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Firm Response to Low-Reimbursement Patients in the Market for Unscheduled Outpatient Care

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Abstract
Americans spent 13,400 person-years waiting in emergency departments (EDs) in 2009 alone, a figure that has been increasing at a compounded rate of 3.5% per year since at least the early 1990s. Furthermore, the quantity of emergency department services demanded has increased by 3.1% annually, but the supply of ED services has not increased concomitantly. This dissertation develops a theoretical model which explains this lack of supply response. In the model, consistent with anecdotal and cross-sectional evidence, hospitals are constrained from setting individual wait times based on non-clinical factors. However, the hospital chooses an overall set of policies (staffing levels, adoption of operations management innovations, etc.) which produces a hospital-wide baseline wait time. The hospital's wait time is endogenous to the mix of patient profitabilities. Demand depends on the time price of services. The model predicts that higher wait times result from increased proportions of Medicaid and uninsured patients.

A novel census of emergency department wait times in two states (MA, NJ) is used to test these predictions. First, the model's assumption that hospitals are constrained in setting individual wait times based on profitability is supported by cross-sectional regression coefficients: hospitals with 50 percentage point greater uninsurance rates have 26.0 minute longer wait times ($p<.01$; national mean wait time is 58 minutes), whereas conditional on hospital uninsurance rate individuals who are uninsured are not shown to have longer wait times (coefficient of 0.86 minutes, $p=0.13$). Next I use cross-sectional models which instrument for area uninsurance/Medicaid rates, models assessing the effect of entry of urgent care clinics into the market (since these clinics see predominantly insured, less severely injured patients), and triple-difference estimates of the differential effect of Massachusetts' insurance expansion across the change in hospital insurance mix. Results support the theoretical model's conclusions.

The recent national expansion of insurance may mitigate the negative externality on the privately insured, providing a substantial welfare gain to those who do not otherwise benefit from the Affordable Care Act. Given the uncertainty as to the marginal costs of ED care, however, the full welfare implications are unknown.

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FIRM RESPONSE TO LOW-REIMBURSEMENT PATIENTS IN THE MARKET FOR UNSCHEDULED OUTPATIENT CARE

Ari B. Friedman

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FIRM RESPONSE TO LOW-REIMBURSEMENT PATIENTS IN THE MARKET FOR UNSCHEDULED OUTPATIENT CARE

For Erik and Viola, who don't yet mind waiting.

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ABSTRACT

FIRM RESPONSE TO LOW-REIMBURSEMENT PATIENTS IN THE MARKET FOR UNSCHEDULED OUTPATIENT CARE

Ari B. Friedman

Mark V. Pauly

Americans spent 13,400 person-years waiting in emergency departments (EDs) in 2009 alone, a figure that has been increasing at a compounded rate of 3.5A novel census of emergency department wait times in two states (MA, NJ) is used to test these predictions. First, the model's assumption that hospitals are constrained in setting individual wait times based on profitability is supported by cross-sectional regression coefficients: hospitals with 50 percentage point greater uninsurance rates have 26.0 minute longer wait times ($p<.01$; national mean wait time is 58 minutes), whereas conditional on hospital uninsurance rate individuals who are uninsured are not shown to have longer wait times (coefficient of 0.86 minutes, $p=0.13$). Next I use cross-sectional models which instrument for area uninsurance/Medicaid rates, models assessing the effect of entry of urgent care clinics into the market (since these clinics see predominantly insured, less severely injured patients), and triple-difference estimates of the differential effect of Massachusetts' insurance expansion across the change in hospital insurance mix. Results support the theoretical model's conclusions. The recent national expansion of insurance may mitigate the negative externality on the privately insured, providing a substantial welfare gain to those who do not otherwise benefit from the Affordable Care Act. Given the uncertainty as to the marginal costs of ED care, however, the full welfare implications are unknown.

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1.1. Introduction

Emergency Department (ED) crowding–which for the present purposes can be viewed as excess quantity demanded relative to quantity supplied–has increased dramatically since the early 1990's, particularly for non-emergent conditions treatable in other settings. The rise in ED demand is not inherently problematic–when demand increases for iPads, we do not intervene. However, one symptom of this increase has been a 3.5% annual compound growth in wait times (see Figure 1). This is an important problem with substantial welfare consequences both in lost health and time[1]. Suggestively, patients in 2009 collectively spent 7.06 billion minutes (13.4 millennia) waiting to be seen by an ED clinician (Becker and Friedman 2014).

As such, there have been many explanations of increased crowding put forth. All, however, focus on increased demand as the driver of crowding. For instance, researchers have pointed to the decline of primary care in driving more patients to EDs, increased uninsurance (Miller 2011, DeNavas-Walt et al. 2012), and defensive medicine as ex-

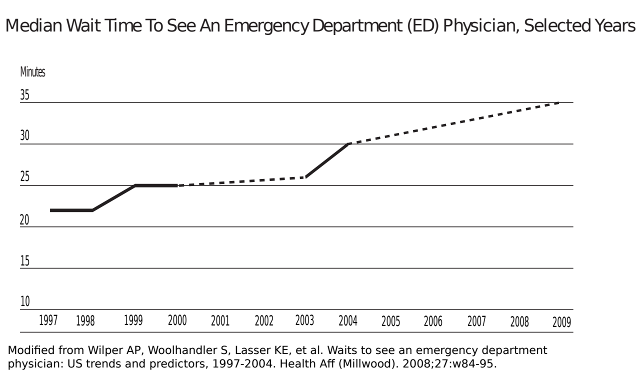


Figure 1: Growth in wait times, 1997-2009

[1]See Section A.4 for an enumeration of these costs.

planations. These explanations are unsatisfactory, however, in that none explain why capacity has not increased to meet increased demand for ED services–returning to the iPad example, both Apple and other competitors raced to expand production of tablets when they proved popular, eliminating temporary shortages. The central question of this thesis, then, is why increased wait times have persisted in response to a shift in long-term demand for ED care.

The persistence of this phenomenon suggests that maintenance of high wait times may be profit-maximizing[2]. Like all questions of profit, the incentive to improve wait times hangs on the balance of how much doing so changes revenues relative to costs. For instance, it could be that it is simply very expensive to maintain the capacity required to handle peak loads, and that wait times serve as the overflow when unpredictable surges in patient flow occur. However, the temporal patterns of patient demand are eminently predictable (Pitts et al. [2012]), which mitigates this concern. Moreover, solutions to efficiently improve thoroughput exist (bed management, fast-track, instant labs, consult priority, and others – Hoot and Aronsky [2008]), yet the problem persists. Furthermore, other firms–namely urgent care clinics, retail clinics, and primary care clinics–profit from seeing the less severely injured patients on an unscheduled basis at $\frac{1}{3}$ to $\frac{1}{5}$ the price . Thus for it to be an issue of cost, it has to be an issue of scope–whether it is substantially less expensive to treat patients in firms that handle only less severe cases versus firms that handle the full spectrum of time-sensitive severities. While this is certainly possible, EDs in affluent suburbs tend to advertise their low wait times, despite their broad scope, suggesting that they find it profitable to see them. Resource input studies also show costs of delivering uncomplicated care in emergency departments that are well below billed

[2]At least for for-profits, and likely for non-profits as well assuming that they are maximizing ED profit in order to fund their altruistic goals (and that outpatient ED care is not amongst them).

prices. Instead, I argue that the marginal patient does not bring in a price greater than the opportunity cost of serving her, leaving hospitals with no incentive to reduce wait times, and possibly even with an incentive to increase them. In other words, quantity supplied ("ED capacity") is endogenous to profitability.

I posit that supply has not expanded to meet demand because of a particular distortion: firms are disallowed from turning away unprofitable patients, which has created an incentive to reduce quality in ways that differentially reduce demand by unprofitable patients. Wait times provide hospitals that have many uninsured outpatients with just such a mechanism, through their ability to reduce outpatient emergency department demand without substantially affecting inpatient emergency department demand.

I will frame the discussion and estimation strategy as follows. Section 1.1.1 describes how emergency department visits exist on a spectrum of *ex ante* severity in patient disease, proxied for by triage scores. Section 1.1.2 then conceptualizes two types of crowding which differentially affect two parts of this spectrum: crowding which impacts high-severity patients, and those that primarily impact low-severity patients. Section 1.1.3 reviews the mechanisms by which hospitals can control their wait times. Section 1.1.4 then posits that unprofitable patients are those who are uninsured and low income, but not admitted to the hospital; by contrast, low income inpatients are frequently profitable for reasons elaborated in that section. This correspondence between different profitabilities and differing types of crowding, combined with the mechanisms to control wait times and the incentive to do so, means that hospitals may be able to discourage unprofitable patients from visiting their ED without much impact on profitable patients. Sections 1.1.4.2 and 1.2 model this effect.

1.1.1. *Unscheduled care as a spectrum of severity*

Many commenters on either the increased rates of ED crowding or increasing health-care costs have viewed the ED as an inappropriate place for care that can be provided in a primary care clinic. Market participants seem to maintain similar views; for instance, insurers have increased copays on ED care, and occasionally even attempted utilization review on the appropriateness of ED visits (Kellermann and Weinick [2012]). Viewed in a market framework, however, the idea of 'inappropriate' care is less straightforward: individuals are simply responding to the incentives they are given. Rather than emphasizing the time-sensitive nature of emergency department care provisioning, then, this thesis will consider the unscheduled nature of such care. In this view, the appropriate/inappropriate dichotomy is replaced with a spectrum of *ex ante*[3] severity which relates to the likely ability of different clinics to treat the patient.

Unscheduled care can be delivered in emergency departments, traditional primary care clinics (PCCs), or new entrants such as urgent care clinics (UCCs) and retail clinics (RCs). Traditionally, a patient with an uncomplicated fracture or similar need would see their regular primary care physician. Such access to acute primary care is increasingly rare (Group [1994]). Yet a return to the traditional model in which low- or moderate-severity time-sensitive care needs are seen by primary care physicians seems unlikely. The forces driving the decline of primary care, from physician preference for predictable schedules to low reimbursement rates for cognitive work[4] to integration

[3] I.e. at the moment the patient decides which provider to seek care or first arrives at the clinic (including triage in EDs), not the severity as assessed after the clinician has exerted diagnostic effort with an eye towards treatment, such as obtaining lab values or a detailed clinical history.

[4] Which according to the target income hypothesis increases the density of patient appointments in a physician's day, contrary to basic economic theory though the hypothesis may be. Instead, income effects are a more promising explanation.

of providers into ever-larger corporations, simply will not allow it.

Into this void have stepped a variety of new entrants: retail clinics (RCs), urgent care clinics (UCCs), and even free-standing emergency departments[5] (FEDs). Because urgent care clinics handle a variety of acuities (unlike retail clinics), making them competitors with EDs for the markets which they cover, and because they are quite numerous (unlike free-standing emergency departments) and growing rapidly (8.6% annual compound growth; see Section 1.3.0.2 for a detailed description of what is known about UCCs), I will utilize UCC entry as a disruption in the market for unscheduled care in order to observe emergency departments' responses.

These entrants promise faster access times and a customer service-oriented model (Mehrotra et al. 2009, Wang et al. 2010, Weinick et al. 2010), which may help improve the delivery of both acute and non-acute (yet unscheduled) care. They also decrease the travel costs of accessing care (Figure 19). In addition, emergency departments are essentially local monopolies or oligopolies, and breaking that market power could not only provide more choice to patients seeking unscheduled care but also force EDs to compete in welfare-improving ways, such as by reducing wait times.

At the same time, these disruptive innovators are almost uniformly for-profit entities with a corporate structure (in contrast to hospitals, which are largely non-profit, and PCPs, who tend to be in for-profit small group practice). To the extent that their corporate structure frees them to rethink traditional practices, and their for-profit status excludes patient welfare from their objective functions[6], these new entrants could unobservably reduce quality. Furthermore, as freestanding entities, these entrants could

[5]FEDs exist in only a few states, most notably Texas.

[6]And, of course, this degree is highly debatable, given evidence that non-profits do not act differently than for-profitsDuggan [2002] and that physicians still retain a large degree of power and professional obligation despite being corporate employees.

undermine the emphasis on care coordination in the PPACA [7].

Whether the negative or positive impact of urgent care entry on emergency departments predominates is an open question and, ultimately, an empirical one–and one to which this thesis will bring data. To understand how urgent care entry impacts ED crowding, however, we must understand how ED crowding affects different customers (Section 1.1.2), how hospitals can control their wait times (Section 1.1.3), and how the interaction of those two factors provides hospitals with a disincentive to reduce wait times (Section 1.1.4).

1.1.2. Different types of crowding impact different parts of the spectrum of unscheduled care

I argue that emergency department crowding is not a single phenomenon, but at least two. For instance, there seems to be a type of crowding that affects only patients who are admitted, as when patients are 'boarded' waiting for an inpatient bed to be made available. Because patients with a high *ex ante* severity (as measured by the triage score) are much more likely to be admitted–"emergent" patients are 6.7 times more likely to be boarded than "semi-urgent" ones–this high-type crowding primarily affects more severe cases[8] (see Table 18).

Similarly, there seems to be a separate type of crowding (measured through wait times) which primarily affects those with low *ex ante* probability of admission, as those given high priority at triage wait substantially less than those deemed non-urgent (see Figure 16). Median wait time for "immediate" triage is 20 minutes, compared to 37 and 35 minutes for "semi-urgent" and "urgent," respectively[9].

[7] Although skepticism as to the true value of such coordination is prudent.

[8] Author's calculations, NHAMCS.

[9] Author's calculations, NHAMCS.

Table 1.1.2 classifies common crowding metrics by their impact on patients of different levels of *ex ante* severity.

ED crowding metric	Primarily affects which *ex ante* severity?	Mode of arrival
Wait time[a]	Low	Walk-in
Left without being seen[b]	Low	Walk-in
Occupancy ratio[c]	All	Ambulance[d] / Walk-in
Boarding[e]	High	Ambulance[d] / Walk-in
Ambulance diversion[f]	High	Ambulance

Table 1.1.2: The relationship between acuities and ED crowding metrics

[a] The time for patients of each acuity level to be seen by a clinician.
[b] The proportion of patients leaving without being seen by a clinician.
[c] The ratio of number of patients in ED to number of staffed beds.
[d] The mechanism here is through an increase in the probability of diversion.
[e] The practice of holding patients in ED beds after the decision to admit has been made, generally because an inpatient bed is not available for an ED admission at that time.
[f] The practice of notifying an area's emergency medical system that ambulances are to be directed to other hospitals, generally triggered by hospital-specific criteria based on boarding or wait times. Diversion is disallowed in some states.

This decoupling of wait times for the more- and less-severe *ex ante* patients is an appropriate and necessary function of the triage system. However, it also gives hospitals the ability to selectively discourage only patients not likely to result in admission. An ED might have hours-long waits for patients with conditions as severe as fractures, while a patient with chest pain and difficulty breathing might face no wait at all. Fig-

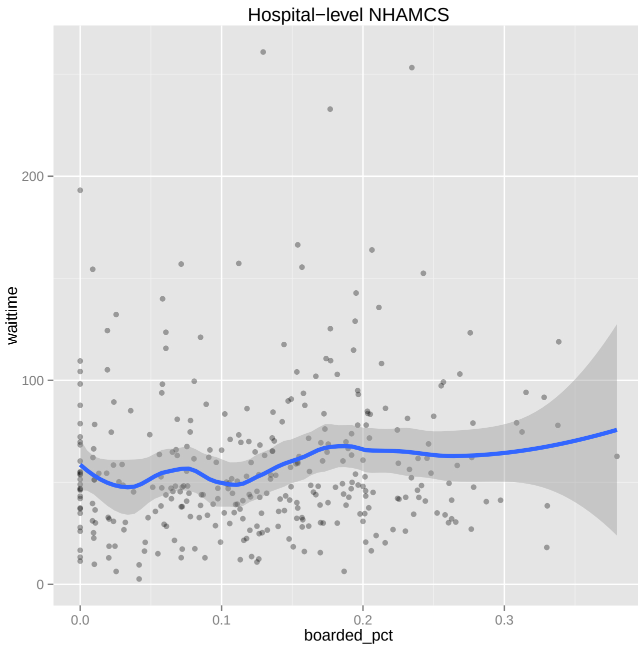


Figure 2: Hospital-level median wait time vs. percent boarded

ures 2 and 15 shows just that: the relationship between ED wait time and boarding is extremely weak[10].

If hospitals have control over these different aspects of wait times–if they are not merely subject to them but can control them through investment in reducing them via fixed- or variable-cost expenditures such as physical plant investment, staffing, and predicting and intervening during periods of high demand–and if patients subject to these two types of crowding are differentially profitable, they could use these two different types of crowding to selectively filter unprofitable patients. In support of this assumption, Pitts et al. [2014] find no association between ED boarding and uninsurance or Medicaid rates, but I find that hospital emergency departments with higher uninsurance rates (but not Medicaid) have longer wait times (Section 3.2.1). Section 1.2 formalizes this argument.

[10]Figure 15 further investigates this relationship.

1.1.3. Hospitals can control their wait times (and potentially do so independently of other aspects of care)

Despite considerable attention having been paid to reducing ED wait times, they have only increased. In the past, the medical literature has spoken as though this is a result of "ED capacity," (Hoot and Aronsky [2008]) but in fact ED capacity is simply a function of fixed (facilities) and variable (labor, supplies) costs. Thus capacity rests firmly within the hospital's control.

This then provides an alternative lens through which to view Figure 2: the underlying incentives to improve wait times versus boarding may be different for different hospitals. The claim that hospitals are 'choosing' their wait times and boarding levels deserves scrutiny. This section will briefly explore hospitals' ability to control their wait times at a reasonable cost, where 'reasonable' here means a cost sufficiently low to make it profitable to reduce wait times substantially were all patients paying the average private insurer rate.

There are challenges to improving wait times for hospitals. Temporally, crowding is not a continuous phenomenon, complicating efforts to match variable-cost resources such as staff time with patient flows and driving up average expense (since fixed cost resources such as physical space must be sized for maximum rather than average capacity). However, the ED census tends to be highly time-dependent (Flottemesch et al. [2007], Pitts et al. [2012]), making staffing needs relatively predictable.

A second challenge is the complex nature of the hospital organization in which emergency departments operate. The health services research and operations management literatures have posited that ED crowding is frequently the result of a lack of availability of inpatient beds for ED admissions[11] (Derlet and Richards [2000]). ED crowding can thus be conceptualized as a hospital-wide flow problem[12]. Consequently, naive solutions to crowding such as increasing ED size are generally ineffective (Han et al. [2007]).

Despite these challenges, it is technically feasible to improve wait times, and hospitals can easily access information on doing so, both through consultants and the academic literature. Many of these process improvements require expenditure of effort and resources to conceive and implement initially, but little or no subsequent expenditure. For instance, New York Presbyterian Hospital implemented a number of initiatives over a six-year period such as reallocating staff hours, providing feedback to staff about performance, and improved coordination with inpatient admitting teams (Green [2007]). There was a concomitant decline in crowding metrics: 13% fewer left without being seen, and an approximately 90% decline in diversion hours.

Other solutions to improve wait times include better inpatient bed management, 'fast track' programs which divert low-priority patients to a dedicated mid-level provider, priority laboratory results, and priority consultations with specialty services.

In summary, various solutions to crowding exist (Hoot and Aronsky [2008]), but their adoption remains low (Rabin et al. [2012]). A lack of incentive for hospitals to reduce ED wait times might explain this phenomenon. Section 1.1.4 will examine those incentives and compare them to the incentives to reduce boarding.

[11]Note that this is complexity which proves the point, as it is under hospital control.

[12]Jesse Pines, personal correspondence

1.1.4. Hospital disincentives to improve wait times

1.1.4.1 More acute patients are more likely to be profitable

The Federal Emergency Medical Treatment and Active Labor Act (EMTALA) prohibits hospitals from simply turning patients away[13]. We might expect, therefore, that hospitals seek an alternative mechanism by which to discourage unprofitable patients from seeking care.

The view that uninsured patients are unprofitable is likely too simplistic. Instead, it is ED visits from the low-income uninsured and Medicaid patients that do not result in admission which are most likely to be unprofitable after variable costs, opportunity costs, and the marginal fixed cost related to increased capacity to routinely treat such patients is taken into account. In 2001, EDs received a mean of $1,104 for a visit from a privately-insured or Medicare patient, $508 for a Medicaid visit, and $792 for a visit by the uninsured[14]. Assuming that the marginal cost of treatment is related primarily to clinical factors rather than insurance status, this implies that there is some cost and visit proportion of uninsured and Medicaid outpatients above which outpatient ED care is profit-reducing. Wilson and Cutler [2014] find that across both inpatient and outpatient care, hospital profit margins for the privately-insured are positive (39.6%) and margins for Medicare (-15.6%), Medicaid (approximately -35%), and the uninsured (-54.4%) were negative.

Inpatient care is less likely to be affected by such concerns. First, because of di-

[13] An explanation which is traditional, but not quite satisfactory, given that most ED crowding is driven by non-life-threatening conditions which EMTALA does not cover. Indeed, at least one major for-profit hospital chain (HCA) has begun aggressively turning away patients who are not in immediate risk of death. For a legal analysis of EMTALA, see Bitterman [1992].

