.00	1.00
Online care	111,715	0.76	0.43	0	1	1	1
Avg. no. comp.	111,715	79.24	102.50	0	30	75	632
FewerThan19	103,217	0.13	0.33	0.00	0.00	0.00	1.00
FewerThan9	103,217	0.04	0.19	0.00	0.00	0.00	1.00
Ins. Accepted	111,715	0.40	0.49	0	0	1	1
No. specialities	104,784	2.97	0.21	1.00	3.00	3.00	6.00
No. therapy types	108,397	12.07	6.61	1.00	7.00	15.00	63.00
No. modality types	102,667	2.24	0.81	1.00	2.00	3.00	6.00
Title=Counsellor	111,715	0.24	0.42	0	0	0	1
Title=Other	111,715	0.05	0.21	0	0	0	1
Title=Psychologist	111,715	0.20	0.40	0	0	0	1
Title=Psychotherapist	111,715	0.25	0.44	0	0	1	1
Title=Social worker	111,715	0.26	0.44	0	0	1	1
FSA-level variables							
Population	909	26,611.76	17,568.49	0	14,545	34,720	111,372
Household size	905	2.50	0.40	1.40	2.20	2.70	4.40
Age	905	41.13	3.76	28.80	38.80	43.40	57.50
After tax income	900	83,373.85	27,914.79	36,933.00	65,918.25	94,503.25	364,719.00
Retail share	904	0.11	0.02	0.00	0.10	0.12	0.34
Health care share	904	0.06	0.01	0.00	0.05	0.07	0.15
Participation rate	904	0.01	0.001	0.003	0.01	0.01	0.01
Density (pop/km2)	905	1,768.26	2,812.21	0.15	64.84	2,390.99	29,873.03
Apartment share of housing	905	0.28	0.23	0.00	0.10	0.41	0.98
Atlantic provinces	909	0.09	0.29	0	0	0	1
British Columbia	909	0.19	0.39	0	0	0	1
Ontario	909	0.50	0.50	0	0	1	1
Praire provinces	909	0.23	0.42	0	0	0	1

Note: I describe variables here whose meanings are not evident from their names. Exit is leaving the directory by the next month; sliding scale is a dummy for whether income-based discounts are offered; the average number of competitors (avg. no. comp) is constructed as described in Section 3; FewerThan19 and FewerThan9 are the treatment and treatment intensity variables used in the regressions and describe whether the average number of competitors pre-supply-shock are below 19 and 9, respectively; ins. accepted is whether insurance is accepted by that therapist in that month; no. specialities are the number of mental health issues treated by that therapist; no. therapy types are the number of therapy types offered, e.g. cognitive behavioural, hypnotherapy, etc.; no. modality types are what types of patients are treated e.g. children, men, women, couples, etc.; COVID-19 announcement length is how long in characters a therapist's emergency announcement is; days since last update is how many days since the therapist updated their profile page.

B Additional analysis results

B.1 Share of rural therapists

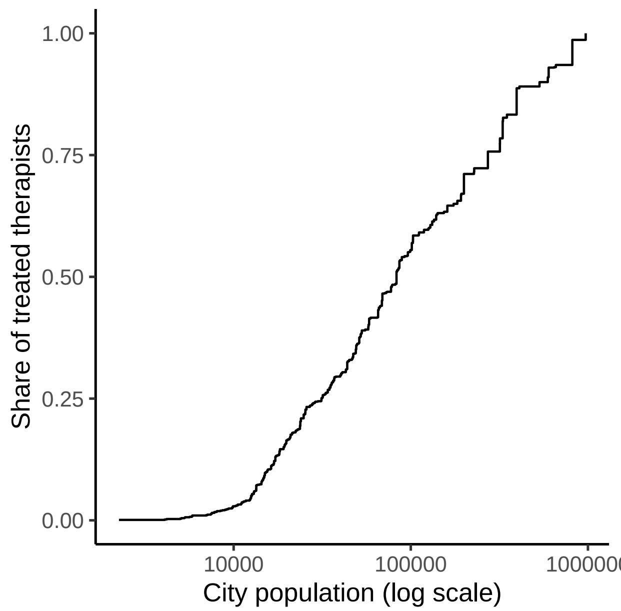


Figure B.1: Cumulative share of treated therapists, by city population
Note: Drawing a vertical line from any population on the x axis, the intersection with the curve indicates the share of treated therapists (out of the 1136 total treated therapists) who live in a city with that population or less.

