



City Research Online

City St George's, University of London

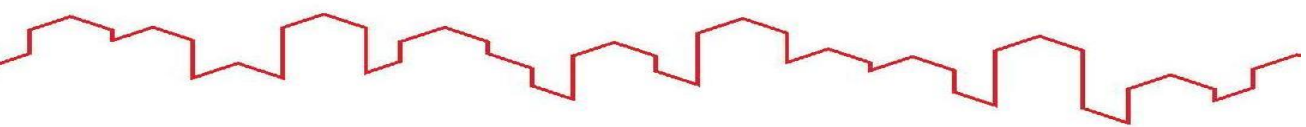
Citation: Pinchbeck, E. (2018). Convenient Primary Care and Emergency Hospital Utilization (19/04). London, UK: City, University of London.

This is the published version of the paper.

This version of the publication may differ from the final published version. To cite this item please consult the publisher's version.

Permanent repository link: <https://city-ref-test.eprints-hosting.org/id/eprint/21514/>

Copyright and Reuse: Copyright and Moral Rights remain with the author(s) and/or copyright holders. Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge, unless otherwise indicated, provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way. For full details of reuse please refer to [City Research Online policy](#).

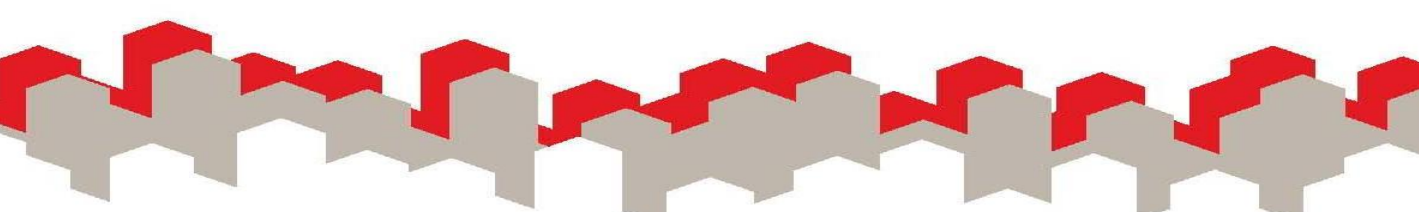


Department of Economics

Convenient Primary Care and Emergency Hospital Utilization

Edward W. Pinchbeck¹
Department of Economics,
City, University of London
and
Centre for Economic Performance,
London School of Economics and Political Science

Department of Economics
Discussion Paper Series
No. 19/04



¹ Corresponding author: Edward W. Pinchbeck, Department of Economics, City, University of London, Northampton Square, London EC1V 0HB, UK.
Email: edward.pinchbeck@city.ac.uk

Convenient Primary Care and Emergency Hospital Utilization

Edward W. Pinchbeck*

February 1, 2019

Participation and utilization decisions lie at the heart of many public policy questions. I contribute new evidence by using hospital records to examine how access to primary care services affects utilization of hospital Emergency Departments in England. Using a natural experiment in the roll out of services, I first show that access to primary care reduces Emergency Departments visits. Additional strategies then allow me to separate descriptively four aspects of primary care access: proximity, opening hours, need to make an appointment, and eligibility. Convenience-oriented services divert three times as many patients from emergency visits, largely because patients can attend without appointments.

JEL codes: I11, I12, I18, D12

Keywords: primary care, emergency care, access, utilization decisions

*City, University of London and Centre for Economic Performance. Address: City, University of London, Northampton Square, London, EC1V 0HB. Email: edward.pinchbeck@city.ac.uk. My thanks to Gwyn Bevan, Philippe Bracke, Peter Dolton, Steve Gibbons, Christian Hilber, Alex Jaax, Alistair McGuire, Henry Overman, Sefi Roth, and Olmo Silva as well as participants at the LSE/Spatial Economics Research Centre seminar and the Royal Economic Society conference for helpful comments, suggestions, or other input to earlier versions of this work.

For some services discrepancies between social and individual benefits warrant government action on efficiency grounds. In other cases, society may intercede to ensure individuals can access some hitherto unattainable level of service. Interventions to improve the accessibility of services conceivably come in many guises, for instance improving affordability or widening eligibility; providing more, closer, or better services; shorter waiting times; or more convenient opening hours (e.g. [Millman et al., 1993](#); [Hiscock et al., 2008](#)). The ways in which interventions are designed and structured may have consequences for utilization, service costs, and the attainment of policy objectives, particularly given mounting evidence that psychological factors can lead seemingly minor service features to play a part in utilization and participation decisions (e.g. [Duflo et al., 2006](#); [Bertrand et al., 2006](#); [Baicker et al., 2015](#)).

This paper investigates how dimensions of access to primary care affect the demand for unplanned use of hospital Emergency Departments (EDs). I draw on *Equitable Access to Primary Medical Care (EAPMC)*, a policy reform in the English National Health Service (NHS) designed to make primary care more convenient across the country, and to address geographical imbalances in access. Under *EAPMC*, around 250 new primary care services were deployed between 2008 and 2012. More than half were “walk-in clinics”: practices with evening and weekend opening hours, and offering walk-in services with no need to register or make an appointment. The remainder, targeted to administrative districts with the lowest concentration of primary care physicians, were “extended hours practices”: regular services requiring registration but open at least 5 hours per week more than conventional practices. The comprehensive nature of the English NHS (where all patients have access to free primary care), allows me to abstract from insurance issues, and to focus on physical proximity and other less well-understood, but potentially important, convenience dimensions of access.

To contrive a quasi-experimental research design from the *EAPMC* policy reform I use hospital records to capture the evolution of hospital utilization in small neighborhoods, then generate a measure of primary care access as a non-parametric function of distance to *EAPMC* services.¹ Restricting regression samples to places receiving new facilities under

¹More concretely access intensity is computed by counts of open services in a series of distance buffers centered on the neighborhood centroid, where distance buffers vary across space based on the distribution of distances traveled to access emergency care locally.

the policy, specifications estimate an average treatment effect on the treated (ATT) from changes in hospital outcomes when an *EAPMC* service opens or closes, with a control group composed of areas suitable for similar services but not experiencing access changes at that particular time. Using timing differences for identification is underpinned by evidence that: (i) service roll-out is unrelated to pre-reform primary care access measures; and (ii) trends in ED visits are broadly parallel across cohorts. This aligns with policy documents that indicate service deployment timetables were driven by administrative factors that are plausibly unrelated to the determinants of hospital utilization.

This research design is leveraged to generate three sets of findings. The first documents policy relevant estimates of the impact of walk-in clinics on neighborhood wide ED utilization. Conditional on fixed neighborhood factors, labor-market trends, and demographic changes, proximity to these convenience-oriented services results in strongly significant reductions in unplanned ED visits. Reductions in ED visits are in the order of 1.5 – 4%; implying that each facility reduces annual ED throughput by approximately 1,000 – 2,000 visits. The robustness of these estimates is bolstered by auxiliary analyses, robustness and falsification tests.

A second set of results exploits data richness to show that diversion from EDs is subject to a strong, near-linear, decay with distance to a walk-in clinic. Further findings indicate that diversion from EDs is largely driven by patients whose visit does not result in a hospital admission, and by patients that were neither referred to the ED nor conveyed there in an ambulance. This points towards a conclusion that the effects of walk-in clinics mainly arise from influencing care utilization decisions of agents with less urgent health problems, and with more discretion over the location of their treatment.

The third and final part of the analysis unpicks further channels through which primary care access determines ED utilization. Here I rely on a descriptive approach that compares walk-in clinics and extended hours practices in under-doctored administrative districts which received both types of service under *EAPMC*. When estimated simultaneously, walk-ins divert three times as many patients from EDs. Although both types of service have meaningful effects on ED visits outside of standard practice hours, the greater bite of walk-in services predominantly occurs during these standard hours. To the extent that services are well matched on unobserved features, being able to attend without registering

or pre-booking strongly influences where agents seek treatment.

This paper provides new evidence on the extent to which convenient primary care reduces visits to hospital EDs, and by using a national policy reform and the universe of hospital visits, I build on a small literature that obtains plausibly causal estimates in narrower empirical settings (e.g. [Dolton and Pathania, 2016](#)). Shifting care from EDs to primary care is likely to represent a social benefit because some 15 to 40% of ED visits are for health problems that could be safely treated in less costly settings outside hospitals ([Mehrotra et al., 2009](#); [Weinick et al., 2010](#); [Lippi Bruni et al., 2016](#)). Moreover, strong recent growth in ED use in many OECD countries ([Berchet, 2015](#)) has found many hospitals operating above capacity and resulted in well-documented congestion in EDs, such that reducing pressure at EDs has become an increasing priority ([Rust et al., 2008](#); [Pines et al., 2011](#)).²

Findings indicate that *EAPMC* walk-in clinics significantly reduced ED activity in areas of England with and without primary care shortages. The ATT estimates are directly relevant to any *ex post* evaluation of the *EAPMC* policy, and may generalize to other settings in which policy-makers are seeking to reconfigure existing services or expand primary care in suitable locations. Coefficients imply that 5–20% of walk-in clinic visits substituted for a trip to an ED. Despite the lower costs of primary relative to ED care, by itself this implies a net increase in health care spending, but says nothing about patient benefits or diversion from regular primary care services. A full welfare analysis would need to take account of these factors. However, NHS primary care physicians are paid a capitation fee for each registered patient so this analysis is a relevant metric in understanding the effects of the policy on the NHS budget.

This paper’s second more general contribution is to adopt a multi-dimensional view of health care access, and to demonstrate that several dimensions simultaneously drive health care utilization patterns. Related research has typically focused on individual components of access in isolation — for example affordability ([Selby et al., 1996](#)); service opening hours ([Dolton and Pathania, 2016](#); [Whittaker et al., 2016](#)); or physical proximity ([Van Dort and Moos, 1976](#); [Currie and Reagan, 2003](#); [Buchmueller et al., 2006](#)). The results documented here suggest that a wider view is warranted, and could help to resolve puzzles and anomalies in care utilization patterns. For example, as [Chen et al. \(2011\)](#)

²Between 1995 and 2010 visits to US EDs increased by 34% ([National Center for Health Statistics, 2013](#)), while visits to Accident & Emergency departments in the England rose by 40% ([Appleby, 2013](#)).

acknowledge, the *availability* of primary care physicians may be behind heterogeneity in how reforms that alter *affordability* lead to changes in ED utilization and substitution across care settings.³

Finally, the paper is related to a growing literature that allows for behavioral factors in models of individual participation and utilization decisions (e.g. [Mullainathan et al., 2012](#)). [Baicker et al. \(2015\)](#) document numerous examples where psychological factors plausibly result in underutilization or overutilization of health care. In this paper, I make a start in applying these insights to agents' choice of treatment setting. Proximity and the ability to attend without appointment are important factors in determining the extent to which primary care diverts agents from EDs, which chimes with evidence from other settings that inconvenience and hassle can be powerful barriers to participation (e.g. [Bertrand et al., 2006](#); [Kahn and Luce, 2006](#)).

1 Background

1.1 Institutional Context

Patients desiring unplanned care from the NHS in England and Wales have traditionally had two main options: visit a hospital Accident and Emergency (A&E) Department, a Consultant-led 24 hour services with full resuscitation facilities catering for all kinds of emergency (equivalent to Emergency Departments, or EDs); or consult with a family physician – know locally as a General Practitioner (GP) – at a primary care practice. It is widely acknowledged that providing care in EDs is considerably more costly than in settings outside hospitals such as physicians' offices (e.g. [Mehrotra et al., 2009](#)). This is also true in the NHS context: for example, recent figures indicate that a visit to A&E costs £124 while a GP practice consultation costs £32.

Despite universal coverage and no demand-side cost sharing, patients using NHS emergency care incur time and travel expenses. In addition, EDs and primary care are subject to access frictions. In this regard EDs are arguably more convenient than conventional

³Such heterogeneity is evident in recent research: [Miller \(2012\)](#) find that expansion of health insurance under the 2006 Massachusetts reform led to a 5–8% reduction in ED visits and imply substitution from hospital visits to primary care, whereas work using later reforms in Oregon by [Taubman et al. \(2014\)](#) and [Finkelstein et al. \(2016\)](#) finds that health insurance resulted in 40% increases in ED visits with no evidence of substitution to primary care.

primary care: patients can visit any ED whenever they wish, and due to closely monitored performance targets, can normally expect to wait less than 2 hours for treatment. Conversely, access to specific primary care services requires registration, and is usually only available to patients living within a practice's catchment boundary. Access is via an appointment, an emergency appointment, or – where available – by using a primary care Out of Hours service on evenings and weekends. Although almost all individuals are registered at a primary care practice, they may have to wait a week or longer to obtain a regular appointment with a family doctor; and, although often available, same day emergency appointments can be difficult to book. Even then, appointments may not be convenient.⁴

From the late-1990s, alternative ways to access unplanned care emerged in the shape of new urgent care services designed for patients with minor medical problems. These included a telephone advice service and facilities offering easy access to face-to-face advice and treatment. NHS Walk-in Centres are one type of urgent care service that were introduced in this period.⁵ These facilities provide routine and emergency primary care for minor ailments and injuries with no requirement for patients to pre-book an appointment or to register (Monitor, 2014). Most are located away from hospitals although some are co-located with hospital EDs, so that on arrival patients are directed (triaged) to the appropriate service. In total approximately 230 Walk-in Centres have opened in England since 2000. Some 150 (or 65%) of this total number were commissioned following a report in 2007 that led to the creation of the Equitable Access to Primary Medical Care (*EAPMC*) policy reform.

EAPMC was set-up with the twin objectives of delivering more personalized and responsive primary care across England, and improving access in the most under-doctored areas. To meet these objectives *EAPMC* comprised two discrete initiatives. The first funded 100 new primary care practices in the 38 Primary Care Trusts (PCTs) with the

⁴For example, surveys indicate the average wait to get a GP appointment is around 13 days *Pulse* (2016). Average waiting time for GP appointment increases 30% in a year, June 10. In the July 2017 GP Patient survey, 32% of patients did not find it easy to get through to their practice by phone; 29% were not able to see or speak to someone at the time they wanted; 31% who wanted a same day appointment could not get one; 24% say that their practice is not open at times that are convenient for them; and only two thirds of patients rate their overall experience of out-of-hours NHS services as good.

