The Rise of Urgent Care Centers: Implications for Competition and Access to Health Care

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Abstract

The rise of urgent care centers (UCCs) in the US health-care industry over the last thirty years has generated questions on how these establishments integrate into the broader health-care landscape. In this paper we study the implications of UCCs' location decisions for competition and access in health care markets. Using detailed data on a comprehensive set of UCCs' locations across the US, we first document the expansion of this sector and correlates of location decisions. We then estimate a model of endogenous market structure in which UCCs and hospitals make joint entry decisions, and excluded variation in hospital Certificate of Need (CON) regulation identifies the competitive effect of hospitals on UCC profits. We have three main findings. First, while UCCs enjoy some degree of market power, hospital presence negatively impacts UCCs' profitability, thus deterring entry. Second, UCCs are more likely to enter traditionally underserved markets. Third, counterfactually raising the cost of entry for UCCs by subjecting them to CON laws decreases the number of UCCs by 13 to 26 percent. These results suggest a role for UCCs in expanding access to health-care services, which entry regulation could meaningfully limit.

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1 Introduction

The last twenty years has seen dramatic changes in where Americans go to receive medical care. Before 2000, the vast majority of Americans had to visit their local doctor's office or a hospital for treatment. More recently, however, there has been a large proliferation in the number and types of establishments offering medical services for non-life-threatening conditions. In particular, the United States health-care sector has seen an important expansion of urgent care centers (UCCs), and the number of these establishments has more than doubled from 2008 to 2018. UCCs are freestanding ambulatory care centers, typically open on nights and weekends, where patients can receive treatment for ailments such as minor injuries or the common cold.

This proliferation raises many questions about how UCCs interact with the rest of the health-care system. The existing literature predominantly focuses on the impact of UCCs on health-care costs (see e.g., Currie, Karpova, and Zeltzer, 2021), taking as given UCC location decisions. In this paper, we focus on the complementary question of where UCCs locate and what drives that choice. This is an important question for two main reasons. First, location decisions are informative about the extent of competition both among UCCs and between UCCs and other health-care establishments. For example, if UCCs have a high degree of market power, this may have detrimental consequences for overall health-care costs. Second, UCC location decisions may have first-order consequences for access to health care. For example, if UCC entry decisions are influenced by the presence of hospitals, this could promote access to health care in areas traditionally underserved by other establishments.

To study UCC location decisions, we identify the geographic locations of UCC establishments from the Your Economy Time Series (YTS) database, which contains geo-coded locations of all business establishments in the United States from 1997 to 2019, including years of operation, company name, employment, NAICS codes, SIC codes, location, and parent organization. These data allows us to document several interesting patterns. First, we observe tremendous growth in UCCs since 2000, in line with that reported by the Urgent Care Association, a trade association for UCCs. Second, we show that this expansion is not homogeneous across the country and across markets. While they tend to locate in higher income, urban areas, UCC presence is also positively correlated with the percentage of residents who are uninsured or Hispanic.

We use these descriptive facts as motivation for a model of UCC entry into geographic markets, in the spirit of Bresnahan and Reiss (1991). Importantly, we jointly model hospital

¹See e.g., https://www.ucaoa.org/About-UCA/Industry-News/ArtMID/10309/ArticleID/877/Booming-Urgent-Care-Industry-Filling-the-Gaps-in-Patient-Care.

entry alongside UCC entry to account for competition between UCCs and hospitals. Thus, our model follows Mazzeo (2002) and Schaumans and Verboven (2008) in accommodating two types of firms. In the model, UCCs and hospitals make decisions to enter markets, defined as Zip Code Tabulation Areas (ZCTAs). These decisions depend on both observable and unobservable determinants of profitability. We allow for the unobservable determinants of profitability to be correlated across UCCs and hospitals in a given market. We further assume that, while hospital entry decisions are not directly affected by UCC entry decisions, UCC market-level profits can depend on hospital entry. As hospital entry is endogenous, we identify the competitive effect of hospitals on UCCs by leveraging state-level variation in Certificate of Need (CON) laws. These laws affect the entry decisions of hospitals but are excluded from UCCs' payoffs. We estimate the model as a bivariate probit using maximum likelihood.

Our estimates show that hospitals have a pronounced negative effect on the profitability of UCCs, and that accounting for hospital entry is essential for this result. Consistent with our descriptive evidence, our model estimates imply a positive relationship between UCC entry and both market level median income and the uninsurance rate. Following Bresnahan and Reiss (1991), we compute entry thresholds, which indicate the requisite population to sustain a given number of firms in a market. We find a minimum population threshold for UCC monopoly markets of around 37,000 people, and up to 71,000 people for markets with at least four UCCs. Bresnahan and Reiss (1991) show that the rate at which these thresholds increase in the number of firms is informative about the nature of competition. We find that UCCs maintain market power even with four establishments in a market.

The fact that UCCs have an incentive to locate in markets without hospitals suggests that UCCs expand the provision of medical services to new markets. To better understand who is impacted by this entry, we re-estimate our model on separate subsamples of the data. In doing so, we aim to capture heterogeneity in the determinants of entry across markets with different demographics. We focus on traditionally underserved markets, defined as those with lower incomes, higher rates of uninsured individuals, and higher social vulnerability. We find that entry thresholds are lower in these markets. Thus the perception that UCCs are avoiding these areas (Solomon, Popkin, Chen, Uttley, and Baruch, 2020), thereby contributing to the lack of access to health care, is not consistent with our results.

Beyond access, another important policy debate centers around the extent to which regulatory oversight of UCCs should be expanded. In most states, UCCs are considered physician's offices, which exempts UCCs from much of the regulation imposed on hospitals, including Certificate of Need (CON) laws.² These laws require hospitals to receive state

 $^{^2}$ See e.g., https://www.jucm.com/states-grapple-with-their-own-regulatory-approach-to-urgent-care/ and McCluskey (2020).

approval to enter a market, and compliance is associated with high fixed costs. As applying CON laws to UCCs has been one prominent proposal (Cavanaugh, Brothers, Griffin, Hoover, LoPresti, and Wrench, 2020), we further use our model to evaluate the impact of this form of entry regulation to UCCs. Specifically, we simulate counterfactual UCC entry decisions when subject to CON laws by extrapolating our estimates of the impact of CON laws on hospitals' fixed costs to UCCs. We find that such regulation would lead to sizable decreases in UCC entry: depending on the intensity of CON regulation, the number of UCCs decreases by 13 to 26 percent nationally. This is a sizable effect, corresponding to eliminating more than one year of UCC growth. Thus, any potential benefit of extending CON laws to UCCs needs to be weighed against these effects on entry.

This paper is part of a recent literature that explores the expansion of UCCs in the US. Most of this literature studies demand-side questions related to the impact of UCCs on health-care use and costs (Weinick, Burns, and Mehrotra, 2010; Uscher-Pines, Pines, Kellermann, Gillen, and Mehrotra, 2013). Current evidence is mixed: some estimate a negative relationship between UCC availability and emergency room use (Allen, Cummings, and Hockenberry, 2020) while others estimate null or positive effects (Currie et al., 2021). Other papers document descriptive evidence of UCCs' locations (Le and Hsia, 2016; Corwin, Parker, and Brown, 2016). Complementary to these studies, which take market structure as given, we examine the determinants of market structure in the UCC industry. In particular, we highlight the competition with hospitals and the demographic patterns of UCC entry.

We also contribute to the broader literature on entry in US health-care markets. Work in this area investigates the determinants of entry of doctors' offices and dentists (Bresnahan and Reiss, 1991), hospitals (Abraham, Gaynor, and Vogt, 2007), outpatient substance abuse treatment facilities (Cohen, Freeborn, and McManus, 2013), retail clinics (Hollingsworth, 2014), and hospices (Chung and Sorensen, 2018). Using a static entry framework, papers in this area make inference on the nature of competition, and typically consider types of establishments in isolation. As UCC entry may be affected by hospital entry in a market, we show the importance of accounting for the interdependence of entry decisions between different types of health-care establishments.

Finally, our paper is related to a literature that studies the effects of CON laws. Most work in this area concentrates on the effects on hospital entry (e.g., Cutler, Huckman, and Kolstad, 2010) and its downstream effects on health outcomes (e.g., Bailey, 2018; Chiu, 2021). Exceptions include work on the effects of CON laws in the home health care industry (Polsky, David, Yang, Kinosian, and Werner, 2014) and hospice industry (Chung and Sorensen, 2018). We contribute to this literature by exploring potential effects of CON law

³A related literature studies similar questions for retail clinics (clinics typically located in grocery stores or "big box" stores like Target and Walmart); see, for example, Alexander, Currie, and Schnell (2019); Ashwood, Gaynor, Setodji, Reid, Weber, and Mehrotra (2016).

expansion to UCCs.

The paper proceeds as follows. Section 2 introduces our data and provides background and descriptives on the UCC industry. Section 3 describes our model of endogenous market structure and discusses identification and estimation of the model. Section 4 presents our results. Section 5 provides counterfactual estimates of UCC entry under CON regulation. Section 6 concludes.

2 Industry Background and Data

In this section we provide background on urgent care centers, documenting their expansion. We also provide preliminary evidence on their interaction with hospitals.

2.1 Urgent Care Centers

Urgent care centers (UCCs) are health-care establishments that specialize in the treatment of minor, non-life-threatening health conditions such as respiratory infections, digestive issues, fevers, sprains, lacerations, fractures, back pain, headaches, dermatological conditions, urinary infections, and allergies (Urgent Care Association, 2019). UCCs provide walk-in, extended hour services like X-rays and laboratory testing, as well as diagnostic and screening services for more acute illnesses, but do not serve as a patient's primary care physician. Patients requiring more sophisticated services (e.g., surgery or CT scans) are sent to other medical establishments such as hospitals. UCCs typically employ family practice physicians, emergency medicine physicians, nurse practitioners, and radiology technicians for imaging services (Urgent Care Association, 2019).

Health-care establishments are subject to a variety of state and federal regulations that oversee the conditions under which they are allowed to operate, including licensing requirements and Certificate of Need (CON) laws. For UCCs, however, this type of oversight is still relatively limited. For example, most states treat UCCs under the same rules as physician's offices (or under a hospital's license if affiliated with a hospital). This implies that, beyond requiring physicians to be licensed in the state, the only form of state oversight concerns disciplining malpractice. This also implies that UCCs are often exempt from entry regulation like CON laws. While 35 states and the District of Columbia subjected hospitals to CON laws in 2011 (Bailey, 2018), these laws additionally applied to UCCs in only New York and North Carolina (Solomon et al., 2020).

