

Decline in Healthcare Services during COVID-19 in the United Kingdom

By

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Abstract

There are growing concerns that the COVID-19 pandemic could have an adverse impact on the health care sector, an industry that has been historically shielded from the business cycle. In this thesis, we study one aspect of this issue by estimating the magnitude of the COVID-19 pandemic impact on use of outpatient health services in the UK. We use 2017-2020 data from the United Kingdom National Health Service's (NHS) Monthly Activity Return (MAR) and the survey waves 1-6 of the COVID-19 web-survey released by the Understanding Society Longitudinal Study. Our findings indicate that the COVID-19 pandemic is associated with a sharp decline of 74% in the total number of outpatient visits per provider by the month of April, 2020 relative to the same month in prior years. Our results were consistent for all commissioning regions of the NHS. We also studied the mechanisms involved in this decline and determined that the drivers depended on the type of NHS service but were largely supply related for outpatient and inpatient services. Finally, we assessed the inequality of access to healthcare in the month of April, 2020 for patients with long term health conditions based on their age, gender, ethnicity and disease type.

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Table of Contents

Abstract	2
Acknowledgement	3
1 Introduction	9
2 Literature Review	14
2.1 The Decline in Healthcare Service Activity	14
2.2 The Drivers of the Decline	17
2.3 Unequal Health Outcomes for Socio-economic Groups	19
2.4 The Role of Telehealth	23
2.5 Post Pandemic Implications	25
3 Data	29
3.1 Monthly Hospital Activity	29
3.2 Monthly Referral Return	30
3.3 Understanding Society	31
4 Methodology	36
5 Results	39
6 Conclusion	49
A Descriptive Statistics	55

B Regressions	58
C References	74

List of Figures

1	Outpatient Referrals (2013-2020)	40
2	Outpatient Referrals by Region (2018-2020)	43
3	Proportion of respondents with long term health conditions who required NHS services	44
4	Percent of respondents who required specific NHS service and whether or not they received them	46
5	Yearly Percentile Distribution of Outpatient Visits (MAR)	56
6	Monthly Percentile Distribution of Outpatient Visits (MAR)	56

List of Tables

1	Invitation Mode for Wave 1	34
2	Response for Wave 1	34
3	Region wise decline in April 2020	40
4	Regression: Decline by Regions	41
5	Regression: Logged Decline by Regions	42
6	Cancellation for Shielded Individuals by Disease Type	45
7	Regression: Impact on Health Outcomes	47
8	Marginal Effects for the Probit Model	48
9	Descriptive Statistics: MAR Commissioning Regions	55
10	Descriptive Statistics: Understanding Society Wave 1	57
11	Regression: Decline for all providers	58
12	Regression: Logged Decline for all providers	59
13	Regression: Decline for bottom 20 percentile Providers	60
14	Regression: Logged Decline for bottom 20 percentile Providers	61
15	Regression: Decline for top 20 percentile Providers	62
16	Regression: Logged Decline for top 20 percentile Providers	63
17	Regression: Decline for North of England Region	64
18	Regression: Logged Decline for North of England Region	65
19	Regression: Decline for Midlands and East of England Region	66
20	Regression: Logged Decline for Midlands and East of England Region	67
21	Regression: Decline for London Commissioning Region	68
22	Regression: Logged Decline for London Commissioning Region	69

23	Regression: Decline for Southwest of England Region	70
24	Regression: Logged Decline for Southwest of England Region	71
25	Regression: Decline for Southeast of England Region	72
26	Regression: Logged Decline for Southeast of England Region	73

1 Introduction

The COVID-19 pandemic has impacted health systems and economies throughout the United Kingdom and the world. It is expected that the total economic cost of the pandemic may reach 16 trillion dollars (Cutler and Summers [2020]). The pandemic caused the demand for goods and services to decrease because of orders to quarantine and shelter in place (SIP), as well as because of increased uncertainty, income loss, and fear of contagion. At the same time, the pandemic caused a decrease in the supply of goods and services, due to government mandates to close businesses, but also due to sick and dying workers, workers' increased caregiving responsibilities, disruptions in supply chains, and increasing prices of inputs (Gopinath [2020]). The resulting loss of output from these demand-side and supply-side shocks are partly due to the disease itself, and would occur even in the absence of social distancing. The larger effects on output, however, are likely to be due not to the virus itself but rather to social distancing, one of the only tools we have at our disposal to save lives (Gourinchas [2020]).

In the United Kingdom, policymakers responded to the pandemic by enacting shelter-in-place (SIP) policies in March 2020 that encouraged social distancing. Previous research suggests that these policies had their intended effect and reduced spread of COVID-19 infection (Amuedo-Dorantes [2020], Courtemanche [2020], Ma-trajt [2020]). However, evidence on the impacts of social distancing and SIP policies on healthcare utilization remains limited (Ziedan [2020]). The trends in hospital visit indicate towards a sharp decline in outpatient visits. The reduction in visits is likely due to patient fears of infection and reduced access to traditional in-person

health care owing to public health regulations that have restricted elective procedures. However, it is unclear whether the decline in utilization was in response to implementation of SIP policies or due to patients' fears of COVID-19 infection while in a healthcare facility. While the decline in COVID-19 cases associated with these policies might instill public confidence and encourage people to seek healthcare, SIP policies might encourage the public to stay at home and avoid doctors' offices and hospitals. If these policies do reduce necessary medical care, then, while they may limit the spread of COVID-19, they may also impose costs. If delayed or forgone care worsens patient health outcomes, then the positive COVID-related health impacts of SIP policies must be balanced with the potentially adverse consequences of SIP policies on non-COVID care. Appropriately weighing these trade offs requires precise estimation of the impact of SIP policies on non-COVID care.

This is an important aspect of the COVID-19 as the ensuing economic downturn has affected healthcare, a sector of the economy that historically has been somewhat shielded from the business cycle. The health care sector has been relatively insulated from recessions since "people get sick during both good and bad times" and because public healthcare lowers the barriers to medical care (Cutler, [2020]). But in the current pandemic, the situation appears to be unprecedented, particularly for providers in outpatient settings. Social distancing, fear of contagion, quarantining of providers, and other factors appear to be drastically reducing physician visits, putting severe financial strain on outpatient providers. On the supply side, there is concern that primary care, our front lines in the war against COVID-19, may be on the edge of financial disaster (Mostashari [2020], Abelson [2020]). On the demand

side, if patients delay needed outpatient care due to the pandemic, they may face serious and costly adverse outcomes in the future. In the popular press, there is concern that fear of contagion is delaying childhood immunizations, and preventing individuals with chronic health conditions, as well as serious medical events, from getting care (Hollander [2020], CNBC [2020], Kasanagottu [2020]). Additionally, the National Health Service (NHS), the publicly funded healthcare systems of the United Kingdom, has recommended that all elective and non-urgent surgery and procedures should be delayed during the COVID-19 pandemic to preserve resources and prevent the spread of disease (CMS [2020]). These actions have unknown consequences for health outcomes.

In this thesis, we examine the intensity and magnitude of the decline in healthcare services in the United Kingdom in the early months of the pandemic. We investigate the mechanisms for this decline and ascertain the demand or supply related forces behind them. Finally, we assess the effects of demographic and healthcare related parameters towards the unequal access to health care during the pandemic.

Our results indicate that the early months (April 2020) of the pandemic were associated with a 74% decline in outpatient services in the United Kingdom which was consistent across all commissioning regions. Although the decline in outpatient services was demand related, the mechanism for the decline largely depended on the type of NHS service, and the decline is not due solely to SIP policies. Instead, variation in reductions in care were driven by both the implementation of SIP policies and variations in the intensity of the COVID-19 pandemic across regions. Some NHS services such as general practitioner services, pharmacy, prescription medica-

tion, and NHS 111, the United Kingdom emergency helpline, saw decline due to demand related reasons. On the other hand, outpatient services and inpatient services experienced supply related contractions. Our analysis of COVID-19 household survey indicates that the individuals with certain health conditions such as Cancer, Diabetes, Epilepsy and Hypertension were likelier to access healthcare than those with health conditions such as cardiac or pulmonary ailments. Furthermore, younger individuals and women of ethnic minority found it challenging to receive healthcare even though NHS promotes an egalitarian public health structure.

Our findings show that necessary care has been delayed and additional policies designed to restore avoided care may be required. A concern echoed by other studies (Jain [2020]; Ziedan [2020]; Czeisler [2020]). For some patients, delaying necessary care could have potential adverse health impacts in the future. These non-COVID-19 health impacts are currently not fully accounted for in the health impacts of the COVID-19 pandemic nor the impact of SIP policies (Woolf [2020]). These impacts are also not a major focus in the current discussion on the impact of the pandemic on healthcare disparities despite the fact deferred care is happening disproportionately in some populations (Czeisler [2020]). The pandemic, SIP policies and their associated decline in utilization might also affect the supply side of the market. For example, the NHS decided to move from price based model to a block contract structure which impacted the finances of several providers. The decline in health care utilization also seems to be impacting employment in the health care industry. Himmelstein et al. [2020] found that, in the US, the number of ambulatory workforce fell by 1.19 million persons, a 14.9% drop and the number of hospital employees

decreased by 135,000 (2.6% decline).