⁵Others include Urgent Care Centres and Minor Injury Units, both of which usually do not provide primary care services. See Monitor (2014) for a review.

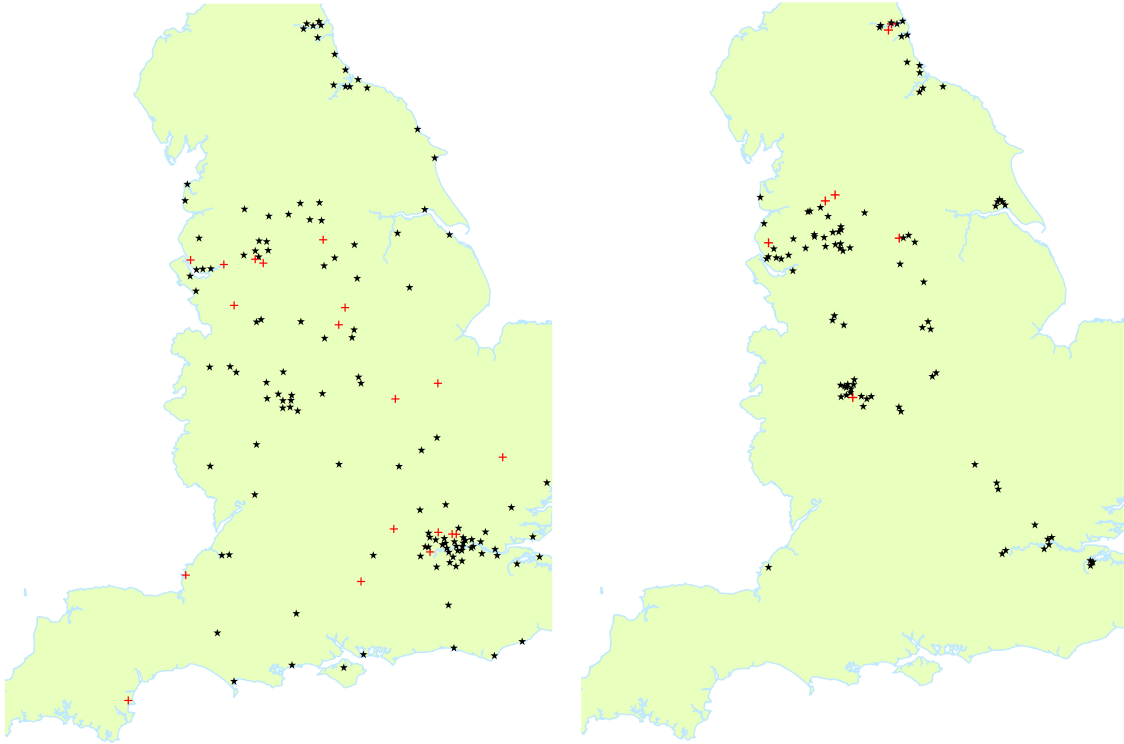
lowest provision of family doctors.⁶ These practices were similar to conventional primary care services already available, but had to meet certain core criteria such as having at least 6,000 patients and being accredited training practices. They were also required to facilitate access opportunities through extended opening hours, with a minimum of 5 hours per week beyond Monday to Friday 8.30am–6.30pm, and by setting large catchment boundaries (Department of Health, 2007) (see Appendix A for the full list of criteria). I refer to these services henceforth as “extended hours practices”. The second strand of *EAPMC* compelled each of the 152 PCTs to establish a “GP-led Health Centre”, a new service type designed to offer more convenient access to primary care. These facilities — which I refer to throughout as “walk-in clinics” — had to offer both a regular registered primary care service with bookable appointments, as well as a walk-in service for any member of the public from 8am–8pm, 365 days a year. Core criteria required the centers to be located in areas maximizing convenient access and opportunities to integrate with other local services (Department of Health, 2007).

Figure 1 shows the spatial distribution of *EAPMC* walk-in clinics (LHS) and extended hours practices (RHS). The policy brought walk-in services to a wide range of locations, including some less urban areas in England while the extended hours practices were mainly located in cities, particularly those in northern England. Figure 2 charts counts of walk-in services (LHS) and primary care practices (RHS) between 2006 to the end of 2012. During this period walk-in clinics more than doubled in number, peaking in 2010, before falling again. This variation is driven by openings and closings of *EAPMC* services. The right-hand plot shows the *EAPMC* extended hours practices temporarily reversed a secular downward trend in primary care practice numbers. The sharp rise in practices between 2009 and 2011 was driven by *EAPMC* services, but the steep fall in 2012 was not related to the *EAPMC* policy. This fall potentially poses a threat to identification and is addressed in robustness checks in Section 3.6.

Figure 2 demonstrates that *EAPMC* came on stream in a staggered fashion between late 2008 and the end of 2011. For example, the first walk-in clinic (the Hillside Bridge Centre in Bradford) opened in December 2008; roughly a third of all *EAPMC* walk-in clinics

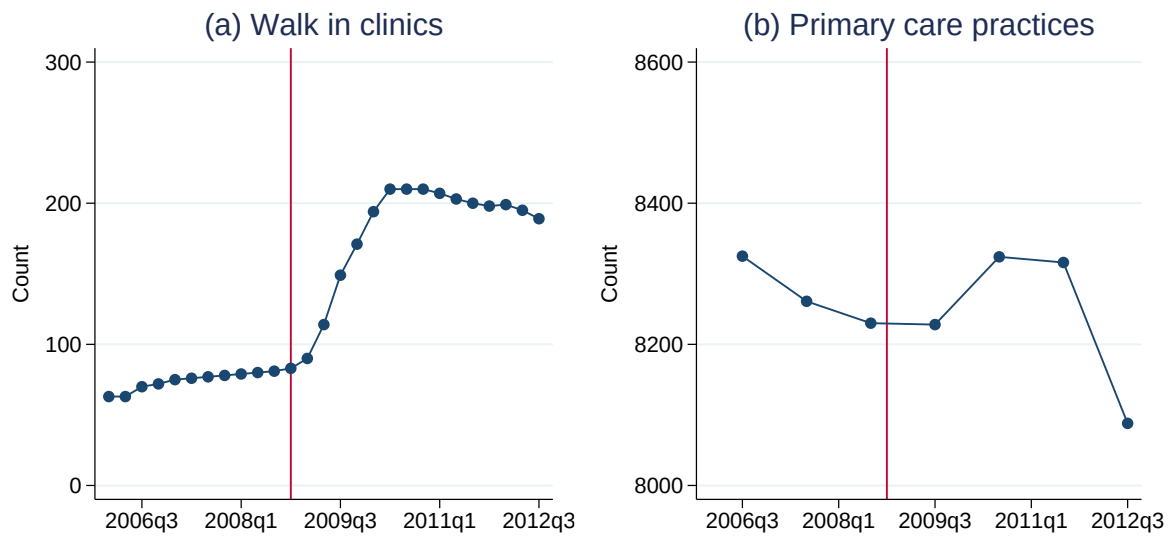
⁶Until 2013 Primary Care Trusts were legal entities responsible for purchasing and managing NHS health care for all residents living in defined geographical areas of the country. Between 2006 and 2013 England was split into 152 such areas.

Figure 1: *EAPMC* walk-in clinics (LHS) and extended hours practices (RHS)



Notes: Black stars are facilities still open in September 2014; red plus symbols had closed by that date.

Figure 2: Walk-in clinics and primary care practices in England



Notes: Walk-in clinic plot constructed by author using regulator reports. Primary care practice plot based on data contained in [HSCIC \(2016\)](#) and excludes walk-in clinics. Vertical line indicates the first *EAPMC* service opening (fourth quarter of 2008). Note that walk-in clinics open prior to *EAPMC* were mainly led by nurses.

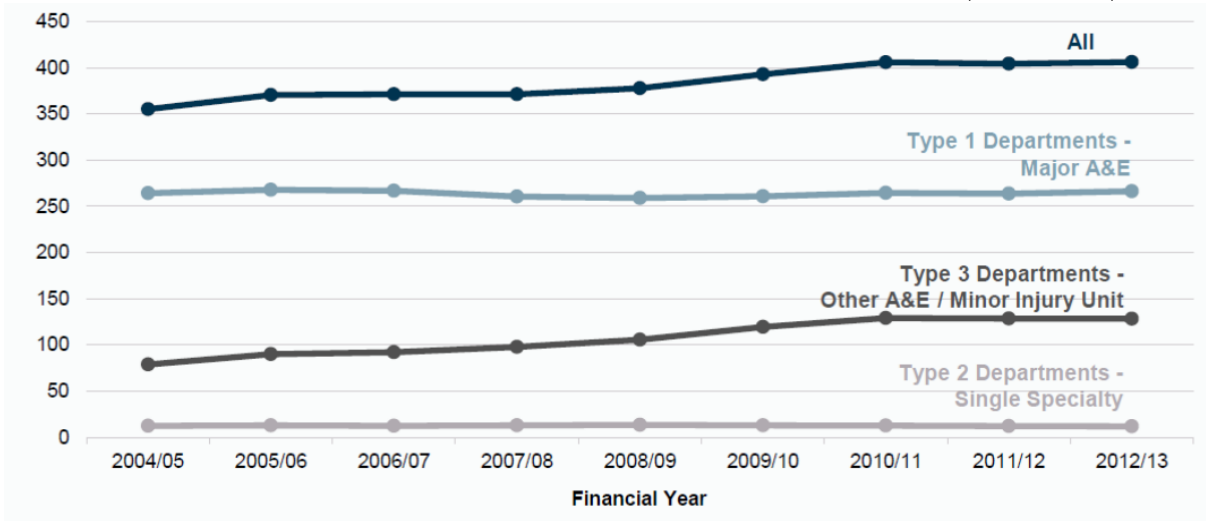
had opened before May 2009, more than two thirds by the end of 2009, and all but two before 2011. What drove this pattern of deployment? Guidance issued by the Department of Health highlights that local administrators were under pressure to establish the new services quickly, with an expectation that all procurements should be finished in financial year 2008/9 ([Department of Health, 2007](#)). Although some did meet this timetable, many others did not, with sources suggesting that deployment timings were mainly driven by local administrative factors, for example readiness on the part of administrators to specify services and identify suitable premises, the speed of procurement processes, and the time needed to prepare sites.

1.2 Primary care and ED utilization

In standard formulations, individuals seek care when the private costs of obtaining treatment p are lower than the perceived private treatment benefits $b(\sigma)$, which are increasing in illness severity σ . From a social perspective, treatment is warranted when private benefits are higher than the social costs of treatment c ; such that when $p < c$ there is moral hazard and some over-treatment. When EDs and primary care are substitutes, patients seek treatment in primary care when they perceive a net private benefit from primary care ($b_{PC} - p_{PC} > 0$); and when primary care offers a higher perceived net benefit than an ED ($b_{PC} - p_{PC} > b_{ED} - p_{ED}$). A more general case allows for behavioral biases and is set out in [Appendix B](#).

Primary care access interventions reduce private costs of primary care, either through lowering co-pays or, as in the English NHS, by reducing time costs and travel expenses. Any such intervention can have an effect at the extensive margin by inducing marginal agents to utilize primary care instead of not seeking any kind of care. Additionally, through the second condition an intervention can divert patients from EDs to primary care. The stylized facts presented in [Section 1.1](#) suggest the following. First, EDs can treat all patients, but those with illness severities above some point $\bar{b}(\sigma)_{PC}$ are not treatable in primary care. Second, ED care is available at any time but primary care can only be accessed during practice opening hours. Third, treatment costs in EDs are strictly higher than primary care ($c_{ED} < c_{PC}$). These stylized facts predict that following an increase in primary care access: *(i)* agents with less severe medical problems should be

Figure 3: Attendances per thousand population by unit type, 2004/5 to 2012/13



Source: Health and Social Care Information Centre

expected to divert to primary care; (ii) diversion should take place primarily during primary care opening hours; and (iii) diversion of primary care treatable patients from EDs to primary care represents a social gain.

Later analysis uses micro-data to estimate the extent to which *EAPMC* services divert patients from EDs. This is warranted because the aggregate utilization data depicted in Figure 3 is inconclusive. In the period when *EAPMC* services were being deployed (2008/9–2010/11), visits to walk in clinics and other urgent care services for minor problems (denoted “Type 3 units”) rose steadily while ED visits (denoted “Type 1 Departments”) remained flat. These trends could be consistent with effects purely at the extensive margin i.e. walk in clinics meeting previously unsatisfied demand.⁷ However, the same outcome can also arise when walk-ins substitute for ED care. In the limit aggregate demand for emergency care is perfectly inelastic, such that all else equal every clinic visit is offset by one less visit to an ED. Under such conditions, the aggregate trends in Figure 3 could reflect unrelated shifts in emergency care demand, for example from, say, an aging population or increased patient expectations.

⁷Note that this setting is unlikely to induce supplier-induced demand (in the sense of doctors encouraging patients to consume more health care) as emergency care is unplanned and not influenced by doctor behavior.

2 Data and Empirical Approach

2.1 Data

Subsequent analysis rests on two separate quarterly panel data sets for 2009 to 2012 that combine measures of access to primary care services with data on hospital activity throughout England. The panels are constructed for two different spatial scales. In the main neighborhood level panel, the units of analysis are 32,844 Lower Super Output Areas (LSOA). LSOAs are a census geographical unit that house 1,630 residents on average, making them comparable to but somewhat smaller than US Census tracts. The second is a provider level panel in which the units of analysis are 144 NHS Trusts that contain at least one ED. Population demographic data for LSOAs from the Office for National Statistics and primary care access measures are then appended to the activity data. The latter are generated using reports issued by the hospital regulator and the Department of Health by first compiling a list of *EAPMC* services, geocoding each site using the full postcode, then adding facility opening and closing dates using information provided by the Health and Social Care Information Centre (HSCIC). Shapefiles released by NHS England identify patient registration boundaries for a sub-set of practices.