2.2 Data

Our main data source for geo-coded locations of UCCs is the Your Time Series (YTS) database. This database contains information on the universe of business establishments in the United States from 1997 to 2019, including years of operation, company name, employment, NAICS codes, SIC codes, location, and parent organization. We impose several sample restrictions from the full YTS data to obtain our final sample. We start by selecting all establishments that are classified under SIC code 80 (health-care services) at any point during their years of operation.

To isolate UCCs in our data, we obtain the name of all urgent care operators with at least 15 locations⁵ across the country from the SolvHealth website (see Appendix Table 2 for the names of all operators in our dataset) and manually match the operator name in SolvHealth with the company name in YTS. We then drop operators that correspond to retail clinics, including Walmart, Target, and CVS Minute Clinic. Finally, we drop duplicate establishments in YTS as defined as establishments with the same operator that are within 2 meters of one another.

We aggregate this data to the market level, where a market is defined as a Zip Code Tabulation Area (ZCTA). We chose this level of aggregation because most patients who seek urgent care are unlikely to travel long distances, and indeed most UCC website queries are based on ZIP codes. We proceed by dropping markets with less than 1,000 and more than 65,000 residents and keeping only ZCTAs in the continental US. This helps ensure that there are no spillovers across markets, which can be problematic for cross-sectional entry models that rely on variation across markets for identification of profit parameters. With these restrictions, our final sample includes 5,601 UCCs in 2015, and we focus on this year when estimating our model. In the Appendix, we report how each sample restriction imposed changes our sample size (Appendix Table 1) and show that the results of our main specification are robust to alternative subsets of UCC operators, market definitions, and years.

We supplement our YTS data with several ZCTA-level characteristics. We use the Hospital Compare database maintained by the Centers for Medicare and Medicaid Services (CMS) to get the number of hospitals in each ZCTA. This dataset is a panel of all Medicare-certified hospitals from 2005 to 2019, containing information about hospital type,

⁴This database is supported by the University of Wisconsin System Institute for Business and Entrepreneurship. It is based on InfoGroup's RefUSA database that has been used in several other studies (e.g., McDevitt, 2014; Suárez Serrato and Zidar, 2016).

⁵We limit the list of operators as these need to be manually matched between the YTS and SolvHealth data. Our cutoff corresponds to the top 100 operators in the data.

 $^{^6}$ ZCTAs are "generalized aerial representations of ZIP codes" created by the Census Bureau, while ZIP codes are a "collection of mail delivery routes" managed by the United States Postal Service. There are roughly 32,000 ZCTAs and 42,000 ZIP codes.

an indicator of whether the hospital has an emergency room, location, and years of operation. We also get demographic data from 5-year American Community Survey (ACS) estimates from 2013 to 2017 hosted by IPUMS-NHGIS. These characteristics include: total population; median per capita income; percentage of Hispanics, non-Hispanic Blacks, non-Hispanic Whites, and other races; percentage of uninsured; educational attainment; and percentage of population age 65 or older. We use an annual hospital wage index from CMS as a shifter of fixed costs. This index is measured at the level of Core-Based Statistical Areas (CBSAs), which we map to ZCTAs. Finally, we obtain the county-level Social Vulnerability Index (SVI) from the Agency of Toxic Substances and Disease Registry and assign the same SVI to all ZCTAs within a county.

2.3 The Expansion of UCCs

The urgent care sector experienced dramatic growth during the last decade, surging from around 4,000 establishments in 2008 to 8,000 in 2018 (see Figure 1). In line with this growth in the number of UCC establishments, other work has shown that health-care utilization at UCCs also increased by 1,434 percent, thus representing 19 percent of claims lines in 2017 (FAIR Health, 2019). In contrast to the growth of urgent care centers, the number of hospitals has stagnated since 2012 at around 4,900 hospitals (see Figure 1). Overall, the data indicate a fast expansion of UCCs in both absolute terms, and in relative terms with respect to hospitals.

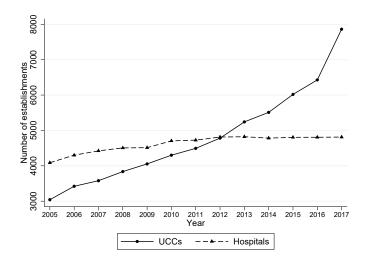
The expansion of UCCs is not homogeneous across the entire country. Figure 2 shows the number of UCCs per 10,000 residents in 2015 across different US states. There is wide variation in the number of UCCs per capita, with states in the Southwest having more than three times the number of UCCs per capita than states in the Northeast.

While suggesting geographic heterogeneity in entry patterns of UCCs, a more systematic analysis of the correlation between demographics and UCC entry requires looking at market level patterns. Table 1 presents summary statistics of market characteristics in the full sample, consisting of almost 22,000 ZCTAs, and separately by number of UCCs in a market. Unsurprisingly, more populous ZCTAs support more health-care establishments. ZCTAs with four or more UCCs have an average population of over 37,000 residents, while ZCTAs without UCCs tend to have less than 11,000 residents. The average per capita income is mildly increasing in the number of UCCs. While there is little variation in the percent Black in markets with and without UCCs, the percent Hispanic goes from 10 percent in ZCTAs without UCCs to 19 percent in markets with at least four UCCs. The table also

⁷This descriptive fact, obtained using our data, is consistent with reports from the Urgent Care Association of America (UCAOA).

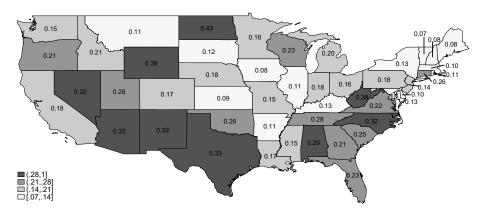
⁸See Appendix Table 3 for the distribution of UCCs by sample construction.

FIGURE 1: Urgent Care and Hospital Sector Growth



Note: Data for UCCs come from the Your Economy Time Series (YTS) database, which contains establishment level information on all businesses in the United States. Data for hospitals come from Hospital Compare, which contains all Medicare-certified hospitals.

FIGURE 2: Number of UCCs per 10,000 State Residents in 2015



Note: Data come from the Your Economy Time Series (YTS) database, which contains establishment level information on all businesses in the United States.

shows a positive correlation between the number of UCCs and the percentage with at least high school education, and a negative correlation with the percentage of individuals aged 65 or older. Finally, there is a positive correlation between the number of UCCs and the number of hospitals in a market.

Table 1: Market Characteristics by Number of UCCs

	Full sample		N	umber of UC	Cs	
		0	1	2	3	>=4
Population (1,000s)	13.5 (14.2)	10.8 (12.3)	26.4 (14.5)	30.5 (13.9)	33.8 (14.0)	37.2 (14.6)
Rural	0.44(0.50)	0.51(0.50)	0.10(0.3)	0.06 (0.24)	0.03(0.17)	0.02(0.13)
Per cap. income (\$10K)	3.10(1.34)	3.03(1.30)	3.44(1.53)	3.49(1.39)	3.64(1.65)	3.62(1.47)
Hispanic	0.11(0.16)	0.10(0.16)	0.15(0.17)	0.15(0.16)	0.18(0.18)	0.19(0.17)
Black	0.09(0.16)	0.09(0.16)	0.11(0.16)	0.12(0.14)	0.11(0.13)	0.12(0.11)
Other race	0.06(0.09)	0.06(0.10)	0.08(0.09)	0.08(0.07)	0.10(0.10)	0.09(0.08)
High school or more	0.46(0.07)	0.46(0.07)	0.47(0.07)	0.48(0.07)	0.48(0.07)	0.48(0.06)
Age 65 and over	0.17(0.06)	0.18(0.07)	0.16(0.06)	0.16 (0.06)	0.16 (0.06)	0.15(0.05)
Uninsured	0.09(0.06)	0.09(0.06)	0.09(0.06)	0.09(0.05)	0.09(0.06)	0.09(0.05)
CMS wage index	0.97(0.17)	0.97(0.17)	1.00(0.18)	0.99(0.16)	1.00(0.18)	0.99(0.17)
Any hospital	0.19(0.39)	$0.15 \ (0.36)$	$0.37 \ (0.48)$	$0.42\ (0.49)$	0.49 (0.50)	$0.46 \ (0.50)$
T	21,728	18,423	1,966	802	302	235

Note: Table presents means and, in parentheses, standard deviations of market characteristics in the full sample and in subsamples conditional on the number of UCCs, and total number of markets in the final row. Rural, Hispanic, Black, other race, high school or more, age 65 and over, and uninsured are proportions of total population. Any hospital is the proportion of hospitals in the sample.

These descriptive statistics raise important questions about UCC entry decisions. For one, the positive association at the market level between the presence of hospitals and UCCs suggests the possibility of strategic complementarities between these two types of establishments. Moreover, if UCCs tend to locate where hospitals are also present, underserved areas may be left without either type of establishment. Insofar as these correlations may be driven by unobservables, however, relying on the patterns in Table 1 alone to draw conclusions about determinants of UCC entry may be misleading.

3 An Empirical Model of UCC Entry

To study more systematically the determinants of entry behavior and evaluate the effects of counterfactual entry regulation, we develop a static entry model in the spirit of Bresnahan and Reiss (1991). In the model, market structure outcomes arise as an equilibrium. Following Mazzeo (2002) and Schaumans and Verboven (2008) we explicitly model the joint entry decisions of two types of firms: UCCs and hospitals. In this section, we first describe the model, then provide identification and estimation details, as the model can be estimated with our data on market level entry outcomes and covariates.

3.1 Model

In each market t, UCCs and hospitals decide whether to enter the market. For a set of independent markets t = 1, ..., T, we observe the number of UCCs n_t and the number of hospitals n_t^h . All firms of a given type (UCCs or hospitals) are assumed to be identical. Thus, each of the n_t UCCs in market t earns total profits according to:

$$\pi_t(n_t, n_t^h) = V(n_t, n_t^h, x_t, S_t) - F_t(w_t),$$

where the variable profits earned by each entrant in market t, are a function V of the number of UCCs, the number of hospitals, market characteristics affecting demand and variable cost x_t , the market size S_t . Furthermore, F_t represents the fixed cost of entry for a UCC in market t as a function of observable cost shifters w_t .