B.2 Baseline robustness checks

Table B.1: Estimated effect of online competition, therapists with 15-25 competitors in May 2020

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	-0.0005	-0.009	-0.031^{**}	-0.003
	(0.006)	(0.007)	(0.014)	(0.028)
Therapist FE	✓	✓	✓	✓
Region×Month FE	✓	✓	✓	✓
Observations	10,053	9,364	9,337	11,076
R^2	0.350	0.982	0.977	0.842

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses only therapists with between 15 and 25 competitors. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

Table B.2: Estimated effect of online competition, therapists with fewer than 25 competitors in May 2020

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	0.004	-0.011	-0.062^{***}	0.009
	(0.005)	(0.008)	(0.015)	(0.025)
Therapist FE	✓	✓	✓	✓
Region×Month FE	✓	✓	✓	✓
Observations	14,024	12,771	11,027	15,057
R^2	0.195	0.967	0.943	0.749

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. Only matched control therapists with 25 or fewer competitors are included as part of the control group. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

Table B.3: Estimated effect of online competition, therapists in medium-sized cities

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	0.002	0.001	-0.028**	-0.012
	(0.005)	(0.006)	(0.012)	(0.020)
Therapist FE	✓	✓	✓	✓
Region×Month FE	✓	✓	✓	✓
Observations	11,451	10,747	9,511	12,471
R^2	0.191	0.959	0.954	0.735

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses only therapists based in cities with between 30 000 and 250 000 residents. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

Table B.4: Estimated effect of online competition, with city-by-month fixed effects

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t$	0.003	-0.005	-0.023**	0.013
	(0.004)	(0.006)	(0.010)	(0.020)
Therapist FE	✓	✓	✓	✓
City×Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.299	0.971	0.958	0.776

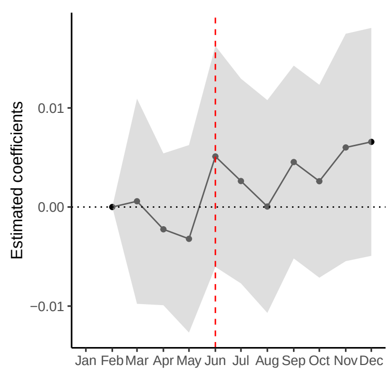
Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses the entire matched sample, but includes fixed effects at the city-by-month level. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

B.3 Parallel trends and timing tests

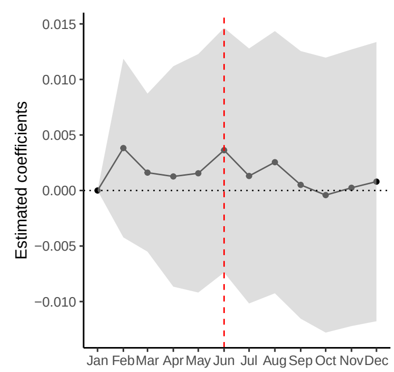
I run the following specifications to recover coefficients for the timing tests:

$$y_{imt} = \sum_{\tau} \beta_\tau \cdot \text{FewerThan19}_i \times \text{D}_\tau + \alpha_i + \alpha_{rt} + \epsilon_{imt}.$$

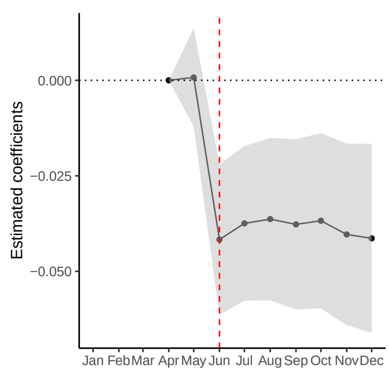
where τ indexes the different dates in the sample, and D_τ equals one for observations where $t = \tau$. As before, α_i is a therapist-level fixed effect and α_{rt} is a region-month-level fixed effect. I plot the β_τ coefficients with their associated standard errors, clustering at the FSA level, in Figure B.2.