Hospital activity data is drawn from two main sources: the Quarterly Monitoring of Accident and Emergency (QMAE) dataset published by NHS England, and Hospital Episode Statistics (HES) records provided by HSCIC. QMAE was the official source of information on ED activity in the period 2009 to 2012, and is generally considered to be the most comprehensive and reliable source of aggregate information on emergency care activity. It captures aggregate ED visit counts at the NHS Trust, rather than the site, level. For most NHS Trusts this is inconsequential as there is only one ED, but some NHS Trusts have multiple emergency care sites, in which case the split of attendances across sites cannot be observed. To account for mergers, I group together earlier data for NHS Trusts which will eventually merge in order to create a consistent panel.

For the neighborhood level analysis, three hospital utilization variables are derived from two distinct HES data resources. Both contain anonymized patient records, and include the patient's residential location (LSOA) as well as details of care received. The first and principal utilization measure records *unplanned visits* to hospitals: (1) the total number

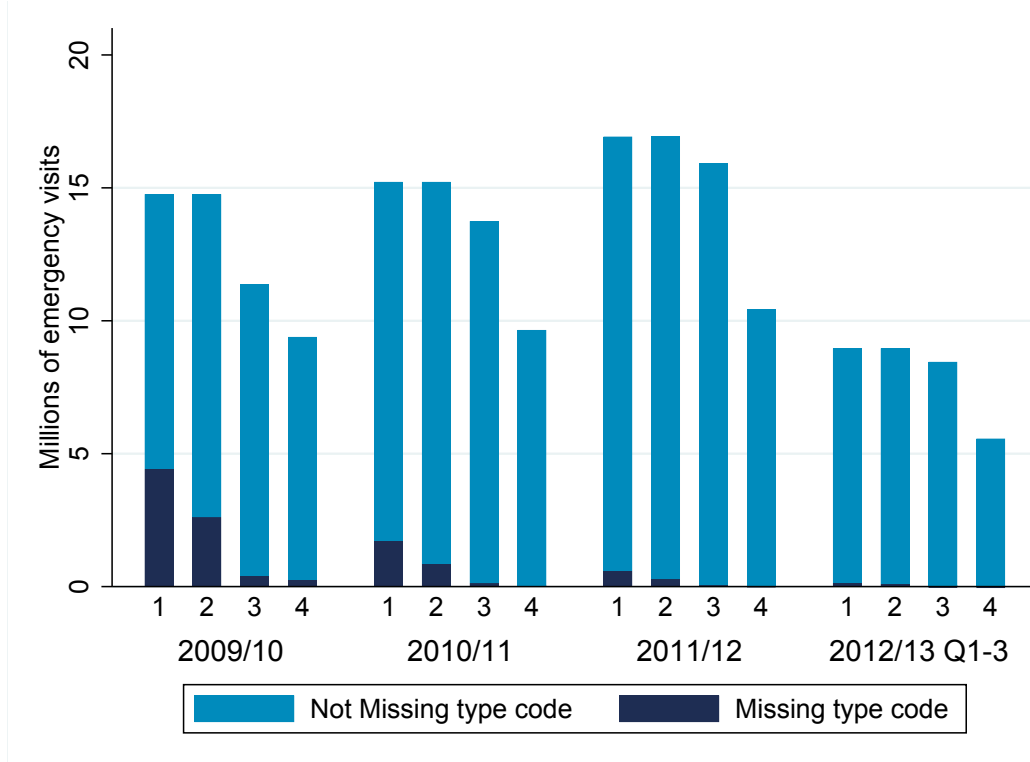
of visits to hospital EDs. Two further measures relate to *admissions* to hospital: (2) the total number of admissions, and (3) the proportion of unplanned admissions that could potentially have been avoided with appropriate primary care.⁸ The source for the second and third variables is the HES Admitted Patient Care dataset while the first is by necessity drawn from the (separate) HES A&E dataset. This distinction is important because Admitted Patient Care data contain detailed diagnosis information but A&E data do not. This omission precludes analysis of ED visits by the categories used in [Taubman et al. \(2014\)](#) i.e. "Non-urgent," "Urgent, primary-care treatable," etc.

The HES A&E dataset is a rich source of data on ED activity but was published as experimental statistics until 2012/13. The use of these data to compute ED visits is challenging because in early iterations of the data collection health care service providers were not strictly required to record the type of emergency unit that a patient attended (for example an ED or another type of emergency care facility, such as an eye hospital or Minor Injury Unit). Completing this field in the data then subsequently became mandatory. As a result emergency unit type codes are missing for close to 30% of patient records for NHS Trusts in 2009/10. The share of missing codes then falls to around 11% in 2010/11, 3.5% in 2011/12, and 1.5% of records by 2012/13, a trend depicted in the series of bars labeled 1 in [Figure 4](#).

The implication of this is that changes in ED visits observed in the raw data between 2009 and later years will in part reflect better coding practices rather than genuine ED activity changes. This is problematic as better coding coincides strongly with the introduction of *EAPMC* services. I circumvent this problem in two steps, which are visually illustrated in [Figure 4](#). First, I exploit that the QMAE data described above indicates that some hospital-quarter cells only contain ED attends whereas others contain only non-ED attends. Cross-referencing to QMAE thus allows me to impute true type codes for more than half of the the uncoded NHS Trust attendances in the HES A&E dataset in my sample window. Nevertheless, as depicted in the second series of bars in [Figure 4](#), a substantial number of missing codes remain.

⁸Avoidable admission are admissions for conditions that could potentially have been avoided with appropriate primary care, for example by preventing the onset of disease preventable by vaccination, managing an acute illness such as dehydration, or a chronic condition such as diabetes. I follow earlier literature in defining these admissions using ICD-10 codes for a set of 19 presenting conditions – see [Appendix Table A1](#) for the ICD-10 codes used.

Figure 4: HES Data operations and remaining visits missing type code



Notes: Figure shows total visits to emergency care units not missing type code (light blue bars) in NHS Trusts and missing unit type codes (dark blue bars), 2009/10 to 2012/13 Q3. Four sets of bar pairs are shown (1) the raw data; (2) after imputing missing codes using QMAE; (3) after dropping quarter-neighborhood cells that contain fewer than 50 ED visits; (4) as (3) but retaining a balanced panel of neighborhoods with non-missing data in each quarter.

Second, after removing duplicate records and collapsing the data to quarter–neighborhood cells, I then exclude any quarter–neighborhood cells that contain fewer than 50 ED visits from the final estimation sample. As shown in the third (the resulting unbalanced neighborhood panel) and fourth (the associated balanced neighborhood panel) series of bars in Figure 4, this strategy is effective in eliminating missing codes problem because it reduces the number of uncoded emergency care visits to inconsequential levels. However, and while this strategy is unlikely to be a source of bias, it potentially raises generalizability concerns as results may be specific to places with high ED use. Later findings that indicate a close correspondence between the neighborhood and NHS Trust level results, as well as an alternative strategy detailed in full in section 3.6, give reassurance that this is not the case.

2.2 Empirical Approach

My data constitutes two quarterly panels of hospital utilization measures outcomes at the NHS Trust and the LSOA administrative geography and a database of *EAPMC* services including opening and closing dates. The general estimation framework common across both panels is:

$$y_{it} = EAPMC'_{itb}\beta + x'_{it}\gamma + f(i, t) + \epsilon_{it} \quad (1)$$

where observation units indexed by subscript $i \in (\text{LSOAs, NHS Trusts})$. The dependent variable is a hospital utilization outcome in quarter t . *EAPMC* is a primary care access intensity measure that captures *EAPMC* services within distance buffer b from unit i at time t . Time varying controls variables are contained in the vector x , and $f(i, t)$ are fixed effects which allow for unobserved time and place variation.

The majority of estimates that follow are generated from neighborhood-level ($i = \text{LSOA}$) regressions that take the form:

$$y_{it} = EAPMC'_{itb}\beta + x'_{it}\gamma + \phi_i + \phi_{tm(i)} + \phi_{T(t)b} + \epsilon_{it}; \quad (2)$$

Here x captures time varying counts of population in five age bands (aged less than 10, aged 10-19, aged 20-49, aged 50-69, aged 70+) and their squared values to control flexibly for changes in neighborhood population and demographics. To account for unobserved

variation, specifications include LSOA fixed effects (ϕ_i), quarter indicators interacted with labor–market area (indexed by m) dummies (ϕ_{tm}), and separate year (indexed by T) indicators for all neighborhoods that obtain exposure to services in distance buffer b at any time in the panel ($\phi_{T(t)b}$). These fixed effects are intended to eliminate factors that could bias results, including any time invariant neighborhood characteristics such as access to a walk-in clinic that existed prior to the *EAPMC* policy, as well as general labor–market wide changes, for example in the supply of hospital or community care.

Ancillary specifications at the hospital level (i = NHS Trust) are useful as they require no sample restrictions to deal with data coding issues. Regressions take the form:

$$y_{it} = EAPMC'_{itb}\beta + \phi_i + \phi_{tg(i)} + \phi_{T(t)b} + \epsilon_{it}; \quad (3)$$

Besides the different unit of observation, in contrast to equation 2 these regressions omit demographics given there is no simple way to assign population to NHS Trusts, and account for area trends at the level of 9 regions (London, South East, South West, West Midlands, North West, North East, Yorkshire and the Humber, East Midlands, and East of England, indexed by g), reflecting that in many cases a labor–market area contains only a single ED.

In both panels, the principal object of interest is *EAMPC*, a vector that captures time–varying primary care access intensity as a non-parametric function of proximity to services. These measures are generated from counts of the number of open walk-in clinics (or extended hours practices) within concentric distance buffers surrounding the centroid of each neighborhood or NHS Trust. As shown in Appendix Figure A2, the median travel distance to access emergency care in England differs considerably over space, so I allow distance buffers to vary according to the distribution of observed distances in the data. In practice, this means buffers are computed for each of the 149 labor–markets in my data then assigned to all neighborhoods/NHS Trusts with centroids falling in that area.⁹

⁹The Office for National Statistics calculates labor–market areas, known locally as Travel to Work Areas (TTWAs), using commuting data. They each contain one or more cities and they nest LSOAs. The labor–market distance buffers are computed using distances traveled to attend EDs in the HES data between 2008/9 to 2012/13. I approximate patient starting location as registered primary care practice and ED visit location as the closest ED (relevant if an NHS Trust has more than one ED). Using patient trips to EDs is driven by practical considerations (walk-in clinic attendances are not well recorded in HES) but also has the benefit of ameliorating concerns about the endogeneity of resulting buffers.

Results in an earlier working paper (Pinchbeck, 2014) show that computing buffers across alternative

Buffers are constructed in a discrete way such that each service falls into only one buffer for each neighborhood or NHS Trust. In most cases effects in three distance buffers are estimated: the lower quartile distance traveled (p25), the median (p50), and the upper quartile (p75). Around 15 of the walk-in clinics in my data are co-located at hospital EDs. To allow for different effects for these services I create a separate treatment for all such services within the median travel distance i.e. within the first two buffers. This yields four buffers in total, and the following estimated equation for walk-in clinics:

$$y_{it} = \beta_1 WiC_{it}^{p25} + \beta_2 WiC_{it}^{p50} + \beta_3 WiC_{it}^{p75} + \beta_4 WiC_{it}^{ED} + x'_{it}\gamma + f(i, t) + \epsilon_{it} \quad (4)$$

2.3 Endogenous Primary Care Availability

When identification rests on policy-induced variation a key methodological challenge is endogenous policy targeting. Here, primary care access is determined by a series of decisions by health administrators, for example where and when to open a new facility. This decision-making process is a black-box, and the suspicion must be that local service availability is correlated with unobserved underlying drivers of hospital outcomes. It might be reasonable to assume that *EAPMC* services were targeted to places experiencing increasing ED attendances, or to places expected to experience future ED attendance growth. If true, any estimate of associations between primary care access and ED attendances that ignore policy targeting would be biased towards finding that better access to primary care leads to more ED visits i.e. results would be underestimated.

To mitigate these issues all specifications use difference-in-difference strategies on samples composed solely of neighborhoods or NHS Trusts that already have close access to an *EAPMC* primary care service, did so in the past, or will do so in the future. With this sample restriction in place I estimate an average treatment effect on the treated (ATT) based on localized changes in hospital outcomes in places close to centers when the availability of services changes, against a control group provided by other places that have (or had, or will have) a similar facility close by, but where the availability of services

administrative geographies other than TTWAs leaves results materially unchanged, but that setting buffer distances universally based on national averages introduces substantial noise. Later results are unaffected when the sample is restricted to places with median buffers that lie between the 25th (3km) and 75th (5km) percentiles of the buffer distribution, in which case buffers distances are very similar.

does not change at that particular time. This strategy is particularly helpful because *EAPMC* prescribed criteria for facility location and service specification (see Appendix A), suggesting services should be similar on observable and unobservable dimensions.

3 Results

Table 1 provides descriptive statistics for hospital utilization and control variables. The “NHS Trust sample” refers to the 118 NHS Trusts that were exposed to walk-in clinics under the *EAPMC* policy. The “Walk-in clinic sample” refers to the sample of neighborhoods that were exposed to walk-in clinics under the *EAPMC* policy. The “Underdoctored sample” refers to neighborhoods in areas of the country eligible to receive new extended hours practices under *EAPMC*. The latter two samples overlap as *EAPMC* introduced new walk-in clinics in all areas of the country.

Table 1 refers to information underpinning regression samples, with that neighborhood level descriptives excluding duplicated or incomplete records in the underlying patient-level data, including around 2% of records missing patient’s residential neighborhood, and after dropping LSOA-quarter cells with low counts of ED visits. The mean number of LSOA ED visits per quarter is 140 (national average 95), which implies around 35 annual visits to the ED per 100 residents. As expected, neighborhoods exposed to *EAPMC* services have different characteristics to the average neighborhood. For example, in 2010 neighborhoods in the main sample were more deprived (mean Index of Multiple deprivation score of 30 against national average 22) and had lower average house prices (£170,000 vs. national average £196,000).