Each of the n_t^h hospitals in market t earns instead profits according to:

$$\pi_t^h(n_t^h) = V^h(n_t^h, x_t, S_t) - F_t^h(w_t, z_t),$$

where the function defining variable hospital profits is denoted V^h and hospital fixed entry costs are denoted F_t^h . Fixed costs are a function of w_t and additional shifters z_t that do not affect UCCs' fixed costs. Variable profits for hospitals are a function of the number of hospitals in a market and the same exogenous covariates affecting UCC profitability.

Thus we assume that, while hospitals can have a competitive effect on UCCs, UCCs entry decisions do not affects hospitals' presence in a market. Our assumption is supported by recent studies that find little evidence of a competitive effect of UCCs on the demand of certain hospital services (Currie et al., 2021). Moreover, the assumption is also consistent with Figure 1, which suggests that the number of hospitals is stable over time and not affected by the rise of UCCs. We further assume that a firm's type (i.e., UCC or hospital) is set exogenously; that payoff functions, exogenous variables and fixed costs are common knowledge; and that UCCs make entry decisions knowing the number of hospitals n_t^h . Under these assumptions, the game has a unique equilibrium prediction for (n_t, n_t^h) .

Following Bresnahan and Reiss (1991), we further parametrize payoffs to derive intuitive equilibrium conditions. We assume that UCCs' variable profit $V(\cdot)$ is separable in S_t :

$$V(n_t, n_t^h, x_t, S_t; \theta) = S_t v(n_t, n_t^h, x_t, \theta)$$

⁹This is in line with the entry literature that considers industries with large and small players, where the competitive effect of the small player on the larger firms is assumed to be zero (see e.g., Ackerberg and Gowrisankaran, 2006; Grieco, 2014).

¹⁰This can be seen as a timing assumption in a sequential game, or as the standard perfect foresight property of pure strategy Nash equilibrium in a complete information game.

where, if market size is measured relative to population size, $v(n_t, n_t^h, x_t, \theta)$ are the average variable profits earned by a UCC for each person in market t. We assume that the data are generated by a Nash equilibrium of this entry game. Thus, the n_t UCCs present in market t must earn positive profits taking as given the n_t^h hospitals in the market, while profits with an additional entrant would be negative, or $\pi(n_t, n_t^h) \geq 0 \geq \pi(n_t + 1, n_t^h)$. Given our parameterization of profits, the equilibrium condition requiring entrants to make positive profits can be rewritten as

$$S_t \ge \frac{F_t}{v(n_t, n_t^h, x_t, \theta)}.$$

Thus, for n_t UCCs to enter market t, the market size must exceed the ratio of fixed costs to the average variable profit per person.

To summarize how market size and entry patterns are linked, we consider the smallest market size accommodating $n_t = n$ UCCs. Formally we define a threshold τ_n as the minimum level of market size for which n entrants can be sustained on average across different markets:

$$\tau_n = \frac{1}{T} \sum_t \frac{F_t}{v(n, n_t^h, x_t, \theta)}.$$

These thresholds are useful to study the extent of competition among UCCs in a market. In particular, Bresnahan and Reiss (1991) show that the change in threshold ratios of the form $\frac{\tau_{n+1}}{\tau_n}$ as n increases is informative on how firms compete. For monopoly and perfect competition, threshold ratios are constant in n. Instead, imperfect competition is generally associated with declining ratios. We make the same assumptions on the function $V^h(\cdot)$, permitting us to derive separate population thresholds for hospital entry.

The model maintains a set of restrictive assumptions. In particular, it requires us to maintain that (i) markets are independent, (ii) entry is a static decision, and (iii) that payoffs are homogeneous within a market for each type of establishment. Market independence amounts to maintaining that chains of UCCs or hospitals do not take into account spillovers across markets in their decisions. While these have been found to be important in other industries, such as discount retail where the logistics of distribution naturally creates spillovers (e.g., Jia, 2008; Houde, Newberry, and Seim, 2021), we believe these factors to be less relevant for the industry we study. We also follow a large literature in modeling market structure outcomes, which unfold over time, as a static equilibrium (see, e.g., Berry and Reiss, 2007). Dynamic factors, which would require a more complex modeling approach, are not a primary object of interest in our study. Finally, we treat UCCs and hospitals as homogeneous. While UCCs tend to be similar in the services they provide, geographic

differentiation could be relevant. Ultimately, avoiding spillovers across market (which could arise when markets are defined too narrowly) and geographic differentiation within a market (which could arise when markets are too large) requires an appropriate market definition. After presenting our main results, we show that they are robust to different choices along this dimension.

3.2 Identification and Estimation

To bring this model to the data, we further parameterize the profit functions of UCCs and hospitals as:

$$\pi_t(n_t, n_t^h) = S_t(x_t \theta_x + n_t^h \delta + \theta_n) - w_t \gamma_w - \gamma_n + \varepsilon_t,$$

$$\pi_t^h(n_t^h) = S_t(x_t \theta_x^h + \theta_n^h) - w_t \gamma_w^h - z_t \gamma_z^h - \gamma_n^h + \varepsilon_t^h,$$

where x_t are market characteristics determining variable profit, and w_t is a measure of wages in the market. Following studies that use a similar model (e.g., Abraham et al., 2007), we use this variable as a shifter of fixed production costs. The parameters θ_n, γ_n are respectively variable profit and cost fixed effects that depend on the number of UCCs in a market. Similarly, for hospitals θ_n^h, γ_n^h are fixed effects that depend on n_t^h . We let market size S_t be proportional to market-level population. Variables in x_t are market demographics: per-capita income, percent of the population that is, respectively, Black, Hispanic, other race, age 65 and over, uninsured, and an indicator for rural markets. As only 1.58 percent of markets have more than one hospital, we convert n_t^h into an indicator for at least one hospital.

The econometric unobservables ε_t and ε_t^h capture deviations from average profit for UCCs and hospitals, respectively. An important feature of our estimation approach is to carefully address the interrelated nature of hospital and UCC location choices. In particular, because the number of hospitals in a market affects UCC profit, unobservable characteristics ε_t and ε_t^h may be correlated: ignoring this aspect could bias the estimate of δ . Thus, we assume that $(\varepsilon_t, \varepsilon_t^h)$ are jointly iid according to a bivariate standard Normal distribution with correlation ρ .

Allowing for correlation in unobservables, however, makes identification harder: positive correlation between n_t and n_t^h conditional on other observables could be due to a positive δ , or to a positive ρ . To identify the parameters of the model, we include a variable z_t which affects hospital profitability (and therefore the number of hospitals), but is excluded from the UCC profit function. In particular, we define $z_t = \text{CON}_t$, a measure of the intensity of state level Certificate of Need Laws (CON). Under these laws, state boards must approve the entry of new health-care establishments on the basis of whether they respond to the

economic needs of a locality. These laws have been shown to have an impact on both the entry of hospitals and the provision of new hospital services (e.g., Cutler et al., 2010). CON laws vary in scope across states in terms of what hospital services are subject to approval requirements, e.g., cardiac care, psychiatry, or equipment purchases such as MRIs. To capture this variation in regulatory environments across states, we adopt the measure of CON intensity in Bailey (2018), rescaled as the fraction of types of hospital expansions that are restricted by state laws in 2011. In order to satisfy our exclusion restriction, CON laws must not directly impact the entry decision of UCCs. According to Bailey (2018), 36 states had CON laws in 2011. For most of these states, CON laws do not apply to UCCs.

Overall, our assumptions give to our model the structure of a triangular system. Under our parametric assumptions, the model becomes a bivariate ordered probit which we estimate via maximum likelihood using the cross-section of UCCs and hospitals in 2015. Our choice of 2015 is a compromise between using a recent year of data so as to capture the rapid expansion of UCCs while maximizing the relevance of our measure of CON intensity for 2011. Given the time it takes for hospitals to be approved and built, we maintain that CON laws from 2011 are relevant for entry outcomes in 2015.

4 Results

Table 2 reports parameter estimates from two versions of our model: Column 1 reports estimates from a univariate ordered probit model of UCC entry that ignores the joint entry decisions of hospitals, while columns 3 and 5 report estimates for the bivariate ordered probit model in which entry of UCCs and hospitals are modeled jointly (hospital estimates in column 3 and UCC estimates in column 5).

Comparing columns 1 and 5 of Table 2 reveals the consequences of ignoring the endogeneity of hospital entry. Without accounting for endogenous hospital entry, we estimate a positive effect of hospital presence on UCC profitability in column 1, at odds with economic intuition which would suggest a competitive effect. In contrast, we estimate a negative coefficient on the number of hospitals in column 5. This is in line with hospitals having a competitive effect on UCCs by decreasing their expected profits from entry. Ignoring the

¹¹By including CON laws as a variable CON_t in hospitals' profit functions, we assume that CON laws affect the cost of entry, as opposed to specifying a maximum number of hospitals that can enter a market. See Schaumans and Verboven (2008) for a modeling approach that allows for restricted entry.

¹²The only possible exceptions are New York and North Carolina, which require a CON to operate some UCC establishments, such as those sufficiently large to qualify as diagnostic centers (Solomon et al., 2020). To address this concern, we run a robustness check in the appendix in which we drop New York and North Carolina and show the results are quantitatively similar to our main estimates.

¹³An alternative way to deal with endogeneity in probit models is the control function approach (Rivers and Vuong, 1988). However, this approach is problematic in our context, as the endogenous variable is discrete (see Wooldridge, 2015).