2 Literature Review

2.1 The Decline in Healthcare Service Activity

For the longest time it has been claimed that the demand for the healthcare products and services is inelastic and the healthcare industry is mostly unaffected by economic crisis. Although it is expected in any crisis that demand for goods and services will dip, healthcare sector was expected to be largely insulated from these effects because health insurance lowers the price of medical care, protecting access to care to some extent for insured patients. But due to social distancing measures, one of the few tools at the disposal of the society to combat COVID-19 infection, both the healthcare services experienced a decline in the early weeks and months of the pandemic. The possible ramifications of this are largely unknown.

There is consensus in the literature that the COVID-19 pandemic has had a significant impact on the healthcare sector (Mehrotra et al. [2020], Chatterji et al. [2020], Hoffman et al. [2020]). It was found that the number of outpatient visits declined sharply in mid-March and remained around this level in the first few weeks of April, compared to a baseline of March 1–7, 2020. For the week ending in 4/18, in-person visits had declined 67 percent and the decline in total visits with telemedicine included was 54 percent in the US (Mehrotra et al. [2020]). Moreover, it has been shown that the COVID-19 pandemic is associated with about a 67 percent decline in the total number of outpatient visits per provider by the middle of April (the week of April 12-18th) 2020 relative to the same week in prior years in the US (Chatterji et al. [2020]).

Some studies found that the impact largely depended on the region (Jeffery et al [2020], (Mehrotra et al. [2020])). It was found that the annual Emergency Room (ER) volume decreased, ranging from 41.5% in Colorado to 63.5% in New York. The weeks with the most rapid rates of decrease in visits were in March 2020, which corresponded with national public health messaging about COVID-19 (Jeffery et al [2020])). Furthermore, there were larger declines in the Mid-Atlantic and New England regions vs. other regions (Mehrotra et al. [2020])).

Czeisler [2020] also observed temporary disruptions in routine and nonemergency medical care access and delivery during periods of considerable community transmission of COVID-19. They concluded that medical care delay or avoidance increases morbidity and mortality risk associated with treatable and preventable health conditions and might contribute to reported excess deaths directly or indirectly related to COVID-19. Overall, an estimated 40.9% of U.S. adults avoided medical care during the pandemic because of concerns about COVID-19, including 12% who avoided urgent or emergency care and 31.5% who avoided routine care. The estimated prevalence of urgent or emergency care avoidance was significantly higher among the following groups: unpaid caregivers for adults versus noncaregivers; persons with two or more underlying medical conditions; persons with health insurance versus those without health insurance; racial minorities; young adults aged 18–24 years; and persons with disabilities. If routine care avoidance were to be sustained, adults could miss opportunities for management of chronic conditions, receipt of routine vaccinations, or early detection of new conditions, which might worsen health outcomes.

However, there is disagreement to the claim that there is a correlation between

COVID-19 cases and the number of visits of patients (Reale et al. [2020]). In this study, the authors performed a nested case-control study in which they used a risk set sampling to match patients who tested positive for SARS-CoV-2 infection either during pregnancy or at the time of admission for labor and delivery with up to 5 control patients. They found no meaningful association between the number of in-person health care visits and the rate of SARS-CoV-2 infection in this sample of obstetrical patients in the Boston area. They further found that the obstetrical population who had frequent in-person visits to a health care setting and underwent universal testing for SARS-CoV-2 infection suggested in-person health care visits were not likely to be an important risk factor for infection and that necessary, in-person care can be safely performed. Nevertheless, the study was performed on a small sample size which may affect the quality of the results.

Since the lifting of restrictive measure, stores and other businesses have begun to reopen. At the same time, various areas of each country see a surge of cases. Outpatient practices have been adapting to this new reality, developing new ways of delivering care both in person at their practices and via telehealth.

But while visit numbers have rebounded, they are still substantially lower than before the pandemic began. Forgone visits have created “cumulative deficits” in both patient treatment and practice revenue. The number of visits to ambulatory practices had declined nearly 60 percent by early April 2020. Since that time, the numbers have rebounded substantially, though the rebound has plateaued. (Ganguli [2020])

There are several limitations in the studies done previously. Existing studies

have typically used data from a single health system or geographic market to observe changes in utilization and therefore do not have a generalizable measure of the impact on a larger region or a country. Most of the analysis has been restricted to the United States and few studies have been done on the United Kingdom’s response to the pandemic. Furthermore, the accessibility of healthcare services during COVID-19 across different demographic segments has not been examined extensively.

2.2 The Drivers of the Decline

There is a gap in the literature regarding the mechanism behind the decline in the healthcare service usage during the pandemic (Chatterji et al. [2020]). Some studies imply it to be mostly demand related (Liu et al. [2020]) as Taiwanese hospitals allowed visits to ordinary wards as stated on the official websites of all 472 National Health Insurance-contracted hospitals in during April 2020. However, since most of the data used comes from a specific hospital, region or healthcare provider, the literature is limited in generalizing the results to the entire population of the country. (Jeffery et al [2020]; Reale et al. [2020]).

It has been established that since the great recession, there has been a steady decline in primary healthcare visits (Ganguli et al. [2020]). Since 2008, primary care visit rates in the United States dropped by 6–25% across a range of populations in five sources of national survey and administrative data. There were three likely mechanisms behind the decline: decrease in inpatients’ ability, need, or desire to seek primary care; changes in primary care practice such as greater use of teams and non-face-to-face care; and replacement of in-person primary care visits with

alternatives such as specialist, retail clinic, and commercial telemedicine visits. It has been conjectured that COVID-19 pandemic could have accelerated these trends (Chatterji et al. [2020]).

There is also consensus in the literature that both demand and supply related forces were catalysts for the decline. Cantor et al. [2020] notes that a drastic decline in preventive and elective services occurred due to SIP policies related to the COVID-19 pandemic, but the impact of these policies is lessened when accounting for variations in exposure to the COVID-19 pandemic.

Epidemiologists contend that SIPs—such as stay-at-home orders, closures of non-essential businesses and schools, or bans on large gatherings—combined with testing, tracing, and isolating, are the only options to fight the pandemic until a vaccine is identified and made widely available or societies achieve herd immunity (Ferguson et al., [2006], Pichler et al., [2017], Tian et al., [2020]).

Andersen et al. [2020] estimated the effects of SIPs on surgical abortions during the pandemic. They found that the overall volume of visits to abortion clinics decreased by 32 percent in 2020 compared to 2019, and states that banned elective surgical procedures saw an additional 23 percent decrease. These results can be rationalized through both demand and supply-side explanations. For example, if abortions are a relatively small share of a clinic’s services then it may not be feasible to cover fixed costs if there are no patients coming in for other services to share the costs of providing common services. On the demand side, elective procedure bans may have provided signals about the severity of the pandemic in an area, leading the marginal woman to decide against having an abortion.

Amuedo-Dorantes et al. [2020] explored SIP mechanisms at play, examined how SIP adoption speed affected infections, and conducted state-level analyses of the association between SIPs and non-COVID deaths. It was concluded that moving up the implementation date of SIPs by one day lowers the COVID-19 death rate by 2.4 percent. The effectiveness of acting early is similar for both stay-at-home orders and business closures. They confirmed how the relevance of responding early stems from the ability to slow contagion likely prevented the overburdening of the healthcare system. Finally, they show that a timely adoption of the SIPs helped reduce the burden on the healthcare system, and lowered non-COVID deaths. However, Woolf et al. [2020] documented that non-COVID deaths increased during the months of March 2020 to January 2021 which may be attributed to voluntary postponement of procedures or, in some instances, through an overwhelmed healthcare system.

2.3 Unequal Health Outcomes for Socio-economic Groups

There is growing evidence of disparities in health outcomes from COVID and non-COVID factors for individuals of different race/ ethnicity, genders and economic status and is strongly associated with infection and deaths as well as access to health-care.

In a cross-sectional study, Adhikari, Samrachana, et al. [2020] examined the association of neighborhood race/ ethnicity and poverty with COVID-19 infections and related deaths in urban counties, hypothesizing disproportionate burdens in counties with a larger percentage of the population belonging to minority racial/ethnic groups and a higher rate of poverty. For the less-poverty counties, infection rates

for COVID-19 ranged from 41.7 to 3821.8 per 100 000 individuals, and death rates ranged from 0.34 to 271.3 per 100 000 individuals. In more-poverty counties, those with substantially non-White populations had an infection rate nearly 8 times that of counties with substantially White populations and a death rate more than 9 times greater. Urban counties in large metropolitan areas were among the most affected by the coronavirus disease 2019 (COVID-19) pandemic.

Brown [2020] found that there are theoretical ambiguities in the influence of socioeconomic covariates on the spread of infections, given the induced behavioral responses, also allowing for costs of adjusting behavior to the threat of infections and the potential lags and nonlinearities. They posit that in the absence of effective pharmaceutical interventions, personal social-distancing choices are a plausible channel linking socioeconomic factors to the spread of infections.