By consequence of the research design all neighborhoods in the LSOA regression samples were exposed to at least one type of new *EAPMC* service. To illustrate how access to walk-in clinics varies by neighborhood, I create a variable capturing “maximum exposure” to walk-in clinics – i.e. the highest number of ED and other walk-in clinics that each neighborhood becomes exposed to at any point in the period April 2009 to September 2012, and cross-tabulate results in Appendix Figure A3. Neighborhoods in the main sample were exposed to between 0 and 9 non-ED walk-in clinics and either 0 or 1 ED-based clinics. However, the vast majority of neighborhoods gained access to only one or two clinics at any time: around 60% were exposed to one WiC in the panel period,

Table 1: Descriptive statistics

	NHS Trust sample		Walk-in sample		Under-doctored sample	
	mean	sd	mean	sd	mean	sd
Emergency Department utilization						
Emergency Department (ED) visits	24,692	10,573	140	47	141	45
ED visits - walk-in open times			97	32	98	30
ED visits - walk-in closed times			43	18	43	17
ED visits - regular primary care times			60	21	61	20
Other hospital utilization						
Hospital admissions			110	37		
Potentially avoidable admissions (%)			23	8.6		
Neighborhood demographic controls						
Population aged under 10			222	78	222	80
Population aged 10-19			210	79	215	77
Population aged 20-49			763	235	717	204
Population aged 50-69			326	91	330	80
Population aged 70+			160	73	163	67

whereas some 80% were exposed to no more than two.

3.1 Walk-in Clinics and Hospital Utilization

Table 2 reports the effect of walk-in clinics on ED utilization in regressions corresponding to equations 2 and 3. The first column is the baseline specification that uses the unbalanced panel of LSOAs that comprise the main estimation sample. To allow for arbitrary spatial correlation standard errors are clustered on 7,201 Middle Super Output Areas (MSOAs nest LSOAs and each house between 5,000 and 15,000 inhabitants). The uppermost parameter estimate indicates that neighborhoods in close proximity to walk-in clinics co-located at EDs experience reductions in ED attendances of approximately 3.5%. For other walk-in facilities coefficients are smaller and decay with distance — the strongest impacts are evident in the closest neighborhoods, roughly halve in the next buffer, and are insignificant and close to zero in locations that gain a clinic beyond the median distance traveled to attend an ED. The baseline estimates are robust to restricting attention to a balanced panel of LSOAs (column 2), and estimating equation 3 with NHS Trust data (column 3) yields highly similar, albeit more imprecisely estimated, coefficients. These results serve to demonstrate that the sample restriction noted in section 2.1 is not critical to findings, while additional specification tests reported in Appendix

Tables A2 and A3 further support the robustness of the baseline estimates.¹⁰

The remaining columns in Table 2 report further effects of walk-in clinics in the LSOA panel using the specification described in equation 2. The fourth and fifth columns split ED attendances into visits during walk-in opening times — Monday to Sunday 8am to 8pm — and at other times. Coefficients imply the overall effects estimated in the first column are almost wholly driven by the former.¹¹ These results are a meaningful cross-check on internal validity because they rule out omitted factors which commonly drive ED use during and outside of clinic opening times. For example, a significant role for confounders such as socio-economic changes in the composition of neighborhoods or changes in the local supply of 24 hour hospital care is improbable because these would likely show up in ED visits outside of walk-in opening times.

The last two specifications in Table 2 present regressions on outcomes referring to the volume and mix of admitted patients. Coefficients in the fourth column indicate small and insignificant impacts of access to walk-in clinics on the log count of hospital admissions. Similarly, the last column signals no evidence of effects on the proportion of admissions that may have been prevented with appropriate primary care.¹²

¹⁰Appendix Table A2 demonstrates robustness to using a binary 1/0 WiC exposure variables instead of the count-based treatment intensity variables, specifying the dependent variable in levels, and removing the population and buffer control variables. This Table also shows that effects on ED visits for children and elderly people are slightly smaller than the baseline effects, and that impacts are significantly larger in the most deprived neighborhoods. Appendix Table A3 finds that standard errors are larger when clustering at the MSOA level than standard errors that follow Conley (1999) to allow for continuous forms of spatial autocorrelation up to a distance cut-off of 2km. Allowing for spatial autocorrelation is computationally demanding so here I specify the dependent variable as log ED visits per 1000 residents and drop population controls. Coefficients are robust to this specification change.

¹¹For example, applying the first coefficient (-0.0376) to the sample mean ED visits (140) implies 5.2 fewer ED visits whereas the corresponding calculation for the second column implies 4.8 fewer visits.

¹²Earlier versions of this work used mean ED waiting times as another outcome. However, identification is complicated by possible endogenous responses in hospital resourcing and operating decisions, as well as the likely violation of Stable Unit Treatment Value Assumption (SUTVA) i.e. because to the extent that walk in service affect waiting times, they will do so for all patients using an ED regardless of whether they themselves gain better primary care access. I therefore leave this analysis for future work. Note that results for ED visits are unchanged when controlling for ED waiting times, which should rule out SUTVA-type spillover concerns on my main results.

Table 2: Effects of walk-in clinics on hospital utilization

Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LSOA (unbalanced)	LSOA (balanced)	NHS Trust	WiC hrs	Other hrs (unbalanced)	LSOA (unbalanced)	
Outcome:	ED visits			All		Avoid	
	All hrs	All hrs	All hrs	WiC hrs	Other hrs	Admit.	Admit.
ED WICs	-0.0376 (0.0113)	-0.0379 (0.0118)	-0.0302 (0.0256)	-0.0491 (0.0123)	-0.0148 (0.0169)	0.0232 (0.0154)	-0.0871 (0.5059)
p0-p25 WICs	-0.0265 (0.0049)	-0.0321 (0.0077)	-0.0264 (0.0192)	-0.0414 (0.0059)	-0.0016 (0.0053)	0.0012 (0.0073)	0.1316 (0.1912)
p25-p50 WICs	-0.0144 (0.0040)	-0.0196 (0.0058)	-0.0188 (0.0199)	-0.0207 (0.0046)	-0.0047 (0.0044)	-0.0055 (0.0062)	-0.2339 (0.1592)
p50-p75 WICs	-0.0004 (0.0029)	0.0016 (0.0044)	-0.0037 (0.0089)	-0.0045 (0.0034)	0.0046 (0.0030)	-0.0045 (0.0070)	0.1037 (0.1151)
Quarter-labor market FX	✓	✓		✓	✓	✓	✓
Quarter-region FX			✓				
Year-distance buffer FX	✓	✓	✓	✓	✓	✓	✓
Population controls	✓	✓		✓	✓	✓	✓
Observations	125945	52220	1643	125945	125945	125929	125945
R-squared	0.866	0.837	0.954	0.810	0.791	0.816	0.283

Notes: LSOA panels in columns (1), (2), and (4)-(7) contain quarter-LSOA cells with 50 or more ED visits. LSOA panels are unbalanced except for column (2). Column (3) is estimated on an NHS Trust panel. Dependent variables are in logs except final column which is a rate. WiC hrs are between 8am-8pm Monday through Sunday. Standard errors in parentheses clustered at the MSOA level except in column (2) clustered at the NHS Trust level.

3.2 Substitution and Health Care Spending

Previous results indicate that walk-in services reduce visits to EDs but do not indicate the degree to which they substitute for ED activity. The mean number of ED visits for neighborhood-quarter cells in my main sample is 140 (Table 1), and the average walk-in clinic in my data has slightly under 50 neighborhoods in the first distance buffer, 50 more in the (thinner) second buffer, and a further 100 in the third. The point estimates in column one of Table 2 thus imply that an average ED walk-in clinic reduces annual ED visits by 2106 ($=0.0376*140*100*4$) whereas the average walk-in clinic located elsewhere reduces visits by 1145 ($=0.0265*140*50*4 + 0.0144*140*50*4$). Based on auxiliary information I assume each walk-in clinic is visited 18,000 times annually, suggesting that around 12% of patients visiting an ED walk-in clinic and around 6% of those visiting a clinic elsewhere were diverted from an ED.¹³ The (unreported) 95% confidence intervals indicate that between 5 to 20% of patients attending ED based walk-in clinics and 5 to 10% of patients attending other clinics were diverted from an ED.

These rough calculations imply the lion's share of walk-in visits do not substitute for a visit to an ED. Clearly this is an incomplete analysis of the full possible effects of walk-in services, because the clinics may also substitute for care in regular primary care practices. Such an analysis lies beyond the scope of this paper. Nevertheless, it is possible to make some assessment of the resource implications of the clinics because regular primary care services are funded through capitated budgets in the NHS setting. Available figures indicate that the average unit cost of a visit to an ED is three times the cost of a visit to a walk-in clinic.¹⁴ Based on these direct costs, diversion rates of under 20% imply that walk-in services in the NHS lead to a net increase in health care spending.

3.3 Balancing Tests and Trends

Difference-in-difference applications assume that trends in treatment and control groups are parallel absent treatment. The research design outlined in Section 2.3 means that

¹³This should be considered to be an indicative estimate. Monitor (2014) reports that 70% of clinics surveyed in 2014 provide between 20,000 and 45,000 walk-in appointments per year but that attendances anticipated in commissioning contracts were typically in the range of 12,000 to 24,000 attendances. I use the mid-point of the latter range for these calculations because it provides a better match to the sample window underpinning the analysis.

¹⁴Based on the cost of an ED visit in England of £100 and a cost of a walk-in clinic visit of £36 as reported by the BBC: Wheeler, B. (2012). Are NHS walk-in centres on the way out? BBC. June 28.

places that host *EAPMC* services act as both a treatment and control group, with identification coming off the timing of service deployment. The identifying assumption is that service deployment time should be unrelated to the determinants of ED visits, conditional on general labor-market trends. If in fact new services are deployed to places at times when ED visits are rising or falling more quickly than the general trend, then the control group of past and future locations for services will not provide a valid counterfactual.

The discussion in Section 1.1 suggests the actual timetable for the new centers was driven by administrative factors (e.g. availability of suitable premises and speed of procurements etc.) which are plausibly unrelated to ED visits. To test this premise, pre-reform primary care access variables (measured in both levels and changes) are regressed on the number of quarters between the policy announcement and the neighborhood’s first exposure to a service, as well as the time-invariant analogues of the control variables listed above. As data for pre-reform access is not available at the neighborhood level, values are assigned to neighborhoods from the nearest primary care practice. The upper panel of Table 3 shows no significant correlation between *EAPMC* treatment timing and pre-reform primary care access as measured by the percentage of patients able to obtain an appointment, the percentage satisfied with phone access, and satisfied with practice opening hours in June 2008. The bottom panel of the Table similarly yields no correlation with local trends in primary care access between June 2007 and June 2008. A second strategy visually assesses the extent to which groups of neighborhoods that were first exposed to new services at different times follow similar trends in ED visits. Reassuringly Figure 5, which is displayed in actual time rather than event time due to the seasonal pattern, reveals the unconditional trends in ED visits are broadly similar across all groups throughout the sample period.

3.4 Distance Decay

Section 3.1 reported spatial patterns in the impacts of walk-in clinics on ED attendances. Distance decay is more precisely teased out in Table 4 which drops neighborhoods close to walk-in facilities at EDs and expands the number of distance buffers to seven. Column (a) of Figure 6 summarizes the first two columns of this Table: solid black lines connect point estimates on the buffers (with sign reversed so that values above the horizontal line can be

Table 3: Balancing on pre-policy primary care access measures

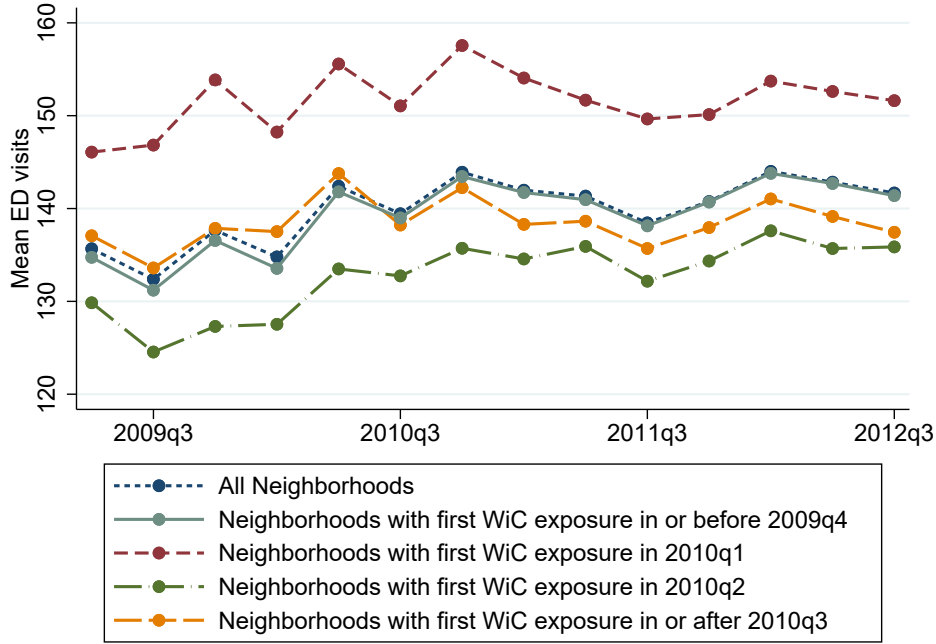
	(1) get appointment %	(2) satisfied hrs %	(3) satisfied phone %
Panel A: Dependent variable is level in June 2008			
Quarters until <i>EAPMC</i>	-0.0338 (0.1994)	0.0651 (0.0893)	0.0997 (0.1532)
R-squared	0.120	0.274	0.124
Panel B: Dependent variable is change June 2007 to June 2008			
Quarters until <i>EAPMC</i>	-0.0382 (0.1010)	0.0000 (0.0490)	-0.0755 (0.0654)
R-squared	0.049	0.049	0.039
Labor-market fixed effects	✓	✓	✓
Distance buffer fixed effects	✓	✓	✓
Population age bands	✓	✓	✓
Observations	10910	10910	10910

Notes: Table reports cross-sectional regressions on neighborhoods that first gain access to a walk-in clinic between April 2009 and September 2012. Dependent variables are drawn from GP Patient Survey, either levels in June 2008 (Panel A) or changes between June 2007 and June 2008 (Panel B), with values assigned to neighborhoods from nearest primary care practice. Outcome variables are: percentage of patients able to book an appointment 2 days ahead; percentage of patients satisfied with primary care practice opening hours; percentage of patients satisfied with phone access. Explanatory variable is number of quarters between April 2008 and neighborhood first access to an *EAPMC* walk-in service. Standard errors in parentheses clustered at the MSOA level.

interpreted as an approximate percentage reduction in ED visits) and dashed black lines bound the 95% confidence intervals. The upper plot confirms the strong distance decay during center opening hours: neighborhoods in the closest proximity experience falls in ED visits of 5.1%, declining to above 2% between the 40th and 60th percentile, and are zero at the 70th distance percentile. The lower plot charts much weaker changes in visits outside of clinic opening hours. There are signs of small (albeit generally insignificant) effects of around 1% for close locations, but for less proximate places coefficients are close to zero.¹⁵

¹⁵In the Appendix I further exploit information about the distance to the nearest ED to test whether these patterns hold for neighborhoods which are closer to EDs than walk-in clinics and the opposite.