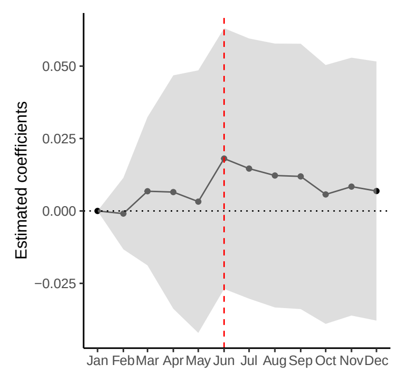
(a) Exit parallel trends



(b) Price parallel trends



(c) Sliding scale parallel trends



(d) Online parallel trends

Figure B.2: **Baseline regression timing tests**
Note: This graph presents parallel trends tests for the baseline difference-in-differences regression. Exit data starts in February since the first observed month is January; sliding scale data starts in April since sliding scale information was not collected in prior months. The vertical dashed line represents the month the supply shock occurred. Error bars represent 95% confidence intervals, standard errors are clustered at the FSA level.

B.4 Competition measure robustness check

Table B.5: Estimated effect of online competition, weighted

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding scale	Online
	(1)	(2)	(3)	(4)
$\text{WeightedFewerThan19}_i \times \text{Post}_t$	0.003	-0.002	-0.042***	0.013
	(0.003)	(0.004)	(0.010)	(0.014)
Therapist FE	✓	✓	✓	✓
Region × Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.172	0.965	0.945	0.729

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable equals one if a therapist had fewer than 19 competitors on average in the FSAs they appeared as a result for from January-May 2020, with weights in the average corresponding to FSA populations, interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

B.5 Continuous treatments robustness check

Table B.6: First continuous treatment alternative

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding scale	Online
	(1)	(2)	(3)	(4)
$\text{ContTreat1}_i \times \text{Post}_t$	0.006	0.004	-0.049***	-0.007
	(0.004)	(0.005)	(0.012)	(0.018)
Therapist FE	✓	✓	✓	✓
Region × Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.173	0.965	0.945	0.729

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable for a therapist is the average across FSAs they appeared as a search result for from January-May 2020 of an indicator that equals one if the FSA had fewer than 19 competitors. Weights in the average correspond to FSA population. Treatment is interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

Table B.7: Second continuous treatment alternative

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding scale	Online
	(1)	(2)	(3)	(4)
$\text{ContTreat2}_i \times \text{Post}_t$	0.001**	0.0001	-0.007***	-0.002
	(0.0004)	(0.0004)	(0.001)	(0.001)
Therapist FE	✓	✓	✓	✓
Region × Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.173	0.965	0.946	0.729

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable for a therapist is the average across FSAs they appeared as a search result for from January-May 2020 of 20 minus the number of results in each FSA. Weights in the average correspond to FSA population. Treatment is interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. **p<0.1,* ***p<0.05,* ****p<0.01.*