Their analysis of the bivariate relationship in the data is consistent with the view that social distancing lowers the COVID-19 infection rate. However, the marginal cost of greater social distancing is likely to be higher for poorer families, who cannot easily maintain their consumption in isolation; this is dubbed the protection effect by them. Against this, the pre-epidemic levels of social and economic interactions are likely to be higher for wealthier people and there are costs of adjustment to a lower level during the epidemic—the adjustment effect. Similarly, there are a priori reasons why a more elderly population can yield lower infection rates but higher death rates conditional on infections, and the results support the view that both these opposing, and roughly equal, channels of impact are present. The signs of both the protection and adjustment effects in the relationship between COVID-19 outcomes across US

counties and incomes can be observed (Brown et al. [2020]).

Counties with higher overall income inequality tend to have higher infection rates, which is in part due to the fact that higher inequality comes with higher poverty rates. Similarly, higher inequality between counties increases the overall (national) infection rate. There is a strong effect of race, separately to poverty and inequality: a higher population share of Black Americans is associated with higher infection rates at county level. The effects of income inequality and poverty within counties largely vanish when one controls for the Black American population share, indicating that the directly relevant factor is race not income inequality or poverty per se. Also, without controlling for the racial composition of counties one substantially overestimates the viral impact of higher population density. These socioeconomic effects on the spread of the virus do not fade over time since the first infection; rather, the effects tend to become even stronger. Thus, there is little to suggest that the mixture of different socioeconomic groups dulls the impacts of the underlying inequalities.

Germain [2020] concluded ethnic minority and migrant women had an increased susceptibility to serious negative health outcomes in the UK which are enabled by the existing underlying barriers to accessing healthcare. They also explain that barriers to accessing care have been exacerbated by the COVID-19 pandemic for these marginalised groups of women. These include barriers stemming from racialised medical perceptions, cultural barriers related to gender including information barriers and stigma, and legal barriers stemming from immigration law. Treating women as a homogenous group disregards the individual needs of ethnic minorities and migrants, as doing so embeds structural inequalities that have been highlighted as a result of

the pandemic (Platt and Warwick [2020]). Razai [2020] conclude that in the UK, people of black ethnicity have had the highest diagnosis rates, with the lowest rates observed in white British people. Moreover, data up to May 2020 show 25% of patients requiring intensive care support were of black or Asian background. These differences are highlighted in the COVID-19 cases among key workers. Although black and Asian staff represent only 21% of the NHS workforce, early analysis showed that they accounted for 63% of deaths among health and social care workers. Otu [2020] and Keys [2020] also argue that Covid-19 has laid bare long-standing racial fault lines in the UK that disadvantage the already vulnerable BAME (black, Asian and minority ethnic) communities. The reticulated links between socioeconomic indices (income, social class, occupational background and educational achievement) and poorer health outcomes have been magnified by this pandemic.

Czeisler [2020] observed that increased prevalence of reported urgent or emergency care avoidance among Black adults and Hispanic adults compared with White adults are especially concerning given increased COVID-19-associated mortality among Black adults and Hispanic adults. In the United States, the age-adjusted COVID-19 hospitalization rates are approximately five times higher among Black persons and four times higher among Hispanic persons than are those among White persons. Factors contributing to racial and ethnic disparities in COVID-19 exposure, illness, and mortality might include long-standing structural inequities that influence life expectancy, including prevalence and underlying medical conditions, health insurance status, and health care access and utilization, as well as work and living circumstances, including use of public transportation and essential worker status.

2.4 The Role of Telehealth

Due to the adoption of restrictive measures such as social distancing and shelter-in-place, health care facilities and providers increasingly offer clinical services through virtual means such as telehealth/telemedicine. Telehealth is the use of two-way telecommunications technologies to provide clinical health care through a variety of remote methods.

There is consensus in the literature that telehealth is replacing in-person health-care visits accelerated by shelter-in-place mandates. (Mehrotra et al.[2020]; Ganguli et al.[2019]; Hollander et al.[2020]). Due to its convenient and inexpensive nature, telehealth has been proposed to take precedence over in-person visits for meeting patient needs. Telehealth gives health systems automated logic flows (bots) that refer moderate-to-high-risk patients to nurse triage lines but are also permitting patients to schedule video visits with established or on-demand providers, to avoid travel to in-person care sites. The healthcare systems that have already implemented telehealth innovations can leverage them for the response to Covid-19. There was an increase in the usage of telemedicine but not enough to reverse the decline of overall primary care (Mehrotra et al.[2020]).

Koonin [2020] examined changes in the frequency of use of telehealth services during the early pandemic period. During the first quarter of 2020, the number of telehealth visits increased by 50%, compared with the same period in 2019. During January–March 2020, most encounters were from patients seeking care for conditions other than COVID-19. However, the proportion of COVID-19–related encounters significantly increased (from 5.5% to 16.2%) during the last 3 weeks of March 2020.

This marked shift in practice patterns has implications for immediate response efforts and longer-term population health.

Mann [2020] also observed that telemedicine’s growth has been incremental, and was used by only 8% of Americans in 2019. Despite many barriers, healthcare systems have been investing in building a telemedicine capacity anticipating a future in which it would become more ubiquitous. Initially, as in-person visits dropped, telemedicine visits increased rapidly. Since that peak in mid-April, telemedicine use has begun to decline, though it remains substantially higher than prior to the pandemic.

Czeisler [2020] noted that medical services for persons with disabilities might be disrupted because of reduced availability of accessible transportation, reduced communication in accessible formats, perceptions of SARS-CoV-2 exposure risk, and specialized needs that are difficult to address with routine telehealth delivery during the pandemic response. Increasing accessibility of medical and telehealth services might help prevent delay of needed care.

Although telehealth is generally well-accepted by patients and clinicians, it is not without challenges (Jain, Snigdha, and Lekshmi Santhosh [2020]). Limited access to the Internet or devices such as smartphones, tablets, or computers, and lack of familiarity with technology might be potential barriers for some patients. In addition, virtual visits might not be appropriate for some persons based on level of acuity or necessity to conduct an in-person physical examination or diagnostic testing. Although several reports have described concern in the decline of emergency department use during the early pandemic period, a very small proportion of telehealth patients in this analysis were referred to emergency care. Increases in the use

of telehealth precipitated by COVID could have long-term benefits for improving appropriate emergency department utilization. Continuing telehealth policy changes and regulatory waivers might provide increased access to acute, chronic, primary, and specialty care during and after the pandemic.

2.5 Post Pandemic Implications

Cutler [2020] found that some individuals who survive COVID-19 are likely to have significant long-term complications, including respiratory, cardiac, and mental health disorders, and may have an increased risk of premature death. Data from survivors of COVID-19 suggest that long-term impairment occurs for approximately one-third of survivors with severe or critical disease. Because there are approximately 7 times as many survivors from severe or critical COVID-19 disease as there are COVID-19 deaths, long-term impairment might affect more than twice as many people as the number of people who die. Given the predominance of respiratory complications among COVID-19 survivors, affected individuals may be like those with moderate chronic obstructive pulmonary disease, which has been estimated to have a quality-of-life disutility of approximately 0.25 to 0.35. Assuming a total reduction in quality-adjusted life expectancy, including length as well as quality of life, of 35% and taking into consideration the assumed value of a year of life yields an estimated loss from long-term complications of \$2.6 trillion for cases forecast through 2021. Even individuals who do not develop COVID-19 are affected by the virus. Loss of life among friends and loved ones, fear of contracting the virus, concern about economic security, and the effects of isolation and loneliness have all taken a

toll on the mental health of the population. The proportion of US adults who report symptoms of depression or anxiety has averaged approximately 40% since April 2020; the comparable figure in early 2019 was 11.0%. (Cutler et al. [2020]) These data translate to an estimated 80 million additional individuals with these mental health conditions related to COVID-19. If, in line with prevailing estimates, the cost of these conditions is valued at about \$20,000 per person per year and the mental health symptoms last for only 1 year, the valuation of these losses could reach approximately \$1.6 trillion. The estimated cumulative financial costs of the COVID-19 pandemic related to the lost output and health reduction is estimated at more than \$16 trillion, or approximately 90% of the annual gross domestic product of the US. For a family of 4, the estimated loss would be nearly \$200,000 (Cutler et al. [2020]). Approximately half of this amount is the lost income from the COVID-19-induced recession; the remainder is the economic effects of shorter and less healthy life.

There has been a marked decline in children vaccination, although its broader health impacts are not known (Hoffman [2020]). During the week of April 5, the administration of measles, mumps and rubella shots dropped by 50 percent; diphtheria and whooping cough shots by 42 percent; and HPV vaccines by 73 percent compared to February 16 as a pre-coronavirus baseline. The doses that states distribute in a federally funded program for uninsured patients called Vaccines for Children have also dropped significantly since the beginning of March. In the early weeks of the shelter-in-place orders, doctors concentrated efforts on vaccinating infants up to 2 years old, and waved off the disruption to the schedule for older children as temporary, saying it could readily be addressed once the restrictions lifted. But the longer

that the orders continued, the more worried the doctors became about vaccine protection for older children. Health experts fear that assuming parents returning to work could swiftly get immunization appointments for their young children, most vaccines take between two and four weeks before providing full protection.