Figure 5: Trends in ED visits by time of first exposure to walk-in clinics



Notes: Figure assesses whether neighborhoods are on parallel trends by plotting quarterly ED visits for neighborhoods (LSOAs) grouped by date of first exposure to an *EAPMC* walk-in clinic.

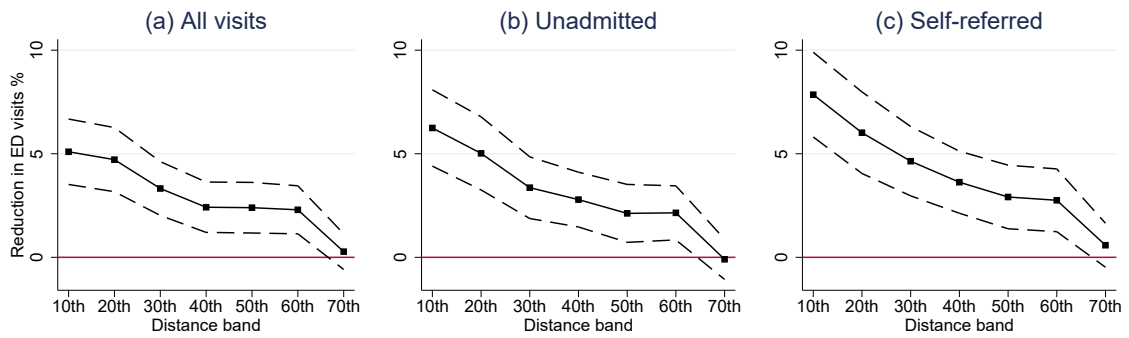
The conceptual framework in Section 1.2 suggests walk in clinics should divert patients with less serious medical problems from EDs. Most patients that are not admitted during an ED attendance likely fall into this category. These outpatient visits make up around three quarters of all ED visits in this setting. Column (b) of Figure 6 plots the effect of walk-in access on these patients, corresponding to the third and fourth columns of Table 4. The pattern of effects is highly similar to the first column. During walk in hours effects in the first buffers are slightly larger and the distance decay is a little steeper, although these differences are not statistically distinguishable. The corollary is that around three quarters of the overall effect of walk in services arises through diverting patients who would not be admitted through an ED, with the remainder of the effect coming through patients who would be admitted.

Hospital records also indicate how patients came to be at the ED. Column (c) of Figure 6, corresponding to columns five and six of Table 4, tracks impacts on patients recorded as self-referring to the ED. This group represents around 60% all visits to EDs. The remain-

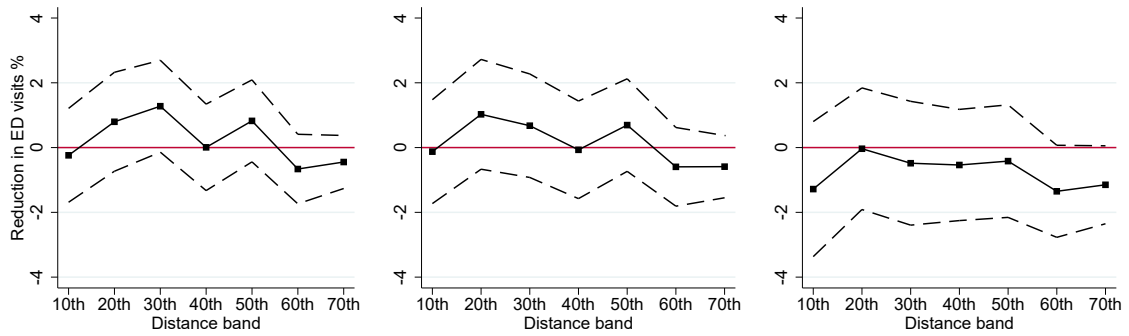
Figure A4 shows that results are highly similar but that effects are slightly larger at very short and very long distances for neighborhoods closer to walk-ins than EDs.

Figure 6: Distance decay by ED visit type

8am - 8pm



Other times



Notes: Figure plots point estimates reported in Table 4 (black lines) and the bounds of the associated 95% confidence intervals.

Table 4: Distance decay by ED visit type

	(1) - All ED visits - WiC hrs	(2) Other	(3) - Non-admitted - WiC hrs	(4) Other	(5) - Self-referred - WiC hrs	(6) Other
p0-p10 WiCs	-0.0510 (0.0081)	0.0024 (0.0074)	-0.0625 (0.0094)	0.0013 (0.0082)	-0.0785 (0.0104)	0.0128 (0.0106)
p10-p20 WiCs	-0.0472 (0.0079)	-0.0080 (0.0078)	-0.0502 (0.0090)	-0.0103 (0.0086)	-0.0602 (0.0100)	0.0004 (0.0096)
p20-p30 WiCs	-0.0332 (0.0066)	-0.0128 (0.0072)	-0.0336 (0.0076)	-0.0068 (0.0081)	-0.0464 (0.0085)	0.0048 (0.0097)
p30-p40 WiCs	-0.0242 (0.0062)	-0.0001 (0.0068)	-0.0279 (0.0067)	0.0007 (0.0077)	-0.0363 (0.0076)	0.0054 (0.0088)
p40-p50 WiCs	-0.0240 (0.0062)	-0.0082 (0.0065)	-0.0212 (0.0071)	-0.0069 (0.0073)	-0.0291 (0.0078)	0.0042 (0.0089)
p50-p60 WiCs	-0.0230 (0.0059)	0.0066 (0.0055)	-0.0215 (0.0067)	0.0059 (0.0062)	-0.0275 (0.0077)	0.0135 (0.0072)
p60-p70 WiCs	-0.0028 (0.0044)	0.0045 (0.0042)	0.0009 (0.0050)	0.0059 (0.0049)	-0.0058 (0.0054)	0.0115 (0.0061)
Quarter-labor market FX	✓	✓	✓	✓	✓	✓
Year-distance buffer FX	✓	✓	✓	✓	✓	✓
Population controls	✓	✓	✓	✓	✓	✓
Observations	109399	109399	109399	109399	109399	109399
R-squared	0.812	0.792	0.789	0.777	0.751	0.680

Notes: Sample contains quarter-LSOA cells with 50 or more ED visits but drops neighborhood exposed to walk-in facilities co-located at EDs. Dependent variables are in logs. WiC hrs are between 8am-8pm Monday through Sunday. Standard errors in parentheses clustered at the MSOA level

der are patients that ostensibly had less discretion in the location of their treatment. This is because they were referred to the ED from another source (most commonly a family doctor), or conveyed to the ED in an ambulance. As with the non-admitted group of patients the effects are qualitatively similar to the overall patterns shown in column (a), but here coefficients during clinic open times are roughly one to one and a half times as large. One possible explanation is that self-referred patients have less severe health needs which can be treated in lower acuity facilities like walk-ins more readily. This finds support in the data: only 12% of the self-referred group are admitted following their attendance compared to more than 40% of the other group.

3.5 Dimensions of Access

What further dimensions of access drive diversion from EDs? This section aims to shed light on this question through a descriptive comparison of the impacts of walk-in services and extended hours practices (denoted PCPs in this section) opened under the *EAPMC* policy. As noted previously, PCPs are conventional primary care services that require patients to be registered to receive services. They offer extended opening relative to core primary care hours but operating hours fall short of the 7 day services at walk-in clinics. Making comparisons across these service-types can help to ascertain how opening hours and the need to make an appointment condition the extent to which patients are diverted from EDs.

The PCPs opened under the *EAPMC* policy were located in areas of the country with the lowest concentration of family doctors. To ensure a like-for-like comparison samples underpinning all regressions in this section are restricted to neighborhoods in administrative areas eligible for both types of *EAPMC* service. Regressions, reported in Table 5, first estimate the impacts of walk-in services and extended hours practices separately, then simultaneously in the third and fourth columns. Because of the narrower geographical sample these regressions differ in two ways to earlier specifications. First, they include region rather than labor-market trends here as there is insufficient variation to separately identify the latter from changes in primary care access driven by the policy reform. Second, because there are very few walk-in facilities co-located at EDs in this sample, all neighborhoods in close proximity to such services are dropped throughout this section.

Before comparing service types I first use this sample to assess the robustness of prior results for walk-in services. The first column of Table 2 estimated the impact of walk-in clinics across the country as a whole. In Table 5 walk-in impacts are estimated in under-doctored areas of the country on their own (in column 1), and conditional on changes in regular primary care access (in column 3). The coefficients on the walk-in service variables across these three specifications are remarkably similar, giving reassurance that the omission of variables capturing access to regular primary care in earlier regressions is unlikely to be a major source of bias.

The third and fourth columns of Table 5 estimate the effect of both types of primary care service concurrently. The third column uses a dependent variable constructed from

Table 5: Dimensions of primary care access

	(1)	(2)	(3)	(4)
	—— ED visits at any time ——			Core hrs
p0-p25 WiCs	-0.0248 (0.0066)		-0.0255 (0.0066)	-0.0415 (0.0081)
p25-p50 WiCs	-0.0142 (0.0047)		-0.0131 (0.0047)	-0.0214 (0.0060)
p50-p75 WiCs	0.0007 (0.0031)		0.0010 (0.0030)	-0.0000 (0.0040)
p0-p25 PCPs		-0.0112 (0.0046)	-0.0128 (0.0046)	-0.0143 (0.0060)
p25-p50 PCPs		-0.0003 (0.0038)	0.0004 (0.0038)	-0.0006 (0.0044)
p50-p75 PCPs		-0.0055 (0.0028)	-0.0037 (0.0028)	-0.0014 (0.0035)
Quarter-region FX	✓	✓	✓	✓
Year-distance buffer FX	✓	✓	✓	✓
Population controls	✓	✓	✓	✓
Observations	63864	63864	63864	63864
R-squared	0.868	0.868	0.868	0.769

Notes: Sample contains quarter-LSOA cells with 50 or more ED visits. Dependent variables are in logs. Columns 1-3 include ED visits taking place at any time, Core hrs in column 4 counts ED visits between 8.30am–6.30pm Monday through Friday. Standard errors in parentheses clustered at the MSOA level

ED visits taking place at any time (including evenings and weekends), which facilitates a comparison of the *overall* effects of the two service-types in my data. Relative to the extended hours practices, walk-in services divert more patients and have effects over greater distances. Because the first two buffers contain a similar number of neighborhoods so a comparison can be obtained by summing the coefficients across the first two buffers. This implies that walk-in clinics divert roughly three times as many patients from EDs as the extended hours practices. Annual diversion can be estimated by applying the coefficients to the mean number of ED and grossing up by the number of neighborhoods (as in Section 3.2). Walk-in clinics divert 1081 patients per year from EDs whereas PCPs divert 358, or 723 fewer visits.

The final column of Table 5 compares effects on ED visits in core primary care hours: 8.30am and 6.30pm on Monday–Friday. During these hours, both types of service are open so any differences in diversion cannot be driven by variation in opening hours of services. The mean number of ED visits taking place during these times is 60 (see Table 1), so that results imply that walk-in clinics divert roughly 755 ED trips whereas PCPs divert 172, or 583 fewer visits. Both service types thus appear to divert a significant proportion of patients outside core primary care opening hours, but some 80% of the difference in the overall effects arise when both types of service are open. If *EAPMC* walk-in clinics and extended hours practices are similar on unobserved dimensions, these findings signal that the ability for patients to attend without registering or making an appointment may have a large bearing on the ED diversion.