B.6 Sample selection: drop therapists in more than 8 FSAs

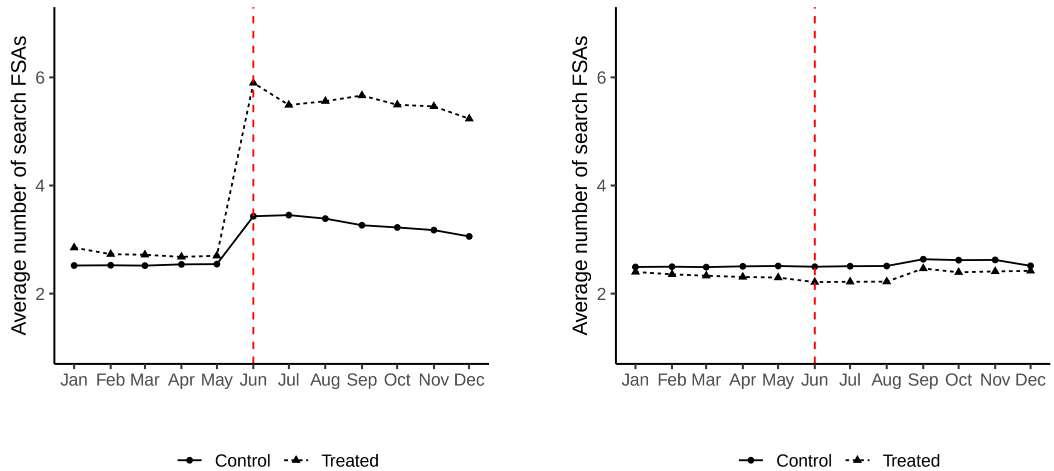


Figure B.3: Average number of search FSAs by treatment

Note: The left graph presents the average number of search FSAs a therapist appears in by treatment group for the whole sample, and the right graph presents the same numbers but only for therapists who appear in at most 8 search FSAs in every month of the data.

Table B.8: Estimated effect of online competition, removing therapists who are added to new markets

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding scale	Online
	(1)	(2)	(3)	(4)
FewerThan19$_i$ × Post$_t$	0.004	0.002	-0.031***	0.007
	(0.003)	(0.004)	(0.010)	(0.015)
Therapist FE	✓	✓	✓	✓
Region × Month FE	✓	✓	✓	✓
Observations	20,702	19,228	17,154	22,531
R^2	0.175	0.970	0.952	0.737

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. The matched sample is trimmed to only include therapists who appear in at most 8 search FSAs in any month of the sample in which they appear. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. $*p<0.1$, $**p<0.05$, $***p<0.01$.

B.7 Intraprovincial movement

I identify which FSAs are likely destinations for intraprovincial movement, and check whether the difference between treated and untreated therapist behaviour is driven by treated therapists in these FSAs. Letting Dest_j be a new dummy variable that equals one if FSA j is a destination for intraprovincial movement, I augment the baseline regression as follows:

$$\begin{aligned} y_{ijt} = \beta_1 \text{FewerThan19}_i \times \text{Post}_t \times \text{Dest}_j + \beta_2 \text{FewerThan19}_i \times \text{Post}_t + \\ \beta_3 \text{Dest}_j \times \text{Post}_t + \alpha_i + \alpha_t + \epsilon_{ijt}. \end{aligned} \tag{B.1}$$

Note that I do not include the interaction term $\text{FewerThan19}_i \times \text{Dest}_j$ because there is essentially no movement of therapists in the data, so the term is absorbed by the therapist fixed effect α_i. If I fail to reject that $\beta_1 = 0$, then I conclude that the treatment effect is not driven by the decisions of therapists in FSAs that are targets for patients' intraprovincial movement.

I focus on FSAs in cottaging or vacation areas as being likely destinations for intraprovincial movement. Since the end of May and beginning of June is the traditional beginning of the summer vacation season in Canada and since policymakers were concerned about a potential flood of individuals heading towards cottaging areas, this type of migration presents the most likely source of confounding variation given the timing of the platform's policy change in June. Other large movements of people—for instance, students leaving universities in March when classes went online or in April when exams end—do not coincidence temporally with the platform's policy change.

I code FSAs using information from the website https://www.cottagesincanada.com/. The website allows individuals to search for cottages for rent in Canada by region, with a region appearing on the website if there was ever a cottage for rent available in that region. I gather 686 region names across all 10 provinces, and drop the 47 regions that are not associated with a unique FSA—from visual inspection, these tend to be regions containing larger cities. The remaining region names yield 192 unique FSAs, 111 of which appear in the therapist dataset, for which I code $\text{Dest}_j = 1$.

I validate the data by plotting the distribution of the share of homes occupied by their usual owner by Dest_j, and by plotting the distribution of the share of the housing stock that is comprised of apartments by Dest_j, both in Figure B.4. Dwellings in cottaging FSAs are substantially less likely to be occupied by their usual owner and apartment buildings are a much smaller share of the housing stock for cottaging FSAs, which accords with intuition that these areas are filled with detached and semi-detached second homes.

Results from estimating Equation B.1 are reported in Table B.9, and show that there is no differential effect of being in a "cottage-country" FSA on therapists' decisions. Changes in competition, and not differential demand shifts due to intra-provincial movement, are what drives the treatment effects.