[14] Source: 2011 MEPS ED file, author's calculations using appropriate survey weights. See Appendix, Section A.6 for details.

minished access to primary care and perhaps also due to hospital discretion over admission decisions, uninsured and Medicaid patients likely comprise a much smaller proportion of inpatient stays than they do outpatient stays, even amongst inpatients admitted from the ED. Second, the disparity between revenues from the uninsured and those with private insurance is smaller for inpatient vs. outpatient care (Ho et al. [0], page 14). Third, hospitals have been forced to expand the number of ED beds, whereas they have been contracting the number of inpatient beds (Resources [2008]). Thus if much of the cost of a hospital-based visit of either type is fixed cost, fixed ED costs act more like marginal costs if they increase the probability of having to invest in further capacity expansion, whereas the opposite is true for inpatient stays.

Wilson and Cutler [2014] provide evidence in support of these conclusions:

> ED discharges were markedly less profitable than admissions for patients with Medicaid and private insurance. For Medicare visits, the profit margin for ED discharges was -53.6 percent, compared to an admission profit margin of 18.4 percent. For patients with private insurance, ED discharges were profitable, but less so than hospital admissions. For patients with Medicaid and the uninsured, both ED discharges and admissions were associated with negative profits.

Thus hospitals may attempt to discourage uninsured patients with a low probability of admission from seeking ED care. When combined with the concept of different types of crowding impacting different markets elaborated in Section 1.1.2, it becomes clear that wait times may provide hospitals with just such a mechanism. Indeed, uninsured and lower-income patients face greater wait times, as Figure 20 documents for individual-level effects and Figure 9 for hospital-level effects, with the latter expected to be larger due to factors such as practice style-changes, hospital-wide policy changes, and a strong aversion to differential treatment of patients within a single ED by both patients and providers. Section 1.1.4.2 provides a graphical model of hospital incentives to filter the uninsured, and Section 1.2 more formally models hospital profits as a function of wait time filtering of the uninsured with a low probability of admission.

1.1.4.2 EMTALA as a price ceiling

Consider Figure 3. $D2$ is the total demand for emergency department services from insured customers. Quantity is greater because they are presumed to be more numerous. For simplicity, I assume that the price is the out-of-pocket price, abstracting away the moral hazard effect of insurance. $D1$ is the demand of the uninsured. It is kinked because at prices above $\bar{p}$, a proportion of the customers will find it more advantageous to declare bankruptcy or seek to have the debt written off rather than pay[15]. Thus EMTALA induces what acts somewhat like a price ceiling, in that any price above $\bar{p}$ is not paid by these patients. This mandated distortion has the usual effect of price ceilings: quantity demanded is greater than quantity supplied. In this case, there is too little investment in ED capacity (fixed cost) and staffing (variable cost), resulting in high waits.

There is, however, an additional distortion which this ceiling might introduce. Suppose $\bar{p}$ actually represents a price at which emergency departments lose money supplying care ($MC > MR$). Then $q1$ is below zero. Were uninsured patients the only patients in the market, EDs would simply shut down or rely on more altruistic motives. However, they might still choose to operate if the profits from serving the insured patients made up for the gap. In this environment, however, hospitals have

[15] This is obviously an abstraction of the "true" situation, in which different individuals are likely to have different cutoffs, and therefore the curvature would be continuous rather than sharply kinked.

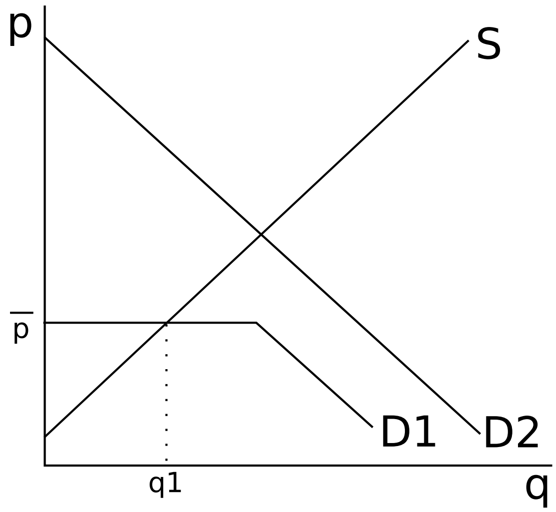


Figure 3:

a strong motive to attempt to dissuade the uninsured from visiting. One potentially potent way to do so might be through increasing wait times above what the 'natural' capacity constraints imposed by the price ceiling demand.

Section 1.2 spins this intuition into a more fully fleshed-out model. In the model, it is not necessary that elasticity of demand of the uninsured with respect to wait times be higher than the insured. Rather the hospital considers its total proportion of uninsured patients, and uses wait times to discourage outpatient emergency department demand when the net outpatient emergency department case mix is unprofitable.

The remainder of this chapter proceeds as follows. Having provided an informal argument that ED wait times are endogenous to hospital profitability and that one consequence of this endogeneity is that hospitals may use wait times to filter unprofitable patients, Section 1.2 provides a formal model.

Section 1.3 gives background and institutional details about the unscheduled care market. Section 1.4 reviews the previous economic work on quality, hospital objective functions, economies of scope, and the miscellaneous economic forays into the unscheduled care market to date.

Section 1.5 continues the arguments begun here and points to the areas of the thesis where each is elaborated and tested.

1.2. Modeling the competitive response of EDs

This section models emergency department response to increased low-reimbursement case mix, assuming that those with higher *ex ante* severity (and thus higher probability of admission, and thus who are less impacted by wait times) are more profitable even if they are uninsured or on Medicaid (see Section 1.1.4.1 for justification). Appendix A.7 lists the variable definitions in a convenient format.

In order for a profitable case mix to cause higher wait times, the model must produce the following prediction:

$$\frac{\partial w^*}{\partial \alpha} > 0 \tag{1.1}$$

Where w^* is the optimized wait time and α is the proportion of uninsured in the market. In other words, hospitals find it profitable to increase wait times as the proportion of uninsured increases.

Assume there are two types of patients along each of two dimensions, denoted by $s = 0$ for those less sick, $s = 1$ for those more sick, $i = 0$ for uninsured/Medicaid, and $i = 1$ for privately insured/Medicare patients. According to the motivation for this model, $s = 0, i = 0$ patients are assumed to cost more to serve than they deliver in revenue to the hospital (e.g. they are unprofitable).

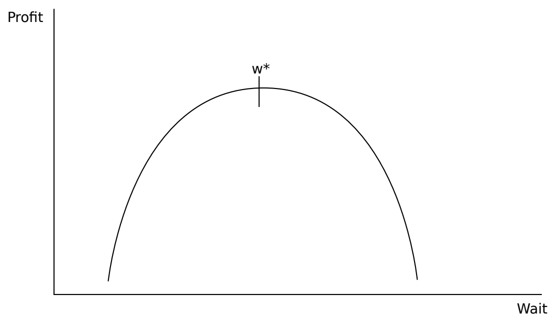
We formalize the assumption that the profitability of unprofitable ED outpatients is increasing in waittime, but decreasing in waittime for profitable ED outpatients as,

$$\frac{\partial \Pi_{s=0,i=0}}{\partial w} > 0 > \frac{\partial \Pi_{s\neq 0,i\neq 0}}{\partial w}$$

and

$$\left|\frac{\partial \Pi_{s=0,i=0}}{\partial w}\right| > \left|\frac{\partial \Pi_{s\neq 0,i\neq 0}}{\partial w}\right|.$$

We posit that for a given insurance rate, the profit-wait time relationship is inverted and approximately U-shaped:



More generally, we require that $\frac{\partial^2 \Pi}{\partial w^2} < 0$.

This, in combination with the earlier assertion that $\frac{\partial w^*}{\partial \alpha} > 0$, the single-crossing theorem implies $\frac{\partial^2 \Pi}{\partial w \partial \alpha} > 0$.

In all of the following, we assume that $\frac{\partial market\, size}{\partial w} = 0$. This is a strong and likely unrealistic assumption.

1.2.1. Per-patient profit

Let $\Pi(s, i)$ denote the profit to the hospital for a patient of type (s, i).

By assumption, uninsured low-severity/outpatient customers are unprofitable, $\Pi(s = 0, i = 0) = \pi_{s=1,i=0} < 0$.

The insured are given constants for these per-patient profitabilities:

$\Pi(s=1,i=1)=\pi_{s=1,i=1}$

$\Pi(s=0,i=1)=\pi_{s=0,i=1}$

Where $\pi_{s=1,i=1} > \pi_{s=0,i=1} \overset{?}{>} \pi_{s=1,i=0}$.

The uninsured high-severity cases are given a distribution of profitabilities which relates to their probability of admission:

$\Pi(s=1,i=0)=\rho\pi_{prf}+(1-\rho)\pi_{charity}>0$

Where π_{prf} is the profit when an uninsured patient is admitted and turns out to be profitable, and $\pi_{charity}$ is when the hospital cannot recoup the cost. ρ is the $Pr(prf|i=0,s=1)$.

This profitability $\Pi(s=1,i=0)$ is positive but small (presumably smaller than $\pi_{s=1,i=1}$), although the model conclusions do not depend on it being so.

Define $\sigma_1 = Pr(s=1|i=1,x=1)$ and let $\frac{\partial\sigma_1}{\partial w}>0$, where $x=1$ if the patient seeks ED care and $x=0$ if they instead utilize their outside option.

Then $1-\sigma_1 = Pr(s=0|i=1,x=1)$.

Similarly,$\sigma_0 = Pr(s=1|i=0,x=1)$ and $\frac{\partial\sigma_0}{\partial w}>0$.

Further assume that $\frac{\partial\sigma_0}{\partial w}<\frac{\partial\sigma_1}{\partial w}$ if insured patients have a better outside option or higher valuation of time relative to other costs.

1.2.2. Total profit

Total profit is then:

$$\Pi(w)=(1-\alpha)\left[\sigma_1(w)\overbrace{\pi_{s=1,i=1}}^{>0,high}+(1-\sigma_1(w))\overbrace{\pi_{s=0,i=1}}^{>0,medium/small}\right]$$

$$+\alpha\left[\sigma_0(w)\overbrace{\pi_{s=1,i=0}}^{>0,small/medium}+(1-\sigma_0(w))\overbrace{\pi_{s=0,i=0}}^{<0}\right]$$

Differentiating with respect to w gives us:

$$\frac{\partial\Pi}{\partial w}=(1-\alpha)\left[\sigma_1^{'}(w)\,\pi_{s=1,i=1}-\sigma_1^{'}(w)\,\pi_{s=0,i=1}\right]$$

$$+\alpha\left[\sigma_0^{'}(w)\,\pi_{s=1,i=0}-\sigma_0^{'}(w)\,\pi_{s=0,i=0}\right]$$

Further differentiating with respect to α yields:

$$\frac{\partial^2\Pi}{\partial\alpha\partial w}=-\left[\sigma_1^{'}(w)\,\pi_{s=1,i=1}-\sigma_1^{'}(w)\,\pi_{s=0,i=1}\right]$$

$$+\left[\sigma_0^{'}(w)\,\pi_{s=1,i=0}-\sigma_0^{'}(w)\,\pi_{s=0,i=0}\right]$$

$$=\overbrace{\sigma_1^{'}}^{>0}(w)\left[\overbrace{\pi_{s=0,i=1}-\pi_{s=1,i=1}}^{<0}\right]$$

$$\underbrace{+\sigma_0^{'}(w)\left[\pi_{s=1,i=0}-\overbrace{\pi_{s=0,i=0}}^{<0}\right]}_{>0}$$

$\implies$ a sufficient condition for $\frac{\partial^2\Pi}{\partial\alpha\partial w}>0\implies\frac{\partial w^*}{\partial\alpha}>0$ is

$$\sigma_0^{'}(w)\left[\pi_{s=1,i=0}-\pi_{s=0,i=0}\right]>\sigma_1^{'}(w)\left[\pi_{s=1,i=1}-\pi_{s=0,i=1}\right]$$

Since $\sigma_1^{'}(w)>\sigma_0^{'}(w)$, sufficient conditions under which the hypothesized effect occurs are:

1. That hospitals experience a sufficiently large loss on $(s=0,i=0)$ types, OR

2. That there is a sufficiently high probability of $(s=1,i=0)$ types being profitable, OR

3. That there is a sufficiently small difference in profitability between $(s=1,i=1)$

and $(s = 0, i = 1)$ types.

This model makes the argument of wait time filtering formal, and helps us understand the dynamics of wait time-based screening and its interaction with area factors such as the percent uninsured in a county or HRR/HSA.

1.2.3. The mechanical effect of volume

Because many of the sources of exogenous variation in emergency department uninsurance visitation rates involve changes in the total volume of patients visiting the hospital, a discussion of the impact of volumes on wait times is warranted. In the short term, increased average volumes should unambiguously increase wait times. In the long run, as hospitals have time to adjust relatively fixed resources (e.g. building more facilities, hiring more staff, investing in better flow management), wait times should weakly increase relative to the baseline (i.e. be equal or greater to the wait times observed immediately before the patient volume increase). Compared to the short-term elevation they should weakly decrease. The rate of adjustment will be determined by the cost of adjusting, the profitability of the case mix, and the elasticity of demand of different patient types with respect to wait times.

1.3. Study setting and institutional details

Americans seek acute care 354 million times per year (Pitts et al. [2010]). The classic model of acute care–in which patients either call their regular PCP for urgent care needs not requiring a hospital, or go to the emergency department (ED) for urgent problems which do–is seen as having "broken down" compared to the (possibly mythical) ideal of the past (on the Future of Emergency Care in the United States Health System [2007]). Indeed, only 42% of all acute care visits in 2010 involved the patient's primary physician, compared to 28% seen in emergency departments and 20% seen by specialists (Pitts et al. [2010]). As early as 1994, 16% of Medicaid patients were told to call 911 or transport themselves to the ED when they called their PCP about an urgent health need (Group 1994), and the number is thought to be substantially higher now. One mechanism for increased PCP referrals to EDs may have been the decline of after-hours care, with nearly 90% of Western European PCPs providing care outside of normal business hours but only 40% of American PCPs doing so (Schoen et al. [2006])[16].

At the same time, acute and even routine primary care which would have have rarely been seen in the ED has become common in that setting, with 28% of all acute care visits now seen in the ED versus only 45% in primary care outpatient offices (Pitts et al. [2010])[17]. This parallel trend has been driven by the combination of the rise of the uninsured (DeNavas-Walt et al. [2012]) and the unintended consequences of the Federal Emergency Medical Treatment and Active Labor Act (EMTALA)'s mandate that EDs stabilize patients regardless of their ability to pay. Crowding, and ensuing increases in wait times, have increased since then, although no data is available to assess whether the law coincided with accelerating problems.

1.3.0.1 Crowding and its impact on ED profitability

A recent study has taken the perspective that crowding is endogenous to profitability, and used hospital data to determine whether hospitals see increased revenues as a result of maintaining crowded EDs relative to their revenues if they maintained the level of (un)crowding that clinicians, patients, and commentators might prescribe (Pines et al. [2011]). The study examines the relationship between boarding (see Section

[16] No citation specifically showing the trend could be found, but anecdotally there has been a sharp decline.

[17] Again, the available data is cross-sectional due to data limitations in early years, but there is considerable anecdotal support for a trend.

1.1.2) and revenues at a single ED using medical record and billings data. It builds a counterfactual using simulated diversion strategies, under which hospitals might improve revenues by reducing boarding selectively. While the study is promising for casting a critical eye towards hospitals as passive observers of ED crowding and for its thorough modeling using detailed microdata, its emphasis is on a different domain. This thesis addresses ED profitability from a perspective which differs in important ways.

First, Pines et al. focus on boarding, which largely affects higher-acuity patients (see Table 1.1.2), for whom sanctions from EMTALA and the court of public opinion are most severe. Furthermore, their hospital stays are more likely are profitable than the outpatient visits of the same patients, as many of the uninsured can be signed up for Medicaid while inpatients. Finally, their demand is likely relatively inelastic with respect to crowding due to the importance of receiving medical care, potentially diminished opportunity costs given that they would likely not be working or engaging in leisure activities anyway[18], and the timing of the delay (due to behavioral issues surrounding the sunk cost fallacy, as boarding happens after the patient has already seen the clinician). The effects of using ED crowding as a filter (as modeled in Section 1.2) to improve profitability may instead be greatest for those seeking time-sensitive primary care and, to a lesser but still substantial degree, those seeking care for urgent health needs (fractures, etc.).

Second, Pines et al. take a simulated counterfactual of a single ED, and look only at revenues. The finding that decreased boarding can increase revenue assumes adopting an optimal strategy. This is equivalent to studying a single firm at the production possibilities frontier–many other firms in the market may not be able to achieve such

[18]On the other hand, they might be more sensitive to the discomfort of waiting in the hospital relative to waiting at home.

results. Indeed, in the two years since the study, the investigated ED did not even adopt the recommended intervention to improve revenues, suggesting either inefficiency or some other overriding constraint not modeled in the study. It is therefore desirable to examine actual firm behavior across many firms. This thesis utilizes data from all hospitals in two states to do so.

1.3.0.2 Urgent care clinics

Clinics calling themselves "urgent care" have existed for decades, but interviews in the lay press indicate that there seems to have been a substantive shift in the number and retail orientation of these clinics in the mid-2000's. For our purposes, it is important to note that urgent care clinics offer little or no unreimbursed care, as they are not subject to EMTALA if they are not operating on the campus a hospital. These clinics also emphasize customer service and speed as a key aspect of their business model.

Acute unscheduled medical care can be delivered in a number of clinical settings. While historically the purview of the primary care office, acute unscheduled care is increasingly delivered in other settings–most frequently the emergency department (Pitts et al. [2010]) but also retail clinics (Mehrotra and Lave [2012]) and urgent care clinics (Weinick et al. [2009b]). This move towards alternative settings for acute care delivery is in part driven by the declining availability of conventional primary care offices (Asplin BR [2005]), but also as a result of patient preference for cost-transparent and convenient patient-centered solutions that do not require advanced planning.

Retail clinics are different in business model and clinical capabilities compared to urgent care clinics: Retail clinics treat a strictly limited set of conditions, are owned by the pharmacies they locate inside, and serve as "loss leaders" to increase pharmacy sales, whereas urgent care clinics treat more severe (but still limited) conditions requiring diagnostics and interventions, are located in a variety of settings, and must be independently profitable to remain in business. Nevertheless, similarities abound: they both utilize nurse practitioners and physician assistants extensively, emphasize rapid walk-in care, are relatively new, and tend to locate in retail (as opposed to medical) settings.

What little is known about urgent care clinics comes primarily from a survey conducted in 2008. Several of the findings of this survey relate to market structure (Weinick et al. [2009a,b]). 33.7% of UCCs had been open fewer than 5 years, which implies an annually-compounded growth rate of 8.6%[19]. 28.6% were hospital-owned or -affiliated. 17.5% were chains. The remaining 54.3% were independent, physician-owned practices. Payment sources of UCC are compared to primary care clinics (PCCs) and EDs in Figure 4, and reinforce the general impression that UCCs lie somewhere between PCCs and EDs.

Other relevant findings of this survey include that there were between 8,000 and 10,000 urgent care clinics in the country, that the typical collection from insurance was $109, similar to that of a primary care clinic (and about $\frac{1}{3} - \frac{1}{5}$ the price of an uncomplicated emergency department visit at the time.

1.4. Previous literature

This analysis has the potential to address theoretical questions in several economic literatures. The question of whether firms utilize high wait times to reduce volume among certain patient types is the inverse of the typical quality competition story, the literature for which is reviewed in Section 1.4.1. Because the questions throughout

[19] Obtained by solving for $\frac{1}{(1+x)^5} = 1 - 0.337$, which makes the assumption that the growth process is neither accellerating nor decelerating.

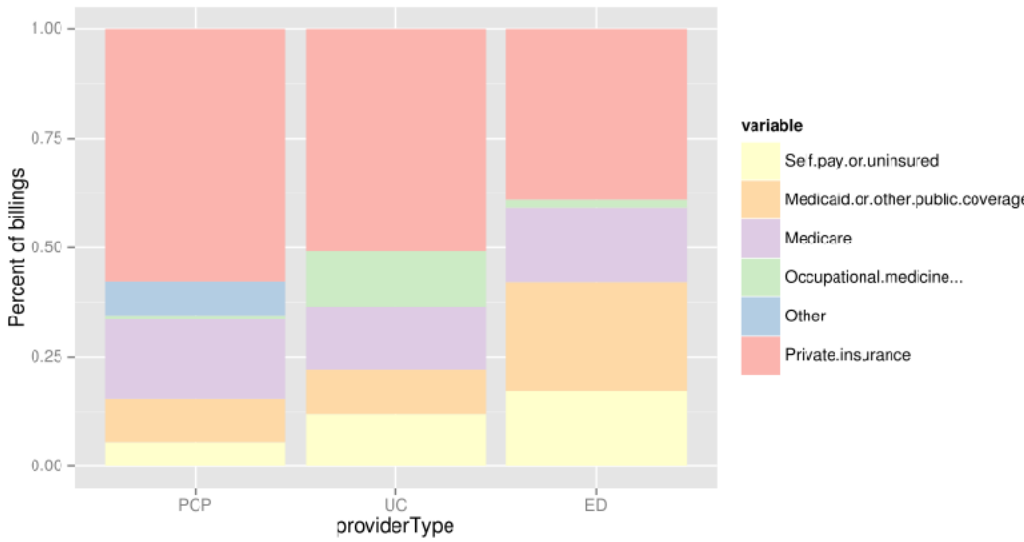


Figure 4: Urgent care payment sources

this thesis all touch directly or indirectly on economies of scope, that literature is reviewed here as well. Finally, this analysis touches on longstanding questions related to what firms of different ownership types optimize–a question associated with two substantial bodies of literature, the behavior of non-profits (reviewed in Section 1.4.4) and the behavior of physicians (reviewed in Section 1.4.5).