The decline in non-COVID healthcare services includes less elective procedures that are lucrative for a lot providers. The economic impact of this source of income will greatly cripple the sector. The American Hospital Association reported that hospitals are losing more than \$50 billion per month (Farr, Christina. 2020). Private equity investor and public policy professor Meghan Fitzgerald, estimated through her own research that it's about \$1 to \$1.2 billion per day noting that many of these procedures were medically necessary, and – yes – profitable, enabling these institutions to serve all patients.

The chairman of the Department of Medicine at UC San Francisco, Dr. Bob Wachter said that his hospitals lost more than \$5 million per day in April alone, and that many of the wards are sitting mostly empty. Making matters more challenging, many hospitals say they are currently spending big sums to treat patients and keep their staff safe during the pandemic. There's some reimbursement revenue associated with COVID-19 patients, but it's typically not on par with what they typically make from elective procedures.

This situation is not sustainable for long. In the US, some hospitals are laying off staff, cutting hours for medical providers, and even filing for bankruptcy. The federal government has set aside some assistance, but reports show that it's far from enough and some of the poorest hospitals are getting bypassed altogether.

While hospitals are struggling financially, health insurers are seeing a bump in profits. As people delay elective surgeries and avoid preventative care during the pandemic, declines in spending have more than offset the added costs of paying for COVID-19 care. Experts believe that it could take years for hospitals to bounce back and find their financial foothold. (Farr, Christina. 2020).

3 Data

3.1 Monthly Hospital Activity

We use the Monthly Activity Return (MAR) data published by the NHS of the UK for the months up to May 2020. From June 2020, MAR is replaced by the Monthly Referrals Return (MRR), which is a streamlined version of MAR focusing on referral elements only.

Monthly activity data includes the statistics relating to elective and non-elective inpatient admissions (FFCEs) and outpatient as well as inpatient referrals and attendances for first consultant outpatient appointments. Data is available from April 2008 on both a provider and commissioner basis. Figures are submitted monthly on the Monthly Activity Return (MAR) by NHS Trusts, Clinical Commissioning Groups (CCGs) and also Independent sector providers treating NHS patients.

The outpatient activity data gives the number of written referrals from General Practitioners (GP), whether doctors or dentists, for first consultant outpatient appointment. All written GP referral requests to a Consultant whether directed to a specific consultant or not, is recorded, regardless of whether they result in an outpatient attendance. An electronic message is counted as written, as is a verbal request which is subsequently confirmed by a written request. Prison referrals are be recorded as GP referrals as well. The referral request received date of the GP referral request is used to identify referrals included in the return.

3.2 Monthly Referral Return

From June 2020 data, the Monthly Referrals Return (MRR) replaced MAR and the Quarterly Activity Return (QAR). Monthly Referral Return (MRR) captures referrals for first consultant-led outpatient appointments for NHS patients. Following a consultation with users of the Monthly Activity Return (MAR) a decision was made to retire the collection in its current format. Referral element from MAR can be used from the period April 2008 to May 2020 which are comparable to MRR.

Replacement information covering the consultant-led outpatient and inpatient activity previously collected in MAR and QAR are published as part of NHS Digital’s existing monthly official statistics publication series (Monthly Hospital Episode Statistics for Admitted Patient Care, Outpatients and Accident and Emergency) released on the same day as the previous MAR data.

All written GP referral requests for a first consultant-led appointment whether directed to a specific consultant or not, are recorded, regardless of whether they result in an outpatient attendance.

In order to estimate a decline in health care services, we use the monthly referrals for outpatient services both at the provider level as well as commissioning region level. Since outpatient services has very little overlap with COVID-19 related hospital visits, which are covered by General Practitioners and Inpatient services, we think that the outpatient activity is a good measure for overall non-COVID healthcare service activity. Furthermore, due to the introduction of MRR in June 2020, we are unable to use the actual attendance data in the MAR. Hence, we use the outpatient referrals as a proxy to outpatient attendance.

3.3 Understanding Society

Understanding Society is a UK Household Longitudinal Study. The Study is based at the Institute for Social and Economic Research at the University of Essex where the researchers follow the participants over a long period of time, giving a long-term perspective on people's lives. As a longitudinal study, Understanding Society explores how life in the UK is changing and what stays the same over many years. The sample size for the study is large, allowing researchers to investigate the experiences of different sub-groups and ethnic minorities over time.

From April 2020 participants from the main Understanding Society sample have been asked to complete a short web-survey. This survey covers the changing impact of the pandemic on the welfare of UK individuals, families and wider communities. Participants complete a regular survey, which includes core content designed to track changes, alongside variable content adapted as the coronavirus situation develops. The COVID-19 study was funded by the Economic and Social Research Council and the Health Foundation. Fieldwork for the web survey was carried out by Ipsos MORI and for the telephone survey by Kantar. Both agencies have also conducted COVID-19 youth surveys.

A telephone interview had been offered to respondents who wished to take part but who live in a household where no-one is a regular internet user. Fieldwork for the first telephone interviews was late-May to early-June 2020; fieldwork for the second telephone interviews was late-November to early-December 2020. Young people aged 10-15 were also asked to contribute to the COVID-19 study: they were sent a paper self-completion Strengths and Difficulties Questionnaire (SDQ) in July 2020 and a

longer paper self-completion questionnaire in November 2020.

The COVID-19 survey started in April 2020, with Wave 2 in May 2020, Wave 3 in June 2020, Wave 4 in July 2020, Wave 5 in September 2020, Wave 6 in November 2020, Wave 7 in January 2021 and Wave 8 in March 2021. There were no survey in August 2020, October 2020, December 2020 and February 2021. From September 2020 onwards the survey is fielded every two months.

The 20 minute questionnaire includes core content repeated at each data collection to track changes through the pandemic, as well as rotating content. For the May survey onwards, researchers and analysts were invited to suggest questionnaire content through an open call. In selecting content for the questionnaires, priority is given to content that:

- Focuses on Understanding Society core priority areas: employment, income, health, family, education, civic engagement;
- Builds on the longitudinal strengths of Understanding Society, and links to data we have collected before or will collect in the future;
- Needs to be collected “in the moment” rather than being asked retrospectively in a future annual survey;
- Is enhanced by the household structure of the Study;
- Is of significant research and/or policy interest;
- Complements existing Understanding Society content.

The COVID-19 study includes all members of the main Understanding Society samples: the Understanding Society General Population Sample (GPS), the Ethnic Minority Boost Sample (EMBS), the Immigrant and Ethnic Minority Boost Sample (IEMBS), and the former British Household Panel Study (BHPS). The eligible sample includes everyone in households who have participated in at least one of the last two waves of data collection. These samples are probability samples of postal addresses. In England, Wales and Scotland they are clustered and stratified, in Northern Ireland unclustered systematic random samples. Northern Ireland and areas in Great Britain with high immigrant and ethnic minority populations were oversampled. In eligible sample households, all household members who were aged 16+ in April 2020 were invited to the COVID-19 study, except those who were adamant refusals or mentally or physically unable to make an informed decision to take part, and those with unknown postal addresses or addresses abroad. In waves 2 to 4, everyone eligible in wave 1 continued to be eligible irrespective of whether they had participated in any of the previous surveys. From the September 2020 (wave 5) survey onwards, only sample members who had completed at least one partial interview in any of the first four web surveys were invited to participate.

Datasets containing the Understanding Society COVID-19 geographical identifiers can be used to link the main Understanding Society COVID-19 dataset (SN 8644) to the LSOA 2011 or Local Authority District location for each respondent. Each dataset consists of a file for every wave. Each survey contains PIDP (the linking variable) and the appropriate geographical identifier. This means that we can track the responses by tagging individuals by location and comparing that with how the

pandemic situation developed in their geographical region.

In our study, we primarily focus on Wave 1 which ran from 24th April 2020 to 30th April 2020. Table 1 and Table 2 summarize the sample distribution of the first Wave.

Email & SMS	7,560
Email not SMS	4,897
SMS not Email	3,620
Letter only	5,769
Letter & Email/SMS	78
Total	41,846

Table 1: Invitation Mode for Wave 1

Survey outcome	All invited (N)	%
Full interview	16,662	39.4%
Partial interview	1,099	2.6%
Full or partial interview	17,761	42%
Non-respondent	24,483	78 58%
Total	42,244	100%

Table 2: Response for Wave 1

There are several modules in the survey, of which the core modules will be featured in every wave. We will primarily be using the Long term health condition management module, ID check and household composition module which are all

core modules. The following modules were included in Wave 1:

- ID check and HH composition
- Coronavirus illness
- Long-term health conditions
- Loneliness
- Employment
- Finance
- Financial security
- Mental health (GHQ)
- Caring outside household
- Time use
- (Home) schooling
- Food
- Alcohol consumption
- Smoking
- Exercise
- HH relationships

4 Methodology

Our primary approach for estimating the decline of healthcare services from COVID-19 is a fixed effects design that uses 2017-2019 NHS outpatient activity data both at the provider levels and region levels as the comparison group for monthly outpatient activity in 2020. We define post pandemic period as months starting from March 2020 to February 2021 as the first shelter in place order was enacted on March 23rd 2020.