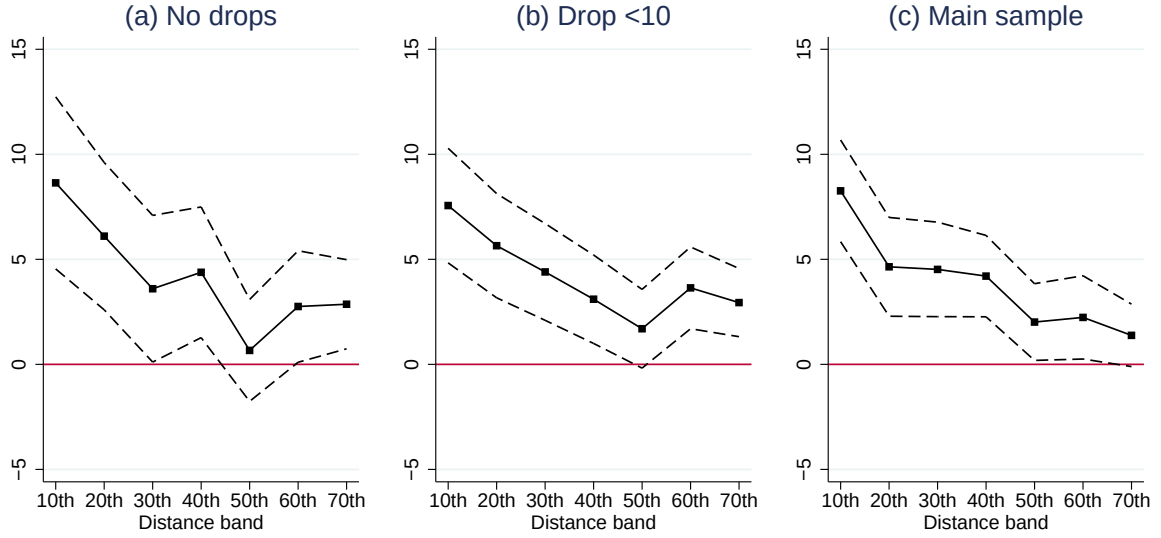
Appendix Table A4 finally reports the impacts of access to primary care services inside and outside practice catchment boundaries during core primary care practice hours. In theory a patient living outside a practice’s boundary cannot register for regular primary care services but can attend a walk-in clinics (where these exist) as a non-registered patient. In line with this prior, extended hours practices have zero impacts in neighborhoods outside catchment boundaries. For walk-in clinics ED diversion occurs inside and outside boundaries but is systematically larger in neighborhoods falling inside boundaries. Although I provide no direct tests, I speculate these patterns could reflect benefits from continuity of care or competition from walk-in clinics driving improvements in practices outside my sample.¹⁶

3.6 Further Robustness Checks and Placebos

In all preceding estimations fixed effects partial out time-invariant unobservables at the neighborhood level and region- or labor market-wide trends, while population counts control for demographic changes. Besides these controls, previous sections reported some natural robustness checks, for example by examining the impacts of services during service open or closed hours and inside or outside practice catchment boundaries. A number of further placebo and robustness checks that lend further support to these results. In all cases I report graphical evidence, relegating associated regression outputs to Appendix

¹⁶The difference in overall effects between the service types could also be driven by differences in boundary sizes. In Table A5 I show that access boundaries are indeed much larger for walk-in services.

Figure 7: Sample restriction robustness



Notes: All plots generated from regressions of $\log(\text{self-referred ED visits}) - \log(\text{other ED visits})$ on walk-in access changes. Left-most plot uses the full sample; middle plot drops neighborhood-quarter cells with less than 10 visits in each group; right-most plot as main sample.

Tables [A6](#) and [A7](#).

A first robustness check evaluates the sample restriction under which neighborhood quarter cells with few ED visits were dropped. This restriction was adopted to avoid conflating changes in data reporting practices with genuine changes in ED volumes and to circumvent problems inherent in using count data. To test this strategy I re-estimate walk-in impacts under different samples but now using the difference between the logarithm of self-referred ED visits and the logarithm of ambulance or referred ED visits as the dependent variable. Changes in reporting should affect both of these patient groups symmetrically. The three plots in Figure 7 demonstrate that distance decay of walk-in clinics on this measure are qualitatively similar when no cells are dropped (left-most plot), when cells with less than 10 ED visits are dropped (middle plot), and with the full sample restriction (right-most plot). Given earlier findings these estimates are driven largely by the self-referred patient group so it is reassuring that the patterns in all plots are broadly consistent with those in Figure 6. More generally, differencing between these types of attendances partials out any unobserved time varying neighborhood factors that affect both groups so provides a powerful check on earlier results.

Figure 8 presents two more general checks on walk-in access effects. In the first, I re-run

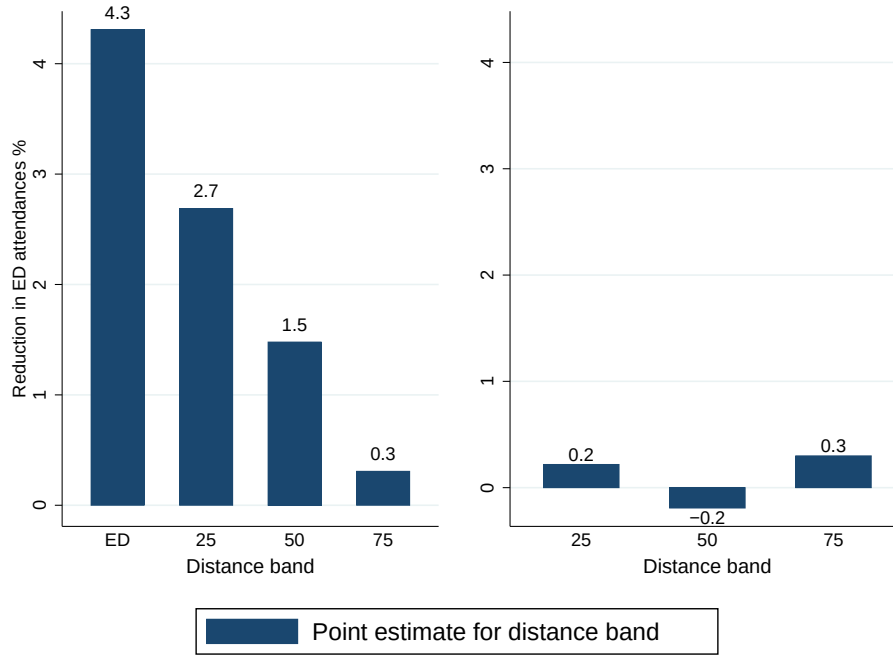
the first regression in Table 2 but excluding observations in quarters in 2012. This has two implications. First, it means estimation excludes the material drop in practices in 2012 evident in Figure 2. These access changes are not driven by the *EAPMC* policy and are unobserved in my regressions so could bias earlier results. Second, excluding 2012 essentially eliminates closures of *EAPMC* clinics, so this also serves as a test of relying only on openings for identification. The left-hand plot in Figure 8 (corresponding to the first column of Table A7) shows that this restriction leaves my findings unchanged.¹⁷ The second check is a falsification test that exploits that some neighborhoods outside my main sample host walk-in clinics established prior to 1 Apr 2008 (and as such do not figure in my earlier estimations). I generate pseudo changes in primary care access in these places during my sample frame by assigning the older clinics opening and closing dates matching a random *EAPMC* walk-in clinic from my main sample. The right-side of Figure 8 shows these bogus access changes have no effects on ED visits.

The walk-in clinic regressions in section 3.1 control for shocks to labor markets through the inclusion of labor market-by-quarter interactions whereas regressions in section 3.5 control only for less granular regional trends. The coefficients for walk-in services are similar across these specifications yet it remains possible that the latter estimates are partially driven by common shocks within labor markets. Figure 9 follows the approach in Busso et al. (2013) by estimating the effect of primary care access on the neighborhoods (log) rank position on ED visits within the labor-market distribution, where rank 1 is assigned to the neighborhood with the lowest count of ED visits in the labor-market that quarter. The estimated pattern of effects is qualitatively similar to those in Table 5 albeit stronger for walk-in services relative to the extended hours primary care practices.

A final robustness check reflects the possibility that the *EAPMC* policy may be part of a wider set of interventions targeted to specific neighborhoods such as localized employment schemes or neighborhood regeneration. It is possible, albeit unlikely, that a combination of such policies have spatially decaying effects that are strongest at times when primary care facilities are open. Given that they are unobserved in my data such policies could

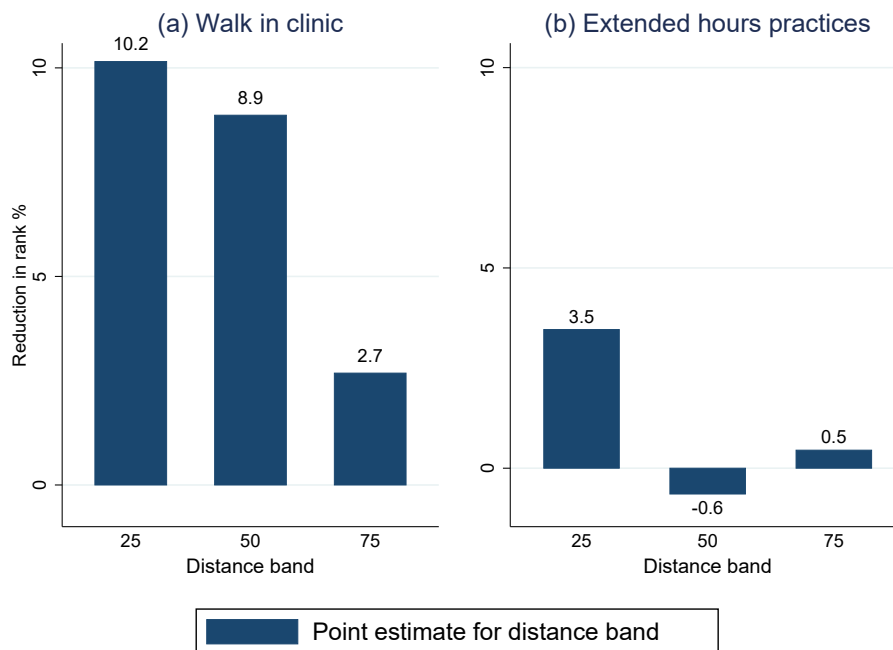
¹⁷A number of other unreported specifications provide further support. For example findings are unchanged if I restrict attention to quarters from 2010/11 onwards, or restrict attention to places with similar median distance buffers, or retain a balanced panel of neighborhoods. Data availability and uncertainty over precise clinic opening dates precludes an in depth leads and lags analysis. However, a one quarter lead and one quarter lag analysis is reported in Appendix Figure A5.

Figure 8: Further walk-in clinic robustness



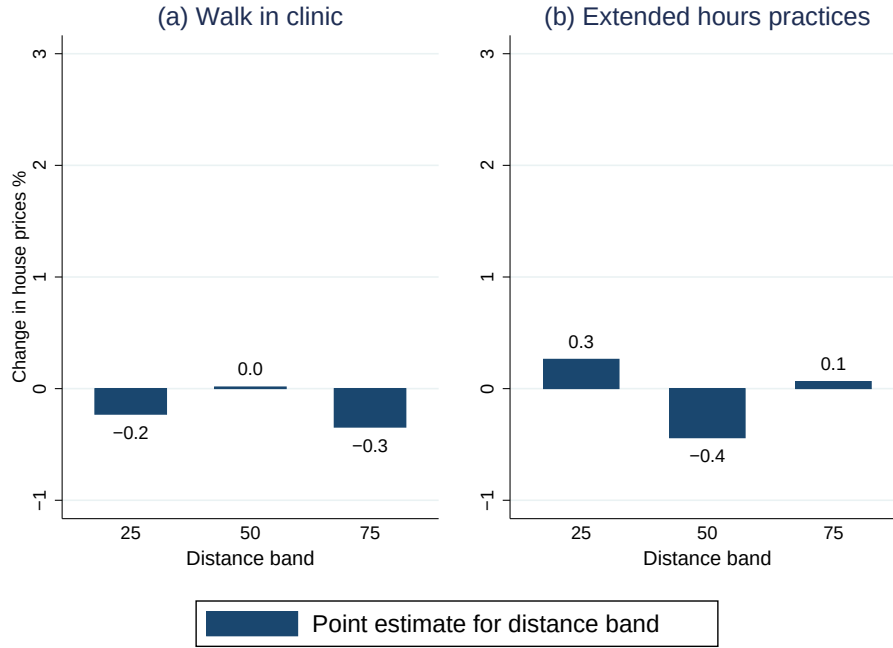
Notes: Figure shows robustness checks on results in Table 2. LHS plot refers to the same regression in column 1 of Table 2 but excluding all quarters in 2012. RHS plot refers to placebo check using bogus changes in walk-in access in approximately 1,000 neighborhoods that fall outside my main sample.

Figure 9: Robustness to common labor market shocks



Notes: Dependant variable is $\log(\text{rank})$ where rank is the neighborhood rank in the count of ED visits within the labor-market distribution in a given quarter.

Figure 10: Placebo: house prices



Notes: Dependant variable is log average house prices in the neighborhood, computed from the Land Registry Price Paid dataset.

confound estimates should they correlate with factors driving hospital utilization and directly coincide with *EAPMC* service changes. Figure 10 indicates that changes in access are uncorrelated with average house prices which goes some way to alleviating this concern.¹⁸

4 Conclusion

This paper examines a policy reform that introduced a substantial change in primary care access across England within a short time-frame. The reform is helpful because its implementation provides a source of plausibly exogenous variation, and of particular interest because it created new primary care services which differ along several organizational dimensions. The first part of the analysis finds that access to convenient primary care services significantly reduces visits to hospital Emergency Departments, and documents a range of further findings that support the robustness of this result.

Parameter estimates imply that somewhere between 5 and 20% of patient visits to a

¹⁸In the last Column of Table A7, I also show that *EAPMC* services have no significant impact on ED visitors arriving by ambulance.

walk-in facility substitute for a visit to an ED. The lower unit costs of care in the clinics relative to EDs is insufficient to offset the costs of the new utilization, so that walk-in clinics imply a small net increase in health care spending. A full assessment of the welfare implications of walk-in services lies outside the scope of this work. Shifting care outside of EDs is likely to be socially beneficial because of the lower costs of care in primary care settings. However, further work would be needed to evaluate whether the social benefits of the substantial new utilization of walk in clinics outweigh the social costs of providing the services.

Subsequent sections of this article then distinguish empirically between four aspects of primary care access: proximity to services, convenience of opening hours, the need to make an appointment, and eligibility to receive care. Estimates indicate that two convenience dimensions of access — proximity and the ability to attend without appointment — are paramount in determining the extent to which primary care services divert patients from hospitals. Given that the private costs of distance and making appointments are small, these results suggest that psychological factors influence how agents' choose to obtain treatment. This tallies with recent evidence showing that hassle factors can prove to be an important barrier to participation decisions.