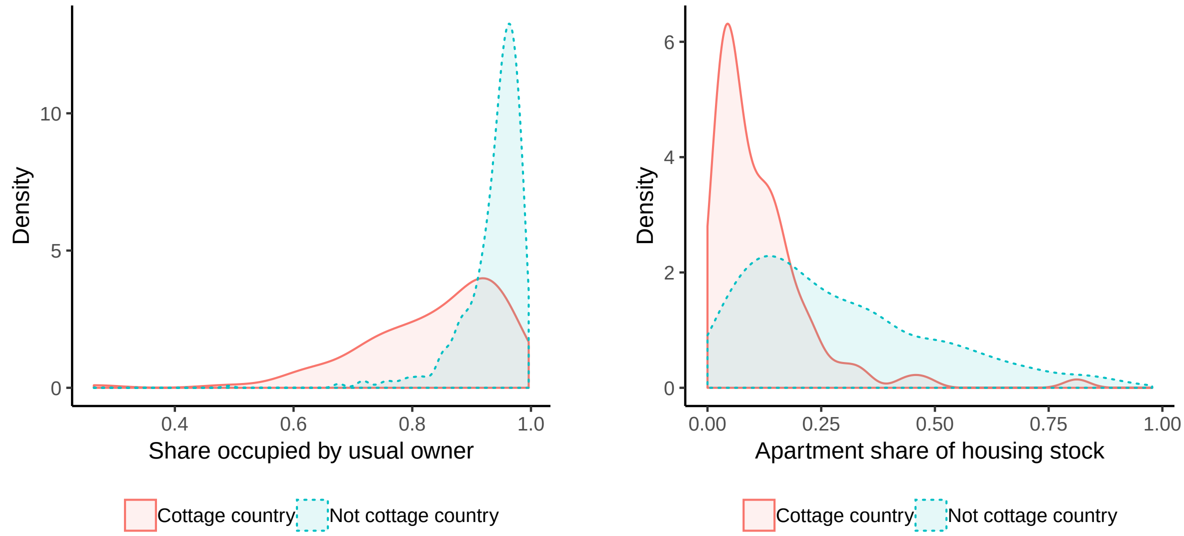


Figure B.4: Distribution of dwelling characteristics in FSAs *Note: These figures validate the cottage country coding by showing that dwellings in cottage country FSAs are much less likely to be occupied by their usual owner, and less likely to be apartments.*

Table B.9: Heterogeneity by FSA type

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t \times \text{Dest}_j$	-0.005	0.015	0.027	-0.014
	(0.010)	(0.017)	(0.028)	(0.035)
$\text{FewerThan19}_i \times \text{Post}_t$	0.005	-0.002	-0.043^{***}	0.010
	(0.003)	(0.004)	(0.010)	(0.015)
$\text{Post}_t \times \text{Dest}_j$	-0.001	-0.005	-0.018	0.003
	(0.006)	(0.011)	(0.012)	(0.027)
Therapist FE	✓	✓	✓	✓
Region × Month FE	✓	✓	✓	✓
Observations	23,434	21,837	19,465	25,511
R^2	0.173	0.965	0.945	0.729

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later. This specification uses the full matched sample. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

B.8 Pricing of new entrants

Table B.10: Difference in pricing for incumbents (organic) vs new entrants (padded)

Variable	Organic	Padded	Diff. of means p
Min. Cost ($/hr)	125.09	120.69	0
	(0.64)	(0.36)	
Sliding scale	0.47	0.52	0
	(0.01)	(0.005)	

Note: The table presents averages and standard deviations (in brackets) for prices and the sliding scale indicator for all therapists appearing in search FSAs that received new telemedicine entrants in June 2020 (1030 search FSAs total, 3686 therapists total.) The averages and sample standard deviations are split by whether a therapist is an organic result (incumbent) in an FSA or a padded search result (new telemedicine entrant) in an FSA. p values for the difference of means tests across each group are presented in the final column.