We begin our analysis by estimating Ordinary Least Squares (OLS) models of the following form:

$$y_{rmt} = \alpha + \sum_j \beta_j S_j + \delta_m + \delta_t + \delta_r + \mu_{rmt}$$

where t and m represent the year and month respectively, and p represents the region. y_{rmt} is the main outcome variables of interest and stands for the number of outpatient referrals for first consultant outpatient appointments per region, month and year. The coefficients of interest are the β_j which measure the difference of the months in the post pandemic period and the months in the prior years. S_j are a series of binary variable which are 1 when the year for the observation is in post pandemic and when the month for the observation is j and are 0 otherwise. δ_m , δ_t , and δ_r represent month fixed effects, year fixed effects and region fixed effects respectively to account for seasonality and trends. We cluster standard errors at the region, month and year level.

We estimate our declines using a logged version of our model. Here the β_j give

the percentage decline in j^{th} month in the post pandemic period.

$$\ln y_{rmt} = \alpha + \sum_j \beta_j S_j + \delta_m + \delta_t + \delta_r + \mu_{rmt}$$

We use the same methodology to evaluate the decline at the provider level, which provides a more granular view. We also use this design to estimate the declines for each region to check for variability. Furthermore, we also segregate the providers into different percentile groups and run separate regressions for each to measure the impact for different size of providers.

Next, we use the the Understanding Society COVID-19 Survey Wave 1 (April), to estimate the drivers for decline in six types of NHS services:

1. General Practitioners
2. Prescription Medication
3. Outpatient Services
4. Inpatient Services
5. NHS 111
6. Pharmacists

To estimate the effects of this decline on accessibility to services, we use the data from the Understanding Society COVID-19 Survey Wave 1 (April) and the following Probit model:

$$O_i = \sum_g \lambda_g D_g + \pi_1 A_i + \pi_2 (E_i \times G_i) + \varepsilon_i$$

Here O_i is a binary variable which is 1 if an individual i is able to access NHS service in the past four weeks preceding the survey and is 0 otherwise. D_g are the set of long term health conditions. Each D_g will be 1 if the respondent has g^{th} health condition and 0 otherwise. A_i and G_i represents the age and gender of the i^{th} individual respectively. E_i is binary variable which is 1 if the individual is an ethnic minority and 0 otherwise. π_2 is a coefficient on the interaction variable $E_i \times G_i$. The interaction variable is 1 if the individual is a woman of ethnic minority but it's 0 in all other cases. A list of disease types is given below:

- Arthritis
- Cardiac Ailments
- Pulmonary Ailments
- Hypothyroidism
- Cancer
- Epilepsy
- Hypertension
- Diabetes
- Obesity ($BMI \geq 40$)

5 Results

The mean total number of referrals per commissioning region per month is 205875, with the 10th percentile equal to 92658 visits and the 90th percentile equal to 332006 visits. On the provider level, the mean total number of referrals per commissioning region per month is 3412, with the 10th percentile equal to 54 visits and the 90th percentile equal to 9037 visits [Appendix A]. In figure 1, we can see that the year 2020 saw major dip in the number of out patient referrals per region per month. The sharpest deviation is seen around the month of April 2020 with subsequent recovery trend. Table 4 shows regression findings based on our main specification in its natural units. Table 5 show findings based on a logged version of the dependent variable. We can see that the month of April 2020 was associated with a 74% decline compared to the same month in previous years. We can also see that every month after pandemic showed a decline from the average of same months in their previous years.

We have isolated each region and performed the same regression. The decline for each region in the month of April 2020 is given in Table 3. We see that each region was following the same trend as shown in figure 2. We can conclude that the impact of the pandemic on healthcare services was largely the same regardless of the region in its early months.

We use the same methodology to perform an analysis on a more granular data set of provider level referrals. We find that the month of April 2020 was associated with 73% decline compared to the same month in previous years. We also see that the providers with lowest 20 percentile of outpatient referrals saw a much larger decline

of 82% compared to providers with highest 20 percentile of outpatient referrals who saw a decline of 72% in the month of April 2020 [Appendix B].

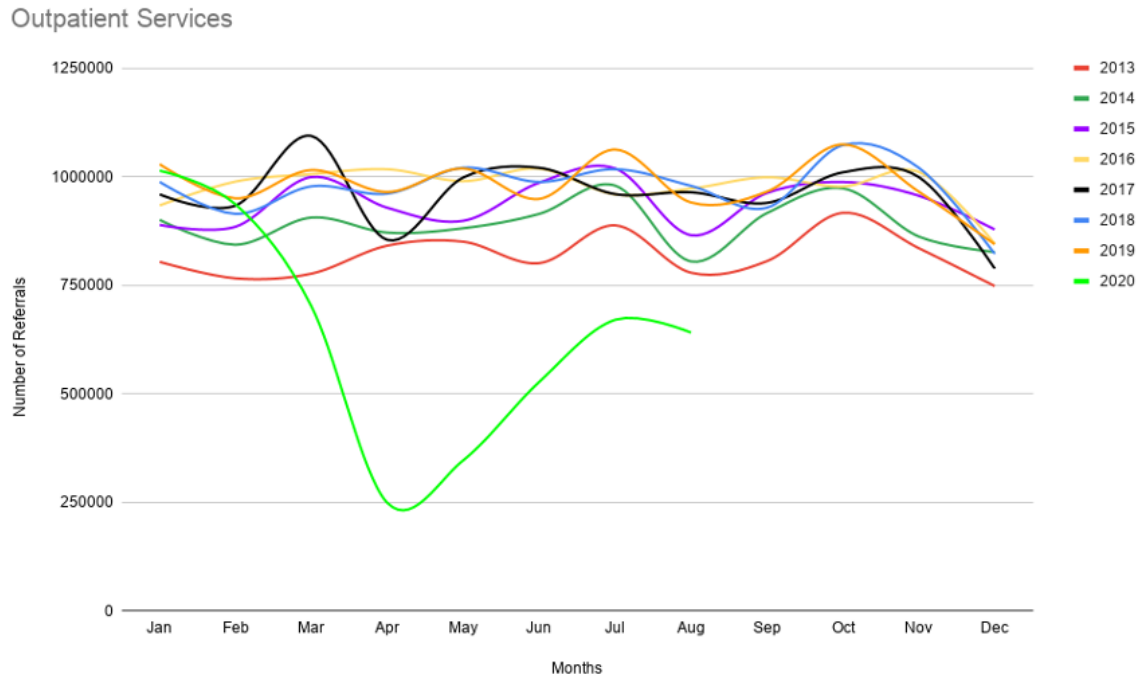


Figure 1: Outpatient Referrals (2013-2020)

North of England	75%
Midlands and East of England	72%
London Commissioning Region	78%
Southwest of England	71%
Southeast of England	73%
Overall	74%

Table 3: Region wise decline in April 2020

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 4: Regression: Decline by Regions

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.17	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.28	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.40	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.74	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.70	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.44	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.29	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.29	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.18	2.72E-2	-6.78	0	-0.23	-0.13