1.4.1. Literature on quality competition

Interest in modeling quality competition dates back at least as far as Chamberlain [1931], Abbott [1953], and Dorfman and Steiner [1954]. The latter of these models is the most formalized, most general, and most focused on quality. Dorfman and Steiner's model considers quality to be a product attribute that increases both demand and unit cost, and primarily focus on the firm's decision under certainty.

Spence [1975], in keeping with the times, considers the informational problem that results from market failure. Specifically, they find that product characteristics under monopoly or monopolistic competition will differ from the social optimum because the firm chooses to increase quality if the benefit to the marginal consumer exceeds the cost of increasing quality, whereas the inframarginal consumers' potential valuation from increased costs are not taken into account. Swan [1970], by contrast, shows that market structure has no effect on quality. Schmalensee [1979] surveys the literature and finds that the effect of increased competition on quality is generally ambiguous: on the one hand increased competition brings lower margins per-product, on the other, firms now must compete harder for customers and quality is a potential mechanism to do so. He concludes that, "There is an obvious need for empirical work to confront the implications of the theoretical literature with data." 35 years later, there are still relatively few articles doing just that–testament to the difficulty of studying quality.

More recent models have considered quantity-quality competition as a two-stage game, but find similarly ambiguous predictions depending on the particulars of the game's timing. Motta (Motta [1993]) sets up the game with duopolistic firms choosing quality simultaneously in first stage. The second stage is then Cournot or Bertrand (both situations are analyzed). Motta also considers both what Dorfman and Steiner would deem 'advertising'–where a fixed expenditure results in increased demand–and 'quality'–where a per-unit expenditure results in increased demand. Motta finds that in all models, firms choose distinct quantities at equilibrium. He finds that price competition produces more differentiation in quality than quantity competition under both cost structures. Partly as a result, he finds higher welfare under price than quality competition.

Aoki (1994), by contrast, has firms choose quality sequentially in first stage, resulting in a split quality choice (the first-mover chooses higher quality; the responding firm lower). In a later paper, Aoki and Prusa [1997] examine the implications of this difference: for at least the model studied, simultaneous choice yields higher quality and welfare than sequential choice.

Chaudhuri [2000] has firms choose sequentially in both stages, with the higher-quality firm moving first. He finds that quality strictly declines relative to the models of both Aoki and Motta.

Chioveanu [2010] has firms choose price and quality simultaneously in an oligopolistic setting, with heterogeneous consumer preferences for price and quality, then considers the impact of governmental intervention. She finds that, while minimum quality regulation improves quality in this model, welfare reduction results. This finding of increased quality from regulation adds to the general literature on the topic, with similar findings (reviewed in Krishna [1989])–even when what is regulated is not quality directly but quantity, when the firms facing quantity restrictions are of lower quality (typically the setting these authors had in mind was American automobile tarrifs), quality improves. One exception is Chaudhuri's model, which under its relatively narrow assumptions finds quantity regulation harming quality.

To the best of my knowledge, no paper models regulation of price and predicts the effect on quality. This is the closest analogue to the situation documented in this thesis, and might well prove the exception to the general trend of regulation acting to improve quality in two-stage games.

Furthermore, there may be more than one type of quality. In the healthcare market, demand tends to respond more to perceived quality–which in turn hinges on easily-observable factors such as clinician likeability and facility amenities–than to clinical factors such as adherence to clinical guidelines or surgical morbidity and mortality. Predictions about how firms shift between the two types of quality depend on the cost of investment in each and the elasticity of demand with respect to each. However, given reasonable assumptions about both, it is not much of a stretch to say that in the face of increased competition, *unobservable quality will weakly decrease and that the effect on observable quality is ambiguous.*

Dranove and Satterthwaite model a related problem relevant to a time when greater price transparency was being considered (Dranove and Satterthwaite [1992]). To answer that question, they model a Bayesian consumer for whom price and quality are both imperfectly observable. Given an increase in price transparency, they find conditions under which quality supplied might decline, even though its observability was not exogenously altered. This model supports the stylized assertion above that the affect of competition on imperfectly-observed quality is ambiguous.

While individual models make strong predictions about change in quality as a result of increased competition, changing relatively small assumptions seems to reverse those predictions. Thus it is difficult not to conclude that, despite the passage of more than three decades, Schmalensee's admonition to turn to the data holds. This thesis will consider wait times as a proxy for observable quality, with Section 3.2 also using ambulatory care-sensitive conditions as a measure of unobservable quality.

As we might expect given that the predictions of theoretical models are highly dependent on the technical assumptions made, empirical results on the effects of quality competition are inconsistent. The study of any particular industry thus hinges on the particulars, but some generalizations can be made. In dozens of studies across a wide variety of firms and industries, there is considerable heterogeneity in the link between quality and profitability (Zeithaml [2000]). In a seminal paper, Matsa [2011] develops a quantitative measure of quality (proportion of stock-outs in grocery stores) and uses Walmart's geographically contiguous expansion for identification. He finds that increased competition yields increased quality.

Investment in quality is typically expensive (Griliches [1971]), particularly for "highly-customized, big-ticket service" industries (Rust et al. [1995]) such as healthcare. For investment in quality to be profitable, then, it must result in an increase in revenue weakly greater than the cost incurred. The revenue gain from higher quality can come from attracting new customers or from improving retention rates ("repeat customers") (Rust et al. [1995]). In the literature on service industries, repeat customers are assumed to be more valuable since selling costs are substantially lower (Peters [1988]). It is unclear whether this assumption holds in the context of EDs, however, given the distortion which EMTALA induces. The pejorative term "frequent fliers" suggests that repeat customers to the ED may not, in fact, be profitable.

It is this very distortion which gives rise to the central prediction of this thesis: hospitals will use wait times as a filter to screen unprofitable patients to the extent possible. EDs in areas of high uninsurance and low income might thus be expected to have high wait times, and those in areas of low uninsurance and high incomes should have low wait times. Similarly, EDs in areas with many unprofitable patients will not respond to increased competition by increasing patient-observable quality (reducing wait times), whereas those in areas with profitable patients will respond aggressively.

Finally, we consider the question of the interaction of quality investment with the non-profit objective functions discussed in Section 1.4.4. We can predict that for-profit EDs minimize unobservable quality[20], but we cannot sign their investment in observable quality. By contrast, depending on the objectives of non-profit EDs, they may or may not decrease investment in unobservable quality as competition increases. In extreme cases, they may even increase investment in quality if they perceive that

[20] Although the change therein with increased competition could be zero if they are already optimizing. Also note again that there are external constraints such as physician behavior on their ability to minimize unobservable quality.

a greater proportion of their regional market is being harmed by poor quality of the new competition and they have area welfare in mind.

1.4.2. Existing work on the economics of the unscheduled care market

1.4.2.1 Emergency departments

Most of the existing work on the economics of the unscheduled care market has tried to understand whether insurance increases or decreases emergency department utilization. The theory that insurance should decrease ED utilization rests on two pillars. The first is that uninsured patients do not pay the full cost of their care. EMTALA acts as a binding constraint on hospitals, preventing them from turning patients away, resulting in what might be termed involuntary charity care being delivered in the emergency department. The second is that patients may prefer to receive primary care from a primary care provider (substitution), or that regular primary care may prevent emergency visits. Miller [2011] compares ED visit trends in counties experiencing large declines in uninsurance as a result of the Massachusetts insurance expansion to those experiencing small declines, and finds that the expansion reduced ED usage by 8%. The contrasting argument that insurance should increase ED utilization is that moral hazard (Pauly [1968]) will increase all healthcare utilization. In contrast with the quasi-experimental design of Miller's study, Taubman et al. [2014] exploit the Oregon Medicaid expansion lottery as an instrument and show that receipt of insurance increased the probability of ED utilization by almost 40%.

1.4.2.2 Retail clinics

Parente and Town use claims data with individual fixed effects and a matched cohort of non-retail clinic users to show that those who use retail clinics decrease their utilization in other settings without an apparent decrease in quality (Parente and Town [2009]). Ashwood et al. [2011] find the opposite, however. Both papers focus on retail clinic quality; neither is designed to address the question of quality competition with other firm types in the unscheduled care market.

1.4.3. Economies of scale and scope

The classic model of economies of scope (Panzar and Willig [1981], Baumol et al. [1988]) defined the ray economy of scale and focuses on the complementarities in cost that result when a firm produces in more than one market. A substantial body of literature exists examining the economies of scope in hospitals (e.g. Grannemann et al. [1986], Fournier and Mitchell [1992]) and health insurers (e.g. Given [1996]). The hospital-specific literature derives from the supply-side economy of scope literature, and thus has primarily utilized firm-specific cost information. Early work made relatively strong assumptions about cost functions such as the trans-log, which more recent work has relaxed.

In general, these studies examine whole-hospital scope in that they are not examining whether the several different markets serviced by a single emergency department[21] might be more efficiently delivered by several smaller firms instead (i.e. retail clinics for non-severe unscheduled needs, primary care for moderate severity scheduled needs, urgent care clinics for moderate severity unscheduled needs, and emergency departments for severe unscheduled needs). For instance, Grannemann et al. [1986] considered the number of emergency department visits and other outpatient department visits using hospital cost data and data on the total number of visits to each hospitals' emergency department, and found substantial economies of scale for emergency department care but not for other outpatient departments. They also found

[21] See Section 1.1.1 for a description of these markets as distinct along a spectrum of acuity.

diseconomies of scope between emergency departments and inpatient care and no economies or diseconomies of scope between EDs and other outpatient departments (marginal cost of an ED visit was \$121, \$124, and \$125 for high, middle, and low volume outpatient departments at the same hospital). The estimate is difficult to interpret, however. Since that study, emergency care has transformed into its own specialty, with its own training and its own department at most hospitals. Furthermore, the relevant scope question is still likely within-ED rather than between ED and other outpatient departments, although if the myth of the primary care provider who squeezed in urgent cases with aplomb reflected reality then a substantial part of a typical outpatient office might well be equivalent to today's urgent care.

To properly assess economies of scope within the unscheduled care market, we would need cost data on the outpatient narrow-scope competitors which collectively comprise a disaggregated emergency department, as well as emergency departments, plus detailed clinical data to ensure that visit acuity was comparable. This, regrettably, is not to be.

1.4.4. Non-profit and for-profit hospital behavior

Whereas the objective function of for-profit firms has long been relatively settled–they maximize profit[22]–the question of what non-profit firms optimize remains less clear. The key differentiator of a non-profit from a for-profit firm is that the non-profit is unable to return its residual income to shareholders or owners, and must either reinvest these "profits" back into the firm, invest them for future expenditures (endowments) or spend them on a social mission or staff salaries.

Within this requirement there is broad scope for different behaviors. Consequently,

[22]Although controversy exists as to whether managers are able to exploit their position to also maximize their own well-being, a principal-agent model.

numerous theoretical models both contradictory and mutually compatible (reviewed in Section 1.4.4) have been developed (Newhouse [1970], Pauly and Redisch [1973], Norton and Staiger [1994], Hirth [1999] *inter alios*)[23]. Because the theoretical models do not point in a clear direction, empirical study is necessary to determine which of the various theoretical models most closely reflects common non-profit objective functions (Duggan [2002]). This literature largely concerns itself with whether firms seek to limit the proportion of low-reimbursement patients through various means, and whether the effect differs by ownership status.

This empirical work has occurred in the context of non-profit hospitals (85% of hospitals are non-profit institutions - Ginsburg [2003]). However, outpatient clinics and small practices may have entirely different objective functions than large, corporate entities. Indeed, the demand inducement literature (reviewed in Section 1.4.5) takes as its baseline perfect patient agency, despite physician practices being typically organized as for-profit partnerships.

Little has been written about emergency departments *per se*. However, the majority of ED closures and openings are due to closure or opening of an entire hospital (Hsia et al. [2011]).

Empirical study is necessary to determine which of the various theoretical models most closely reflects common non-profit objective functions (Duggan [2002]). Duggan examines the behavior of non-profit, for-profit, and government hospitals after a lump-sum transfer and finds no change in non-profit charitable behavior. By contrast, Bayindir [2012] utilizes the Nationwide Inpatient Sample (NIS) to demonstrate that for-profits are less likely to provide expensive procedures to the uninsured to a greater

[23]Hospitals were the primary example of non-profit firms in this literature, and health economics led the development of the various theories of the non-profit Newhouse [1970], Pauly and Redisch [1973].

degree than non-profits.

Norton and Staiger [1994] find that location is a critical mediator of hospital behavior. After instrumenting using (led and lagged) population characteristics as well as a multinomial logit model predicting the probability of a hospital being of a given type, they show that non-profits and for-profits see the same volume of uninsured patients relative to the number of such patients in the area, but that for-profits are less likely to be located in such areas.

Chakravarty et al. [2005] demonstrate one reason why: for-profits move away more readily in response to adverse demand shocks. They demonstrate higher rates of entry and exit for for-profit hospitals, and use an ordered probit model to show that these differences are in response to changes in localized demand. Intriguingly, they find that chain membership for for-profits decreases the probability of exit in response to decreased demand, perhaps because the larger firm strategically covers the space for entry deterrence. This is consistent with the model of Lakdawalla and Philipson [2006], who allow both objectives and costs of capital to differ between firm types. A central prediction of their model is that, because they have non-pecuniary objectives, non-profits are more likely to remain in a market after it has become unprofitable even accounting for their additional revenue (donations) and lower costs (tax breaks).

Having chosen a location, hospital profitability can be modified by more than just the volume of charity care provided. For instance, Horwitz and Nichols [2009] find that for-profits selectively cut unprofitable service lines. Given that psychiatric services are prominent among these service lines (Horwitz [2005]), this may generate negative externalities. Dafny finds that for-profits up-code towards highly reimbursing DRGs to a greater degree than non-profits (Dafny [2005]). Urban non-profits are also more likely to do so than rural non-profits (Horwitz and Nichols [2011]).

The question of what non-profits optimize has far-reaching implications. A better theory of non-profits–or simply knowing which of the existing theories best describes non-profit behavior in which domains–would prove invaluable in predicting counterfactuals following mergers or policy impacts such as Accountable Care Organization-driven consolidation.

Beyond prediction, however, the theoretical implications are significant. Take the example of "cost-shifting"–the theory that public insurance uses its market and fiat power to under-pay for services, whereas private insurance is forced to over-pay as a direct consequence (Morrisey [1996]). In order for cost shifting to occur, firms must have market power (such that they are able to discriminate), and they must not have already been using this market power to its fullest extent[24] (Frakt [2011]). This latter condition implies that cost-shifting is primarily a concern for hospitals maximizing something other than pure profit. Friesner and Rosenman [2002] analyze the situation of "prestige" (non-profits optimizing quantity subject to a bankruptcy constraint Newhouse [1970]) and find that such a utility function could either lead to cost-shifting or the exact opposite effect. Knowing the true extent of cost-shifting would affect assessments of the welfare implications of public insurance, and would alter prominent estimates of the impact of creating a public insurance plan to compete with private plans (e.g. Schoen et al. [2008]) and that failed proposal's replacement, the Multiple State Plan currently being implemented by the federal government. A better estimate of cost-shifting would also inform the most fundamental debates about competition in the market for unscheduled care, as Medicaid is often claimed to induce cost-shifting despite a complete lack of evidence either for or against the assertion.

[24] Although the opposite effect (low public rates driving low private rates) can occur seemingly in the absense of such conditions, e.g. in White [2013].

Thus non-profit hospitals can act like for-profit hospitals (Duggan [2002]), and for-profit partnerships can behave altruistically (Dranove 1988). The longstanding question of what non-profits maximize may thus be considered as having another dimension: size. This brings out new questions in the context of the medical system related to horizontal integration and physician behavior. For instance, whether chains of physician practices are more likely to selectively discourage visits by low-reimbursement patients than individual practices.

This thesis takes as its object of study the unscheduled care market, consisting of some aspects of primary care clinics and emergency departments at the extremes, and in between retail clinics and urgent care clinics (described in Section 1.3). In the context of this episodic care market (i.e. without the fabled longitudinal relationship with a primary care provider), firms may be more constrained, because they lack the trust that comes with an ongoing relationship, or less constrained, because of the same ability to ignore a person with whom one does not have a relationship that underlies the under-valuation of "statistical lives" relative to observed lives[25].

Finally, the emphasis on the unscheduled care market brings new light to the original objective function dilemma, that of non-profit hospitals. I identify a specific phenomenon (emergency department wait times) that may be the distortion resulting from a specific constraint (the inability to turn way uninsured patients).

1.4.5. Objective function of individual clinics

While the question of what non-profits optimize has centered around hospitals, for free-standing outpatient clinics the questions are somewhat different, because virtually all were historically structured as partnerships of a small number of individual

[25] Witness the disparity between public funding of Provenge vs. vaccination campaigns.

physicians. Even now, the majority remain partnerships, although they are merging with and into larger firms and hospital systems at an increasing rate. They are thus for-profit entities, but run by a small number of individuals with various professional obligations that may cause them to forgo profit in certain circumstances (this assumption is inherent in the various supplier-induced demand models in which physicians trade off the internal cost of deviating from what they believe to be the ideal treatment option in order to induce the desired profit level, although in practice physician altruism may be limited - Gruber and Owings [1994]).

The major consideration of the objective function of outpatient clinics has come from the demand inducement literature. Demand inducement is the concept that physicians can create demand for their own services by making recommendations that are different than what they would have been were they not profiting from the additional service provided . In essence, it is a statement about the objective function of the handful of physician worker-owners who comprise the typical outpatient clinic. The platonic ideal is a firm whose decisions are made as a perfect agent–they take only the patient's interest into account. The "inducement," then, is the introduction of the firm's profit into the objective function at all. This conceptualization of the for-profit practice contrasts with that of the non-profit hospital, where the dual objective functions include both profit and some variety of social welfare, although the weighting between them must be empirically determined.

Initially, demand inducement was considered to be costless (Evans 1974, Fuchs 1978)[26]. Later models incorporated a cost in various ways. Pauly (1980) considers the patients to be Bayesians updating their priors as to whether the physician agent is acting in

[26]A criticism of this model is that it implicitly requires physicians to not be profit maximizers (Dranove 1988); yet if they are not maximizing profit, they are presumably doing so for altruistic reasons, which implies a cost to choosing care not in the patient's best interest.

their own best interests. The cost is therefore borne in the form of reduced demand for future services. Further review of the theoretical models is provided in Dranove [1988].

1.5. Outline

In Chapter 2, I test the theoretical model developed in Section 1.2, which predicts that hospital emergency departments will increase their wait times in response to increasing proportions of low-reimbursement insurance patients among low-severity visits, but that wait times will decrease in response to lower patient volumes. This chapter utilizes the AHRQ HCUP State Emergency Department Databases to test the theory. Cross-sectionally, hospitals with higher levels of uninsurance have substantially greater wait times. To better assess causality, I utilize three approaches: hospital fixed effects, using the area uninsurance rate as an instrument for the hospital's uninsurance rate, and difference-in-difference across the Massachusetts health reform. The first two approaches demonstrate significant and substantial increases in wait times due to higher uninsurance rates. The latter approach does not, possibly due to simultaneous reforms and mandates surrounding emergency department crowding.

Urgent care clinics might also serve as a semi-exogenous disruptor of the emergency department *status quo*. To utilize the clinics in service of studying the impact of the uninsured on emergency department wait times in Chapter 3, I first provide evidence that urgent care clinics pull substantial patient volume from emergency departments, but that this effect does not change the proportion uninsured in nearby EDs, using data from two large, non-profit emergency departments in northern Delaware. To causally attribute the effects to the clinic entry, I utilize Census block fixed effects, cluster by Census tract, and identify off of the change in distance to the nearest clinic when a clinic enters. I find large decreases in the volume of visits from the less severe patients (5.6% decline in emergency department visits per clinic which enters), but no evidence that the for-profit competitors are selectively taking Medicare and private insurance patients over Medicaid and the uninsured. I then use similar regressions to those in Chapter 2 to examine the model's prediction for situations where there is no change in reimbursement mix that there should be no change in wait times, and find that, indeed, the changes in wait times are minimal.

This project will contribute to the existing literature in four ways. First, to the extent that wait times are a form of quality, it adds to the very limited econometric literature on quality competition, a domain with theoretical roots dating back to Abbott and Dorfman-Steiner (Abbott [1953], Dorfman and Steiner [1954]) but with limited empirical evidence (Matsa [2011]).

Second, it helps answer the policy question of whether urgent care clinics should be regulated or instead encouraged. States have enacted numerous regulations with differentially impact UCCs (see Section A.3). Were urgent care clinics shown to have positive spillover effects on emergency departments such as reduced crowding, the rationale for these laws might evaporate. Conversely, these entrants might break the cross-subsidization of care for the uninsured that existed in the *status quo* before the ACA. The resultant loss to a portion of the population must then be balanced against the increased access to unscheduled care and potentially lower marginal costs of treatment that UCCs provide. Additionally, costly policies to induce primary care clinics to provide more unscheduled care to their patients, such as the 'medical home' concept have been adopted. Findings in support of urgent care clinics having neutral or positive effects on EDs, such as those in Chapter 3, then make them a prime alternative solution to such PCC-centric policies.

Third, it brings empirical analysis of the various theories of how objective functions vary by ownership structure to the outpatient setting, where they have not been studied to date.