TABLE 2: UCCs Entry Model Estimates

		Univ	ariate			Bivariate		
				Hosp	pitals		UCCs	
		coef (1)	se (2)	coef (3)	se (4)	coef (5)	se (6)	sim (7)
Variable	Profit Parameters:							
δ	Presence of hospital	23.0	(2.2)	_	_	-29.6	(4.8)	-42.5
θ_x, θ_x^h	Rural	-32.4	(6.2)	4.2	(4.9)	-39.6	(8.2)	-59.6
	Income per capita	3.6	(1.1)	-7.0	(1.0)	2.5	(1.4)	11.4
	Hispanic	-55.7	(7.9)	-94.8	(7.0)	-99.2	(10.5)	-34.9
	Black	-53.2	(7.0)	-47.8	(6.0)	-88.3	(9.3)	-31.8
	Other race	-39.8	(12.3)	-46.3	(11.2)	-70.2	(16.3)	-14.6
	High school or more	109.7	(22.3)	-142.1	(20.0)	90.2	(29.6)	18.4
	Age 65 or more	105.7	(22.0)	186.1	(19.0)	186.6	(29.1)	35.3
	Uninsured	212.3	(26.7)	28.2	(23.6)	270.1	(35.2)	49.1
θ_n, θ_n^h	$ heta_1$	31.9	(12.0)	147.5	(10.5)	106.2	(16.4)	_
	$ heta_2$	22.7	(12.2)	_		98.1	(16.6)	_
	$ heta_3$	17.3	(12.5)	—	_	93.9	(17.0)	
	$ heta_4$	12.5	(12.9)	_	_	89.2	(17.6)	
Fixed Co	ost Parameters:							
γ_w, γ_w^h	CMS wage index	0.3	(0.1)	0.4	(0.1)	0.4	(0.1)	-9.0
γ_z	CON Laws	_	_	0.4	(0.0)	_		
γ_n, γ_n^h	γ_1	1.6	(0.1)	0.9	(0.1)	1.6	(0.1)	
	γ_2	2.1	(0.1)	_	_	2.2	(0.1)	_
	γ_3	2.6	(0.1)	_	_	2.6	(0.1)	_
	γ_4	2.9	(0.1)	_	_	3.0	(0.1)	_
ρ			_	_	_	0.4	(0.0)	_
\overline{T}		21.	,728	21,	728	21.	,728	

Note: Table reports coefficients and standard errors of the univariate ordered probit of UCC entry in columns 1 and 2, respectively. For the bivariate ordered probit, we report coefficients and standard errors for hospitals in columns 3 and 4, and for UCCs in columns 5 and 6. Column 7 reports the simulated percent change in the mean number of UCCs across markets due to a standard deviation increase in that covariate (or due to setting all hospital or rural indicators to 1).

endogeneity of the number of hospitals also results in underestimating variable profits. The estimates for θ_n (representing the additional profit of the *n*-th entrant) are significantly smaller under the univariate than the bivariate specification. Furthermore, we estimate that the correlation between unobservables is 0.4, pointing to a strong positive association between ε_t and ε_t^h . Column 3 of Table 2 provides estimates of the hospitals' profit function for entry in a ZCTAs. We find a strong negative effect of the CON law intensity on hospital entry, as CON laws increase fixed costs.

Because the magnitudes of ordered probit coefficients are not easily interpretable, we perform simulations to understand the economic significance of the bivariate ordered probit model's estimates. To interpret the effect of a single covariate on UCC entry, we compare simulated outcomes for the number of UCCs using the covariates in the data with simulated outcomes obtained from modifying that covariate. In particular, to gauge the effect of hospital presence on UCC entry, we simulate the effect on UCC entry when we impose that hospitals are present in all markets, while for the other variables we simulate the effect on UCC entry when we increase the covariate of interest by one standard deviation.¹⁴ Column 7 reports the percent change in the mean number of UCCs across markets from these simulations.

Our estimates imply that putting hospitals in all markets would decrease the average number of UCCs by 43 percent according to the bivariate model, suggesting an economically significant competitive effect of hospitals on UCCs. Other demographic variables also have a large economic effect on UCC entry. For instance, a one standard deviation increase in the percent uninsured in all markets increases the average number of UCCs by almost 50 percent, and a one standard deviation increase in income per capita increases the average number of UCCs by 11 percent. However, since several of these market-level variables are strongly correlated, the ceteris-paribus effects do not speak to the important question of whether UCCs expand access to health care into traditionally underserved markets. We return to these patterns below.

4.1 How Competitive are UCC Markets?

To study the nature of competition among UCCs, we compute from model estimates the entry thresholds for UCCs and hospitals. These correspond respectively to τ_n , the average minimal market size needed for n UCCs to enter, and analogous τ_1^h , the average minimal size needed for at least one hospital to enter. These thresholds (measured in 1,000s of people) are reported in Table 3. Focusing on the bivariate model (columns 3 and 5), the monopoly entry threshold for UCCs is 37,000 people, and 35,000 for a hospital monopoly. The number of additional individuals needed to support each additional UCC entrant is then decreasing

¹⁴For the rural indicator, we set the variable to one in all markets.

in the number of firms: to support two UCCs, 14,000 additional individuals are needed relative to the monopoly, and 12,000 additional individuals are needed to support three UCCs relative to the duopoly.

Table 3: Entry Thresholds and Ratios

	Univa	ariate		Biva	riate	
			Hosp	oitals	UC	Cs
	coef (1)	se (2)	coef (3)	se (4)	coef (5)	se (6)
Thresholds:						
$ au_1, au_1^h$	45.01	(0.03)	35.21	(1.00)	37.04	(0.97)
$ au_2$	64.68	(0.05)	_	_	50.78	(1.53)
$ au_3$	81.86	(0.07)	_	_	62.13	(2.12)
$ au_4$	96.88	(0.11)	_	_	71.51	(2.84)
Ratios:						
$ au_2/ au_1$	1.44	(0.02)	_	_	1.37	(0.02)
$ au_3/ au_2$	1.27	(0.03)	_	_	1.22	(0.02)
$ au_4/ au_3$	1.18	(0.04)	_	_	1.15	(0.02)
N	21,728		21,728		21,728	

Note: This table reports entry thresholds and entry ratios for UCCs from the univariate ordered probit in column (1) and the bivariate ordered probit in column (2). Column (3) presents the entry threshold for a monopoly hospital from the bivariate ordered probit. Entry thresholds are measured in 1,000s of people. Standard errors based on the delta method are reported in parenthesis.

The fact that entry thresholds are increasing at a decreasing rate with the number of firms suggests that additional entry makes the urgent care sector more competitive. This can be seen more directly from the entry ratios in the lower panel of the table. In column 5 we find that entry ratios are greater than one even for the fourth entrant, suggestive of imperfect competition and market power. Furthermore, these ratios are monotonically decreasing with the number of firms, indicating that competition intensifies and market power declines in markets with more entrants.

Compared to the entry thresholds in Abraham et al. (2007) for hospitals, we find a larger threshold for a monopoly hospital. This could be a result of our market definition. In Appendix Tables 6 and 7, we explore the robustness of our results to alternative market definitions. When defining markets similar to Abraham et al. (2007), we find comparable estimates of the hospital monopoly threshold. However, the thresholds for UCCs are qualitatively unchanged.

More broadly, our results are robust to other data and modeling choices as well. Appendix Tables 4 and 5 shows that the conclusions are similar using alternative sample construction measures. Appendix Tables 6 and 7 shows that the conclusions are similar using alternative market definitions. Appendix Tables 8 and 9 show similar results when

estimating the model based on years 2014 or 2016, and Appendix Tables 10 and 11 show robustness to alternative definitions of UCC state regulation.

4.2 UCCs and Access to Care

In the previous subsection, our results suggest that UCCs have some degree of market power in markets where they locate. However, the degree of competition in markets with UCCs is not the only concern to policymakers. Much of the recent policy debate has focused on whether UCCs choose to locate in areas that are traditionally well served by health-care establishments or instead broaden access by locating in markets that are underserved.

In line with existing definitions of underserved populations in health care¹⁵ we define underserved markets in our sample as those with lower incomes, higher rates of uninsured individuals, and larger percentages of underrepresented minorities. Our main estimates in Table 2 provide some evidence on the ceteris paribus effects of hospital presence and market demographics on profitability. In reality, market characteristics are often highly correlated so that underserved areas are characterized by a combination of demographic variables.

Thus, to evaluate whether UCCs expand access in underserved markets, we need to take into account this correlation in market-level demographics. To do this, we estimate our bivariate ordered probit on different subsamples, considering splits along dimensions of demographics that may correlate with lack of access. In particular, we consider the percentage uninsured, income, and Social Vulnerability Index (SVI), and split the sample into above median and below median along these dimensions. Across types of markets, we ask: what is the level of population needed to sustain a given number of UCCs? If this number is not consistently higher in underserved markets, we interpret this as evidence that UCCs display similar (or favorable) entry patterns in these markets, thus expanding access to underserved markets.

Table 4 presents UCC entry thresholds and ratios in these subsamples. ¹⁶ Our results are in general consistent with UCCs expanding access to care. We find that an urgent care monopoly in a market with a high percentage of uninsured requires nearly 8,000 fewer people than in a market with a low percentage of uninsured. Entry thresholds for the second, third, and fourth firms are all smaller in ZCTAs with higher percentages of uninsured. We obtain similar patterns from the decomposition of the sample based on per capita income. If underserved markets are characterized by these dimensions, then UCCs need a lower threshold of population to enter these markets and expand access to care. When splitting

 $^{^{15}} For some definitions of underserved populations, see e.g., <math display="block">https://www.hhs.gov/guidance/sites/default/files/hhs-guidance-documents/vulnerable-and-underserved-populations.pdf.$

¹⁶The bivariate ordered probit estimates associated with these entry thresholds and ratios are presented in Appendix Table 12.

Table 4: Entry Thresholds and Ratios in Subsamples

	Percent 1	ıninsured	Per capit	a income	S	VI
	High	Low	Low	High	High	Low
Thresholds:						
$ au_1$	35.06	42.95	33.70	41.07	35.83	38.74
	(1.16)	(2.16)	(1.13)	(1.71)	(1.22)	(1.57)
$ au_2$	48.32	59.14	45.20	58.10	48.10	54.91
	(1.86)	(3.41)	(1.72)	(2.85)	(1.84)	(2.69)
$ au_3$	58.15	75.83	54.01	72.72	57.69	69.41
	(2.44)	(5.36)	(2.26)	(4.10)	(2.41)	(4.08)
$ au_4$	66.53	89.07	60.79	85.34	67.42	78.60
	(3.19)	(7.49)	(2.87)	(5.69)	(3.48)	(5.08)
Ratios:						
$ au_2/ au_1$	1.38	1.38	1.34	1.41	1.34	1.42
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
$ au_3/ au_2$	1.20	1.28	1.19	1.25	1.20	1.26
	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
$ au_4/ au_3$	1.14	1.17	1.13	1.17	1.17	1.13
	(0.03)	(0.05)	(0.02)	(0.04)	(0.03)	(0.04)
T	10,335	11,393	12,563	9,165	9,781	11,947

Note: Table reports entry thresholds and ratios for UCCs from bivariate ordered probits estimated from subsamples of ZCTAs: above median percent uninsured, below median percent uninsured, below median income, above median Social Vulnerability Index (SVI), and below median SVI. The thresholds for each sample are computed with the corresponding estimates of the bivariate ordered probit model reported in Appendix Table 12. Entry thresholds are measured in 1,000s of people. Standard errors in parentheses.

the sample into ZCTAs with high and low SVI, we find no significant differences between the entry thresholds for different number of firms across the two subsamples, though this may be due to the fact that we do not have variation in the SVI within counties.