References

- Alexander, D., J. Currie, and M. Schnell (2017). Check up before you check out: Retail clinics and emergency room use. Technical report, National Bureau of Economic Research.
- Appleby, J. (2013, April). Are Accident and Emergency Attendances Increasing? The King’s Fund blog, 29 April 2013.
- Ashwood, J. S., M. Gaynor, C. M. Setodji, R. O. Reid, E. Weber, and A. Mehrotra (2016). Retail Clinic Visits for Low-Acuity Conditions Increase Utilization and Spending. *Health Affairs* 35(3), 449–455.
- Baicker, K., S. Mullainathan, and J. Schwartzstein (2015). Behavioral hazard in health insurance. *The Quarterly Journal of Economics* 130(4), 1623–1667.
- Berchet, C. (2015). Emergency Care Services: Trends, Drivers and Interventions to Manage the Demand. OECD Health Working Papers, No. 83.
- Bertrand, M., S. Mullainathan, and E. Shafrir (2006). Behavioral Economics and Marketing in Aid of Decision Making Among the Poor. *Journal of Public Policy & Marketing* 25(1), 8–23.
- Buchmueller, T. C., M. Jacobson, and C. Wold (2006). How Far to the Hospital?: The Effect of Hospital Closures on Access to Care. *Journal of Health Economics* 25(4), 740–761.
- Busso, M., J. Gregory, and P. Kline (2013). Assessing the Incidence and Efficiency of a Prominent Place Based Policy. *The American Economic Review* 103(2), 897–947.
- Chen, C., G. Scheffler, and A. Chandra (2011). Massachusetts’ Health Care Reform and Emergency Department Utilization. *The New England Journal of Medicine* 365(12), e25.
- Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics* 92(1), 1–45.
- Currie, J. and P. B. Reagan (2003). Distance to Hospital and Children’s Use of Preventive Care: Is Being Closer Better, and for Whom? *Economic Inquiry* 41(3), 378–391.
- Department of Health (2007). Delivering Equitable Access to Primary Medical Care: Local procurements for GP practices and Health Centres. Letter to SHA Directors of Commissioning, December 21.
- Dolton, P. and V. Pathania (2016). Can Increased Primary Care Access Reduce Demand for Emergency Care? Evidence from England’s 7-day GP Opening. *Journal of Health Economics* 49, 193–208.
- Duflo, E., W. Gale, J. Liebman, P. Orszag, and E. Saez (2006). Saving incentives for low-and middle-income families: Evidence from a field experiment with h&r block. *The Quarterly Journal of Economics* 121(4), 1311–1346.
- Finkelstein, A. N., S. L. Taubman, H. L. Allen, B. J. Wright, and K. Baicker (2016). Effect of Medicaid Coverage on ED use—Further Evidence from Oregon’s Experiment. *The New England Journal of Medicine* 375(16), 1505–1507.
- Hiscock, R., J. Pearce, T. Blakely, and K. Witten (2008). Is Neighborhood Access to Health Care Provision Associated with Individual-Level Utilization and Satisfaction? *Health Services Research* 43(6), 2183–2200.
- HSCIC (2016). General Practice Trends in the UK to 2015. Health and Social Care Information Centre.
- Kahn, B. E. and M. F. Luce (2006). Repeated-adherence protection model: “i’m ok, and it’s a hassle”. *Journal of Public Policy & Marketing* 25(1), 79–89.

- Lippi Bruni, M., I. Mammi, and C. Ugolini (2016). Does the Extension of Primary Care Practice Opening Hours Reduce the Use of Emergency Services? *Journal of Health Economics* 50, 144–155.
- Martsolf, G., K. R. Fingar, R. Coffey, R. Kandrack, T. Charland, C. Eibner, A. Elixhauser, C. Steiner, and A. Mehrotra (2017). Association Between the Opening of Retail clinics and Low-Acuity Emergency Department Visits. *Annals of Emergency Medicine* 69(4), 397–403.
- Mehrotra, A., H. Liu, J. L. Adams, M. C. Wang, J. R. Lave, N. M. Thygeson, L. I. Solberg, and E. A. McGlynn (2009). Comparing Costs and Quality of Care at Retail Clinics with that of other Medical Settings for 3 Common Illnesses. *Annals of Internal Medicine* 151(5), 321–328.
- Miller, S. (2012). The Effect of Insurance on Emergency Room Visits: An Analysis of the 2006 Massachusetts Health Reform. *Journal of Public Economics* 96(11), 893–908.
- Millman, M. et al. (1993). *Access to Health Care in America*. National Academies Press.
- Monitor (2014). Walk-in Centre Review. Final report and recommendations.
- Mullainathan, S., J. Schwartzstein, and W. J. Congdon (2012). A reduced-form approach to behavioral public finance. *Annu. Rev. Econ.* 4(1), 511–540.
- National Center for Health Statistics (2013). Health, United States, 2012: With a Special Feature on Emergency Care. Report.
- Pinchbeck, T. (2014). Walk this way: Estimating impacts of Walk in Centres at Hospital Emergency Departments in the English National Health Service. Working paper, Spatial Economics Research Centre, LSE.
- Pines, J. M., J. A. Hilton, E. J. Weber, A. J. Alkemade, H. Al Shabanah, P. D. Anderson, M. Bernhard, A. Bertini, A. Gries, S. Ferrandiz, et al. (2011). International Perspectives on Emergency Department Crowding. *Academic Emergency Medicine* 18(12), 1358–1370.
- Rust, G., J. Ye, P. Baltrus, E. Daniels, B. Adesunloye, and G. E. Fryer (2008). Practical Barriers to Timely Primary Care Access: Impact on Adult Use of Emergency Department Services. *Archives of Internal Medicine* 168(15), 1705–1710.
- Selby, J. V., B. H. Fireman, and B. E. Swain (1996). Effect of a copayment on use of the emergency department in a health maintenance organization. *New England Journal of Medicine* 334(10), 635–642.
- Taubman, S. L., H. L. Allen, B. J. Wright, K. Baicker, and A. N. Finkelstein (2014). Medicaid Increases Emergency Department Use: Evidence from Oregon’s Health Insurance Experiment. *Science* 343(6168), 263–268.
- Van Dort, B. E. and R. H. Moos (1976). Distance and the Utilization of a Student Health Center. *Journal of the American College Health Association* 24(3), 159–162.
- Weinick, R. M., R. M. Burns, and A. Mehrotra (2010). Many Emergency Department Visits Could be Managed at Urgent Care Centers and Retail clinics. *Health Affairs* 29(9), 1630–1636.
- Whittaker, W., L. Anselmi, S. R. Kristensen, Y.-S. Lau, S. Bailey, P. Bower, K. Checkland, R. Elvey, K. Rothwell, J. Stokes, et al. (2016). Associations between Extending Access to Primary Care and Emergency Department Visits: A Difference-in-Differences Analysis. *PLoS Med* 13(9), e1002113.

Appendices

A Core criteria for new primary care services

Figure A1: Criteria described in [Department of Health \(2007\)](#)



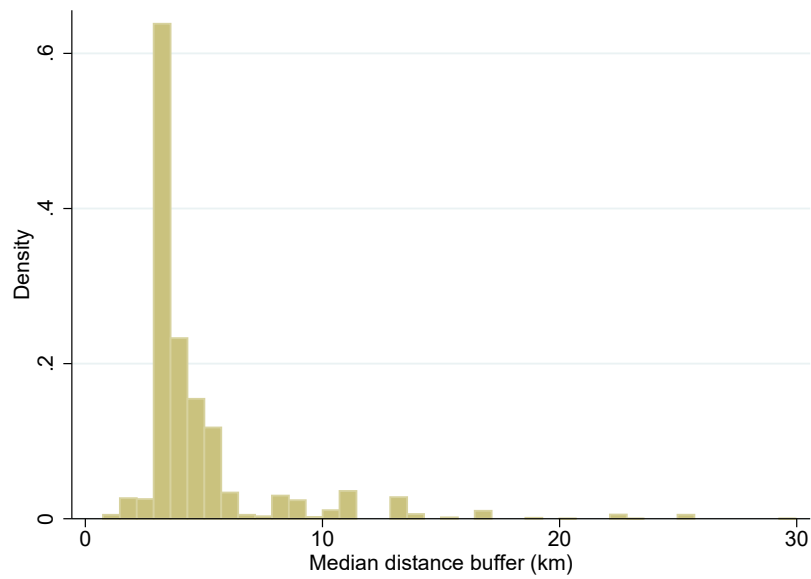
B Behavioral factors and ED use

Given evidence of non-standard decision-making in a health context, [Baicker et al. \(2015\)](#) modify the standard treatment decision to $p < b(\sigma) + \epsilon(\sigma)$ where ϵ is a general behavioral bias factor that can encompass several phenomena such as hyperbolic discounting, non-standard beliefs, or inattention. Some behavioral hazards lead to under-utilization of care, for example $\epsilon < 0$ when treatment benefits are delayed and agents are present biased, when agents underestimate the benefits of treatment, when obtaining care is subject to “hassle” factors, or when symptoms are not salient. Conversely, $\epsilon > 0$ implies behavioral hazards that lead to over-utilization even when $p = c$.

Agents then seek treatment in primary care when two conditions hold: patients perceive a net private benefit from primary care ($b_{PC} + \epsilon_{PC} - p_{PC} > 0$); and primary care offers a higher perceived net benefit than ED care ($b_{PC} + \epsilon_{PC} - p_{PC} > b_{ED} + \epsilon_{ED} - p_{ED}$). Primary care access intervention then work through two channels. First, they may reduce the private costs of obtaining treatment in primary care, either through lowering co-pays or — as in the NHS case — by reducing the time and travel expenses incurred to access services. Second, for behavioral agents, policies that ease access can also work through an additional channel, for example by mitigating or eliminating inconvenience and hassle factors associated with obtaining treatment ([Bertrand et al., 2006](#)).

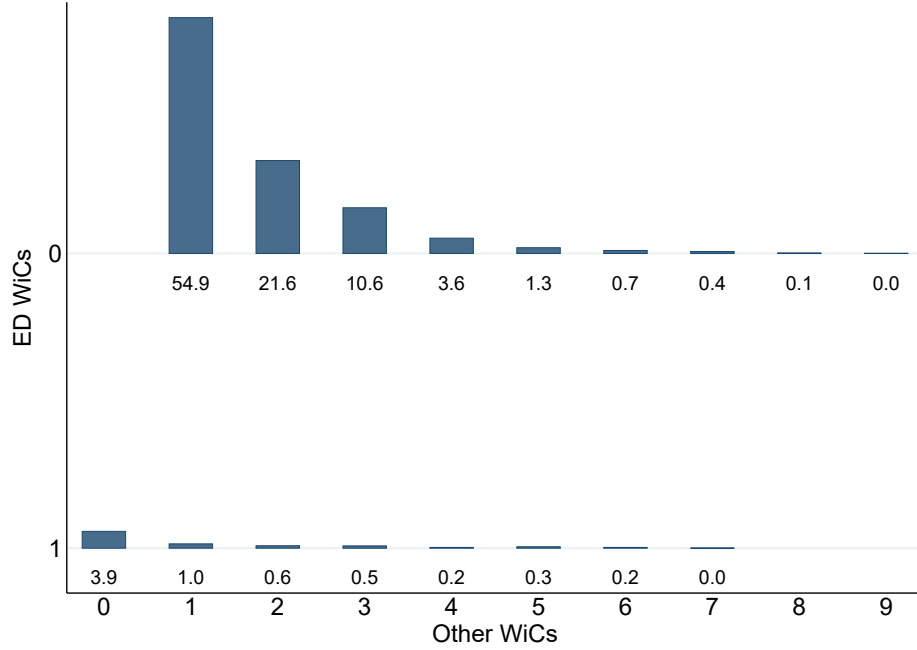
C Additional Tables and Figures

Figure A2: Median distance buffers



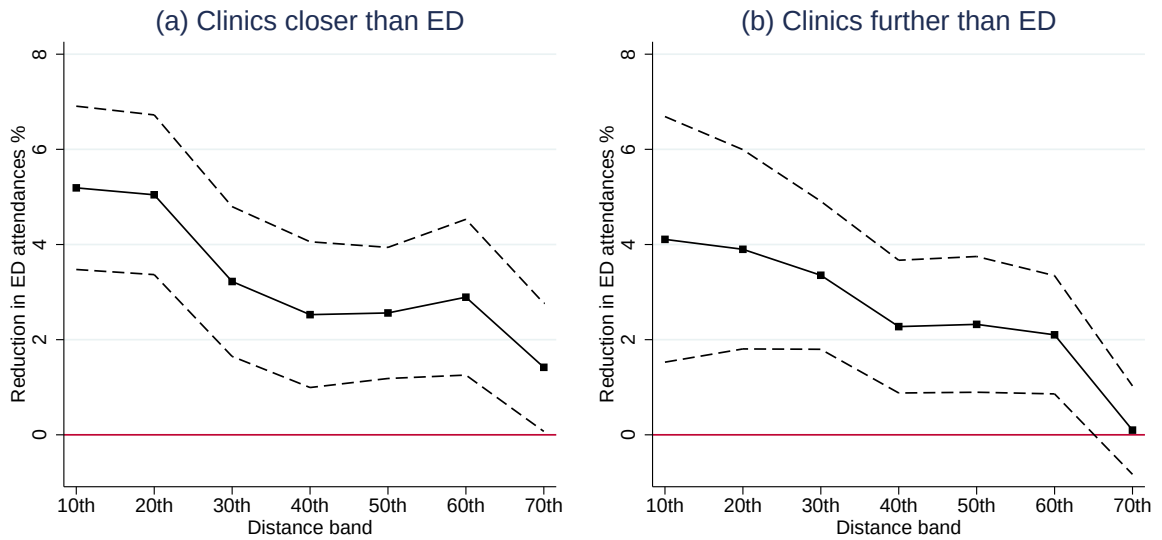
Notes: Histogram of the median distance buffer in the “Walk-in clinic sample”