Finally, this project will help understand fundamental aspects of current, historical, and future hospital behavior with respect to capacity and wait times. By using urgent care entry and insurance expansion to study emergency department behavior, we may be able to quantify the welfare spillover that occurs when wait times are used as a filter to discourage unprofitable patients. Proposals to disincentivize this behavior can then be assessed. For instance, Disproportionate Share (DSH) payments are made to hospitals on a fairly discrete basis. Their replacement in the PPACA by insurance expansions (which for Medicaid might not mean additional revenues but for exchange plans will) should mean potentially greater profitability as a continuous function of the number of patients in the ED means that hospitals may face less of a disincentive to discourage uninsured patients from seeking care. Similarly, the addition of emergency departments to the Federally Qualified Health Center program–legitimizing unscheduled care as a valid consumer choice amongst many–might prove welfare-improving despite the additional fiscal cost if it reduced wait times as well. HHS might also add wait times to its Hospital Value-Based Purchasing initiative as a quality metric.

CHAPTER 2 : Emergency department uninsurance as a determinant of wait times

2.1. Introduction

This chapter investigates the claim at the heart of this thesis, that emergency departments–the largest of the unscheduled care firms–respond to higher proportions of low-reimbursement outpatients in the context of constraints against turning away patients or increasing price by decreasing patient-observable quality.

As the law which prevents EDs from turning away patients was put into place in 1986, I cannot observe changes in hospital behavior before and after its implementation. Instead, I will utilize three different sources of exogenous variation in the rates of uninsurance. The first, instrumenting for the emergency department's uninsurance rate with the area uninsurance rate (Section 2.4), is a relatively pure test of the theoretical model outlined in Section 1.2 in that it isolates the proportion of uninsured patients in the absence of large changes in the overall volume of patients in the emergency department (due to moral hazard, the uninsured visit emergency departments weakly less than the insured of all kinds). The remaining two sources of exogenous variation both induce large volume changes.

One of these models exploits the change in wait times across Massachusetts' health reform (Section **??**). This reform ocurred in a non-representative setting and had diverse effects, including occurring during a period where emergency department crowding was being specifically addressed by various mandates. For instance, ambulance diversion was banned in 2009, with a six-month phase-in period beginning in 2008. Nevertheless, the insurance expansion was a substantial component of reform.

Reform in Massachusetts appears to have decreased emergency department volumes (Miller [2011]), complicating interpretation of the minimal observed changes in wait times.

The final set of models analyze how hospitals change their wait times in response to increased market pressure resulting from entry of urgent care clinics (UCCs)–clinics which specialize in unscheduled care for the less severe cases. Because so little is known about the effects of urgent care clinics, they are modeled in their own chapter, Chapter 3.1.

2.2. Data sources

2.2.1. Clinic location data

2.2.1.1 Emergency departments

ED location data came from the American Hospital Association database (EDs) and was geocoded using a custom script utilizing the Bing Maps or Google Maps application programming interface[1].

2.2.1.2 Urgent care clinics

The Urgent Care Association of America (UCAOA) agreed to provide counts of the number of addresses on their mailing list in each ZIP code in 2012 (see Figure 5). These addresses are mailing list addresses, but the list began from a systematic survey conducted in 2008 (Weinick et al. [2009a]), at which point all met the UCAOA's definition of an urgent care clinic laid out in Section A.2. Subsequent additions were added according to the UCAOA's membership expansion rather than systematically.

[1]Available at https://github.com/gsk3/taRifx.geo.

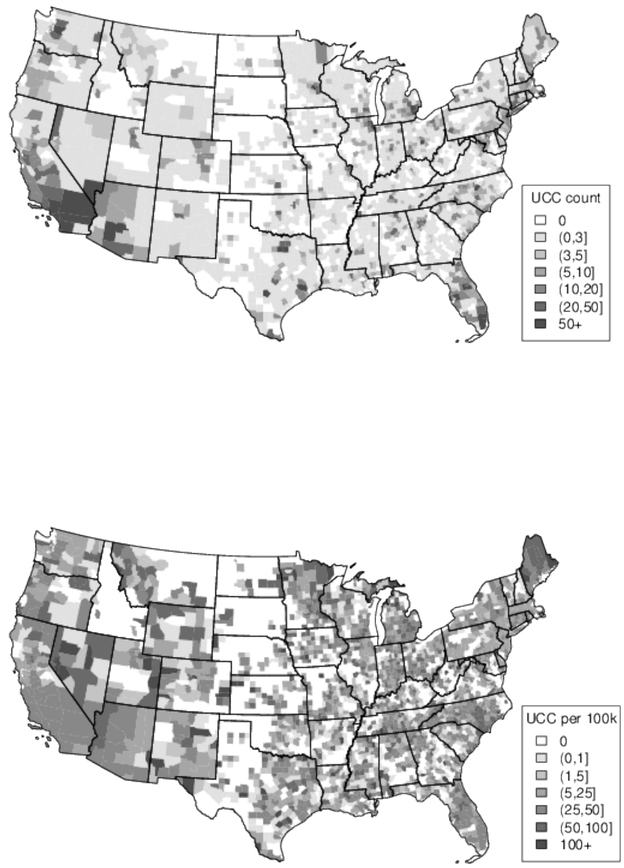


Figure 5: Urgent care clinics, count and per capita count by county

2.2.1.3 Historical UCC data strategy

The Urgent Care Association of America provided UCC data for the handful of other studies of UCCs in the literature. However, that data is not available for years prior to 2012. Because of the rapid growth rate amongst urgent care clinics (1/3 opened in the past 5 years - Weinick et al. [2009b]), I assume that all regions had 0 clinics in 2005, interpolate linearly, and address the resulting measurement error statistically.

2.2.1.4 Change-of-support problem

Where data comes from different areal units that do not nest entirely within each other, there is no perfect method to align the data. Since Census blocks and tracts are designed to nest within counties, this problem arises in the data for this project when utilizing data at the ZIP code level, as with the UCC location data.

The proper solution to this problem is to propagate the uncertainty that results through the entire statistical model. The models which do this are Bayesian and not particularly tractable for large problems (Banerjee et al. [2003]). Instead, I apportioned results according to the proportion of each ZIP code's area lying within each county (see Figure 6 for an illustration of this process, and Figure 5 for the interpolated result)[2].

2.2.2. Area health system factors

The Area Resource File supplied county covariates on provider density and population insurance rates.

[2] Doing this at high resolution took approximately twenty days of computing time, but it only needs to be run once for each variable for the entire project.

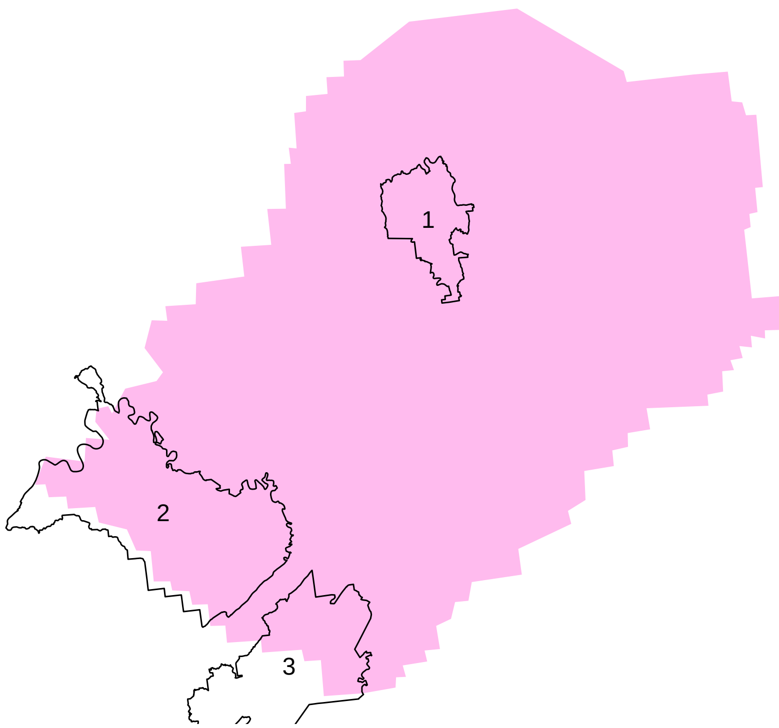


Figure 6: Change-of-support problem interpolation strategy. ZIP 1 nests entirely within one county; ZIPs 2 and 3 do not. Clinics within ZIPs 2 and 3 are apportioned between counties in proportion to the fraction of their area contained in each county.

2.2.3. Population data

All population data not in the ARF was obtained from the U.S. Census. Data used is at the smallest available level of aggregation for which data is available.

2.2.4. Waittimes and clinical emergency department data

2.2.4.1 State Emergency Department Database

The State Emergency Department Database (SEDD) of the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project (AHRQ HCUP) provides data on measurements of emergency department competitive responses. The SEDD contains a census of patient records from the majority of EDs in each state (see Table 16 for completeness data). Fifteen states in the SEDD contain AHA database identification numbers (see Table 15), allowing each emergency department to be individually identified and geocoded. Most of these are available from 2005-2010, with 2011 pending release (see Table 17).

This dissertation utilizes 2005-2011 Massachusetts and New Jersey data from the SEDD, with MA data available approximately every other year due to its expense.

Variables of interest for EDs include metrics of patient-observable quality such as crowding (measured through wait times, diversion hours, boarding, numbers of patients who left-without-being-seen, and occupancy rate[3]), proxies for unobservable quality in the area's providers (e.g. Ambulatory Care Sensitive Conditions), and patient volumes for different submarkets within the unscheduled care market (number of TSPC, UC, and EC seen). Of these, the latter two (volumes and ACSCs) are available directly in the SEDD. Duration data (total time spent in ED by each patient) is

[3]The ratio of the number of ED patients to the number of ED treatment "bays"McCarthy et al. [2008] or ED physicians.

also available in the SEDD, and is used to impute wait times as described in Section 2.2.4.4.

2.2.4.2 National Hospital Ambulatory Medical Care Survey

The National Hospital Ambulatory Medical Care Survey (NHAMCS) is an annual, nationally-representative sample of ED visits in the U.S. To produce the NHAMCS, the Centers for Disease Control and Prevention's National Center for Health Statistics first samples 350 EDs. Each of these EDs are then contacted by subcontracted Census Bureau employees to randomly sample and abstract 100 patient records from a random month. Response rates are approximately 90%.

In addition to a variety of abstracted clinical data, the NHAMCS has collected data on wait times since 1997.

2.2.4.3 Emergency department competitive response data

The SEDD does not natively contain wait times, but does contain a variable measuring the total time spent in the emergency department. This measurement of the total ED time can be decomposed into,

$$TotalTime = TriageTime + WaitTime + ClinicianTime + DispositionTime$$

, where $TriageTime$ is the time from the door to completion of triage, $WaitTime$ is the time from completion of triage to being seen by a clinician (physician or NP/PA), $ClinicianTime$ is the time from when the patient is first seen by the clinician to when the clinician gives the order to either admit or discharge the patient, and $DispositionTime$ is the time from when that decision is made to when the patient leaves the ED by foot or gurney. Because $TriageTime$, $ClinicianTime$, and $DispositionTime$ all should be strongly correlated within a severity type (and less correlated with ED crowding than $WaitTime$), using $TotalTime$–while controlling for each case's severity through the inclusion of the large number of case variables available through the SEDD–should correlate strongly with the true variable of interest.

2.2.4.4 A strategy to correct wait time data from the SEDD

The NHAMCS measures wait times. Because the NHAMCS public use files do not contain geographic identifiers for each ED, it has only been used thus far to study aggregate patterns of wait time relationships (Pitts et al. [2012]). I use relationship between wait times and overall duration in the NHAMCS (adjusted for detailed clinical, demographic, temporal, and health system covariates as described in Table 1) to predict wait times from duration data in the SEDD. While this still estimates only the mean relationship and leaves considerable room for the three other components to be unobservably correlated with market structure, it should go a long way towards reducing bias.

Table 1 shows 10 variables in common between NHAMCS and SEDD, comprising 543 variable levels after diagnosis codes appearing fewer than 50 times were excluded[4].

[4] There may exist as many as 63 variables (representing 1,709 dichotomized levels when categorical variables are 'dummied out') which have consistent definitions between the SEDD and NHAMCS, including the total duration of the visit. Some (e.g. uninsurance) were omitted out of concern that including them in the prediction equation would invalidate their explanatory ability in the main analysis. Others (typically hospital characteristics) were omitted because another dataset would need to be purchased and the explanatory power they might add was not thought to be sufficient to justify the expense.

Characteristics	Variable	Number of levels
Patient	Gender	2
	Age	(Continuous)
Hospital	Region of the country	4
Disease	Diagnosis (ICD-9-CM)	521
	Admitted to hospital	2
Time	Time of arrival (hour:minute)	(Continuous)
	Month of arrival	12
	Year of arrival	(Continuous)
	Weekend arrival	2
	Total ED length-of-stay	(Continuous)

Table 1: Variables used in NHAMCS-SEDD imputation

These variables were regressed on the individual visit's wait time in the NHAMCS in a linear regression model. The model's R^2 was 0.21; by comparison, a 23-question evaluation of average wait times at various times of day by trained observers in a narrowly-defined set of institutions (Weiss et al. [2004]) yielded an R^2 of 0.49 compared to measured data. Using that relationship, I predicted each visit's wait time, and plotted predicted waittimes vs. individual (Figure 7) and median hospital measured wait times (Figure 8), using a 10% holdout sample.

The concave relationship in Figure 8 is clearly non-linear, suggesting that linear regression may not be sufficiently flexible for optimal prediction. However, highly non-linear supervised machine learning techniques such as the random forest model (Breiman [2001]) and the Multivariate Adaptive Regression Splines algorithm (Friedman [1991]) failed to substantially improve prediction accuracy. Furthermore, variable selection/regularization methods such as Lasso/Ridge regression (Tibshirani [1996]) failed to reach convergence.

Overall, the prediction accuracy seems sufficient; any measurement error resulting from the imputation will be handled by the regression models in the analysis phase.

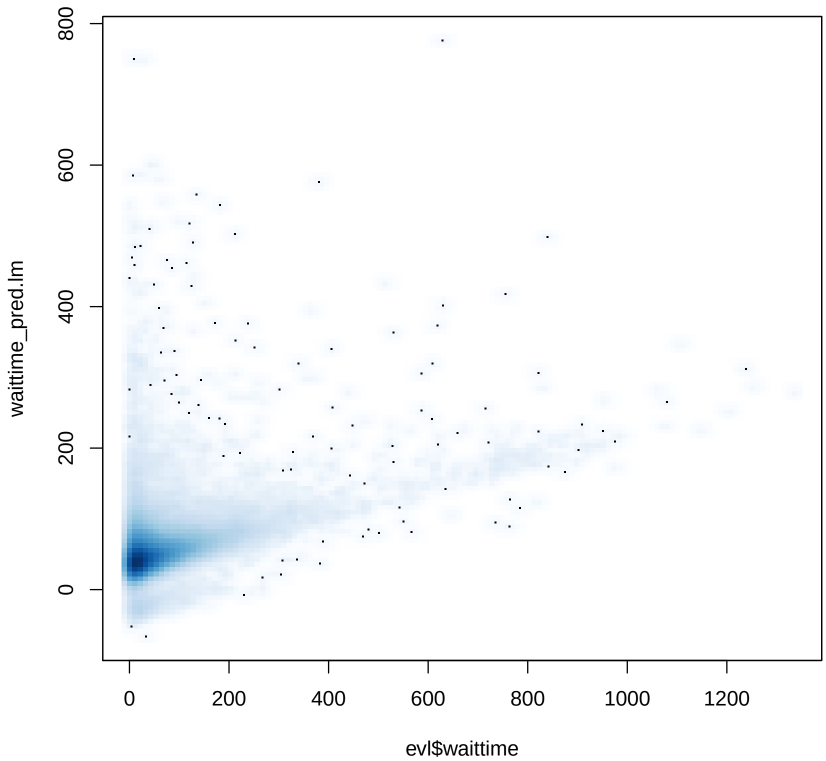


Figure 7: Predicted vs. measured individual wait times in NHAMCS

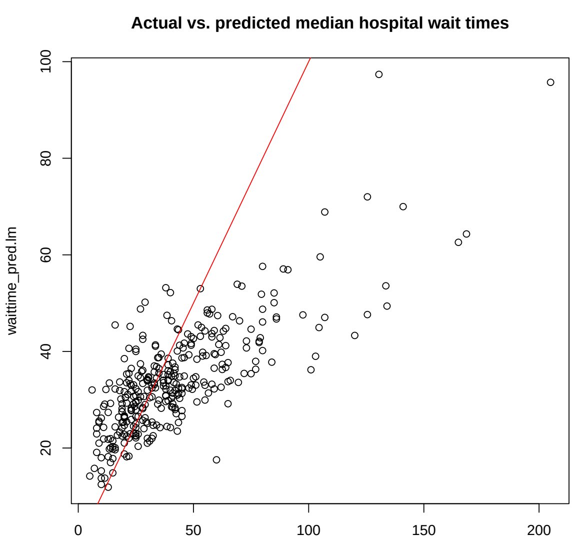


Figure 8: Predicted vs. measured median hospital wait times in NHAMCS

Because it does not specifically only measure waiting time, the imputation strategy can be seen as an economically-relevant improvement over measured wait times in the sense that it accounts for strategic delays ("foot dragging") once the clinician has first seen the patient.

2.3. Demonstrating that hospital uninsurance rate is the relevant unit of analysis

There is a substantial body of literature on physician behavior that demonstrates that physicians typically choose a practice style (determined by their overall reimbursement mix) and apply it to all their patients consistently rather than discriminate on a case-by-case basis. For that reason, I assume in all the models that the whole emergency department's proportion of low-reimbursement patients is what dictates their behavior *vis a vis* wait times. Figure 9 provides evidence of this effect using NHAMCS data. Hospitals are divided into insurance quartiles, and median wait times for each hospital insurance quartile are displayed separately for individual insured and uninsured patients. There are no substantial, significant differences at the individual level, but major differences at the hospital level of uninsurance. Regression models include individual and hospital uninsurance terms (and in general they show that the hospital term is significant and substantial whereas the individual term is not).

2.4. Cross-sectional, fixed-effect, and instrumental variable analysis

I first investigate whether wait times are indeed higher in hospitals emergency departments with a high proportion of uninsured patients using cross-sectional regression on a 0.1% sample of the AHRQ HCUP State Emergency Department Databases for New Jersey (2004-2011 inclusive) and Massachusetts (2005, '07, '09, '10, and '11).

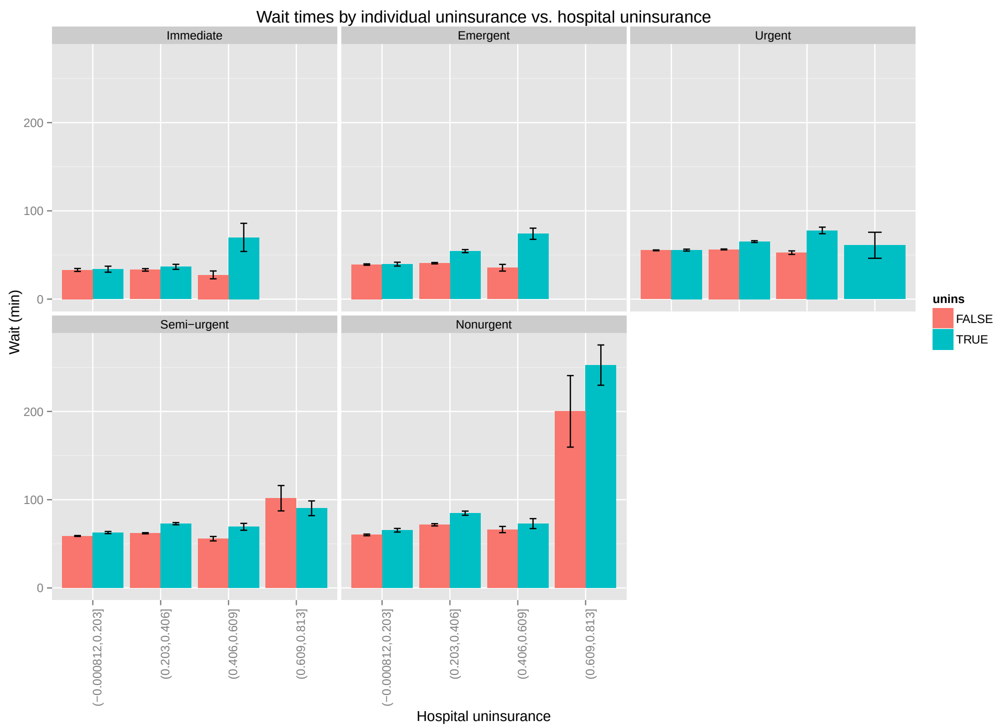


Figure 9: Wait times vs. insurance and income (odd values in high uninsured percentages are due to small numbers)

Further models attempt to infer causality, rather than mere association. Next, I examine whether hospital-specific changes in the proportion of uninsurance are associated with higher wait times by including hospital fixed effects. I then re-estimate the cross-sectional regression, this time instrumenting for the emergency department's proportion of uninsured patients with the uninsurance rate of the county in which the hospital is located. Finally, I apply both the instrument and fixed effects in a single model.