While population thresholds suggest a role for UCCs to expand access in underserved markets, a potential concern is that UCCs entering these areas enjoy more market power. However, the threshold ratios across different types of markets are similar. Thus, the nature of competition among UCCs does not seem to vary across different types of markets.

5 Counterfactual Regulation of UCCs

One important policy debate surrounding UCCs concerns their lack of regulation, which critics worry could result in low quality care or predatory services (see Cavanaugh et al., 2020). Applying CON law regulations to UCCs has been proposed as one way to address this. On the other hand, larger entry costs could result in higher market power among establishments that still enter, and could change the implications for access to care. We use our model to explore the consequences of such a proposal by subjecting UCCs to higher

fixed costs of entry. CON laws include fixed costs such as application costs, consultant fees, and attorney fees. The application costs alone can be substantial: for example, the District of Columbia levies an application fee up to \$300,000, and in several states the total cost includes both a flat fee and a percentage of the total cost of constructing the facility (Solomon et al., 2020). Thus, CON laws, if applied to UCCs, impose barriers to entry.

To capture the effect of CON laws within our model, we simulate an increase in fixed costs for UCCs. While we recover the fixed costs stemming from CON laws for hospitals from our estimates of the model in Table 2, it is not obvious how to translate that cost to UCCs. We use the fact that CON law application costs are often a percentage of a hospital's total fixed costs of entry to simulate the additional fixed costs that CON laws would create for hospitals. More precisely, hospitals' fixed costs have an observable component that depends on a local hospital wage index and state-level CON laws, or $\text{wage}_t \gamma_{\text{wage}}^h + \text{CON}_t \gamma_{\text{CON}}^h$. As the levels of costs associated with CON laws may vary systematically between hospitals and UCCs, we construct a relative measure of the effect of CON laws on fixed costs by computing the ratio of costs due to CON laws as $r_{CON} = (\text{CON}_t \gamma_{\text{CON}}^h)/(\text{wage}_t \gamma_{\text{wage}}^h)$, and obtain counterfactual CON law costs for UCCs as $r_{CON} \times (\text{wage}_t \gamma_{\text{wage}})$. These costs are added to UCC fixed costs in our counterfactual. The key assumption for this scenario is that, if CON laws were to apply to UCCs, they would increase costs by the same proportion of the wage index as they do for hospitals.¹⁷

Panel A of Table 5 reports the results of this counterfactual in terms of percent change and absolute change in the number of UCCs. The estimates in column 1 are based on the value of CON_t , which describes CON law intensity for hospitals in the data. This corresponds to a policy where states impose the current CON law intensity that applies to hospitals in that state to UCCs. Overall, the application of current CON laws to UCCs would lead to a 10 percent decrease in the number of UCCs, or a decrease of 613 establishments (equivalent to removing the last two years of aggregate UCC expansion). Many states, however, do not have CON laws, so the 10 percent national decrease in UCCs is a weighted combination of a mechanical zero effect in states with no existing CON laws for hospitals plus a 16 percent decrease in UCCs for states with CON laws.

To paint a fuller picture, columns 2 through 5 apply an equal level of CON law intensity to all states, by quartile of the distribution of observed hospital CON law intensity across states imposing CON laws. For a CON law intensity at the 25th percentile of the current distribution, the number of UCCs would decrease by 13 percent nationally, while at the maximum level of CON intensity the number of UCCs would decrease by 26 percent. Thus, CON laws may have a significant impact on the number of UCCs in the US.

¹⁷Other assumptions on how CON laws would impact UCCs fixed costs are possible. In Appendix Table 13, we explore an additive specification in which we add to UCC costs the hospital CON cost (CON_t γ_{CON}^h), thus assuming that the same level of CON laws costs would apply to both hospitals and UCCs.

Table 5: Counterfactual Effects of CON Laws on UCC Entry

	Observed (1)	p25 (2)	p50 (3)	p75 (4)	p100 (5)
Panel A. Full sample:					
Percent change	-9.41	-12.61	-18.03	-19.85	-26.39
Absolute change	-613	-822	-1175	-1294	-1720
Panel B. Demographic split ($\%\Delta$):					
High uninsured	-9.98	-13.28	-18.78	-20.41	-26.40
Low uninsured	-8.74	-11.82	-17.16	-19.20	-26.37
High income	-9.26	-12.01	-17.32	-19.13	-25.45
Low income	-9.66	-13.64	-19.27	-21.09	-28.00
High SVI	-9.09	-14.14	-19.91	-21.69	-28.66
Low SVI	-9.70	-11.20	-16.31	-18.17	-24.30

Note: Table presents percent change in number of UCCs (as well as absolute change in Panel A row 2) for different counterfactual CON laws, as denoted in the columns. Column 1 applies observed CON laws within a state to that state's UCCs; columns 2 through 5 apply the respective percentile of CON law intensity across all states (conditional on having a CON law) to all UCCs nationwide.

We also explore how applying CON laws to UCCs may impact markets with different demographics. Panel B of Table 5 reports counterfactual results for different subsets of markets. Overall, applying CON laws to UCCs does not differentially impact markets with different demographics to a large extent, especially at high levels of CON intensity. However, we see larger counterfactual decreases in the number of UCCs for markets with a higher percentage of uninsured population, lower income, and high SVI when considering scenarios where CON laws are applied across all states at low to moderate intensities. This suggests that CON laws may have slightly more adverse effects on UCC entry in underserved markets.

6 Conclusion

UCCs are an important sector of the US health-care system, and have experienced fast growth over the last decades. In this paper we use data on UCC locations to estimate an equilibrium model of market structure in this industry. The model captures the interdependent entry decisions of UCCs and hospitals across geographic markets, and uses market-level demographics to uncover the determinants of UCC profitability. Estimation of the model delivers two main results. With respect to competition, estimates suggest that hospitals negatively impact profitability of UCCs, and that UCCs enjoy market power. We also show that these establishments are at least as likely to enter in areas with a high proportion of traditionally underserved populations. Thus, UCCs have a role in expanding access to the underserved. In counterfactuals, we show that raising fixed costs of entry by applying CON

laws to UCCs would result in a meaningful reduction in the number of these establishments throughout the US.

Our results raise several open questions for further research. We find evidence both that UCCs have a role in expanding access but also exercise market power. Our data do not permit us to quantify the welfare effects of these competing forces. A full accounting of the welfare effects of UCC entry would integrate these concerns with the work being done on UCC quality provision and cost savings (e.g., Currie et al., 2021). We leave such an exercise to future work.

References

- ABRAHAM, J., M. GAYNOR, AND W. VOGT (2007): "Entry and Competition in Local Hospital Markets," *Journal of Industrial Economics*, 55, 265–288.
- Ackerberg, D. and G. Gowrisankaran (2006): "Quantifying Equilibrium Network Externalities in the ACH Banking Industry," *RAND Journal of Economics*, 37, 738–761.
- ALEXANDER, D., J. CURRIE, AND M. SCHNELL (2019): "Check Up Before You Check Out: Retail Clinics and Emergency Room Use," *Journal of Public Economics*, 178, 104050.
- Allen, L., J. Cummings, and J. Hockenberry (2020): "Urgent Care Centers and the Demand for Non-Emergent Emergency Department Visits," *NBER Working Paper*, 1–28.
- ASHWOOD, J., M. GAYNOR, C. SETODJI, R. REID, E. WEBER, AND A. MEHROTRA (2016): "Retail Clinic Visits for Low-acuity Conditions Increase Utilization and Spending," *Health Affairs*, 35, 449–455.
- Bailey, J. (2018): "The Effect of Certificate of Need Laws on All-Cause Mortality," *Health Services Research*, 53, 49–62.
- Berry, S. and P. Reiss (2007): "Empirical Models of Entry and Market Structure," Handbook of Industrial Organization, 3, 1845–1886.
- Bresnahan, T. and P. Reiss (1991): "Entry and Competition in Concentrated Markets," Journal of Political Economy, 99, 977–1009.
- CAVANAUGH, J., C. BROTHERS, A. GRIFFIN, R. HOOVER, M. LOPRESTI, AND J. WRENCH (2020): "Conning the Competition: A Nationwide Survey of Certificate of Need Laws," https://ij.org/wp-content/uploads/2020/08/Conning-the-Competition-WEB-08.11.2020.pdf.
- Chiu, K. (2021): "The impact of certificate of need laws on heart attack mortality: Evidence from county borders," *Journal of Health Economics*, 79, 102518.
- Chung, A. and A. Sorensen (2018): "For-Profit Entry and Market Expansion in the Hospice Industry," Working Paper.
- COHEN, A., B. FREEBORN, AND B. McManus (2013): "Competition and Crowding Out in the Market for Outpatient Substance Abuse Treatment," *International Economic Review*, 54, 159–184.

- CORWIN, G. S., D. M. PARKER, AND J. R. BROWN (2016): "Site of treatment for non-urgent conditions by Medicare beneficiaries: is there a role for urgent care centers?" The American journal of medicine, 129, 966–973.
- Currie, J., A. Karpova, and D. Zeltzer (2021): "Do Urgent Care Centers Reduce Medicare Spending?" *NBER Working Paper 29047*.
- Cutler, D., R. Huckman, and J. Kolstad (2010): "Input Constraints and the Efficiency of Entry: Lessons from Cardiac Surgery," *American Economic Journal: Economic Policy*, 2, 51–76.
- FAIR HEALTH (2019): FH Healthcare Indicators and FH Medical Price Index 2019: An Annual View of Place of Service Trends and Medical Pricing, FAIR Health White Paper.
- GRIECO, P. (2014): "Discrete Games with Flexible Information Structures: An Application to Local Grocery Markets," *RAND Journal of Economics*, 45, 303–340.
- HOLLINGSWORTH, A. (2014): "Retail Health Clinics: Endogenous Location Choice and Emergency Department Diversion," Working Paper.
- HOUDE, J.-F., P. NEWBERRY, AND K. SEIM (2021): "Economies of Density in e-commerce: A Study of Amazon's Fulfillment Center Network," NBER working paper 23361.
- JIA, P. (2008): "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry," *Econometrica*, 76, 1263–1316.
- Le, S. and R. Hsia (2016): "Community Characteristics Associated with Where Urgent Care Centers are Located: a Cross-sectional Analysis," *BMJ open*, 6, e010663.
- MAZZEO, M. (2002): "Product Choice and Oligopoly Market Structure," RAND Journal of Economics, 33, 1–22.
- McCluskey, P. (2020): "State Seeks to Rein in Largely Unregulated Urgent Care Industry," Boston Globe, Available at https://www.bostonglobe.com/business/2020/01/2 0/state-officials-seeks-rein-rapidly-growing-urgent-care-industry/w5Bs7q iFsk6lyh6qfSGIyL/story.html.
- McDevitt, R. (2014): "A' Business by Any Other Name: Firm Name Choice as a Signal of Firm Quality," *Journal of Political Economy*, 122, 909–944.
- Polsky, D., G. David, J. Yang, B. Kinosian, and R. Werner (2014): "The Effect of Entry Regulation in the Health Care Sector: The Case of Home Health," *Journal of Public Economics*, 110, 1–14.