Table 5: Regression: Logged Decline by Regions

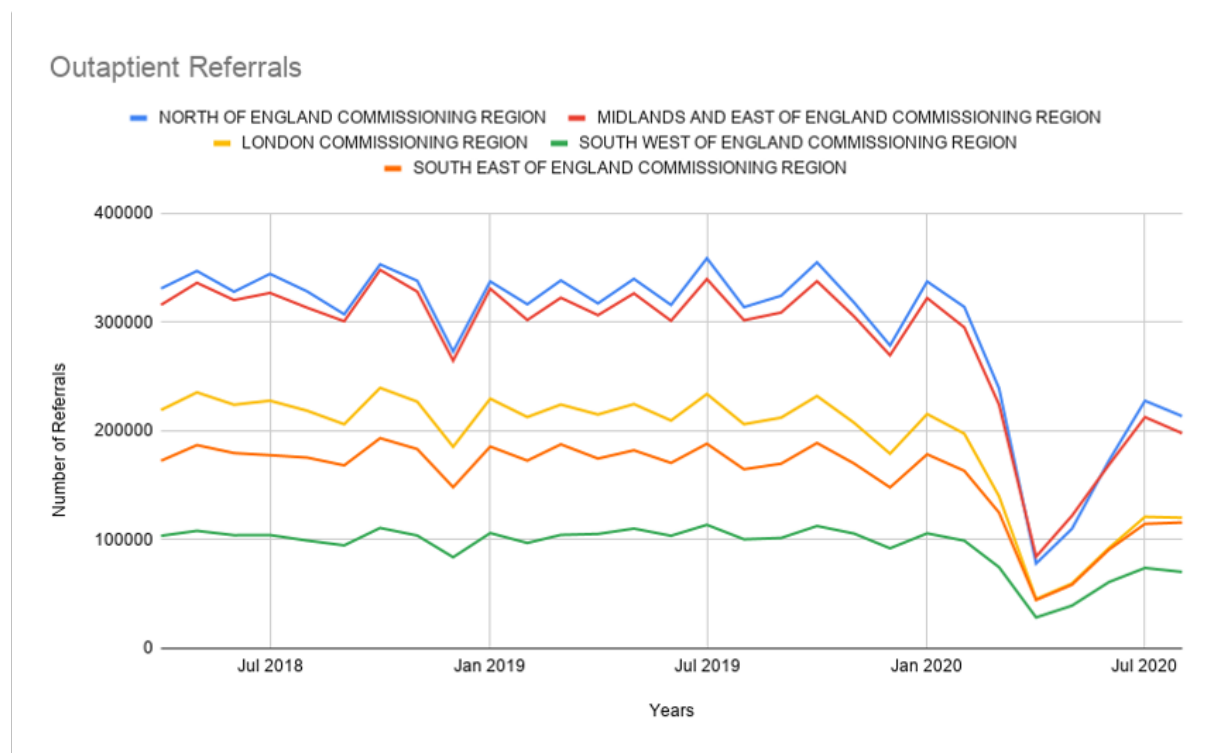


Figure 2: Outpatient Referrals by Region (2018-2020)

Using the survey panel data, we estimated that the decline in Outpatient visits and Inpatient Visits were largely supply related with 82% and 79% of the cancellations attributable to the NHS respectively. While General Practitioner visits (68%), Pharmacists (62%), NHS 111 (70%) and Prescription Meds (100%) cancellations were largely demand driven and were initiated by respondent with long term health conditions.

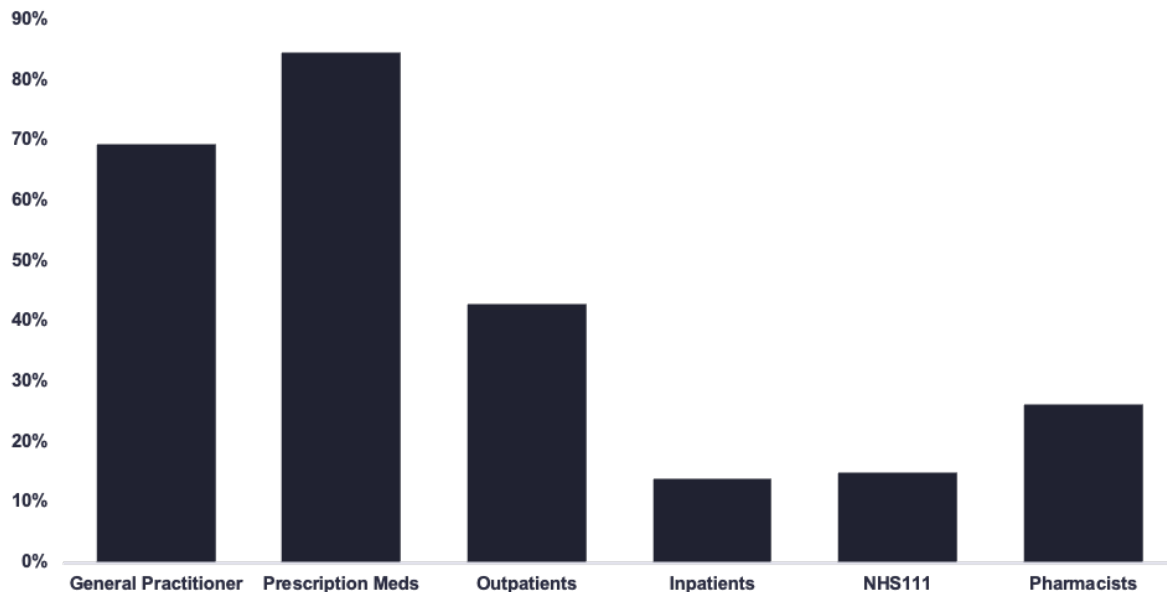


Figure 3: Proportion of respondents with long term health conditions who required NHS services

Since we only included individuals with long term health conditions in the analysis, the distribution for demand for different NHS services in figure 3 may be different for the population as a whole. However, for outpatients visits, individuals with long term health conditions form majority of demand (Mehorotra et al. [2020]).

Finally, we investigated the unequal access to healthcare services among individuals with long term health conditions. The NHS designates certain individuals as high risks if they are likely to develop serious complications through covid infections. These “at risk” individuals are approximately 6% of the total population. Of these, the respondents who wanted to access NHS services and were actually able to do so were only 20%. While 8% percent of the appointments were cancelled by the respondents, 72% were cancelled by the NHS. This overall split is even between men

and women.

The proportion of these shielded individuals increases with age. But, surprisingly, the number of cancellations went down with age (16-34: 81% cancelled by NHS, 70+: 68% cancelled by NHS). In table 6, we can also see proportion of cancellations based the disease type. We see that 20% of the individuals with long term health conditions were able to continue treatment as planned. But there is variation between disease types. For example, 34% of cancer patients were able to continue with their treatments while only 17% percent of diabetes patients were able to do so.

	Cancelled by NHS	Cancelled by respondent	As Planned
Any Condition	63%	10%	21%
Arthritis	68%	9%	21%
Cancer	53%	7%	34%
Diabetes	70%	11%	17%
Hypertension	65%	8%	22%
Obesity	78%	8%	10%
Pulmonary	64%	12%	19%
Cardiac	60%	12%	24%
Neurological	66%	9%	19%
Others	60%	9%	27%

Table 6: Cancellation for Shielded Individuals by Disease Type

Using the regression in Table 7 and marginal effects in Table 8, we found that as the age of the individual increased, they were more likely to access care. Even though the older individuals with co-morbidities were categorised as NHS shielded individuals as their susceptibility to COVID -19 was high, they still had a greater opportunity to access healthcare services. We also found evidence to corroborate Germain et al. [2020] claim that women of ethnic minority found it difficult to access healthcare services. They were 56.3% were less likely to get medical help compared to other individuals with long term health conditions during April 2020 even though NHS provides equal access to all. Furthermore, we found that the individuals with arthritis, cardiac issues, pulmonary issues, hypothyroid, diabetes and obesity found it difficult to access NHS services, while individuals with Cancer, Epilepsy and Hypertension were much more likely to do so.

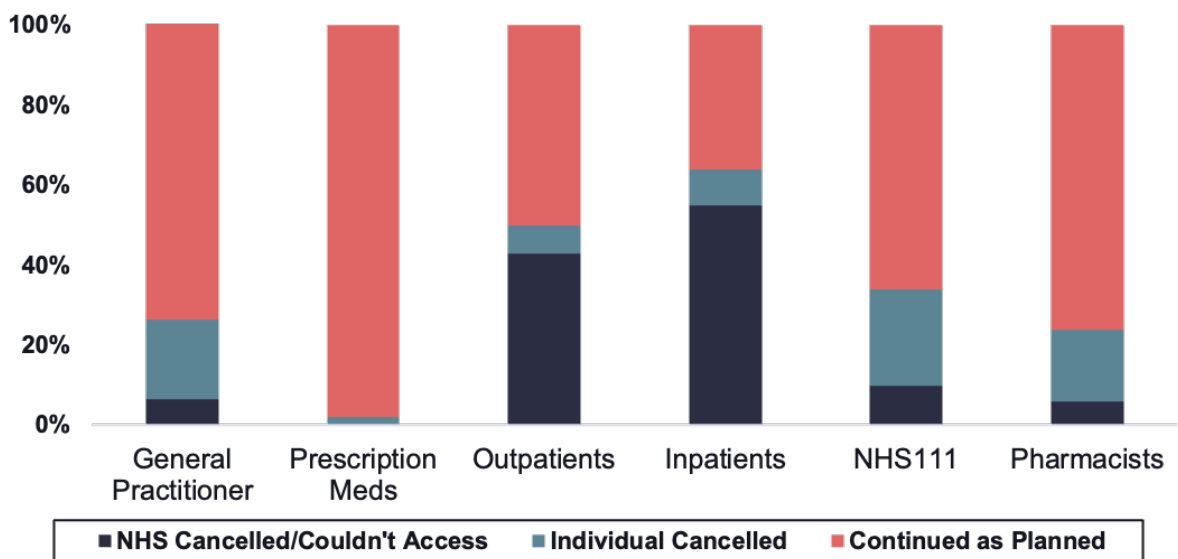


Figure 4: Percent of respondents who required specific NHS service and whether or not they received them