2.4.1. Regression equation

The full regression equation is,

$$y_{iht} = \alpha + \beta X_{iht} + \gamma L_{ht} + \delta v_{ht} + \zeta h + \eta T + \epsilon_{iht}$$

, where y_{iht} specifies the individual visit imputed wait time, α estimates the intercept, X_{iht} represent detailed clinical and demographic covariates (including indicators for whether the visit was made by a Medicaid or uninsured patient), L_{ht} contains the hospital's proportion of Medicaid and uninsured patients, h are hospital fixed effects (in certain models), T are year fixed effects, and v_{ht} provides the number of visits to that hospital in the same hour of the same month of the same year (the day of week of the month is not available but whether it is a weekend day or not is available and included in this contemporaneous number of visits calculation).

2.4.2. Ordinary least squares and instrumental variable analysis

Instrumentation may be helpful: the Durbin-Wu-Hausman test reports a p value of $<$ 0.01, suggesting that hospital uninsurance rates are endogenous to factors influencing wait times. Area uninsurance rate as an instrument is not weak (crude correlation of 0.78 with ED uninsurance rate).

	Coef	SE
year	0.0053	0.0053
female	0.000014	0.0015
race	0.0021	0.0015
age	-0.0001	0.0001
ndx	0.0010	0.0020
npr	-0.0015	0.0063
died	0.0181	0.0200
nchronic	0.0047	0.0023
aweekend	-0.0012	0.0020
unins	0.0294	0.0116
mcaid	0.0016	0.0026
mcaidHosp	0.0238	0.0447
uninsCounty	1.83	0.14

Table 2: First stage of hospital waittime models (dependent variable: uninsHosp), all states, 1% sample.

First stage instrumental variable regression results are shown in Table 2.

Results are presented in Table 3.

Interestingly, the coefficient on hospital uninsurance rates increases after instrumentation, implying that the elasticity of demand with respect to wait times for the uninsured is higher than for the non-uninsured. This could be the case if the uninsured have access to more information about which hospitals have high wait times, or are more sensitive to high wait times because a higher proportion of their outpatient care is delivered in emergency departments.

2.4.3. Fixed effect and instrumented fixed effect regressions

The next set of regressions uses within-hospital variation over time in uninsurance rates and wait times to attempt to discern a causal trend.

Unfortunately, because the data in question is a short, unbalanced panel (see Table 4), common tests of stationarity (Adjusted Dickey-Fuller, KPSS, etc.) failed or were

	(1)	(2)	(3)	(4)
year	2.051*	1.069	1.560	-3.599**
	(0.92)	(0.94)	(1.06)	(0.95)
female	-0.057	-0.148	-0.099	-0.257
	(0.55)	(0.55)	(0.48)	(0.49)
race	0.387	0.084	-0.134	-0.138
	(0.27)	(0.28)	(0.30)	(0.22)
age	-0.014	-0.010	0.007	0.010
	(0.02)	(0.02)	(0.01)	(0.01)
ndx	0.695+	0.740*	0.803	0.700**
	(0.35)	(0.35)	(0.52)	(0.24)
npr	1.625	1.547	0.453	0.633
	(1.36)	(1.32)	(2.13)	(1.36)
died	-5.305	-5.959	-7.181	-7.413
	(7.08)	(7.02)	(11.49)	(9.24)
nchronic	1.241+	1.006	0.979	0.968*
	(0.64)	(0.67)	(0.43)	(0.38)
aweekend	-0.720	-0.740	-0.624	-0.425
	(0.47)	(0.46)	(1.12)	(0.52)
unins	1.873*	0.477	1.819	1.939**
	(0.83)	(0.99)	(1.22)	(0.73)
mcaid	-0.990	-1.069	-0.573	-0.503
	(0.66)	(0.67)	(0.97)	(0.66)
uninsHosp	57.458**	79.362**	-4.626	641.166**
	(7.41)	(6.69)	(16.42)	(108.73)
mcaidHosp	-12.315*	-6.775	18.408	69.204**
	(5.49)	(5.72)	(10.74)	(11.73)
nVisitRelative	-17.345	-53.254	52.993	161.052**
	(58.62)	(60.84)	(116.76)	(49.02)
_cons	-4032.691*	-2060.152	-3063.139	
	(1845.95)	(1886.26)	(2130.77)	
N	46928	46928	46928	46926
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemporaneous Volume	Yes	Yes	Yes	Yes

$+p < 0.1$

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

Table 3: Hospital wait time models for all years, all states, 1% sample.

	MA	NJ
2004	0	1271070
2005	1191659	1343110
2006	0	1372915
2007	1271947	0
2008	0	0
2009	1317059	1512937
2010	1275490	1487052
2011	0	1541375
2012	0	0

Table 4: Number of observations in 2.5 percent sample, by state and year

not valid. Granger Causality using Vector Autoregression is similarly problematic.

Instead, I take two approaches. The first is visual. Figure 10 plots each hospital's uninsurance rate and mean wait over time. While the overall impression confirms the fixed effect regression's result of a positive association, it is far from clear what the optimal lag is.

The second approach is to simply run the same regression with different lags of the hospital uninsurance rate ($p = 0, 1, 2...$).

2.4.4. Sensitivity analysis for imputed wait time

These models all utilize the imputed wait time as the dependent variable. Table 5 shows the same models as above, run using the total duration of stay in the emergency department as the dependent variable, rather than only the wait time. The effect, while notably noisier largely, remains.

As a placebo test, I estimate the OLS regression from Section 2.4.2 on the non-wait time (duration in the ED minus the imputed wait time). The hospital uninsurance coefficient from that model is -20.4 with a standard error of 59.

This result is in some sense unsurprising, given the two previous regressions on the

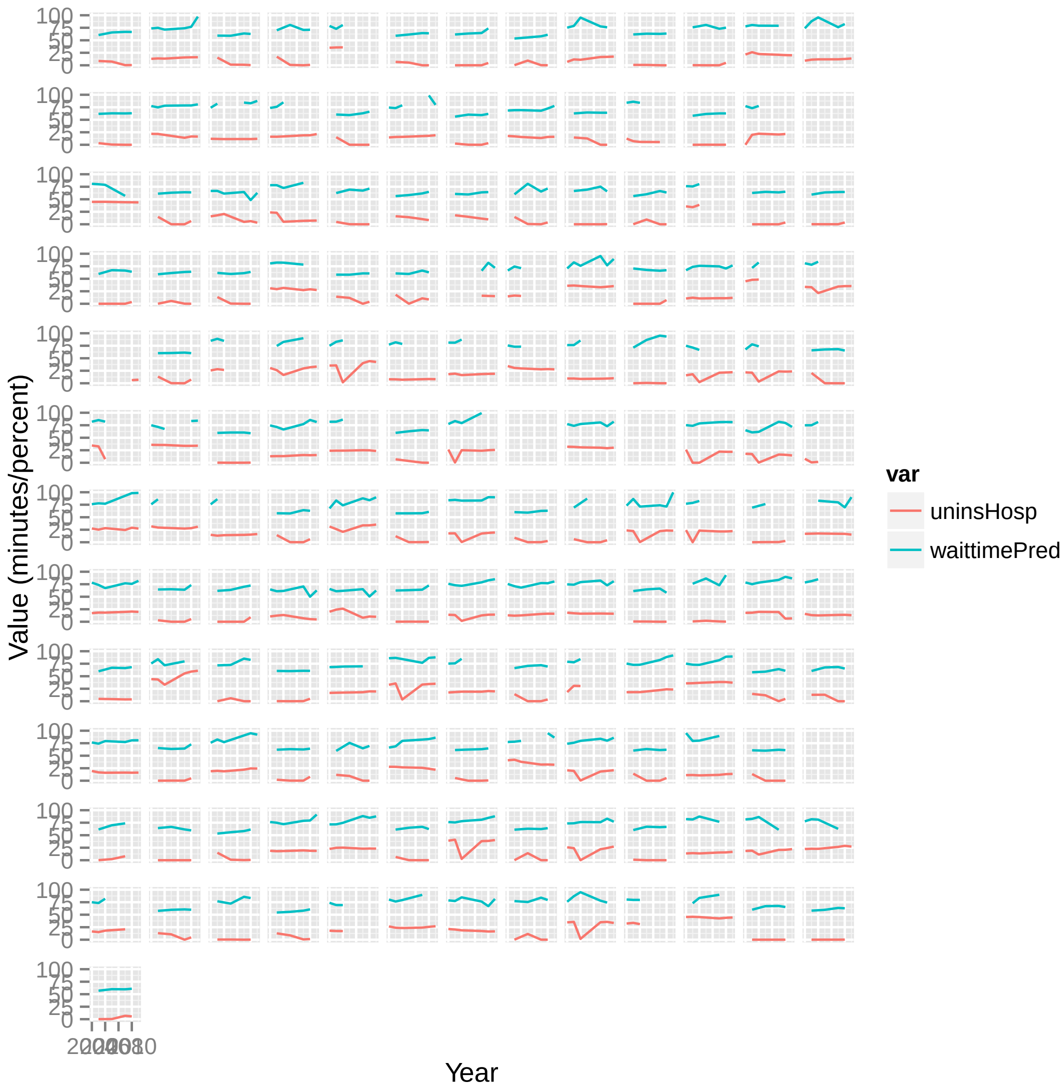


Figure 10: Plot of uninsurance rate vs. mean hospital wait time over time, by hospital

	(1)	(2)	(3)	(4)
year	0.837	-1.097	2.174	-15.737**
	(4.79)	(5.77)	(2.82)	(4.60)
female	2.951	2.770	2.116	1.568
	(2.84)	(2.81)	(1.58)	(2.38)
race	5.329*	4.733*	2.675*	2.660*
	(2.08)	(1.95)	(0.53)	(1.08)
age	0.465**	0.474**	0.505**	0.518**
	(0.09)	(0.09)	(0.05)	(0.06)
ndx	20.214**	20.301**	22.033**	21.673**
	(3.94)	(3.89)	(0.88)	(1.15)
npr	52.555*	52.402*	52.552+	53.174**
	(21.48)	(21.22)	(15.04)	(6.59)
died	-188.366*	-189.654*	-190.459	-191.265**
	(94.89)	(94.29)	(129.39)	(44.85)
nchronic	14.682*	14.219*	12.658	12.618**
	(5.93)	(5.88)	(4.68)	(1.83)
aweekend	0.317	0.278	2.938	3.628
	(2.80)	(2.79)	(6.13)	(2.53)
unins	18.676*	15.928+	17.546	17.962**
	(8.61)	(9.53)	(9.15)	(3.55)
mcaid	-0.676	-0.833	-0.120	0.125
	(4.29)	(4.25)	(7.52)	(3.19)
uninsHosp	76.709	119.827+	-9.815	2231.977**
	(64.08)	(71.19)	(124.95)	(527.61)
mcaidHosp	56.761	67.667	14.848	191.180**
	(49.34)	(47.71)	(60.23)	(56.90)
nVisitRelative	841.435	770.750	3098.721+	3473.833**
	(1149.38)	(1163.67)	(815.23)	(237.86)
_cons	-1323.309	2559.611	-4024.659	
	(9625.04)	(11608.09)	(5683.19)	
N	46928	46928	46928	46926
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

$+p < 0.1$
$*p < 0.05, **p < 0.01$

Table 5: Hospital ED duration models for all years, all states, 1% sample.

other two components. Wait time showed the hypothesized effect. Total duration of stay in the ED showed a similar effect but with increased noise. We now see the noise, without the signal.

Moreover, as discussed in Section 2.2.4.4, the imputation procedure has the benefit of capturing all extensions to the patient's waiting other than the expected treatment time, including clinician "foot-dragging" (extending treatment times for the uninsured).

2.4.5. Between-state differences

As discussed in the introduction, Massachsetts enacted policy changes which directly targeted emergency department crowding at the same time it was expanding insurance. Therefore, the most direct test of the hypothesis put forth in this thesis is not available for empirical exploitation. Results for the models presented above run separately for the two states as well as a balanced panel of only the years where data was available for both states is presented in Tables 6, 7, and 8.

They show that New Jersey's estimates drive the results to a substantial degree, consistent with Massachusetts having larger variation in hospital and area uninsurance over time but also directing policy actions against the dependent variable.

See the appendix (Tables 19, 20, and 21) for models with the measured duration as the dependent variable.

2.4.6. Differences by ownership type

Section 1.4.4 describes the various models of hospital objective functions might vary by ownership type, what predictions that makes for behavior, and how those predictions have withstood empirical scrutiny thus far. This section contributes to the

	(1)	(2)	(3)	(4)
year	2.409*	2.519*	2.104	-5.416**
	(1.13)	(1.12)	(1.17)	(1.69)
female	1.037	1.041	0.838	0.897
	(0.85)	(0.84)	(1.10)	(0.87)
race	-0.050	-0.900*	-0.164	-0.146
	(0.32)	(0.41)	(0.56)	(0.38)
age	-0.008	-0.012	-0.006	-0.007
	(0.03)	(0.03)	(0.02)	(0.02)
ndx	1.171**	1.333**	0.844	0.255
	(0.40)	(0.46)	(0.84)	(0.42)
npr	2.589	1.813	1.651	0.345
	(2.07)	(2.06)	(2.34)	(2.12)
died	-20.408*	-21.894*	-21.659	-24.415
	(9.46)	(9.07)	(14.72)	(17.50)
nchronic	0.976	0.703	1.645	1.898**
	(0.83)	(0.88)	(1.09)	(0.64)
aweekend	-0.814	-0.660	-0.615	0.350
	(0.74)	(0.75)	(2.03)	(0.95)
unins	2.405*	0.739	2.332	-0.104
	(1.03)	(1.37)	(1.43)	(1.21)
mcaid	-3.207**	-3.491**	-3.138+	-4.379**
	(1.11)	(1.12)	(0.92)	(1.39)
uninsHosp	44.027**	102.590**	13.616	2442.460**
	(13.56)	(22.87)	(38.87)	(512.32)
mcaidHosp	6.805	-5.570	22.246	176.106**
	(8.38)	(10.58)	(17.05)	(34.70)
nVisitRelative	-72.770	-84.166	39.593	251.885**
	(60.25)	(73.79)	(124.11)	(73.61)
_cons	-4741.035*	-4969.227*	-4125.581	
	(2278.13)	(2252.93)	(2343.04)	
N	23952	23952	23952	23950
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

Table 6: Hospital wait time models for New Jersey, 1% sample.

	(1)	(2)	(3)	(4)
year	-0.298	-18.257+	-0.578*	-1.815
	(0.85)	(10.83)	(0.04)	(1.26)
female	-1.291*	-2.507*	-1.222	-1.260*
	(0.59)	(0.98)	(1.09)	(0.56)
race	0.905*	2.724*	-0.204	-0.203
	(0.42)	(1.33)	(0.10)	(0.26)
age	-0.014	-0.032	0.018	0.018
	(0.04)	(0.04)	(0.01)	(0.02)
ndx	-0.365	0.556	0.437	0.423
	(0.47)	(0.99)	(0.21)	(0.29)
npr	0.528	1.959	-1.823	-1.773
	(1.58)	(3.26)	(2.63)	(1.95)
died	6.845	-0.269	4.824	4.810
	(9.58)	(12.98)	(4.97)	(10.34)
nchronic	1.158	0.712	-0.151	-0.156
	(0.97)	(1.68)	(0.95)	(0.46)
aweekend	-0.866	-0.967	-0.732	-0.721
	(0.58)	(0.77)	(0.26)	(0.59)
unins	-1.936+	-3.205	-1.237	-1.140
	(1.15)	(2.10)	(0.44)	(1.13)
mcaid	0.256	0.455	1.129	1.160+
	(0.80)	(0.77)	(0.20)	(0.67)
uninsHosp	10.260	957.094+	22.105	84.832
	(16.51)	(492.00)	(3.51)	(57.16)
mcaidHosp	-17.704+	-103.961+	4.086	5.773
	(9.79)	(55.93)	(1.30)	(11.93)
nVisitRelative	20.360	-13.928	41.809	69.026
	(208.22)	(458.97)	(449.18)	(389.14)
_cons	687.785	36779.918+	1235.376*	
	(1711.56)	(21774.40)	(58.44)	
N	22976	22976	22976	22976
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

Table 7: Hospital wait time models for Massachusetts, 1% sample.

	(1)	(2)	(3)	(4)
year	-1.201	-1.608+	-0.746	-4.640**
	(0.81)	(0.82)	(0.12)	(1.66)
female	-0.524	-0.629	-0.520	-0.626
	(0.53)	(0.54)	(0.08)	(0.47)
race	0.707*	0.445+	0.112*	0.112
	(0.27)	(0.26)	(0.01)	(0.21)
age	-0.023	-0.019	-0.002	-0.001
	(0.02)	(0.02)	(0.00)	(0.01)
ndx	0.822*	0.883*	1.120	1.072**
	(0.40)	(0.39)	(0.74)	(0.23)
npr	2.799	2.900+	1.062	1.226
	(1.73)	(1.62)	(3.36)	(1.41)
died	-5.355	-5.545	-7.770	-7.833
	(9.47)	(9.50)	(17.51)	(9.46)
nchronic	1.768*	1.544*	1.331	1.342**
	(0.72)	(0.74)	(0.39)	(0.37)
aweekend	-1.157*	-1.179*	-0.935	-0.898+
	(0.52)	(0.52)	(1.56)	(0.50)
unins	1.913+	0.595	1.706	1.746*
	(0.99)	(1.10)	(1.91)	(0.75)
mcaid	-0.316	-0.362	0.214	0.268
	(0.63)	(0.64)	(0.13)	(0.62)
uninsHosp	53.796**	74.422**	15.183	295.185*
	(9.00)	(9.02)	(4.16)	(114.83)
mcaidHosp	-12.170*	-5.995	4.517	21.021
	(6.12)	(6.43)	(4.88)	(13.20)
nVisitRelative	-43.416	-85.708	160.463	194.727*
	(132.09)	(136.89)	(154.49)	(92.35)
_cons	2501.554	3317.619*	1574.176+	
	(1620.78)	(1657.08)	(239.70)	
N	38356	38356	38356	38353
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

Table 8: Hospital wait time models for balanced panel, 1% sample.

literature by re-analyzing the main specifications (OLS and IV) of Section 2.4.2 above for public, non-Federal hospitals; not-for-profit, private hospitals; and for-profit hospitals. Estimates on these sub-groups are based on a 2.5% sample to obtain adequate numbers of visits for the for-profit and public ownership categories. The results are shown in Table 9.

There is a suggestion of a trend in the ordinary least squares models, with public, non-Federal hospitals having the lowest association between increased uninsurance visitation and wait times, not-for-profit hospitals having higher association, and for-profit hospitals having the highest association. However, due to the low number of for-profit and public hospitals in the data, the standard errors are quite large on this hospital-level variable, despite having 13,606,505 visits in this sample (11,209,478 non-profit, 296,981 for-profit, and 456,384 public). The instrumental variables analysis in the context of so few data points leaves estimates so unstable as to be uninterpretable, with standard errors an order of magnitude larger than the estimated coefficients.

2.5. Ruling out hospital up-triaging of low-reimbursement patients as a potential mechanism

One possibility for hospitals to increase the proportion of high-reimbursement patients in their ED is to up-triage low-reimbursement patients relative to high-reimbursement ones, ensuring that Medicaid and uninsured patients are seen more slowly. Dafny found that hospitals respond to price changes by "up-coding" to higher-reimbursing DRGs, and that for-profit hospitals did so more than non-profit hospitals (Dafny [2005]). However, interviews with clinicians[5] suggest that up-coding in the triage system would be difficult, as patients are cognisant of the wait times of other patients,

[5] K.V. Rhodes and B.G. Carr.

	N-F-P				Public				For-profit			
	OLS		IV		OLS		IV		OLS		IV	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Year	-0.39	0.93	-0.72	0.93	-1.34	6.85	-1.61	6.85	-2.02	5.87	-1.12	27.14
Female	0.08	0.90	0.02	0.89	1.24	0.77	1.21	0.77	-0.24	0.67	-0.18	0.64
Race	0.37	0.52	0.14	0.50	0.19	0.30	0.06	0.29	0.35	0.33	0.33	0.61
Age	-0.03	0.03	-0.03	0.03	0.01	0.02	0.00	0.03	-0.02	0.02	-0.02	0.02
ndx	1.02	0.54	1.05	0.53	0.68	0.97	0.93	0.96	0.23	0.41	0.19	0.70
npr	1.78	3.43	1.94	3.41	14.28	6.53	13.65	6.55	1.47	3.85	1.57	4.00
Died	-1.86	24.02	-1.28	24.17	-13.29	25.54	-13.87	25.50	-2.67	12.03	-2.15	12.21
N Chronic	1.39	1.16	1.21	1.18	-0.56	0.95	-0.58	0.91	-0.01	0.44	0.07	0.84
Weekend	-1.34	0.92	-1.29	0.92	-1.71	1.02	-1.62	1.02	-0.02	0.86	-0.04	0.90
Uninsured	3.99	1.31	2.85	1.49	2.15	2.12	1.42	2.09	0.90	1.58	1.17	1.53
Medicaid	-0.66	1.42	-0.72	1.43	-0.02	4.03	-0.15	4.02	-0.02	1.10	-0.04	1.15
Hosp Mcaid %	-12.22	7.52	-7.47	7.96	-28.43	573.22	-9.53	575.26	21.04	117.09	9.44	219.75
Hosp Unins %	57.08	11.49	74.45	12.69	43.79	216.54	68.46	216.34	73.62	76.18	45.83	541.49

Table 9: Hospital wait time models by ownership status, 2.5% sample.