- RIVERS, D. AND Q. VUONG (1988): "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models," *Journal of Econometrics*, 39, 347–366.
- SCHAUMANS, C. AND F. VERBOVEN (2008): "Entry and Regulation: Evidence from Health Care Professionals," RAND Journal of Economics, 39, 949–972.
- SOLOMON, T., K. POPKIN, A. CHEN, L. UTTLEY, AND S. BARUCH (2020): "Making 'Convenient Care' the Right Care for All: Improving State Oversight of Urgent Care Centers and Retail Health Clinics," Available at https://www.communitycatalyst.org/resources/tools/convenient-care-report/pdf/Urgent-Care-Center-BriefApp endix-2.pdf.
- Suárez Serrato, J. and O. Zidar (2016): "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms," *American Economic Review*, 106, 2582–2624.
- URGENT CARE ASSOCIATION (2019): Urgent Care Industry White Paper: The Essential Role of the Urgent Care Center in Population Health, UCAOA White Paper.
- Uscher-Pines, L., J. Pines, A. Kellermann, E. Gillen, and A. Mehrotra (2013): "Deciding to Visit the Emergency Department for Non-urgent Conditions: A Systematic Review of the Literature," *The American Journal of Managed Care*, 19, 47–59.
- Weinick, R., R. Burns, and A. Mehrotra (2010): "Many Emergency Department Visits Could Be Managed At Urgent Care Centers and Retail Clinics," *Health Affairs*, 29, 1630–1636.
- Wooldridge, J. (2015): "Control Function Methods in Applied Econometrics," *Journal of Human Resources*, 50, 420–445.

Appendix A Additional Tables

APPENDIX TABLE 1: Sample Restrictions and Sample Size

	Number of establishments
1. SIC 80	38,455,053
2. Drop missing company name	30,854,081
3. Drop duplicates in (lon, lat)	12,769,324
4. Keep years 2005-2017	7,936,612
5. Solv Health match	281,065
6. Drop establishments w/in 2 meters, with same operator	62,569
7. Keep 2015	6,018
8. Keep continental US	5,971
9. Market definition	5,601

Note: Table reports all steps in obtaining our main data sample from the raw YTS data and the number of establishment observations at each step.

Appendix Table 2: Urgent Care Operators in Our Sample

- Concentra Urgent Care
- American Family Care
- MedExpress Urgent Care
- US Healthworks
- NextCare Urgent Care
- FastMed Urgent Care
- CareNow Urgent Care
- Fast Pace Urgent Care
- GoHealth Urgent Care
- Advocate Health Care
- CityMD Urgent Care
- Banner Urgent Care
- Doctors Care
- Urgent Team
- MedPost Urgent Care
- Patient First
- Aurora Health Care
- MultiCare Urgent Care Centers
- CareSpot
- HealthCare Partners
- MD NOW Urgent Care Centers
- Physicians Immediate Care
- PM Pediatrics
- MedSpring Urgent Care
- Baylor Scott and White Health
- Intermountain Healthcare
- Sutter Health
- Mercy Jefferson
- UnityPoint Health
- Centra Care
- Carolinas HealthCare Urgent Care
- Baptist Health

- InstaCare
- CRH Healthcare
- Hometown Urgent Care
- ProHEALTH Urgent Care
- FastCare
- Total Access Urgent Care
- Geisinger Careworks
- Texas MedClinic
- PhysicianOne Urgent Care
- Access Medical Centers
- ExpressCare Urgent Care
- UH Urgent Care Centers
- ZoomCare
- Mayo Clinic Health System Urgent Care
- Ochsner Urgent Care
- Novant Health
- Hartford HealthCare Urgent Care
- Med First Primary and Urgent Care
- DMC Care
- Texas Health Emergency Room
- Inova Urgent Care Center
- Metro Urgent Care
- Sanford Health
- Kaiser Permanente
- Primary Health Medical Group
- Urgent Care for Kids
- Mount Sinai Health System
- AppleCare
- UPMC Urgent Care
- BayCare Health System
- Peachtree Immediate Care

- Walk In Urgent Care
- Premier Urgent Care
- Allina Health
- Dignity Health
- NorthShore Immediate Care Centers
- Franciscan Alliance
- Nova Medical Centers
- Centura Health
- CareWell Urgent Care
- Fairview Urgent Care
- MainStreet Family Urgent
- Riverside Urgent Care
- Little Spurs Pediatric Urgent Care
- Five Star Urgent Care
- Urgent Care Group
- Parkview Health
- AfterOurs Urgent Care
- Physicians Care
- $\bullet \ \ \mathbf{MedStar} \ \mathbf{PromptCare}$
- AtlantiCare Urgent Care
- AFC Doctors Express Urgent Care
- Baptist Health South Florida
- First Care Clinics
- Essentia Health
- UCHealth
- Norton Medical Group
- Metro UrgiCare
- Healthpointe
- Next Level Urgent Care
- Rightitme Medical Care
- Prevea Health

Note: Table reports all urgent care center operators with at least 15 locations acording to SolvHealth. We restrict our sample to these companies' establishments.

Appendix Table 3: Robustness of Number of UCCs to Sample Construction

# UCCs	Main	Urgent in Name	No Drop w/in 2 Mts	Locations > 30	Fuzzy Match
0	84.79	77.14	65.14	85.76	81.88
1	9.05	12.27	13.53	8.59	13.13
2	3.69	5.63	7.29	3.35	3.55
3	1.39	2.66	4.39	1.28	1.10
>=4	1.08	2.31	9.65	1.01	0.34
Total UCCs	5,601	8,850	17,357	5,206	5,409

Note: Table reports the percentage of markets with a given number of UCCs for our main sample ("Main") and four alternative samples, constructed by amending the steps in Appendix Table 1. The sample "Urgent in Name" is constructed by replacing step 5 in Appendix Table 1 with a restriction that establishments in the YTS data have the word "urgent" in their name. The sample "No Drop w/in 2 Mts" is constructed by omitting step 6 in Appendix Table 1. The sample "Locations > 30" is constructed by omitting amending step 5 in Appendix Table 1 to restrict to UCC operators with at least 30 establishments according to SolvHealth (as opposed to 15 in the main sample). The sample "Fuzzy Match" replaces the exact match step 5 with a fuzzy match on establishment name in YTS and the name of any establishment in SolvHealth operated by the firms in Appendix Table 2.

APPENDIX TABLE 4: Robustness of Parameter Estimates to Sample Construction

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			Urgent	in Name	No Drop	w/in 2 Mts	Locatio	ons > 30	Fuzzy	Match
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			Hosp	UCCs	Hosp	UCCs	Hosp	UCCs	Hosp	UCCs
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variabl	le Profit Parameters:								
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	δ	Presence of hospitals		-16.0		-17.2	_	-21.7		-21.3
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(3.3)		(3.3)		(3.6)		(3.4)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	θ_x, θ_x^h	Rural	2.8	-33.5	2.9	-39.5	2.7	-27.2	3.3	-31.1
Hispanic (0.6) (1.0) (0.7) (1.1) (0.6) (1.1) (0.7) (1.1) Hispanic -58.9 -102.9 -60.2 -89.2 -59.1 -70.4 -59.0 -59.0 -59.1 -70.4 -59.0 -59.1 Black -29.0 -79.3 -29.7 -68.9 -29.8 -61.1 -29.3 -10.1 Black -29.0 -79.3 -29.7 -68.9 -29.8 -61.1 -29.3 -10.1 Other race -29.0 -88.5 -29.2 -109.1 -28.8 -43.5 -29.7 -68.9 -29.8 -61.1 -29.3 -10.1 High school or more -86.7 -36.5 -86.2 -46.9 -89.2 -53.5 -87.0 -20.1 Age 65 or more -115.8 -264.8 -117.7 -315.0 -116.3 -315.7 -117.9 -217.0 High school or more -115.8 -264.8 -117.7 -315.0 -116.3 -315.7 -117.9 -217.0 High school or more -115.8 -264.8 -117.7 -315.0 -116.3 -150.7 -117.9 -217.0 High school or more -115.8 -264.8 -117.7 -116.0 -116.3 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 -117.9 High school or more -115.8 -117.9 -117.9 -117.9 -117.9 -117.9 High school or more -117.9 High school			(3.1)	(5.5)	(3.1)	(5.2)	(3.1)	(6.2)	(3.1)	(6.0)
Hispanic		Income per capita	-4.2	0.5	-4.4	4.9	-4.3	1.8	-4.4	2.3
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(0.6)	(1.0)					. ,	(1.1)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Hispanic								-36.5
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(4.3)	(7.3)					(4.3)	(7.6)
Other race -29.0 -88.5 -29.2 -109.1 -28.8 -43.5 -29.7 -20.7		Black	-29.0				-29.8		-29.3	-11.9
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(3.7)	. ,		, ,	(3.8)		(3.7)	(6.5)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Other race	-29.0	-88.5		-109.1			-29.7	-35.8
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(11.5)						(11.9)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		High school or more								26.8
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(20.8)			. ,	` /	, ,	(21.5)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Age 65 or more					116.3		117.9	210.3
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(12.0)				(11.9)	(22.0)		(21.3)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Uninsured	18.0	169.6	19.3		17.6	207.4	17.9	83.7
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(14.7)	(24.8)	(14.6)		(14.7)	(26.6)	(14.6)	(25.5)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	θ_n, θ_n^h	$ heta_1$		115.0	91.0	105.5	92.3	79.9	91.2	73.2
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(6.6)		(6.6)		(6.6)		(6.6)	(11.9)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		$ heta_2$	_	101.9	_	95.5	_	73.9	_	72.0
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(11.5)		(11.3)		(12.6)		(12.1)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		θ_3	_	96.6	_	87.3	_	71.0	_	65.8
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(11.7)						(12.7)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		$ heta_4$		93.7	_	81.2		68.9	_	54.1
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(12.0)		(11.5)		(13.3)		(14.1)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Cost Parameters:								
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	γ_w, γ_w^h	CMS wage index		0.3	0.4	0.2	0.4	0.4	0.4	0.1
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	γ_z	CON Laws	0.4	_	0.5	_	0.4	_	0.4	_
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(0.0)		(0.0)		(0.0)		(0.0)	
γ_2 $ 2.0$ $ 1.7$ $ 2.1$ $ 2.$ (0.1)	γ_n, γ_n^h	γ_1	0.8	1.5	0.9	1.2	0.9	1.6	0.9	1.6
γ_3 $ 2.5$ $ 2.1$ $ 2.6$ $ 3.0$			(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
γ_3 - 2.5 - 2.1 - 2.6 - 3.0		γ_2	_	2.0	_	1.7	_	2.1		2.5
				(0.1)		(0.1)		(0.1)		(0.1)
γ_4 $ 2.9$ $ 2.3$ $ 3.0$		γ_3	_	2.5	_	2.1	_	2.6	_	3.0
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$										(0.1)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		γ_4	_	2.9	_	2.3	_	3.0	_	3.5
(0.0) (0.0) (0.0)				(0.1)		(0.1)		(0.1)		(0.1)
(0.0) (0.0) (0.0)	ρ			0.6		0.4	_	0.4		0.4
T 21 798 21 798 21 798 21 798 21 798 21 798 21 798 21 798 21				(0.0)		(0.0)		(0.0)		(0.0)
21,120 21,120 21,120 21,120 21,120 21,120 21,120 21	T		21,728	21,728	21,728	21,728	21,728	21,728	21,728	21,728