B.9 Therapist characteristics by title

Table B.11: Difference in therapist characteristics by title

Title	No.	Sliding scale	Ins. Accepted	Ph.D. share	Min. Cost ($/hr)
Psychologist	429	0.39	0.59	0.33	173
Counsellor	617	0.51	0.52	0.05	106
Social worker	684	0.48	0.56	0.02	119
Psychotherapist	413	0.46	0.45	0.04	115
Other	125	0.47	0.38	0.23	107
All	2,268	0.47	0.52	0.10	124

Note: The sample is the set of treated and matched control therapists in May 2020. The "other" category includes therapists who do not have a title on their profile page. The Ph.D. share includes Psy.D. recipients and Ph.D.s in progress.

Table B.12: Heterogeneity by therapist price

	Dependent variable:			
	Exit	log(Min. Cost)	Sliding Scale	Online
	(1)	(2)	(3)	(4)
$\text{FewerThan19}_i \times \text{Post}_t \times \text{LowPrice}_i$	-0.002	0.015	0.002	0.001
	(0.008)	(0.016)	(0.020)	(0.035)
$\text{FewerThan19}_i \times \text{Post}_t \times \text{MidPrice}_i$	0.003	-0.009	-0.040***	0.031
	(0.005)	(0.006)	(0.015)	(0.023)
$\text{FewerThan19}_i \times \text{Post}_t \times \text{HighPrice}_i$	0.007	0.001	-0.050***	0.006
	(0.004)	(0.004)	(0.014)	(0.025)
Therapist FE	✓	✓	✓	✓
Offerings×Region×Month FE	✓	✓	✓	✓
Observations	20,081	21,679	16,664	21,865
R^2	0.173	0.965	0.948	0.717

Note: Dependent variables are whether a therapist exits the platform, their log posted minimum cost ($/hr), whether they offer prices on a sliding scale, and whether they offer online care or not. The treatment variable is whether a therapist had 19 or fewer competitors from January-May 2020, interacted with an indicator for whether the month is June 2020 or later, and further interacted with whether a therapist is low (less than $100 per hour), middle ($100 to $130 per hour) or high (greater than $130 per hour) priced, where cutoffs correspond to the 33% and 66% quantiles. This specification uses the full matched sample, minus therapists with missing price information. Standard errors are clustered at the FSA level to allow within-FSA correlation across therapists and over time. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

C Model

In this section, I consider a simple, partial equilibrium model of a dynamic, capacity constrained therapist. The model is partial equilibrium in the sense that I only model a single therapist's decision problem, and model competition as a comparative static on a parameter.

C.1 Therapist's decision problem

There are two types of patients, high value and low value, who earn the therapist p_h and p_ℓ per period respectively, with $p_h > p_\ell > 0$. A fraction $\rho \in (0, 1)$ of patients in the population are high value patients. Each period, a capacity-constrained therapist may either draw a patient from the population with probability $\eta \in (0, 1)$ if they currently have a slot available, or may exit the search directory permanently.[20] A therapist who remains on the directory pays fixed cost $f > 0$ per period.

Assume that the therapist is capacity constrained. Once a therapist has filled their available slot with a type j patient, the slot remains filled until the match ends exogenously. There is a $\delta \in (0, 1)$ probability in each period that the match continues, and a $(1 - \delta)$ probability that the match ends.

The therapist's objective is to maximize their profit. I assume prices are fixed, so a therapist chooses between (1) serving only high-value patients at a posted price of p_h, (2) serving all patient types, using a discount to serve ℓ type patients at their WTP of p_ℓ, and (3) exiting the platform.

Taken together, a therapist's problem can be described by the following three linked value functions:

$$\begin{aligned} V(\emptyset) &= \max\Big\{\eta\Big((1-\rho)(p_\ell + \beta V(p_\ell)) + \rho(p_h + \beta V(p_h))\Big) + (1-\eta)\beta V(\emptyset) - f, \\ &\qquad \eta\Big(\rho(p_h + \beta V(p_h)) + (1-\rho)\beta V(\emptyset)\Big) + (1-\eta)\beta V(\emptyset) - f, \quad 0\Big\} \\ V(p_\ell) &= p_\ell - f + \beta\left(\delta V(p_\ell) + (1-\delta)V(\emptyset)\right) \\ V(p_h) &= p_h - f + \beta\left(\delta V(p_h) + (1-\delta)V(\emptyset)\right), \end{aligned} \tag{C.1}$$

where $V(\emptyset)$ is the value of having an empty slot, and is the maximum of serving all patient types (first argument) only serving high value patients (second argument), or exiting (third argument.) $V(p_j)$ is the continuation value of having a type j patient and is equal to the flow payoff, plus the discounted weighted average of the continuation value of the relationship and the value of having an empty slot.