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	-4.2e-05	0.77	
unins	-0.014	0.017	
medicaid	-0.0017	0.04	
medicare	0.039	0.048	
dual	-0.025	0.042	
age	-0.0029	0.0011	*
ahour	-2e-07	4.8e-05	
amonth	0.0064	0.0051	
aweekend	0.0012	0.039	
ayear	0.016	0.004	*
female	0.02	0.037	
region	-0.018	0.015	
admithos	-0.024	0.035	
urbanrur	0.018	0.0074	*
ethun	-0.00013	0.00013	
raceun	0.042	0.024	

Table 10: OLS of triage score vs. insurance plus detailed diagnosis

and triage nurses tend to be among the most experienced nurses in the ED and have a strong sense of pride in their work.

To investigate the possibility that up-triaging occurs, I attempted to fit a cumulative link model to the data. Unfortunately, several implementations of ordered probit and logit all failed to converge. Consequently results presented in this section are for an OLS regression of the numeric triage score (1-5, with higher scores being less urgent) as follows:

$$triage = unins + medicaid + medicare + dual + age + ahour + amonth + aweekend + ayear + female + region + admithos + urbanrur + ethun + raceun + dx1$$

, where $dx1$ is a detailed clinical diagnosis. Table 10 shows the results of that regression. Despite having 2,576 observations, the coefficients which indicate visits by uninsured or Medicaid were small and not significantly different from zero (p=0.42 and 0.97 respectively).

Because this analysis confirmed the clinicians' prior that up-coding would not be prevalent in the triage system, the rest of this analysis considers each hospital ED to make a single decision about the inputs that produce wait times, possibly in accordance with its case mix.

CHAPTER 3 : The impact of urgent care clinic entry on emergency departments

A source of somewhat exogenous variation in emergency department outpatient reimbursement mix is the entry of urgent care clinics. Urgent care clinics have proliferated at nearly a 9% compound annual growth rate (Weinick et al. [2009b]), yet little is known about their impact on the health system as a whole and the emergency department safety net in particular. Because little is known about these clinics, this chapter is divided into two sections. Section 3.1 utilizes data from a two-hospital system in northern Delaware and a spatial regression strategy to determine the volume and reimbursement mix effects of urgent care entry on emergency departments. It finds that urgent care entry reduces the number of visits to nearby emergency departments substantially, but alters the reimbursement mix only minimally. Section 3.2 then performs similar regressions to those of Chapter 2, utilizing the SEDD data with imputed wait times to assess the impact of urgent care entry on emergency department outpatient crowding. It is thus a falsification test of the model advanced in Section 1.2: if urgent care entry does not change the proportion of uninsured, then despite altering the competitive dynamics of an area it should not alter an emergency department's wait times[1]. Indeed, unlike the similar regressions in Section 2.4, difference-in-difference and difference-in-difference-in-difference analysis of urgent care entry demonstrates that clinic entry does not seem to alter nearby emergency department wait times substantially.

Throughout, I use ESI (triage) codes 4 and 5 (semi-urgent and non-urgent) as a proxy for care that could have been seen either in an ED or in an urgent care center, which

[1]Although consideration must be given to a mechanical effect of reducing wait times in the short term by reducing patient volume without reducing hospital capacity.

roughly accords with previous work on the subject.

3.1. The effect of urgent care entry on emergency department volumes: Evidence from northern Delaware

3.1.1. A description of the northern Delaware data

This section seeks to understand the impact of urgent care centers on nearby emergency department (ED) patient visitation patterns. Because urgent care centers are not subject to the Emergency Medical Treatment and Labor Act (which mandates that emergency departments provide a clinical screening exam and, effectively, treatment to patients regardless of ability to pay), they might take only those patients who can afford to pay, leaving EDs with a higher proportion of uninsured patients to serve. Particular consideration is given to understanding the effect of insurance status on volume changes and to describe differences by the type of urgent care facility (e.g. corporate vs. physician ownership).

This section examines the first-order effect of competition between urgent care clinics and EDs: that they reduce emergency department patient volumes. It examines patients in Emergency Severity Index (ESI) triage categories 4 and 5, as those are the most likely to have visits substitutable with urgent care. The effect of urgent care entry on the volume of insured patient visits to the emergency department is examined. The next section (3.2) then examines the second order effect, the emergency department response.

3.1.2. Data

This is a retrospective study of the impact of new urgent care clinics on patient volumes at two large emergency departments in the Christiana Care Health System.

We obtained a limited number of variables on every patient visiting the ED over an approximately 8-year period. All visits were included if the patient underwent triage at one of the two studied emergency departments. Visits were excluded from study if they resulted from a direct admission to hospital without triage in the ED or carried a gynecologic or obstetric diagnosis, as these cases were not seen in the Emergency Department due to a separate triage system seen in a different part of both hospitals.

3.1.2.1 Sampling Method and Data Analysis

Two datasets form the basis of this study: a facility-level database of urgent care centers located near CCHS and patient-level retrospective ED data from CCHS. The two datasets are linked by geography and time.

This data structure allows the use of a spatial regression model. This is a regression model with Census block fixed effects and quadratic terms measuring distance to the nearest urgent care clinic, clustered at the Census tract level to account for spatial autocorrelation. Census blocks are extremely small areas consisting of approximately 50 houses. Census tracts are aggregations of census block groups (themselves aggregations of census blocks). In the study area, the average census tract consisted of 82 blocks.

The combination of Census block fixed effects and continuous distance means that the model identifies the effect of urgent care by comparing the change in volume of ED visits for those census blocks close to where each urgent care clinic opens to those further away.

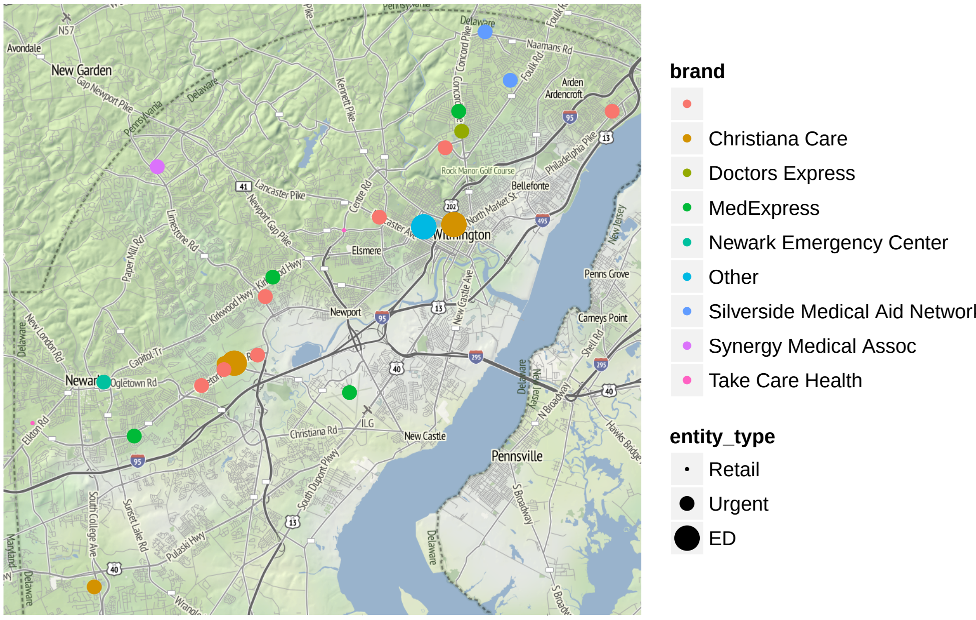


Figure 11: Map of urgent care clinics and emergency departments in northern Delaware

3.1.3. Description of study area

All visits from patients living within 10 miles of either study hospital were included[2]. This area consists primarily of a single county in northern Delaware, although small pieces of New Jersey, Pennsylvania and Maryland are included as well. Figure 11 maps the clinic locations. Figure 12 shows the log population density by Census block in a choropleth map of the study area.

[2]Results not sensitive to a 15-mile inclusion radius.

Figure 12: Log population density (2010 Census) by Census block in northern Delaware

3.1.3.1 Unscheduled care locations of the Christiana Care Health System

The Christiana Care Health System during the study period consisted of two hospitals, each with their own emergency department. The Christiana Hospital Emergency Department is the 24th-largest in the country[3]. The Wilmingon Hospital Emergency Department sees approximately half as much volume. The health system also operates 4 urgent care clinics, 2 which opened during the study period and 2 which opened beforehand.

3.1.3.2 Unscheduled care competitors

We located 21 urgent care and retail clinics in northern Delaware through an extensive search of insurer network lists, phone and business databases (Yellow pages, RefUSA), the Merchant Medicine database of urgent care clinics, and interviews with local clinicians. We found both longstanding and newly-opened clinics. 4 were owned by the studied health system, Christiana Care Health System. 2 were retail clinics. 5 were owned by MedExpress, one of the largest national chains of UCCs. 10 were independently-owned. This pattern of ownership largely mirrors that found in the national survey of UCCs conducted in 2009 by Weinick et al. [2009b]. Attempts to conduct a phone survey of these clinics to obtain more detailed information on each were unsuccessful.

Retail clinics Two retail clinics owned by Walgreens Pharmacy operate in the area. Their opening dates are unknown. The impact of these clinics on hospital ED volumes is likely minimal, as the typical retail clinic sees very low volumes. For both these reasons, they are not included in this study.

[3]http://www.christianacare.org/trauma

Urgent care clinics Delaware is a unique practice environment for urgent care clinics. The state has had a longstanding restriction on the use of the term "urgent," with associated facilities requirements that effectively preclude its use. Consequently, these facilities go by a variety of idiosyncratic names, and are licensed as "Medical Aid Units." While this may signal a willingness on the part of the state to restrict entry of urgent care clinics, the ability to block entry appears anecdotally to be quite limited.

7 clinics were already open at the beginning of the study period. 12 clinics opened during the study period. Figure 13 shows when each clinic opened.

The urgent care clinics opening during the study period varied by ownership type. There were 5 independent clinics at the beginning of the study period, and 5 more opened during the study period, for a total of 10 independent clinics by the end of the study period. MedExpress, a large chain operator of UCCs, established a new presence in this market, opening 5 of 5 clinics within a single year (2012) timeframe. Christiana Care Health System began the period with 2 clinics, and opened 2 more during the study period, for a total of 4 clinics. Figure 13 shows opening dates graphically, and Figure 11 shows a map of the urgent care clinics and emergency departments.

3.1.4. Effect of urgent care entry on emergency department patient volume

3.1.4.1 Unadjusted estimates

Figure 14 shows the number of visits to each of the two study hospitals by week. The vertical panels display data for each hospital (CCH = Christiana Hospital ED, WED = Wilmington Hospital ED). The horizontal panels show the visit counts by acuity. Acuity here is divided into two categories, based on the five triage codes. Codes 1

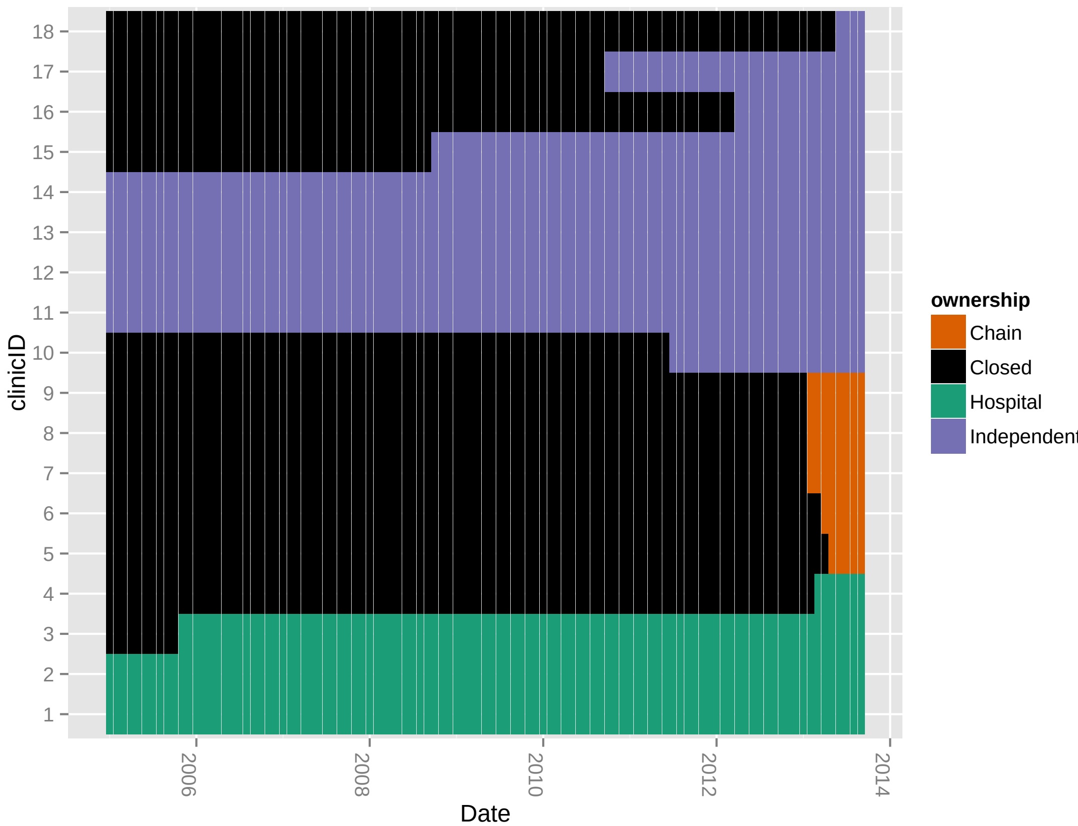


Figure 13: Opening dates for urgent care clinics in northern Delaware

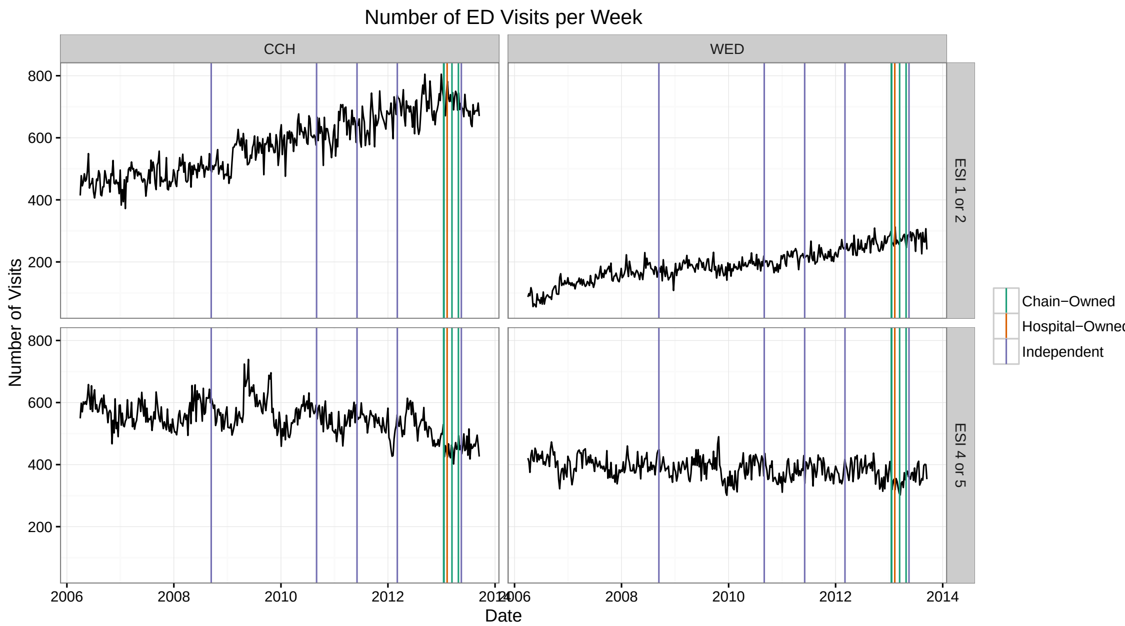


Figure 14: Number of visits to CCHS hospitals per week, by acuity, insurance type (high reimbursement = Medicare+Private; low reimbursement = Medicaid+uninsured), and hospital (CCH = Christiana Hospital ED, WED = Wilmington Hospital ED). Vertical lines represent the date an urgent care clinic entered.

and 2 are combined into an "emergent" category, representing severe cases that are substitutable between EDs but are not capable of being seen at urgent care clinics. Codes 4 and 5 are combined into a "less urgent" category which is generally substitutable across EDs, urgent care clinics, and primary care clinics. A subset of these visits may also be substitutable across retail clinics. Code 3 (omitted) represents the intermediate case, with indeterminate substitutability. The plot is further separated by insurance type, with categories created based on having similar reimbursement rates in the MEPS (see Appendix, Section A.6). The high reimbursement insurance category represents visits from patients with Medicare or private insurance. The low reimbursement category represents visits from patients with Medicaid or who lack insurance entirely. The vertical dashed lines represent the date an urgent care clinic entered, and are color-coded by type.

3.1.4.2 Spatial regressions

The results of the regression approach using Census block fixed effects and including a quadratic term for the distance to the nearest urgent care clinic are shown in Table 11. The model (Model 1) is run separately for the two hospitals as well as both hospitals' data combined:

$$\#visits_{it} = distUC_{it} + distUC_{it}^2 + t + i + \epsilon$$

Where i indexes Census blocks, t indexes months, and $distUC$ measures the distance to the nearest urgent care clinic in miles. The model includes block (i) and month (t) fixed effects (1,197,210 block-months), and is clustered at census tract level (mean 82 blocks per tract).

Each hospital's model is also run in a form that allows examining the effect of insurance status. In this Model 2, the distance to nearest clinic is interacted with payer type (high-reimbursement vs. low-reimbursement insurance, lri) to assess differential effects by patient profitability:

$$\#visits_{it} = distUC_{it} + distUC^2{}_{it} + lri_{it} + distUC_{it} * lri_{it} + distUC_{it}^2 * lri_{it} + t + i + \epsilon$$

3.1.4.3 Results: Patient volume

Results of the spatial regression with patient volume as the dependent variable are presented below. Three different regressions were run, one overall, one including an

Table 11: Regressions of number of visits versus distance to nearest urgent care clinic, with block fixed effects, clustered at Census tract level

	CCH1	CCH2	WED1	WED2	Both1	Both2
distUC	0.026*	0.013*	0.024*	-0.0041	0.05*	0.0093
	(0.0063)	(0.0043)	(0.0048)	(0.0075)	(0.0078)	(0.0081)
distUCˆ2	-0.0023*	-0.0012*	-0.0019*	0.0015	-0.0042*	0.00032
	(0.00063)	(0.00051)	(0.00039)	(0.00096)	(0.0007)	(0.00084)
monthNum	-0.00044*	-0.00022*	-0.00017*	-	-0.00061*	-0.0003*
	(0.000035)	(0.000018)	(0.000049)	0.000083*	(0.000073)	(0.000031)
				(0.000033)		
LRI		-0.011		0.04		0.029
		(0.0074)		(0.021)		(0.031)
distUC:LRI		-0.0006		0.032		0.031
		(0.0057)		(0.016)		(0.016)
distUCˆ2:LRI		0.000082		-0.0049*		-0.0048*
		(0.00068)		(0.0021)		(0.0018)
Visit Count	HRI+LRI	HRI+LRI	HRI+LRI	HRI/LRI	HRI/LRI	HRI/LRI
Non-urgent only	X	X	X	X	X	X
Clustered	Tract	Tract	Tract	Tract	Tract	Tract
Mean visits HRI	0.11	0.11	0.05	0.05	0.16	0.16
Mean visits LRI	0.097	0.097	0.12	0.12	0.22	0.22
Mean dist (weighted)	2.6	2.6	2.3	2.3	2.5	2.5
Mean dist change	0.62	0.62	0.62	0.62	0.62	0.62
Implied change	-0.0096	-0.0047	-0.0102	-0.0012	-0.0196	-0.0066
(%)	-4.6%	-4.2%	-6.0%	-2.3%	-5.2%	-4.1%
Implied change LRI		-0.0045		-0.0076		-0.0139
(%)		-4.7%		-6.4%		-6.3%

indicator of insurance status, and one including both insurance status and clinic type indicators. The coefficients on $distUC$ and $distUC^2$ are interpretable as the increase (decrease) in the number of visits per Census block when the distance to the nearest urgent care clinic increase (decreases) by a mile. In order to aid interpretation, Table 11 includes a final row which gives the percentage change in the number of visits to the emergency department implied by those coefficients. This percentage was calculated as the percentage change in the implied number of visits at the mean distance from an urgent care clinic compared to a move closer by the mean change in miles.

Total volume The estimates from the spatial regression imply that total volume decreases by approximately 5.6% per urgent care clinic that enters.

By insurance status The estimates do not differ by insurance status, although this may be due to a lack of power after clustering at the Census tract level.

By ownership type Table 12 shows the results of separating out the distance to the nearest urgent care clinic by ownership type: chain-owned (MedExpress) urgent care clinics versus independent clinics (neither owned by CCHS nor Med Express).

When interacting by chain ownership vs. independent physician ownership of the urgent care clinics, the chain-owned clinics seem to impact ED volume more than the independent urgent care clinics. The effect for chain-owned clinics is not, however, differential by insurance status.