Note: Table reports coefficients and standard errors of the bivariate ordered probit model for hospitals and UCCs for the four alternative samples to our main dataset (labeled "Urgent in Name", "No Drop w/in 2 Mts", "Locations > 30", "Fuzzy Match"). The construction of these samples is described in the notes to Appendix Table 3.

APPENDIX TABLE 5: Robustness of Entry Thresholds to Sample Construction

	Urgent	in Name	No Drop	w/in 2 Mts	Locatio	ns > 30	Fuzzy	Match
	Hosp	UCCs	Hosp	UCCs	Hosp	UCCs	Hosp	UCCs
Thresholds:								
$ au_1$	35.23	27.84	35.06	21.70	35.22	38.23	35.01	44.54
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.03)
$ au_2$	_	40.19	_	32.13	_	52.10	_	69.00
		(0.02)		(0.01)		(0.03)		(0.05)
$ au_3$	_	49.97	_	40.07	_	63.12	_	90.24
		(0.03)		(0.02)		(0.04)		(0.09)
$ au_4$	_	58.42	_	46.58	_	71.92	_	118.76
		(0.03)		(0.02)		(0.06)		(0.19)
Ratios:								
$ au_2/ au_1$	_	1.44	_	1.48	_	1.36	_	1.55
		(0.01)		(0.01)		(0.02)		(0.03)
$ au_3/ au_2$	_	1.24	_	1.25	_	1.21	_	1.31
		(0.01)		(0.01)		(0.02)		(0.04)
$ au_4/ au_3$	_	1.17	_	1.16	_	1.14	_	1.32
		(0.01)		(0.01)		(0.02)		(0.08)
T	21,728	21,728	21,728	21,728	21,728	21,728	21,728	21,728

Note: Table reports entry thresholds and entry ratios for UCCs and hospitals for the four alternative samples to our main dataset (labeled "Urgent in Name", "No Drop w/in 2 Mts", "Locations > 30", "Fuzzy Match"). The construction of these samples is described in the notes to Appendix Table 3 The thresholds for each sample are computed with the corresponding estimates of the bivariate ordered probit model reported in Appendix Table 4. Entry thresholds are measured in 1,000s of people. Standard errors based on the delta method are reported in parenthesis.

APPENDIX TABLE 6: Robustness of Parameter Estimates to Market Definition

		Sampl	le 1	Sampl	le 2
		Hospitals	UCCs	Hospitals	UCCs
Variable 1	Profit Parameters:				
δ	Presence of hospitals	_	-20.3	_	-7.6
	_		(4.4)		(10.9)
θ_x, θ_x^h	Rural	10.4	-3.0	-3.0	-7.2
ω, ω		(4.8)	(9.3)	(5.9)	(10.2)
	Income per capita	-10.7	-0.4	-38.5	-4.3
		(1.3)	(2.3)	(3.7)	(7.0)
	Hispanic	-70.6	-107.8	-59.6	-100.3
	•	(6.1)	(10.7)	(19.2)	(32.6)
	Black	-46.0	-71.3	-67.7	-19.2
		(6.2)	(10.7)	(13.4)	(23.9)
	Other race	-46.6	-99.0	-56.9	-29.0
		(11.7)	(19.4)	(32.6)	(61.3)
	High school or more	-111.0	-9.7	-17.3	-1.5
		(20.9)	(35.9)	(46.3)	(81.4)
	Age 65 or more	208.9	167.5	296.8	280.9
	_	(19.1)	(36.0)	(43.2)	(75.1)
	Uninsured	-16.1	82.4	-125.8	343.4
		(21.6)	(38.3)	(53.2)	(95.0)
θ_n, θ_n^h	$ heta_1$	124.0	149.4	147.8	92.4
		(10.5)	(18.6)	(22.3)	(40.7)
	$ heta_2$		148.1		87.8
			(18.8)		(41.3)
	$ heta_3$	_	137.7	_	70.4
			(19.3)		(42.5)
	$ heta_4$	_	133.0	_	31.2
			(20.0)		(45.1)
	st Parameters:				
γ_w, γ_w^h	CMS wage index	0.2	0.6	0.1	0.0
		(0.1)	(0.1)	(0.2)	(0.3)
γ_z	CON Laws	0.3		0.3	_
		(0.1)		(0.1)	
γ_n, γ_n^h	γ_1	1.3	1.7	0.4	1.9
		(0.1)	(0.1)	(0.2)	(0.3)
	γ_2		2.3	_	2.6
			(0.1)		(0.3)
	γ_3		2.7	_	3.1
			(0.2)		(0.3)
	γ_4	_	3.0	_	3.3
			(0.2)		(0.3)
ρ		_	0.5	_	0.2
			(0.0)		(0.1)
\overline{T}		12,120	12,120	3,124	3,124

Note: Table reports coefficients and standard errors of the bivariate ordered probit model for hospitals and UCCs for alternative samples. Sample 1 corresponds to all ZCTAs except those within 5 miles of a larger ZCTA. Sample 2 corresponds to all ZCTAs except those within 50 miles of a city, with > 60,000 residents, or within 15 miles of a larger ZCTA.

APPENDIX TABLE 7: Robustness of Population Thresholds to Market Definition

	Sampl	le 1	Sampl	le 2
	Hospitals	UCCs	Hospitals	UCCs
Thresholds:				
$ au_1$	26.54	33.74	10.14	31.25
	(0.03)	(0.03)	(0.01)	(0.04)
$ au_2$	_	44.04	_	44.06
		(0.04)		(0.07)
$ au_3$	_	53.12	_	58.95
		(0.05)		(0.12)
$ au_4$	_	60.70	_	88.73
		(0.07)		(0.34)
Ratios:				
$ au_2/ au_1$	_	1.30	_	1.41
		(0.01)		(0.04)
$ au_3/ au_2$	_	1.21	_	1.34
		(0.02)		(0.06)
$ au_4/ au_3$	_	1.14	_	1.51
		(0.02)		(0.20)
T	12,120	12,120	3,124	3,124

Note: This table reports entry thresholds and entry ratios for UCCs and hospitals from the bivariate ordered probit in different samples. Sample 1 corresponds to all ZCTAs except those within 5 miles of a larger ZCTA. Sample 2 corresponds to all ZCTAs except those within 50 miles of a city, with more than 60,000 residents, or within 15 miles of a larger ZCTA.

APPENDIX TABLE 8: Robustness of Parameter Estimates to Alternative Years of Data

		201	4	2016		
		Hospitals	UCCs	Hospitals	UCCs	
Variable P	rofit Parameters:					
δ	Presence of hospitals	_	-19.1	_	-26.7	
			(3.7)		(3.4)	
θ_x, θ_x^h	Rural	2.7	-31.2	3.7	-29.7	
		(3.1)	(6.3)	(3.1)	(6.0)	
	Income per capita	-4.5	1.4	-4.2	2.4	
	• •	(0.7)	(1.1)	(0.7)	(1.1)	
	Hispanic	-60.9	-73.8	-58.8	-71.8	
	•	(4.4)	(8.0)	(4.4)	(7.7)	
	Black	-31.3	-67.2	-29.0	-64.8	
		(3.8)	(7.1)	(3.7)	(6.8)	
	Other race	-28.4	-44.1	-25.5	-52.6	
		(7.0)	(12.4)	(7.0)	(12.0)	
	High school or more	-87.9	53.8	-93.8	57.0	
		(12.5)	(22.5)	(12.5)	(22.0)	
	Age 65 or more	116.3	134.0	111.7	133.7	
		(11.9)	(22.1)	(11.9)	(21.7)	
	Uninsured	25.7	195.9	16.4	190.1	
		(14.7)	(26.8)	(14.7)	(26.1)	
θ_n, θ_n^h	$ heta_1$	$92.4^{'}$	84.3	93.3	84.4	
10 / 10	1	(6.6)	(12.4)	(6.6)	(12.1)	
	$ heta_2$		$77.2^{'}$		81.9	
	2		(12.6)		(12.3)	
	$ heta_3$	_	$73.5^{'}$	_	77.5	
	3		(12.9)		(12.5)	
	$ heta_4$	_	70.2	_	73.2	
	*		(13.4)		(12.9)	
Fixed Cos	t Parameters:					
γ_w, γ_w^h	CMS wage index	0.4	0.4	0.5	0.4	
		(0.1)	(0.1)	(0.1)	(0.1)	
γ_z	CON Laws	0.4	_	0.4	_	
_		(0.0)		(0.0)		
γ_n, γ_n^h	γ_1	0.9	1.6	0.8	1.5	
		(0.1)	(0.1)	(0.1)	(0.1)	
	γ_2	_	2.1	_	2.1	
			(0.1)		(0.1)	
	γ_3	_	2.6	_	2.5	
			(0.1)		(0.1)	
	γ_4	_	3.0	_	2.9	
			(0.1)		(0.1)	
ho			0.4		0.4	
			(0.0)		(0.0)	

Note: Table reports coefficients and standard errors of the bivariate ordered probit model for hospitals and UCCs for alternative sample years 2014 and 2016. These samples are constructed by replacing step 7 in Appendix Table 1 with the appropriate year.