Y	Coef	Std. Error	z	$P > z$	95% CI	
Age	4.56E-3	2.36E-3	1.93	5.39E-2	7.4E-5	9.20E-3
Ethnicity-gender	-0.19	-0.11	1.66	9.80E-2	-3.55E-2	0.42
Arthritis	-0.24	7.42E-2	3-.26	1E-3	-9.63E-2	0.38
Cardiac Ailments	-0.34	0.25	-1.37	0.17	-0.83	0.14
Pulmonary Ailments	-0.23	0.15	-1.5	0.13	-7.07E-2	0.53
Hypothyroidism	-0.16	0.11	-1.37	0.17	-6.94E-2	0.39
Cancer	0.36	8.85E-2	4.17	0	0.19	0.54
Epilepsy	0.52	0.20	2.52	1.2E-2	0.11	0.93
Hypertension	0.13	7.06E-2	1.9	5.72E-2	-4.09E-3	0.27
Diabetes	-0.16	8.92E-2	-1.83	6.80E-2	-1.18E-2	0.33
Obesity ($BMI \geq 40$)	-0.35	0.12	-2.92	3.01E-3	-0.58	-0.11
Constant	-1.01	0.13	-7.52	0	-1.27	-0.74

Table 7: Regression: Impact on Health Outcomes

Variables	Marginal Effect	Standard Error	z	$P > z $
Age	1.23E-3	6.54E-4	1.89	5.89E-2
Ethnicity-gender interaction	-5.63E-2	3.23E-2	-1.74	8.20E-2
Arthritis	-6.43E-2	2.04E-2	-3.14	2E-3
Cardiac Ailments	-8.37E-2	6.84E-2	-1.22	0.221
Pulmonary Ailments	-5.85E-2	4.26E-2	-1.37	0.16
Hypothyroidism	-4.38E-2	3.24E-2	-1.35	0.17
Cancer	9.36E-2	2.44E-2	3.83	0
Epilepsy	0.15	5.73E-2	2.78	6.00E-3
Hypertension	3.36E-2	1.94E-2	1.73	8.40E-2
Diabetes	-4.78E-2	2.46E-2	-1.94	5.19E-2
Obesity ($BMI \geq 40$)	-8.98E-2	3.33E-2	-2.7	7.01E-3

Table 8: Marginal Effects for the Probit Model

6 Conclusion

The COVID-19 pandemic has been an unprecedented shock to the United Kingdom healthcare system, the NHS. We found a sharp decline in outpatient services both at the regional level and the provider level. Our results also suggest that the COVID-19 pandemic led to drastic reductions in use of overall health care as there were significant cancellations from both the individuals as well as NHS in every NHS service category. Our estimates of decline in healthcare utilization during the early stages of the pandemic are in line with existing studies by Cantor et al. [2020], Mehrotra et al. [2020], Chatterji et al. [2020] and Ziedan et al. [2020].

The magnitude of the drop to 74 percent in the month of April 2020 is unparalleled. It is hard to fathom the impact of this reduction on outpatient providers and their patients. Will patients, particularly patients with chronic health conditions, suffer adverse and costly health outcomes later due to the lapse in care? What will be the financial impact on providers, particularly small practices? Will telemedicine fill the gap if fear of contagion is driving these effects? (Chatterji [2020])

Looking at the mechanism for decline of services, it is clear that for outpatient services and inpatient services, the decline was largely supply related and as the restrictions eased we saw a reversion to the mean levels of service usage. However, as of February 2021, there is still a decline of 28% in utilization compared to the same month in previous years. It can be concluded the financial impact on the providers and NHS should be minimal as the pent up demand will gradually return overall demand to normal as seen in the recovery trends. However, we established that smaller providers were impacted much more severely (82% decline in the month of

April 2021) compared to largest providers (72% in decline the month of April 2021). This isn't particularly troubling for the providers, big or small, in the NHS because they are working on a block contract structure since the inception of the pandemic. However, if similar trends exist in countries without a public healthcare system then smaller providers are likely to struggle or go bust. The reductions in use of non-COVID care as a result of SIP policies should, therefore, be weighed against potential benefits when evaluating the welfare implications of social distancing policies. It is important to study these changes and, as we adjust to a post-pandemic world, it will be critical to study the longer-term effects on not just health service usage but also on health and the health care system (Cutler et al. [2020]).

Some are concerned that the deferred care may cause some individuals with chronic conditions to become sicker and that it might increase aggregate costs (Lucia et al. [2020]). This may also lead to constraints on care capacity post pandemic (Wosik et al. 2020). In addition, how the healthcare sector will be able to provide elective procedures once the pandemic has subsided is not known. Anecdotal evidence from some providers is that they will shift elective procedures to weekends (Lucia et al. 2020). Future researchers should explore this possibility and whether there are impacts on quality of care.

Although our data sets do not differentiate between in-person visits and telemedicine, the literature shows that telemedicine has been rapidly trying cope up with the demand for services. This also suggests that the actual decline in in-person visits may be understated here. Telemedicine services have been used to maintain access and continuity of medical care (Wosik et al. [2020]). However, telemedicine utilization

has not sufficiently replace the entire drop in in-person office visits (Mehrotra et al. [2020]). Whether telemedicine use will be sustained during and following the COVID-19 pandemic remains uncertain. The uncertainty is driven in part by uncertainty if the existing policy landscape for telemedicine will be sustained as the pandemic proceeds and eventually ends (Lucia et al. [2020]).

The pandemic has laid bare long-standing racial fault lines in the UK that disadvantage the already vulnerable BAME (Black, Asian and minority ethnic) communities. It has reinforced the need to deal with the challenges posed by racial access and inequalities that have disproportionately impacted on BAME people in the crisis in complex ways, according to mutually influencing intersections of gender, class, age and disability. The reticulated links between socioeconomic indices (income, social class, occupational background and educational achievement) and poorer health outcomes have been magnified by this pandemic. Although not novel, these issues have often been systematically ignored with catastrophic consequences. Concerted and sustained intersectional approaches are required to mitigate these deep-seated and complex ethnic and gender inequalities. Disaggregated data is invaluable in tailoring government's response to pandemics such as Covid-19. Such data aid the identification of vulnerable populations and factors which impede or promote access to care. Systems should be put in place to facilitate the acquisition and utilisation of disaggregated data during and beyond the Covid-19 pandemic. Emphasis should be placed on identifying trends related to ethnicity, occupation and the wider socioeconomic determinants.

Since the inception of the NHS, the principle of equal access to healthcare ser-

vices for all has been at the heart of the system, and for the past 70 years, waves of healthcare reforms have aimed to uphold aspects of this foundational approach using different policy strategies (Germain [2019]). However, as the number of COVID-19 cases grew rapidly in England, the government implemented healthcare policy prioritising COVID-19 patients to ration resources (NICE [2020]), thereby suspending an equal access approach for the delivery of healthcare services for non-COVID patients (Germain [2020]).

Had healthcare services kept in line with the traditional egalitarian approach, services would have had to be delivered equally to all patients with similar healthcare needs. Patients would have been treated alike, regardless of whether or not they had contracted the virus. The National Institute for Health and Care Excellence (NICE) also introduced COVID-19 rapid guidelines that defined criteria for the admission of patients in critical care in March 2020 (NICE 2020). Emergency measures were put in place to maximise health outcomes, favouring individuals with greater chances of survival and introducing measures to rank patients in need of treatment (Shaw et al. [2020]). Chronically ill patients were most affected by these measures, especially individuals living with diabetes or cancer that saw their treatment delayed or even cancelled (Extance [2020]). These emergency measures have proven to have more permanent consequences in the aftermath of the first peak of infections because of the severe backlog in the system (Neville [2020]).

This study is not without limitations. First, we combine two different data sets used by NHS, the Monthly Activity Report(MAR) and the Monthly Referral Report (MRR). It is unclear whether the NHS changed their mode of data collec-

tion since changing the data set. Second, we use the outpatient referrals data as proxy for outpatient visits due to the discontinuation of MAR. It is possible that there is a difference in the trends for referrals and actual admissions. Third, it is impossible to separate the COVID related referrals in the data. However, it can be assumed that most COVID related visits are counted as inpatient visits and general practitioner visits and do not impact the outpatient referrals significantly. Fourth, there may be unrelated effects of COVID-19 which may have contributed to the decline such as fewer accidents due restrictions of movement. This can impact the number of both referrals and visits and may be a confounding variable. Fifth, when the NHS stepped up national preparations for coronavirus in March 2020, block contracts were established across the entire provider sector to support a clear operational focus on COVID-19 healthcare. By allocating fixed sums to providers, and compensating any additional costs attributed to COVID-19 activity, the message to trusts has been that financial constraints should not stand in the way. However, while giving providers financial certainty, block contracts remove incentives within the NHS financial architecture that usually encourage trusts to contain costs and build up surpluses. It is currently uncertain how long these arrangements will last, what will replace them, and how any transition might work. (Garratt [2020]). This new structure may be a supply related driver as providers are disincentivized to provide care to people in excess to the budget they received.

A Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Y	240	205875.5	90523.25	28475	372191
year	240	2018.66	1.18	2017	2021
s_jan	240	2.08E-2	0.14	0	1
s_feb	240	2.08E-2	0.14	0	1
s_mar	240	2.08E-2	0.14	0	1
s_apr	240	2.083E-2	0.14	0	1
s_may	240	2.083E-2	0.14	0	1
s_jun	240	2.083E-2	0.14	0	1
s_jul	240	2.083E-2	0.14	0	1
s_aug	240	2.083E-2	0.14	0	1
s_sep	240	2.083E-2	0.14	0	1
s_oct	240	2.083E-2	0.14	0	1
s_nov	240	2.083E-2	0.14	0	1
s_dec	240	2.083E-2	0.14	0	1
month	240	6.5	3.45	1	12
region	240	3	1.41	1	5

Table 9: Descriptive Statistics: MAR Commissioning Regions

Column1	Mean	Std. Deviation	10%	25%	50%	75%	90%
2013	5578.97	6993.32	116	332	1146	10202	15486
2014	6072.61	7777.67	144	396	1305	10708	16669
2015	6402.40	8196.91	148	428	1376	11148	17947
2016	6665.87	8520.74	174	504	1474	11759	18408
2017	6553.68	8386.02	180	470	1445	11369	18356
2018	6649.79	8575.29	186	478	1436	11427	18834
2019	6700.49	8507.61	184	466	1524	11492	19290
2020	4338.59	6147.53	12	154	968	7086	13180
March 2020- August 2020	3564.65	5003.91	6	96	729	5754	10781
Obs.	26956 (293 per month)						

Figure 5: Yearly Percentile Distribution of Outpatient Visits (MAR)

Column1	Mean	Std. Deviation	10%	25%	50%	75%	90%
January	6412.08	8186.24	162	440	1418	11274	18001
February	6156.14	7865.20	150	410	1325	10734	17226
March	6377.02	8234.28	151	412	1383	11083	17763
April	5703.48	7712.21	86	338	1253	9863	16669
May	5974.57	7962.71	94	366	1310	10188	17337
June	6145.28	8036.80	117	381	1353	10587	17187
July	6444.96	8307.53	126	410	1424	11103	18069
August	5924.68	7647.01	126	393	1342	10364	16570
September	6353.23	8077.90	158	428	1411	11268	17585
October	6836.21	8681.70	174	488	1525	11986	18909
November	6482.50	8297.29	158	452	1414	11416	18157
December	5608.70	7179.71	138	372	1206	9858	15855
Obs.	26956 (293 per month)						

Figure 6: Monthly Percentile Distribution of Outpatient Visits (MAR)

Variable	Obs	Mean	Std. Dev	Min	Max
O	2030	0.78	0.40	0	1
Hypothyroidism	2030	2.41E-2	0.17	-2	1
Epilepsy	2030	6.65E-2	0.33	-6	3
Obesity	2030	0.10	0.31	-2	1
Cancer	2030	0.13	0.34	-2	1
Hypertension	2030	0.33	0.47	-2	1
Diabetes	2030	0.17	0.38	-2	1
Pulmonary Ailments	2030	0.24	0.45	-4	1
Cardiac Ailments	2030	0.10	0.40	-8	1
Arthritis	2030	0.28	0.45	-2	1
ethnicity_gen	2030	9.85E-2	0.29	0	1
gender	2030	0.57	0.49	0	1
age	2030	57.15	15.05	16	96
ethnicity	2030	0.16	0.37	0	1

Table 10: Descriptive Statistics: Understanding Society Wave 1

B Regressions

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-2514.26	1052	-8.34	0	-1107.2	-3685.14
s_feb	-2268.61	1052	-5.51	0	-809.17	-3811.14
s_mar	-5821.72	1248.31	-6.13	0	-1072.6	-5176.14
s_apr	-7132.23	1248.31	-12.58	0	-8155.9	-1259.4
s_may	-6901.4	1248.31	-12.46	0	-1714.7	-1318.2
s_jun	-4522.13	1248.31	-8.69	0	-1358.29	-8771.81
s_jul	-3799.11	1248.31	-6.62	0	-1667.4	-5807.87
s_aug	-2851.29	1248.31	-6.12	0	-1055.5	-5179.01
s_sep	-3135.3	1248.31	-3.6	0	-6192.02	-2039.54
s_oct	-2901.13	1248.31	-4.62	0	-8151.49	-3315.01
s_nov	-2576.97	1248.31	-4.48	0	-8011.35	-3134.87
s_dec	-2761.76	1248.31	-2.22	0.02	-5015.02	-3518.5

Table 11: Regression: Decline for all providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.17	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.26	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.38	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.73	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.70	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.44	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.28	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.29	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.18	2.72E-2	-6.78	0	-0.23	-0.13

Table 12: Regression: Logged Decline for all providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 13: Regression: Decline for bottom 20 percentile Providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.19	2.8E-2	0.27	0.78	-0.26	-0.13
s_feb	-0.31	2.81E-2	-1.63	0.19	-0.36	-0.27
s_mar	-0.45	2.72E-2	-14.86	0	-0.49	-0.39
s_apr	-0.82	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.70	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.46	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.30	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.31	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.20	2.72E-2	-6.78	0	-0.23	-0.13

Table 14: Regression: Logged Decline for bottom 20 percentile Providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 15: Regression: Decline for top 20 percentile Providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.17	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.28	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.40	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.72	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.71	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.65	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.48	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.45	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.30	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.29	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.15	2.72E-2	-6.78	0	-0.23	-0.13

Table 16: Regression: Logged Decline for top 20 percentile Providers

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 17: Regression: Decline for North of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.17	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.29	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.43	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.75	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.70	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.44	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.27	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.28	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.28	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.18	2.72E-2	-6.78	0	-0.23	-0.13

Table 18: Regression: Logged Decline for North of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 19: Regression: Decline for Midlands and East of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.14	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.29	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.40	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.72	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.69	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.42	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.28	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.26	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.27	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.17	2.72E-2	-6.78	0	-0.23	-0.13

Table 20: Regression: Logged Decline for Midlands and East of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 21: Regression: Decline for London Commissioning Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.19	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.31	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.43	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.78	2.72E-2	-49.41	0	-0.83	-0.66
s_may	-0.76	2.72E-2	-41.11	0	-0.79	-0.61
s_jun	-0.65	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.49	2.72E-2	-16.82	0	-0.53	-0.40
s_aug	-0.45	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.32	2.72E-2	-10.67	0	-0.35	-0.23
s_nov	-0.28	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.20	2.72E-2	-6.78	0	-0.26	-0.13

Table 22: Regression: Logged Decline for London Commissioning Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 23: Regression: Decline for Southwest of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.18	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.28	2.81E-2	-1.63	0.19	-0.31	-0.22
s_mar	-0.38	2.72E-2	-14.86	0	-0.45	-0.35
s_apr	-0.71	2.72E-2	-49.41	0	-0.79	-0.66
s_may	-0.70	2.72E-2	-41.11	0	-0.77	-0.61
s_jun	-0.65	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.48	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.47	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.28	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.29	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.29	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.17	2.72E-2	-6.78	0	-0.23	-0.13

Table 24: Regression: Logged Decline for Southwest of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-89632.66	10752	-8.34	0	-110706.2	-68559.14
s_feb	-59239.66	10752	-5.51	0	-80313.17	-38166.14
s_mar	-76274.38	12448.31	-6.13	0	-100672.6	-51876.14
s_apr	-156657.61	12448.31	-12.58	0	-181055.9	-132259.4
s_may	-155116.4	12448.31	-12.46	0	-179514.7	-130718.2
s_jun	-108170	12448.31	-8.69	0	-132568.29	-83771.81
s_jul	-82469.11	12448.31	-6.62	0	-106867.4	-58070.87
s_aug	-76127.25	12448.31	-6.12	0	-100525.5	-51729.01
s_sep	-44793.78	12448.31	-3.6	0	-69192.02	-20395.54
s_oct	-57553.25	12448.31	-4.62	0	-81951.49	-33155.01
s_nov	-55743.11	12448.31	-4.48	0	-80141.35	-31344.87
s_dec	-27616.78	12448.31	-2.22	0.02	-52015.02	-3218.5

Table 25: Regression: Decline for Southeast of England Region

Y	Coef	Std. Error	z	$P > z $	95% Confidence Interval	
s_jan	-0.17	2.8E-2	0.27	0.78	-0.24	-0.09
s_feb	-0.27	2.81E-2	-1.63	0.19	-0.31	-0.21
s_mar	-0.38	2.72E-2	-14.86	0	-0.42	-0.35
s_apr	-0.73	2.72E-2	-49.41	0	-0.77	-0.66
s_may	-0.68	2.72E-2	-41.11	0	-0.75	-0.61
s_jun	-0.66	2.72E-2	-24.51	0	-0.72	-0.61
s_jul	-0.45	2.72E-2	-16.82	0	-0.51	-0.40
s_aug	-0.48	2.72E-2	-16.22	0	-0.49	-0.38
s_sep	-0.25	2.72E-2	-9.23	0	-0.30	-0.19
s_oct	-0.25	2.72E-2	-10.67	0	-0.34	-0.23
s_nov	-0.28	2.72E-2	-10.99	0	-0.35	-0.24
s_dec	-0.17	2.72E-2	-6.78	0	-0.23	-0.13

Table 26: Regression: Logged Decline for Southeast of England Region

C References

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