3.1.4.4 Results: Ambulatory care-sensitive conditions

Table 13 presents results from three regressions of the number of visits to Christiana emergency departments for ambulatory care-sensitive conditions (ACSCs) using cen-

Variable	Coefficient
distMedExpress	0.0058* (0.0024)
distMedExpressˆ2	-4.7e-05* (2e-05)
LRI	0.0821* (0.0299)
distIndependent	-0.0057 (0.0083)
distIndependentˆ2	0.0012 (0.0009)
Month	-0.000227* (3.3e-05)
LRI X distMedExpress	-0.0036 (0.0033)
LRI X distMedExpressˆ2	2.8e-05 (2.7e-05)
LRI X distIndependent	0.026 (0.0162)
LRI X distIndependentˆ2	-0.0046* (0.0018)

Table 12: Regressions of number of visits versus distance to nearest urgent care clinic of different ownership types, with block fixed effects, census tract clustering

Variable	% ACSC Overall	% ACSC Prevention	% ACSC Substitution
distUC	-0.0007 (0.006)	-0.0012 (0.0023)	0.0005 (0.0056)
distUCˆ2	-0.0004 (0.0008)	0.0001 (0.0003)	-0.0006 (0.0008)
Month	0.00038* (2.3e-05)	3.1e-05* (9e-06)	0.00035* (2.2e-05)

Table 13: Regressions of number of visits for ambulatory care-sensitive conditions versus distance to nearest urgent care clinic, with block fixed effects, robust standard errors

sus block fixed effects and robust standard errors. ACSCs were selected from the standard list (Billings et al. [2000]) on the basis of clinical presumption about which would be particularly relevant in this setting. I categorized ACSCs into those whose effect on ED visits would be primarily through preventing a visit, and those whose effect is likely mediated primarily through substituting an ED visit for one in another setting. The full list of conditions used is included in Table 22.

After selecting several ambulatory care-sensitive conditions likely to be responsive to urgent care entry, I find no difference in the proportion of ambulatory care-sensitive conditions as a result of urgent care entry. Ambulatory care-sensitive conditions capture many dimensions of quality by many firm types, including primary care clinics, urgent care clinics, and emergency departments. They may be a reflection of patient-unobservable quality on the part of urgent care clinics, or they may be observable to patients. This ambiguity means interpretation is difficult, but the findings here combine with those of Reid et al. [2013], who used a matching design to demonstrate that those who visit retail clinics show no difference in subsequent receipt of preventive care, to suggest that large gaps in certain aspects of measurable clinical quality are unlikely to exist, despite differences in ownership and organizational structure.

3.2. The effect of urgent care entry on emergency department wait times

Having determined that the overall effect of urgent care clinics on nearby hospital emergency department patient volumes is to substantially decrease the total number of patients entering emergency departments, but not do so differentially by insurance status[4], this section examines the empirical effect of urgent care entry on hospital emergency department wait times.

The theoretical model (Section 1.2) would predict that a decrease in volume without a corresponding change in the insurance case mix should be accompanied by no change in wait times. Added to this is the mechanical effect of reduced volumes decreasing wait times, although in the medium- to long-term this effect should be muted as capacity adjusts to the new steady-state. Overall, then, we should expect a neutral or slightly negative impact of urgent care entry on nearby emergency department wait times. Any effect is likely an upper-bound due to the endogeneity of urgent care entry, as explained in Section 3.2.1.1.

3.2.1. Empirical model to estimate the competitive response of EDs

While the ideal experiment would randomize emergency department entry (or at least exploit some plausibly exogenous variation in the profitability of opening a new ED), ED entry and exit are fairly uncommon events–in an average year, fewer than

[4] Within the bounds of the statistical power of the analysis.

2% of EDs close[5]–and ED entry and closure are associated with a whole host of confounding factors such as the entry of the associated hospital and the challenging market conditions implied by an area which can put an entire hospital out of business, respectively. Instead, I will use the entry of urgent care clinics into a market as a disruptor of the unscheduled care market.

This section first outlines a difference-in-difference model, which allows for the discussion of threats to causal inference in a simpler setting as well as approaches to mitigate those threats. It then describes a difference-in-difference-in-difference model which more closely parallels the analytic question above, and investigates whether this triple differences model differs by the prevailing insurance rate as well.

I propose the following difference-in-difference estimate:

1. 2007 vs. 2011
2. Markets with UCC entry vs. markets without

The estimating equation for the regression form of the model is:

$$y_i = \beta_0 + \beta_1 X_i + \beta_2 E_i + \beta_3 t_i + \beta_4 (E_i \cdot t_i) + m_i + \epsilon_i$$

Where:

- i indexes observations (a particular patient visit to a particular ED in a particular market)
- X_i are covariates

[5]"From 1990 to 2009, the number of hospitals with EDs in non-rural areas declined from 2446 to 1779, with 1041 EDs closing and 374 hospitals opening EDs" Hsia et al. [2011].

- E_i indicates an area that experiences entry in the second period
- m_i are market fixed effects (indicator for whether case i is in the m^{th} HSA
- t_i is the year
- y_i is the time that patient spent waiting in the ED

The model is clustered at the hospital level. An alternative specification adds a third difference across hospital insurance case mix.

The next section considers the confounding that remains in this model in the next section.

3.2.1.1 Threats to inference

For valid inference, we need to satisfy several assumptions. First, that markets in which UCCs enter are not unobservably different than those which do not: $cov(\epsilon_i, E_i) = 0$. Second, that $cov(\epsilon_i, t_i) = 0$. And finally, that there are no differential trends: $cov(\epsilon_i, E_i \cdot t_i) = 0$. These concerns about the point estimate can be divided into those concerning internal validity and those concerning external validity, whereas the primary concern with the uncertainty associated with that point estimate is that of autocorrelation.

Internal validity The ability of the regression to estimate the causal effect of urgent care entry on emergency department wait times *for the population of clinics like those which appear in our dataset* (internal validity) might be compromised in several ways.

Urgent care clinics might prefer to enter markets which are trending towards higher

ED wait times. This would biases the estimation towards the null.

Alternatively, UCCs might choose to enter markets which are trending towards lower ED wait times. This would be problematic, but it is contrary to profit maximization.

Instead, there could be some unobserved, underlying variable. For instance, dense areas might see a greater pace of systematic reform which affects wait times and because of the density of customers also experience more unoservably desirable entry. This would be problematic, but it is difficult to conceive of even an implausible story that would fall in this category (the preceding example is non-problematic because population density is observable to the econometrician).

Finally, expectations may begin impacting ED wait times before UCC entry–the "Ashenfelter dip." Fortunately, the direction of this bias is likely towards the null, and concerns about differential trends can be addressed by analyzing the pre-trend.

External validity One concern which remains is that urgent care clinics might choose to enter markets on which they can have the biggest impact in reducing wait times. This is likely because those markets are where unmet demand for the rapid service of the entrants may be highest. This is a serious concern, but one of external not internal validity, so we can bound the estimate. Because this is a dimension that UCCs are optimizing when they make entry decisions, the causal estimate of the effect of UCCs on ED wait times reflects an upper bound of impact. Clinics first enter markets where they will have the largest impact on wait times; when those markets are 'taken,' they move on to moderate impact markets, and so forth.

3.2.2. Results

Table 14 shows the results of the double-difference and triple-difference regressions. The first column, the difference-in-difference analysis, shows that an additional urgent care clinic in the hospital's 3-digit zip led to no significant change in wait times (coefficient: year * zip3_pointcountUC).

The second, third, and fourth columns examine the differential effect of urgent care entry by the degree to which it changed the proportion of low-reimbursement insurance at that hospital emergency department. The coefficients on the triple-difference estimator (yearXzip3UCXlriHosp) are all extremely small and not statistically significant for all definitions of low-reimbursement insurance: uninsured, Medicaid, or the combination of the two.

A significant limitation of this analysis is that urgent care clinic counts are only available for 2012. Because nationally approximately $\frac{1}{3}$ of clinics were newly opened in the prior 5 years (Weinick et al. [2009b]), I assumed that in 1997 each 3-digit ZIP area had 0 clinics and interpolated linearly between. This results in substantial measurement error. However, given that the coefficients on the difference estimators were not only statistically insignificant but close to zero, the measurement error would have to be substantial indeed in order to produce a falsely negative result–even a trebling of the coefficients would be insignificant from a clinical and policy perspective. Bias should be limited, except in the case that newer clinics are much more/less likely to open in places where they might have a large impact on emergency department wait times.

	D-D	Uninsured	Medicaid	Both
	b/se	b/se	b/se	b/se
year	-0.076	0.058	1.167***	0.962***
	$? (0.21)	$? (0.23)	$? (0.23)	$? (0.23)
zip3UC	206.143	622.784*	776.072**	824.708**
	$(149.54)	$(264.00)	$(256.32)	$(269.82)
year * zip3UC	-0.102	-0.310*	-0.386**	-0.410**
	$? (0.07)	$? (0.13)	$? (0.13)	$? (0.13)
lriHosp		-14617.699***	-21.077***	-11.139*
		$(3,651.36)	$? (5.60)	$? (4.83)
zip3UCXlriHosp		-1638.193	-2714.656	-2796.951
		$(1,421.54)	$(1,434.74)	$(1,485.14)
yearXlriHosp		7.311***	0.025***	0.029***
		$? (1.82)	$?? - 0	$?? - 0
yearXzip3UCXlriHosp		0.815	1.351	1.392
		$? (0.71)	$? (0.71)	$? (0.74)
Constant	221.938	-53.24	-2274.005***	-1862.936***
	$(426.03)	$(464.37)	$(456.30)	$(452.51)
R^2	0.004	0.024	0.026	0.024
N	6403530	6403530	6403530	6403530
* p<0.05				
** p<0.01				
*** p<0.001				

Table 14: Urgent care double- and triple-difference regressions. zip3UC is the number of urgent care clinics in each 3-digit ZIP code.

3.3. Summary of urgent care's impact on emergency departments

This chapter has demonstrated that urgent care clinic entry reduces the volume of emergency department visit but does not, in the aggregate, seem to alter its case mix. It then tested the implication of the theoretical model presented in Section 1.2 that, absent a change in case mix there should not be a change in wait times. The model passed this falsification test. Yet the findings of this chapter have implications beyond the test of the particular thesis of this dissertation.

Because of the origins of emergency departments as places for the treatment of high-acuity conditions, the cultural view of EDs as being inappropriate for lower-severity care is fading only slowly. There are many competing explanations for why this should be, and why it might change. For instance, perhaps traditionally hospitals feared competing for low-severity patients because they needed PCPs for referrals, but with the decline of direct admissions from primary care as a revenue source they no longer fear this backlash. It may be that EDs really are inefficient places to deliver lower-severity care, and that EMTALA imposes a binding constraint with resulting welfare losses–or it may be that time-sensitive care has a high fixed cost (of being open 24 hours per day) and that both EDs and UCCs can deliver it efficiently once EDs are reoriented towards serving a broader spectrum.

On the other hand, urgent care clinics may have adverse effects on the health system, including costs. While they represent lower-cost competitors to emergency departments, the true marginal cost of emergency department care is unknown, given the presence of substantial market distortions. The volume pulled from emergency departments is substantial, but represents less than 20% of the typical 40,000 visit annual volume of an urgent care clinic (Weinick et al. [2009b]). If the remainder of visits come not from primary care but from the “woodwork effect”–demand increasing when non-price costs decrease–the urgent care may increase resource-use. The efforts of certain insurers to shift demand from EDs to UCCs provides some reassurance on that front.

Just as these questions about the unscheduled care market are intrinsically interesting, there are as many opportunities to extrapolate from the particulars of this market to the questions which concern economists about markets in general. It remains unknown, for instance, how closely firms co-locate when they want to compete, and what factors determine this decision. The unscheduled care market offers further possibilities to study older questions, such as the nature of competition along quality dimensions. To that end, it is notable that urgent care entry did not decrease wait times, but perhaps unsurprising given the sensitivity of quality to competition depending on the assumptions of the games used to model it reviewed in Section 1.4.1.

Intriguingly, when considering the type of for-profit clinic that enters, ownership type (independent vs. chain-owned) does not seem to affect case mix. This finding contrasts with Chakravarty et al. [2005], who find that non-chain for-profit hospitals more tightly target profitable demographics. The substantial differences between hospitals and urgent care clinics make the failure to find such an effect in this market unsurprising, but the finding point to the need for caution in extrapolation.

CHAPTER 4 : Conclusions

This dissertation posits and presents evidence of a market distortion which has received little economic attention to date: the apparent mismatch of supply and demand in the market for unscheduled care delivered at hospital emergency departments. It puts forth a specific hypothesis, that supply has not expanded to meet increased demand due to a set of norms and regulations that acts as a binding constraint against increasing price for a particular class of customers, the uninsured. It demonstrates that those constraints do, in fact, seem to bind. The hypothesis is then formally modeled by maximizing the profit function of a hypothetical emergency department. The predictions of the comparative statics of this model–that hospitals with high uninsurance rates will choose policies that cause high wait times as a filter for unprofitable patients–are then brought to the data in a variety of ways, with the conclusion largely holding. While this does not rule out other explanations which drive similar predictions (most notably, the alternative that resource constraints in emergency departments with unprofitable case mixes are what drive high wait times), the hypothesis-driven nature of this research, combined with the formal model's predictions being borne out in the data, are suggestive.

Several policy implications follow naturally from the findings of this dissertation. The theoretical model's central assumption is that hospitals can neither turn away patients, due to the Emergency Medical Treatment and Labor Act, nor increase only unprofitable patients' wait times, due to a combination of legal, reputational, and soft regulatory constraints. As is typical of well-intentioned regulation, unintended consequences can be severe[1]. While the example of countries without EMTALA-like

[1] Indeed, DSH payments might have done more to mitigate the effect were they crafted to reimburse hospitals on the margin of treating another uninsured emergency department patient.

laws makes it clear that such laws bring many benefits, they should be designed as carefully as possible to mitigate their harms. Even absent narrowly-crafted laws, insurance expansion should help reduce the adverse consequences of high uninsurance burdens coupled with an inability to collect for certain cases. Indeed, we should expect the rate of growth of emergency department crowding to slow or reverse, particularly in states which expand Medicaid relative to those that do not. Monitoring of this natural experiment over the coming years will serve as a significant test of this thesis.

This prediction gives rise to several further policy conclusions. First, there may be a substantial welfare gain from insurance expansions due to reducing the externality imposed on the insured visiting hospital with high wait times due to high hospital uninsurance rates. Given the size of the crowding problem and the frequency of emergency department visits, this welfare effect may substantially offset some of the less positive welfare effects of the PPACA for those who were already insured before the implementation of the law. Second, calls to mandate particular solutions to emergency department crowding (Rabin et al. [2012]) may be sub-optimal if insurance expansion will reduce crowding without the distortionary effect of trying to mandate uniform operations solutions across an entire country. Third, Medicaid fees should be cautiously monitored. Medicaid patients are currently more profitable than the uninsured by a moderate margin. If fees are cut, however, the problem may repeat itself–there is little predicted improvement in crowding from shifting patients from being uninsured to being on Medicaid if the average reimbursement rates between the two equalize[2]. Similarly, the rise of urgent care poses its own challenges, but also brings potential solutions to emergency department crowding.

Finally, this dissertation adds to the limited but growing empirical literature on qual-

[2]Little benefit, rather than no benefit, because the hospital may still prefer a certain Medicaid payment over a stochastic one from the uninsured.

ity competition, while drawing specific attention to strategic uses of negative quality to screen out unprofitable customers. While healthcare's information assymetry, agency, intermediaries, moral hazard, adverse selection, and regulation make it the likeliest market for such negative quality competition, anecdotes such as the "fire your bad customers" movement suggest that negative quality competition may have substantial relevance for the broader economy.

APPENDIX

A.1. Tables and figures

	State	SEDD (2008)	All Payer DB
1	AK	-	-
2	AL	-	-
3	AR	-	-
4	AZ	X	-
5	CA	X	-
6	CO	-	X
7	CT	-	-
8	DC	-	-
9	DE	-	-
10	FL	X	-
11	GA	-	-
12	HI	-	X
13	IA	X	-
14	ID	-	-
15	IL	-	-
16	IN	-	-
17	KS	-	X
18	KY	X	-
19	LA	-	-
20	MA	X	X
21	MD	X	X

22	ME	-	X
23	MI	-	-
24	MN	-	X
25	MO	-	-
26	MS	-	-
27	MT	-	-
28	NC	X	-
29	ND	-	-
30	NE	X	-
31	NH	-	X
32	NJ	X	-
33	NM	-	-
34	NV	-	-
35	NY	X	-
36	OH	-	-
37	OK	-	-
38	OR	-	-
39	PA	-	-
40	RI	X	-
41	SC	-	-
42	SD	-	-
43	TN	-	X
44	TX	-	-
45	UT	X	X
46	VA	-	-
47	VT	X	X

48	WA	-	X
49	WI	X	X
50	WV	-	-
51	WY	-	-

Table 15: Data source availability

State	No. Hospitals	Percent Included
Arizona	64	67.2
California	312	84.6
Florida	184	83.2
Hawaii	23	87.0
Iowa	117	98.3
Kentucky	100	89.0
Maine		
Maryland	44	93.2
Massachusetts	62	69.4
Nebraska	85	91.8
New Jersey	63	77.8
North Carolina	106	84.9
Rhode Island	11	90.9
South Carolina	58	79.3
Utah	43	86.0
Vermont	14	100.0
Wisconsin	123	94.3

Table 16: 2010 SEDD hospital completeness, by state

A.2. Definition of an urgent care clinic

Perhaps because urgent care medicine is seen as new and potentially profitable, many primary care clinics seem to have adopted the moniker alongside one or two features that make them urgent care-like. For instance, a number of clinics which AT&T's Yellow Pages lists as urgent care have barely more than 40 hours per week of clinic time. Such a clinic is unlikely to have much impact on a neighboring ED's competitive

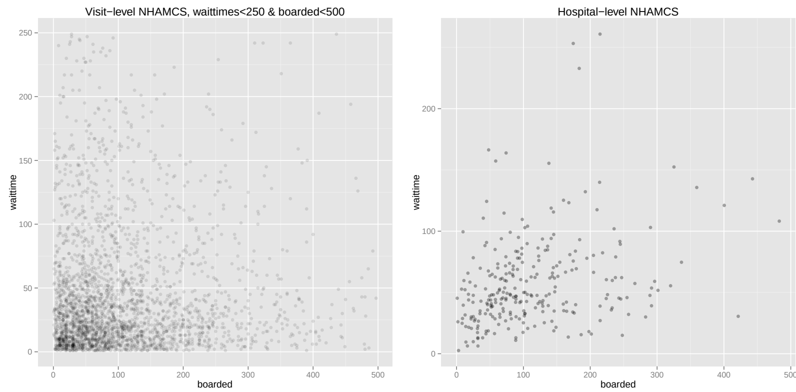


Figure 15: NHAMCS wait time vs. boarding time (conditional on being boarded) relationship