Figure A3: Maximum exposure to walk-in clinics, % of neighborhoods



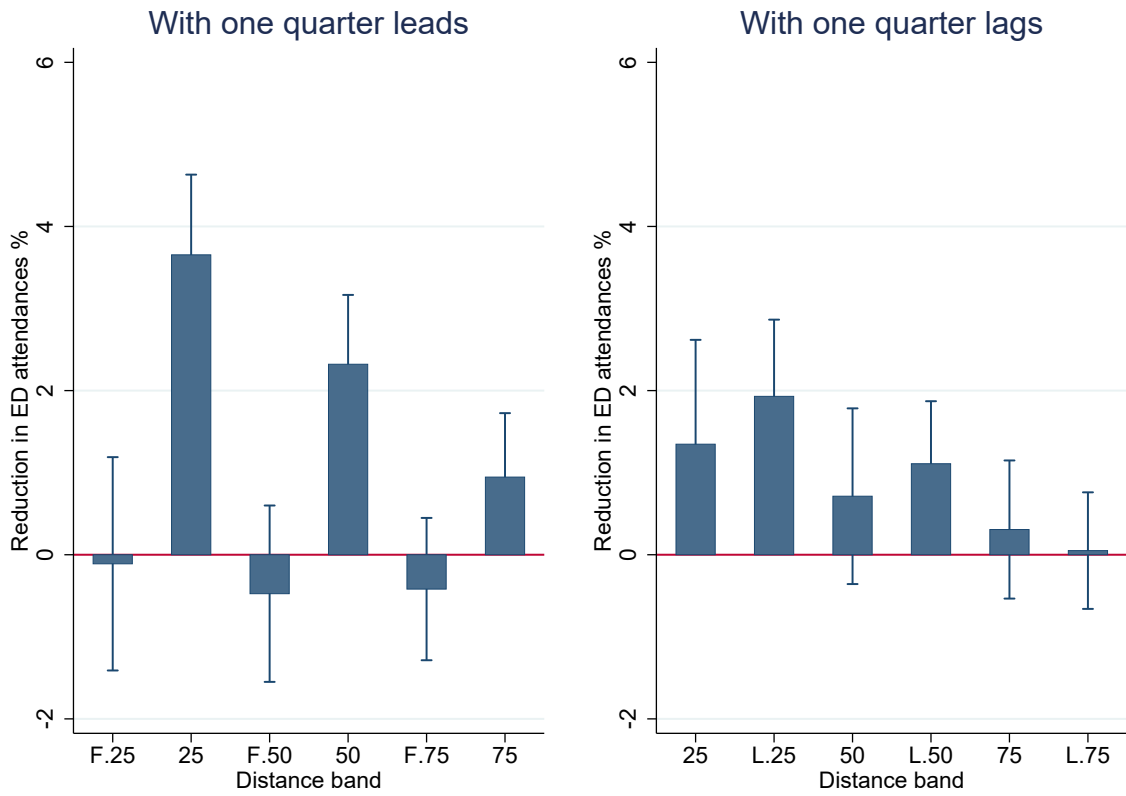
Notes: Figure plots highest exposure of neighborhoods in main sample to walk-in clinics over the sample period.

Figure A4: Clinics closer or further than EDs



Notes: Figure plots coefficients from a regression analogous to column 1 of Table 4 (using ED visits during walk-in open hours) but interacts the count of walk-in clinics in each buffer with a variable that takes the value of 1 when the average distance to walk-in clinics is smaller than the distance to the nearest Emergency Department (LHS) or 0 when the reverse is true (RHS).

Figure A5: One quarter lead and lag effects for walk-in clinics



Notes: Figure plots coefficients and confidence intervals from regressions examining effect of current exposure to walk-in clinics (specified as 1/0 treatment indicators) as well as the one period lead (LHS) or one period lag (RHS) effect.

Table A1: ICD-10 codes used to define potentially avoidable admissions

Condition	ICD-10 codes
Angina	I20, I24.0 I24.8 I24.9 I25 R072 R073 R074 Z034 Z035
Asthma	J45 J46
Cellulitis	L03 L04 L08.0 L08.8 L08.9 L88 L98.0 I891 L010 L011 L020 to L024 L028 L029
Congestive heart failure	I11.0 I50 J81 I130 I255
Convulsions and epilepsy	G40 G41 R56 O15 G253 R568
Chronic obstructive pulmonary disease	J20 J41 J42 J43 J47 J44 J40X
Dehydration and gastroenteritis	E86 K52.2 K52.8 K52.9 A020 A04 A059 A072 A080 A081 A083 A084 A085 A09 K520 K521
Diabetes complications	E10.0–E10.8 E11.0–E11.8 E12.0–E12.8 E13.0–E13.8 E14.0–E14.8 E139 E149
Ear, nose and throat infections	H66 H67 J02 J03 J06 J31.2 J040
Gangrene	R02
Hypertension	I10 I11.9
Influenza and pneumonia	J10 J11 J13 J14 J15.3 J15.4 J15.7 J15.9 J16.8 J18.1 J18 J189 J120 J121 J122 J128 J129 J160 A481 A70x
Iron-deficiency anaemia	D50.1 D50.8 D50.9 D460 D461 D463 D464 D510–D513 D518 D520 D521 D528 D529 D531 D571 D580 D581 D590–D592 D599 D601 D608 D609 D610 D611 D640 to D644 D648
Nutritional deficiency	E40 E41 E42 E43 E55.0 E64.3
Other vaccine-preventable diseases	A35 A36 A37 A80 B05 B06 B16.1 B16.9 B18.0 B18.1 B26 G00.0 M01.4
Pelvic inflammatory disease	N70 N73 N74
Perforated/bleeding ulcer	K25.0–K25.2 K25.4–K25.6 K26.0–K26.2 K26.4–K26.6 K27.0–K27.2 K27.4–K27.6 K280–282 K284–K286 K920 K921 K922 K20x K210 K219 K221 K226
Pyelonephritis	N10 N11 N12 N13.6 N300 N390 N159c N308 N309

Table A2: Additional results on ED visits

Change from baseline:	(1) Binary WiC vars	(2) Dep var levels	(3) No popn. controls	(4) No buffer controls	(5) Elderly & children	(6) Interact deprived
ED WiCs	-0.0377 (0.0113)	-6.8213 (1.7113)	-0.0339 (0.0119)	-0.0407 (0.0109)	0.0028 (0.0167)	-0.0279 (0.0140)
p0-p25 WiCs	-0.0269 (0.0050)	-5.5249 (0.9986)	-0.0243 (0.0049)	-0.0220 (0.0044)	-0.0227 (0.0057)	-0.0171 (0.0059)
p25-p50 WiCs	-0.0151 (0.0044)	-2.9849 (0.7384)	-0.0136 (0.0040)	-0.0110 (0.0037)	-0.0162 (0.0046)	-0.0096 (0.0046)
p50-p75 WiCs	-0.0020 (0.0037)	-0.5165 (0.5817)	-0.0001 (0.0030)	-0.0011 (0.0029)	-0.0056 (0.0035)	0.0028 (0.0030)
ED WiCs*deprived						-0.0205 (0.0118)
p0-p25*deprived						-0.0160 (0.0058)
p25-p50*deprived						-0.0085 (0.0052)
p50-p75*deprived						-0.0054 (0.0044)
Quarter-labor market FX	✓	✓	✓	✓	✓	✓
Year-distance buffer FX	✓	✓	✓		✓	✓
Population controls	✓	✓		✓	✓	✓
Observations	125945	125945	125945	125945	125945	125945
R-squared	0.866	0.818	0.865	0.866	0.797	0.866

Notes: Standard errors in parentheses clustered at the MSOA level. Elderly and children counts only those aged over 60 or under 18. In the final column deprivation indicator takes value of 1 if neighborhood is in the top quartile of most deprived LSOAs, measured by the overall deprivation score in the English indices of deprivation 2010.

Table A3: Standard errors

	Coefficient	(1)	(2)	(3)
		Standard Errors		
		cluster on LSOA	cluster on MSOA	Conley (1999)
ED WiCs	-0.0408	(0.0073)	(0.0111)	(0.0083)
p0-p25 WiCs	-0.0281	(0.0023)	(0.0049)	(0.0036)
p25-p50 WiCs	-0.0141	(0.0019)	(0.0039)	(0.0029)
p50-p75 WiCs	-0.0008	(0.0013)	(0.0030)	(0.0021)

Notes: Table reports coefficients from a regression of log ED visits per 1000 population on the full set of fixed effects. In column (1) standard errors are clustered on LSOAs, in column (2) standard errors are clustered on MSOAs, in column (3) standard errors follow [Conley \(1999\)](#) and are robust to continuous forms of spatial autocorrelation.

Table A4: Inside and outside practice boundaries

	(1)	(2)	(3)
p0-p25 WiCs - inside boundary	-0.0576 (0.0109)		-0.0624 (0.0113)
- outside boundary	-0.0224 (0.0088)		-0.0194 (0.0090)
p25-p50 WiCs - inside boundary	-0.0436 (0.0115)		-0.0431 (0.0116)
- outside boundary	-0.0133 (0.0066)		-0.0125 (0.0066)
p50-p75 WiCs - inside boundary	-0.0421 (0.0121)		-0.0419 (0.0122)
- outside boundary	0.0051 (0.0041)		0.0054 (0.0041)
p0-p25 PCPs - inside boundary		-0.0198 (0.0080)	-0.0248 (0.0081)
- outside boundary		-0.0021 (0.0077)	-0.0014 (0.0077)
p25-p50 PCPs - inside boundary		-0.0067 (0.0098)	-0.0074 (0.0097)
- outside boundary		-0.0006 (0.0048)	0.0042 (0.0048)
p50-p75 PCPs - inside boundary		0.0079 (0.0091)	0.0060 (0.0091)
- outside boundary		-0.0054 (0.0036)	-0.0003 (0.0035)
Quarter-region FX	✓	✓	✓
Year-distance buffer FX	✓	✓	✓
Population controls	✓	✓	✓
Observations	63864	63864	63864
R-squared	0.769	0.769	0.769

Notes: Sample contains quarter-LSOA cells with 50 or more ED visits. Dependent variables are in logs. All columns count ED visits between 8.30am–6.30pm Monday through Friday. Standard errors in parentheses clustered at the MSOA level

Table A5: Practice catchment area

	(1)	(2)
<i>EAPMC</i> walk-in clinic	33.2424 (6.3082)	46.0074 (5.1444)
<i>EAPMC</i> practice	1.8457 (6.7252)	5.7606 (5.3855)
Constant	54.5511 (0.6962)	54.3508 (0.5152)
Labor-market fixed effects	✓	
Postcode district fixed effects		✓
Observations	7466	7466
R-squared	0.446	0.771

Notes: Based on practice boundaries in late 2017. Dependent variable is area within practice boundary in km^2 . Sample contains 98 walk-in clinics and 74 primary care practices with boundary information.

Table A6: Regression outputs for Figure 7

	(1)	(2)	(3)
ED WiCs	-0.2864 (0.0382)	-0.2966 (0.0408)	-0.1550 (0.0346)
p0-p10 WiCs	-0.0864 (0.0209)	-0.0756 (0.0139)	-0.0826 (0.0123)
p10-p20 WiCs	-0.0611 (0.0179)	-0.0565 (0.0126)	-0.0464 (0.0120)
p20-p30 WiCs	-0.0360 (0.0178)	-0.0440 (0.0117)	-0.0452 (0.0115)
p30-p40 WiCs	-0.0438 (0.0159)	-0.0310 (0.0107)	-0.0420 (0.0099)
p40-p50 WiCs	-0.0067 (0.0124)	-0.0170 (0.0096)	-0.0201 (0.0093)
p50-p60 WiCs	-0.0275 (0.0135)	-0.0364 (0.0099)	-0.0224 (0.0101)
p60-p70 WiCs	-0.0286 (0.0108)	-0.0294 (0.0083)	-0.0138 (0.0076)
Quarter-labor market FX	✓	✓	✓
Year-distance buffer FX	✓	✓	✓
Population controls	✓	✓	✓
Observations	213584	188736	117733
R-squared	0.761	0.762	0.780

Notes: Dependent variable in all regressions is $\log(\text{self-referred ED visits}) - \log(\text{other ED visits})$. Columns represent different sample restrictions. First column drops only cells with missing observations. Second column drops quarter-LSOA cells with less than 10 ED visits. Third column as main regressions i.e. sample contains quarter-LSOA cells with 50 or more ED visits. Standard errors in parentheses clustered at the MSOA level

Table A7: Regression outputs for Figure 8–Figure 10 & ambulance visits

	(1)	(2)	(3)	(4)	(5)
	ED visits	ED visits	House prices	Rank ED visits	Ambulance
ED WiCs	-0.0431 (0.0114)				
p0-p25 WiCs	-0.0269 (0.0044)	-0.0022 (0.0091)	0.0023 (0.0073)	-0.1015 (0.0274)	0.0069 (0.0090)
p25-p50 WiCs	-0.0148 (0.0038)	0.0019 (0.0107)	-0.0002 (0.0066)	-0.0887 (0.0194)	0.0050 (0.0075)
p50-p75 WiCs	-0.0031 (0.0028)	-0.0030 (0.0097)	0.0035 (0.0042)	-0.0268 (0.0118)	-0.0009 (0.0049)
p0-p25 PCPs			-0.0026 (0.0066)	-0.0346 (0.0066)	-0.0108 (0.0079)
p25-p50 PCPs			0.0044 (0.0053)	0.0064 (0.0053)	0.0083 (0.0062)
p50-p75 PCPs			-0.0006 (0.0040)	-0.0045 (0.0040)	0.0045 (0.0046)
Quarter–labor market FX	✓				
Quarter–region FX		✓	✓	✓	✓
Year–distance buffer FX	✓	✓	✓	✓	✓
Population controls	✓	✓	✓	✓	✓
Observations	96370	11789	57986	63864	63863
R-squared	0.874	0.846	0.799	0.862	0.694

Notes: Sample contains quarter-LSOA cells with 50 or more ED visits. Dependent variables are in logs. Standard errors in parentheses clustered at the MSOA level