It will either be optimal to only serve high value types, serve all types, or exit, depending on parameter values. I first establish a restriction on parameters under which only high types are served:

Proposition 1 *Assuming exit is not optimal, a therapist will serve only high-WTP patient types under the*

[20] Ching *et al.* (2015) also model capacity constraints in healthcare in the context of nursing homes, however their focus is on rationing and quality.

following parameter restriction:

$$\eta\beta\rho(p_h - p_\ell) > (1 - \beta\delta)p_\ell \tag{C.2}$$

Intuitively, a therapist may choose not to serve lower-value patients—and thereby save on screening costs by not offering an income discount—if the option value of waiting for a higher-value patient exceeds the match value with a lower-value patient. A higher likelihood ρ of drawing a high value patient makes the inequality easier to satisfy, as does greater patience β and a lower break-up rate $1 - \delta$.

C.2 Competition shock comparative static

I assume that increased telemedicine competition in the model reduces p_ℓ, the price that can be charged to the lower-value patients. I make this choice based on results in the literature that telemedicine providers tend to serve lower value patients (see Section 6 for evidence) as well as findings in Table B.10, Appendix B.8 that new telemedicine entrants charge lower hourly prices and offer more income discounts compared to incumbents.

The following lemma rationalizes the finding that telemedicine competition reduces the propensity to offer sliding scale discounts:

Lemma 2 *As p_ℓ shrinks, the relative attractiveness of serving only high types increases, and the relative attractiveness of exit weakly increases.*

The first part of Lemma 2 follows directly from Proposition 1. The second part is intuitive, as a therapist choosing between serving high types and exit is unaffected by p_ℓ, while a therapist choosing between serving all types and exit now earns less from the former option.

C.3 Competition shock along the quality spectrum

Assume that a high-quality therapist tends to attract high-value patients, i.e. has a high ρ. Notice that in the left hand side of Equation (**??**), the effect of a reduction in p_ℓ is larger the higher is ρ. That is, the higher is ρ, the steeper the increase in the attractiveness of serving high types relative to only low types. For high ρ therapists, reductions in p_ℓ make serving high types only especially attractive. Intuitively, a therapist gives up the opportunity to serve an h type by serving an ℓ type. If $p_h - p_\ell$ increases due to telemedicine competition, then for therapists who have a better chance of drawing an h type it is especially costly, and so more high ρ therapists stop serving ℓ types.

For therapists who serve both high and low value patients, the reduction in p_ℓ especially affects therapists who predominantly draw ℓ type patients—i.e., those with low ρ. For therapists who serve only h

type patients, the change in p_ℓ does not affect their incentives to exit, while for low ρ therapists the drop in p_ℓ does drive exit.

C.4 Demand shock comparative statics

Would a differential positive demand shock for treated therapists, exactly concurrent with the supply shock, be consistent with the empirical patterns we see in Table 2 and 3? I consider the effect of an increase in η, which reflects how easy it is for a therapist to find a new patient of any type. If COVID-19 related mental health shocks generate relatively more demand for treated therapists, it would be captured by a higher η for this group.

From Equation C.2, it is clear that an increase in η will increase the attractiveness of serving only high types. Intuitively, in times of high demand, therapists can be more picky since they will be drawing new patients often, while when demand is sparse they prefer to "take what they can get." However, an increase in η makes exit less attractive, for straightforward reasons. It is thus exit that differentiates between the two shocks, and Table 3 shows that therapists tend to exit the directory after the shock, counter to what a contemporaneous demand shock would imply.

C.5 Model proofs

Proof of Proposition 1: I solve analytically for $V(\emptyset)$ from Equation (C.1) under the assumption that the first term in the maximand is greater, and for $V(\emptyset)$ under the assumption that the second term in the maximand is greater. The inequality results when $V(\emptyset)$ under the first assumption is strictly greater than $V(\emptyset)$ under the second assumption. ■