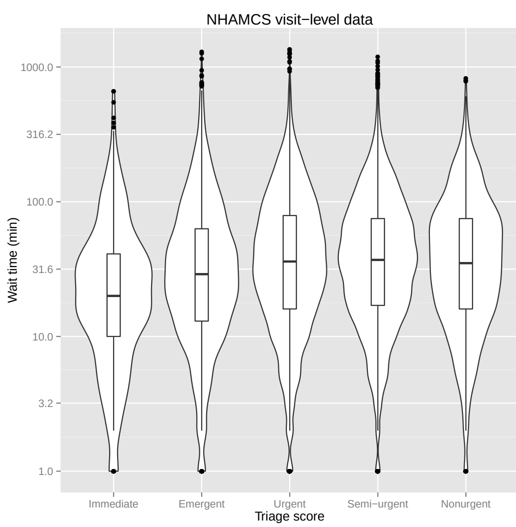


Figure 16: NHAMCS visit-level wait time vs. triage relationship

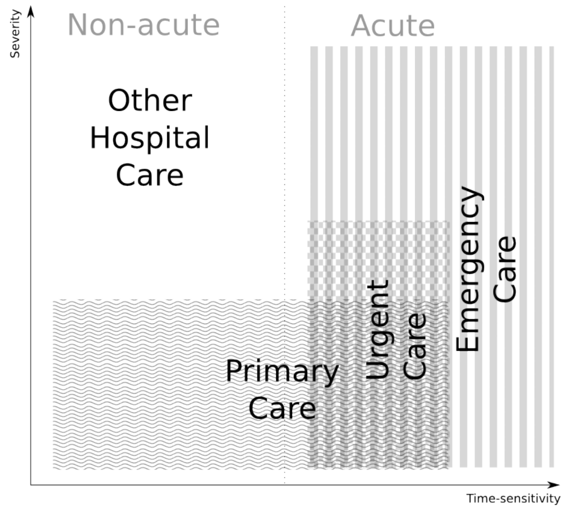


Figure 17: Schematic treatment of the spectrum of unscheduled care

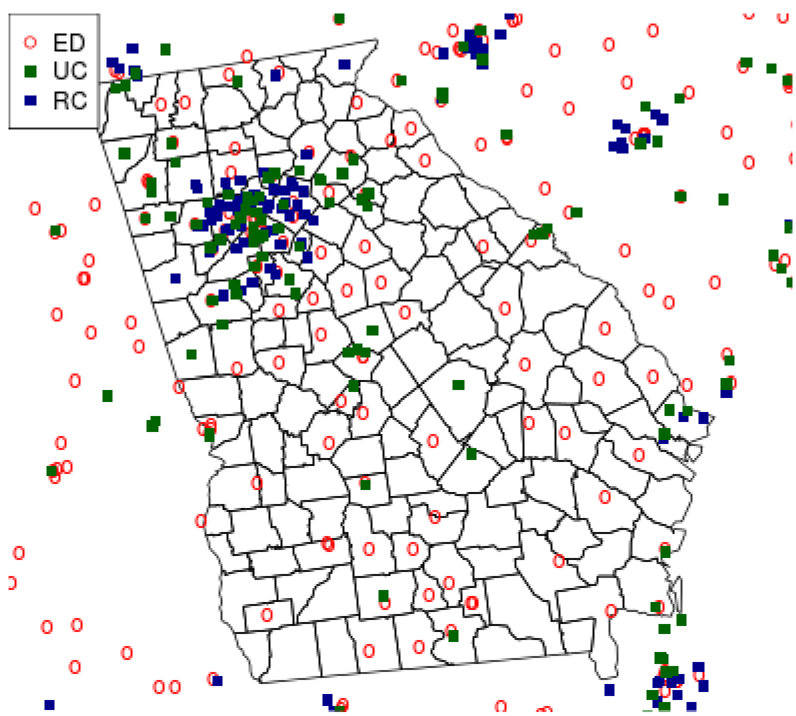


Figure 18: Georgia, an example of clinic location data

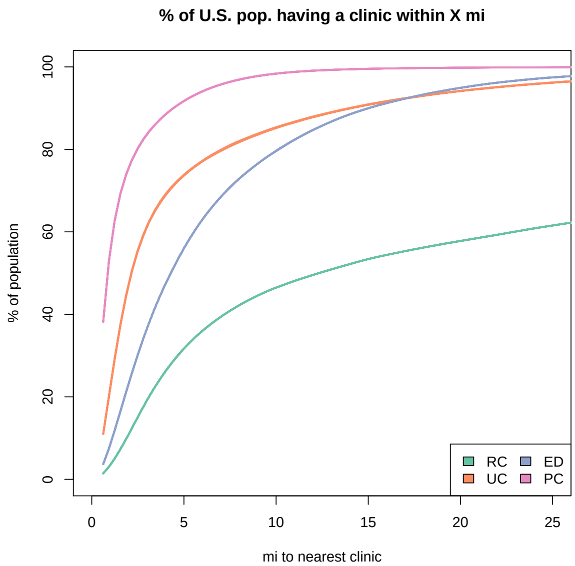


Figure 19: U.S. block group population c.d.f. by distance by entity type

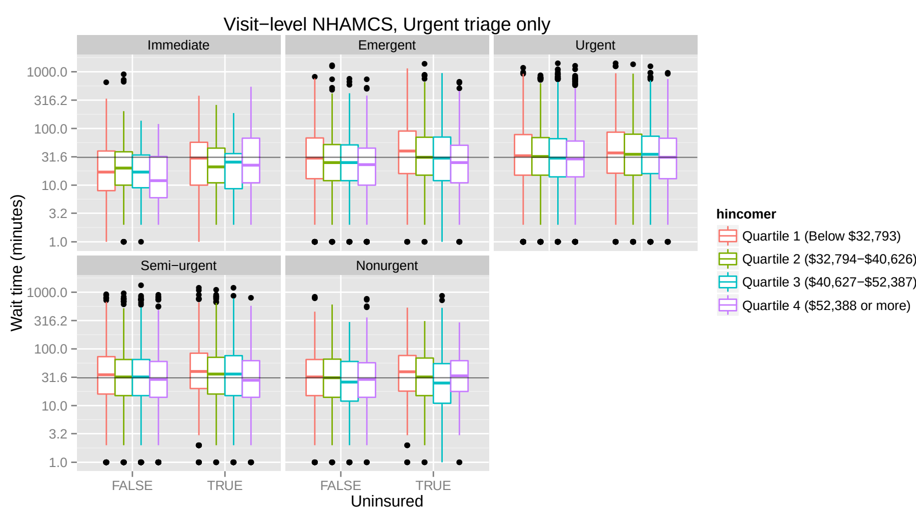


Figure 20: Wait times vs. insurance and income

	2010	2009	2008	2007	2006	2005	2004
AZ	X	X	X	X	X	X	-
CA	X	X	X	X	X	X	-
FL	X	X	X	X	X	X	-
HI	-	-	-	-	-	-	-
IA	X	X	X	X	X	X	X
KY	X	X	X	-	-	-	-
MA	X	X	X	X	X	X	X
MD	X	X	X	X	X	X	X
ME	-	-	-	-	-	-	-
NC	X	X	X	X	-	-	-
NE	X	X	X	X	X	X	X
NJ	X	X	X	X	X	X	X
NV	X	-	-	-	-	-	-
NY	X	X	X	X	X	-	-
RI	X	X	X	X	-	-	-
SC	-	-	-	-	-	-	-
UT	-	X	X	X	X	X	X
VT	X	X	X	X	X	X	X
WI	X	X	X	X	X	X	X

Table 17: SEDD AHA ID availability by year

	Immediate	Emergent	Urgent	Semi-urgent	Nonurgent	No triage
FALSE	76.00	68.30	82.90	95.30	96.40	93.10
TRUE	24.00	31.70	17.10	4.70	3.60	6.90

Table 18: Proportion of patients ever boarded, by triage category, NHAMCS09

landscape. This makes establishing a consistent definition of urgent care critical.

The Urgent Care Association of America has defined an UCCWeinick et al. [2009a] as a clinic that:

- Provides care primarily on a walk-in basis
- Has evening office hours Mon-Friday
- Has office hours at least one day over weekend

	(1)	(2)	(3)	(4)
year	4.691	5.090	3.665	-17.794*
	(5.36)	(5.12)	(4.65)	(7.67)
female	4.517	4.530	3.160	3.328
	(3.91)	(3.86)	(2.38)	(3.94)
race	1.520	-1.567	2.526*	2.578
	(2.46)	(3.09)	(0.54)	(1.74)
age	0.436**	0.425**	0.472*	0.467**
	(0.11)	(0.10)	(0.10)	(0.11)
ndx	23.058**	23.645**	22.432**	20.752**
	(5.50)	(5.47)	(0.86)	(1.90)
npr	55.888*	53.072*	51.905+	48.177**
	(25.14)	(24.99)	(16.22)	(9.61)
died	-374.436+	-379.831*	-374.867+	-382.728**
	(186.83)	(184.89)	(94.95)	(79.36)
nchronic	15.429+	14.437+	17.453+	18.174**
	(8.09)	(8.13)	(5.54)	(2.92)
aweekend	4.944	5.505	8.053	10.809*
	(4.74)	(4.80)	(8.40)	(4.30)
unins	18.698+	12.649	19.713	12.761*
	(10.49)	(12.72)	(8.06)	(5.49)
mcaid	-16.038+	-17.069+	-16.287	-19.830**
	(9.02)	(8.81)	(10.04)	(6.29)
uninsHosp	234.715*	447.370*	116.708	7047.154**
	(115.16)	(192.07)	(236.60)	(2323.46)
mcaidHosp	107.422	62.486	96.720	535.744**
	(70.27)	(76.25)	(80.10)	(157.36)
nVisitRelative	1764.176	1722.793	3268.746+	3874.497**
	(1285.76)	(1268.15)	(765.61)	(333.82)
_cons	-9168.318	-9996.932	-6967.884	
	(10792.89)	(10306.22)	(9134.45)	
N	23952	23952	23952	23950
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

$+p < 0.1$

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

Table 19: Hospital ED duration models for New Jersey, 1% sample.

	(1)	(2)	(3)	(4)
year	-6.190	-86.726	-6.728*	-11.655+
	(6.61)	(73.11)	(0.49)	(6.06)
female	2.209	-3.247	0.615	0.461
	(4.08)	(4.92)	(0.76)	(2.70)
race	7.196*	15.352	2.269	2.271+
	(3.19)	(10.07)	(1.54)	(1.25)
age	0.478**	0.398**	0.541*	0.544**
	(0.12)	(0.12)	(0.03)	(0.07)
ndx	15.166**	19.297**	18.594+	18.537**
	(4.11)	(6.79)	(2.58)	(1.38)
npr	35.592**	42.010*	28.222*	28.422**
	(11.09)	(16.55)	(1.40)	(9.42)
died	1.483	-30.419	2.666	2.612
	(47.84)	(63.84)	(34.55)	(49.92)
nchronic	11.079	9.079	1.772+	1.754
	(7.77)	(9.76)	(0.17)	(2.21)
aweekend	-2.469	-2.918	-2.928	-2.885
	(3.03)	(4.17)	(2.69)	(2.85)
unins	6.145	0.455	5.342	5.728
	(4.62)	(9.73)	(7.28)	(5.45)
mcaid	6.093	6.984+	7.777	7.899*
	(3.79)	(3.92)	(2.36)	(3.22)
uninsHosp	-55.776	4190.251	143.684*	393.439
	(238.19)	(3528.00)	(6.46)	(276.05)
mcaidHosp	-151.842*	-538.658	-218.174*	-211.457**
	(70.88)	(388.47)	(11.04)	(57.60)
nVisitRelative	-4647.237**	-4801.002*	-2231.868	-2123.502
	(1460.17)	(2092.69)	(731.37)	(1879.29)
_cons	12888.714	174741.932	13975.181*	
	(13300.26)	(146934.64)	(909.85)	
N	22976	22976	22976	22976
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

$+p < 0.1$
$*p < 0.05, **p < 0.01$

Table 20: Hospital ED duration models for Massachusetts, 1% sample.

	(1)	(2)	(3)	(4)
year	-9.815+	-10.970*	-9.045*	-25.066**
	(4.99)	(5.39)	(0.37)	(8.20)
female	1.915	1.616	0.891+	0.454
	(3.13)	(3.11)	(0.11)	(2.34)
race	5.588*	4.843*	2.671	2.671*
	(2.23)	(2.04)	(0.74)	(1.06)
age	0.508**	0.521**	0.511+	0.516**
	(0.09)	(0.09)	(0.07)	(0.06)
ndx	18.950**	19.123**	21.289*	21.091**
	(4.25)	(4.18)	(0.84)	(1.14)
npr	39.405**	39.693**	33.713	34.385**
	(11.19)	(10.95)	(7.11)	(6.94)
died	-56.339	-56.878	-55.420*	-55.678
	(43.40)	(42.62)	(3.21)	(46.58)
nchronic	11.761*	11.126*	8.682	8.729**
	(5.35)	(5.23)	(3.43)	(1.82)
aweekend	-5.723*	-5.786*	-3.532	-3.381
	(2.37)	(2.35)	(3.09)	(2.48)
unins	9.442*	5.704	6.082	6.247+
	(4.04)	(4.50)	(3.06)	(3.67)
mcaid	4.635	4.506	5.300	5.522+
	(3.58)	(3.57)	(4.98)	(3.05)
uninsHosp	39.255	97.807	169.509*	1321.441*
	(67.69)	(70.92)	(12.95)	(565.65)
mcaidHosp	-34.378	-16.848	-129.382**	-61.485
	(44.95)	(43.75)	(1.47)	(65.04)
nVisitRelative	-3707.108**	-3827.162**	-146.016	-5.053
	(790.58)	(806.61)	(537.02)	(454.92)
_cons	20132.565*	22449.149*	18581.239*	
	(10022.69)	(10828.69)	(714.14)	
N	38356	38356	38356	38353
Fixed Effects	No	No	Hospital	Hospital
Instrumented	No	Yes	No	Yes
Clustered	Hospital	Hospital	Year	None
Clinical Covariates	Yes	Yes	Yes	Yes
Contemp. Volume	Yes	Yes	Yes	Yes

$+p < 0.1$
$*p < 0.05, **p < 0.01$

Table 21: Hospital ED duration models for balanced panel, 1% sample.

- Provides suturing for minor lacerations

- Provides X-Rays on site

This definition seems to have a reasonable concordance with what people generally mean when they talk of "urgent care," and represents a reasonable competitor for EDs, yet still encapsulates a large number of clinics for study. Wherever possible, I will use this definition in my work.[1]

In the 2009 urgent care survey, 35.0% of the clinics contacted (using a sampling frame derived from phone books) did not meet this definitionWeinick et al. [2009a].

A.3. State laws affecting urgent care clinics

- Laws with direct effects on the cost of opening a UCC

- AZ mandated licensure of UCCs in 2000[2]

- State drug dispensing regulations for clinics[3]

- State licensing rules for NP/PAs

- State licensing rules for laboratory, x-ray

- Restrictions on how UCCs can be named and marketed (IL, DL, NH)[4]

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[1]While this definition is satisfactory, this still leaves open a range of different clinic types, from UCCs open 24 hours per day capable of running CT scans to much more limited "primary care-plus" clinics. I will attempt to explore this distinction as well, if data allows. Specifically, I suspect that UCCs more remote to EDs are more likely to have advanced capabilities, which, absent altruistic motives, would reflect a decision to compete more directly with EDs in product space when more separated in geographic space.

[2]www.touchbriefings.com/pdf/1334/Stern.pdf

[3]http://aaucm.org/Professionals/MedicalClinicalNews/DispensingRegulations/default.aspx

[4]http://www.ucaoa.org/resources_newtourgentcare.php

- Restrictions on non-physician ownership[5]

- HCA hospital located nearby[6]

- State auto liability ins. mandates[7]

- Certificate-of-need laws for UCCs (limited)

A.4. Welfare losses due to ED crowding

ED crowding may cause welfare loss through several mechanisms. First, patients assigned low-priority triage scores are harmed by the greater economic (time + money) cost of obtaining care. While the welfare loss due to this time has not been calculated, the magnitude of the problem is hinted at by the statistic that patients in 2009 collectively spent 7.06 billion minutes (13.4 millennia) waiting to be seen by an ED clinician [8].

Next, patients with more severe conditions seem to face worsened ED performance as a result of crowding. ED crowding has been associated with delays in a variety of time-sensitive processesHwang et al. [2008], Mills et al. [2009], Sills et al. [2011], Pines and Hollander [2008], Schull et al. [2004], Fee et al. [2007], and increased transit times due to ambulance diversion likely cause further morbidity and mortality given the well-established relationship between transit times and outcomes for several widespread

[5] Texas, California, Ohio, Colorado, Iowa, Illinois, New York and New Jersey prohibit non-physician ownership under the Corporate Practice of Medicine doctrine. http://www.ucaoa.org/resources_newtourgentcare.php

[6] HCA hospitals have recently started demanding up-front payment for all but the most critical services in the ED, relying on a narrow reading of EMTALA. This effectively increases the price of UC treatment at HCA EDs.

[7] Auto insurance pays large amounts for ED care, and thus increases the willingness of EDs to operate at a loss

[8] Calculated by summing the 2009 NHAMCS wait times while taking into account the complex survey design weights.

acute disease statesCarr et al. [2006], Ting et al. [2007], Souza and Strachan [2005], Weaver [1995]. Given that the triage system is explicitly designed to prioritize patients identified early as high-priority, these studies, while concerning, likely represent a fairly small component of the overall welfare loss.

While the triage system is mostly reliableHay et al. [2001], triage misclassification–when patients with a high-priority presentation are placed in a low-priority category–remains a regular occurrence. For instance, 3-5% of all ED patients triaged as 'non-urgent' require immediate hospitalization Kellermann and Weinick [2012]. Patients with serious, time-sensitive conditions such as myocardial infarction (MI) or stroke face longer delays before treatment if they are misclassified at triage. This may be one mechanism behind the findings that ED crowding has been associated with worsened cardiovascular outcomesBernstein et al. [2009], Pines et al. [2009] and even mortalitySinger et al. [2010], Sprivulis et al. [2006]. These studies may even underestimate true effects considerably if their adverse outcomes are not recorded in the ED because these mistriaged patients leave without being seen. 8.1% of all patients leave without being seenAsaro et al. [2007], with patients triaged into low-priority categories even more likely to do soBatt and Terwiesch [2013]), and 60% of cases in one study then seeking medical attention within a weekRowe et al. [2006].

Collectively, these findings suggest that ED crowding is a problem with large welfare implications, and the study of its determinants and possible solutions could have potentially large welfare effects in turn.

A.5. Ambulatory care-sensitive conditions

Selected ACSCs used in this study, categorized by author.

	ICD9 Codes	Category	Inclusion criteria
Vaccine-related 1	033.*	Prevention	
Vaccine-related 2	037.*	Prevention	
Vaccine-related 3	045.*	Prevention	
Vaccine-related 4	39[01].*	Prevention	
Hemophilus meningitis	320.0*	Prevention	Age>=1 & Age<5
COPD	49[1246].*	Prevention	
Acute bronchitis	466.0*	Prevention	2ndary dx codes
Asthma	493.[0-9]*	Prevention	
Iron deficiency anemia	280.[189]*	Prevention	Age<5
Failure to thrive	783.4*	Prevention	Age<1
Pelvic inflammatory disease	614.*	Prevention	Gender=='Female'
Hypertension1	401.[09]*	Substitution	
Hypertension2	402.[019]0*	Substitution	
Gastroenteritis	558.9*	Substitution	
Kidney/urinary infection1	590*	Substitution	
Kidney/urinary infection2	599.[09]*	Substitution	
Dehydration	276.5*	Substitution	
Dental conditions	52[12358]*	Substitution	

Table 22: Selected ambulatory care-sensitive conditions categorized into substitution vs. prevention

A.6. Reimbursement rates and out-of-pocket costs by insurance type

Figure 21 shows data from the Medical Expenditure Panel Survey (MEPS) consisting of all 86,918 ED visits from 2008-2011 except the 6,538 visits for newborns or visits with flat-fee arrangements.

Out-of-pocket and total payments for ED patients were compared across insurance types. For each, we calculated two statistics: probability of any expenditure, and log spending conditional on any expenditure. All inpatient expenditures were included where the visit resulted in admission. Spending was inflation-adjusted to 2011 dollars. All estimates were weighted to produce national, population-based estimates using appropriate survey weights.

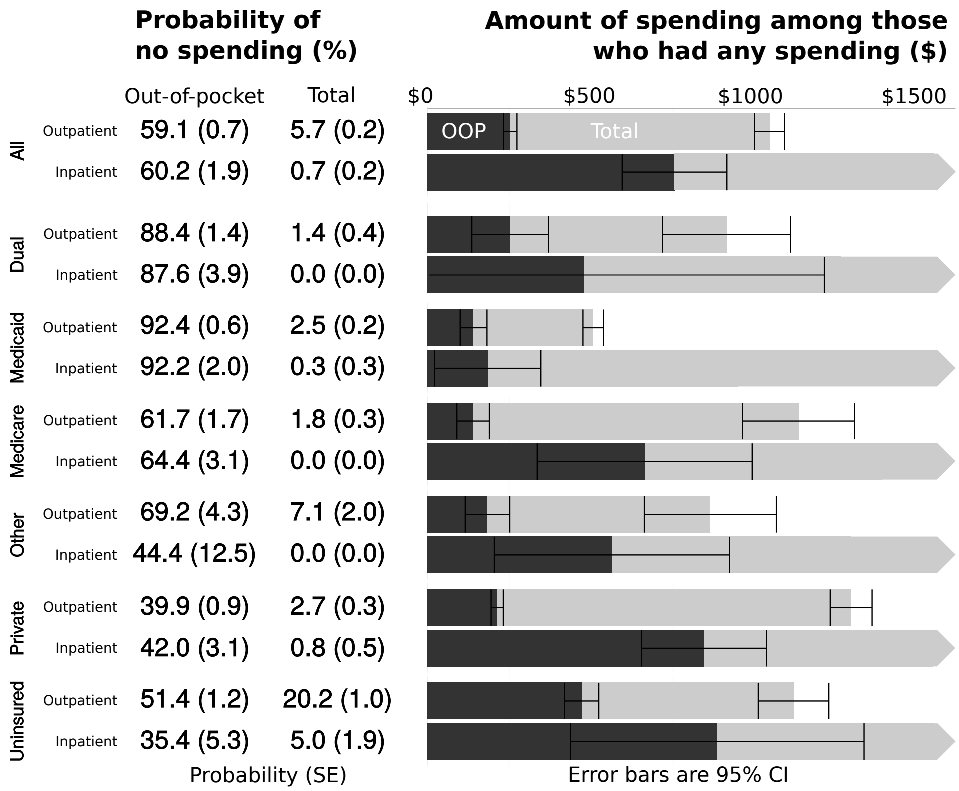

Figure 21: MEPS percentage with no out-of-pocket spending and overall spending.

This joint work with Seth Seabury and Carl Berdahl was presented at the Society for Academic Emergency Medicine 2014 Conference (Dallas, TX).

A.7. Motivating model variable handout

Variable definitions

- w^* is the optimized wait time
- α is the proportion of uninsured in the market
- s is *ex ante* severity: $s = 0$ for those less sick, $s = 1$ for those more sick
- i is reimbursement status: $i = 0$ for uninsured/Medicaid, and $i = 1$ for privately

insured/Medicare patients

- $\Pi(s, i)$ is the profit to the hospital for a patient of type (s, i)
- ρ is the $Pr(prf|i = 0, s = 1)$
- π_{prf} is the profit when an uninsured patient is admitted and turns out to be profitable
- $\pi_{charity}$ is profit when the hospital cannot recoup the cost
- x indexes utilization: $x = 1$ if the patient seeks ED care and $x = 0$ if they instead utilize their outside option
- $\sigma_1 = Pr(s = 1|i = 1, x = 1)$
- $\sigma_0 = Pr(s = 1|i = 0, x = 1)$

Assumptions

- $\pi_{s=1,i=1} > \pi_{s=0,i=1} \overset{?}{>} \pi_{s=1,i=0}$
- $\Pi(s = 0, i = 0) < 0$
- $\Pi(s = 1, i = 0) = \rho\pi_{prf} + (1 - \rho)\pi_{charity} > 0, small$
- $\frac{\partial\sigma_0}{\partial w} < \frac{\partial\sigma_1}{\partial w}$

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