APPENDIX TABLE 9: Robustness of Population Thresholds to Alternative Years of Data

	201	4	201	6
	Hospitals	UCCs	Hospitals	UCCs
Thresholds:				
$ au_1$	35.08	39.19	35.29	45.17
	(0.03)	(0.02)	(0.03)	(0.03)
$ au_2$	_	53.50	_	62.39
		(0.04)		(0.04)
$ au_3$	_	65.80	_	76.97
		(0.05)		(0.06)
$ au_4$	_	76.26	_	89.80
		(0.07)		(0.09)
Ratios:				
$ au_2/ au_1$	_	1.37		1.38
		(0.02)		(0.02)
$ au_3/ au_2$	_	1.23	_	1.23
		(0.02)		(0.02)
$ au_4/ au_3$	_	1.16		1.17
		(0.03)		(0.03)
T	21,728	21,728	21,728	21,728

Note: Table reports entry thresholds and entry ratios for UCCs and hospitals for alternative sample years 2014 and 2016. These samples are constructed by replacing step 7 in Appendix Table 1 with the appropriate year. The thresholds for each sample are computed with the corresponding estimates of the bivariate ordered probit model reported in Appendix Table 8. Entry thresholds are measured in 1,000s of people. Standard errors based on the delta method are reported in parenthesis.

		(1) w/o UCC licensing		(2) w/o NY and NC	
		Hospitals	UCCs	Hospitals	UCCs
Variable I	Profit Parameters:				
δ	Presence of hospitals	_	-22.5	_	-20.8
			(4.1)		(3.8)
θ_x, θ_x^h	Rural	-0.3	-28.5	-0.2	-32.0
		(3.3)	(6.5)	(3.3)	(6.7)
	Income per capita	-5.3	3.4	-5.4	3.1
		(0.8)	(1.4)	(0.7)	(1.2)
	Hispanic	-65.8	-64.9	-58.3	-65.0
	-	(5.4)	(9.8)	(4.5)	(8.1)
	Black	-31.0	-57.1	-31.9	-65.1
		(4.2)	(7.9)	(3.9)	(7.4)
	Other race	-30.8	-56.8	-27.3	-56.8
		(8.0)	(13.8)	(7.4)	(13.1)
	High school or more	-124.2	48.6	-78.6	70.3
	3	(15.5)	(27.7)	(13.1)	(23.3)
	Age 65 or more	273.5	283.0	113.6	138.7
	G	(17.9)	(33.1)	(12.2)	(22.5)
	Uninsured	38.1	209.2	9.6	181.5
		(17.1)	(30.8)	(15.2)	(27.4)
θ_n, θ_n^h	$ heta_1$	92.1	66.2	91.5	75.0
10) - 10		(8.2)	(15.2)	(6.9)	(12.8)
	$ heta_2$	—	59.6	—-	69.0
	. 2		(15.4)		(13.0)
	$ heta_3$	_	56.8	_	65.3
	3		(15.7)		(13.4)
	$ heta_4$	_	53.3	_	62.1
	· 4		(16.1)		(13.8)
Fixed Cos	st Parameters:				
γ_w, γ_w^h	CMS wage index	0.3	0.4	0.4	0.4
		(0.1)	(0.1)	(0.1)	(0.1)
γ_z	CON Laws	0.4		0.3	_
		(0.0)		(0.0)	
γ_n, γ_n^h	γ_1	1.0	1.5	0.9	1.5
		(0.1)	(0.1)	(0.1)	(0.1)
	γ_2	_	2.1	_	2.1
			(0.1)		(0.1)
	γ_3	_	2.6	_	2.6
			(0.1)		(0.1)
	γ_4	_	2.9	_	3.0
			(0.1)		(0.1)
ρ			0.4		0.4
			(0.0)		(0.0)
T		17,600	17,600	19,861	19,861

Note: Table reports coefficients and standard errors of the bivariate ordered probit model for hospitals and UCCs for alternative samples which exclude states regulating UCCs. Column 1 excludes from the main sample states that require any type of UCC licensing. Column 2 excludes New York and North Carolina where CON laws apply to some UCCs. 34

APPENDIX TABLE 11: Robustness of Population Thresholds to UCC State Regulation

	(1) w/o UCC licensing		(2) w/o NY	Y and NC
	Hospitals	UCCs	Hospitals	UCCs
Thresholds:				
$ au_1$	30.53	35.60	35.43	37.53
	(0.02)	(0.02)	(0.02)	(0.02)
$ au_2$	_	48.31	_	51.60
		(0.03)		(0.03)
$ au_3$	_	58.97	_	63.42
		(0.04)		(0.05)
$ au_4$	_	67.23	_	73.03
		(0.06)		(0.06)
Ratios:				
$ au_2/ au_1$	_	1.36	_	1.37
		(0.02)		(0.02)
$ au_3/ au_2$	_	1.22	_	1.23
		(0.02)		(0.02)
$ au_4/ au_3$	_	1.14	_	1.15
		(0.02)		(0.02)
T	17,600	17,600	19,861	19,861

Note: Table reports entry thresholds and entry ratios for UCCs and hospitals for alternative samples which exclude states regulating UCCs. Column 1 excludes from the main sample states that require any type of UCC licensing. Column 2 excludes New York and North Carolina where CON laws apply to some UCCs. Entry thresholds are measured in 1,000s of people. Standard errors based on the delta method are reported in parenthesis.

APPENDIX TABLE 12: UCC Parameter Estimates in Demographic Subsamples

		Percent 1	Percent uninsured Per capit		a income	S	SVI	
		High	Low	Low	High	High	Low	
Variab	le Profit Parameters:							
δ	Presence of hospitals	-17.6	-25.4	-24.7	-25.4	-21.9	-14.3	
	-	(3.9)	(5.4)	(5.0)	(5.1)	(4.0)	(4.1)	
θ_x	Rural	-14.0	-65.8	-11.9	-69.4	-17.4	-32.5	
		(5.9)	(11.5)	(7.3)	(11.6)	(6.7)	(7.3)	
	Income per capita	$4.2^{'}$	2.4			$2.3^{'}$	2.2	
		(2.1)	(1.3)			(1.3)	(1.2)	
	Hispanic	-56.5	-26.6	-96.9	-18.0	-69.4	-60.5	
	-	(6.8)	(16.2)	(9.6)	(15.7)	(7.8)	(12.7)	
	Black	-54.1	-65.2	-79.9	-47.1	-66.1	-41.9	
		(7.0)	(12.7)	(8.5)	(13.4)	(7.0)	(12.2)	
	Other race	-52.4	-55.3	-37.4	-43.0	-45.2	-56.4	
		(15.5)	(16.2)	(21.4)	(15.1)	(13.6)	(14.4)	
	High school or more	15.7	62.1	34.8	106.0	43.3	50.9	
		(26.0)	(34.9)	(30.9)	(31.8)	(23.2)	(25.6)	
	Age 65 or more	92.2	136.0	222.9	128.6	87.5	105.5	
	<u> </u>	(26.0)	(30.7)	(38.9)	(28.9)	(23.7)	(21.5)	
	Uninsured			187.4	196.8	122.0	225.5	
				(32.6)	(48.0)	(25.7)	(38.3)	
θ_n	$ heta_1$	100.2	83.4	110.1	44.6	80.9	57.9	
	•	(12.1)	(19.1)	(17.0)	(20.0)	(12.9)	(12.6)	
	$ heta_2$	95.4	$77.2^{'}$	105.4	38.7	79.5	48.8	
	-	(12.3)	(19.4)	(17.3)	(20.1)	(13.1)	(12.9)	
	$ heta_3$	95.8	67.9	104.6	35.6	80.1	42.6	
		(12.6)	(19.8)	(17.9)	(20.3)	(13.4)	(13.4)	
	$ heta_4$	94.2	62.5	103.0	31.8	72.6	43.9	
	•	(13.2)	(20.4)	(18.8)	(20.7)	(13.9)	(14.0)	
Fixed	Cost Parameters:							
γ_w	CMS wage index	0.4	0.5	0.1	0.7	0.3	0.3	
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
γ_n	γ_1	1.5	1.5	1.9	1.0	1.5	1.7	
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
	γ_2	2.1	2.0	2.6	1.6	2.1	2.2	
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
	γ_3	2.6	2.5	3.1	2.1	2.6	2.7	
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
	γ_4	3.0	2.8	3.4	2.4	2.9	3.1	
		(0.2)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)	
ρ		0.4	0.4	0.4	0.4	0.5	0.3	
		(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
T		10,335	11,393	12,563	9,165	9,781	11,94	

Note: Table reports coefficients and standard errors of the bivariate ordered probit model for UCCs only in different subsamples of the main dataset. The subsamples High and Low correspond to markets that are above and below median for the given demographic variable. The estimates are used to compute the population thresholds in Table 4.

APPENDIX TABLE 13: Robustness of Counterfactual Effects of CON Laws on UCC Entry to Additive Increase of UCC Fixed Cost

	Observed (1)	p25 (2)	p50 (3)	p75 (4)	p100 (5)
Panel A. Full sample:					
Percent change	-20.80	-24.73	-37.73	-42.53	-60.74
Absolute change	-1356	-1612	-2459	-2772	-3959
Panel B. Demographic split ($\%\Delta$):					
High uninsured	-20.18	-25.43	-37.01	-41.23	-60.16
Low uninsured	-21.53	-23.90	-38.57	-44.04	-61.42
High income	-20.39	-23.15	-35.39	-39.98	-58.23
Low income	-21.53	-27.46	-41.78	-46.94	-65.07
High SVI	-19.80	-26.88	-39.21	-43.88	-62.79
Low SVI	-21.72	-22.76	-36.38	-41.29	-58.87

Note: Table presents percent change in number of UCCs (as well as absolute change in Panel A row 2) for different counterfactual CON laws, as denoted in the columns. Column 1 applies observed CON laws within a state to that state's UCCs; columns 2 through 5 apply the respective percentile of CON law intensity across all states (conditional on having a CON law) to all UCCs nationwide. As opposed to the specification in Table 5 we use here an additive specification in which we add to UCC costs the hospital CON cost (CON $_t\gamma^h_{\rm CON}$).