ESSAYS ON HEALTH ECONOMICS

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To Oshane, Denisha, Kimesha, Lititia, Jerome,
and for my mother Nerva, may I inherit half your strength.

Essays on Health Economics

by Melisa M Williams

Abstract   This thesis examines two Health Economics topics: the economics of antibiotic resistance, and the effect of pollution on health and health care costs. Chapter 2 explores the concept of optimal antibiotic use, focusing on antibiotic over/under use. Overuse is defined as any uncoordinated use above the social optimum which would prevail in a coordinated market. We find that overuse depends on the infection transmission rate and the cost of antibiotic use. In the simple case where the transmission rate is 0, there is no over/under use. However, for sufficiently high costs associated with antibiotic use we see under use of antibiotics while sufficiently low costs result in overuse.

Chapter 3 examines the link between knowledge about antibiotic consumption and resistance, and willingness–to–pay for antibiotic–free products. I designed a survey to collect primary data, using the contingent valuation method to obtain the willingness–to–pay. On average, respondents are willing to pay 57% more for the antibiotic–free product they purchase the most and 52% more for the product they purchase the least, compared to the regular option of the good. I find that for the product most purchased, a one standard deviation increase in knowledge, increases the willingness–to–pay for the antibiotic–free product by £0.085 over the price of the regular option of the good.

Chapter 4 investigates the impact of pollution on hospital attendance and subsequent costs in Leicester, using data from the University Hospitals of Leicester NHS Trust. The identification relies on the spatial and temporal variation of pollution, and temporal variation in wind speed and direction. We find that exposure to higher levels of particulate matter with an aerodynamic diameter less than 10 μm ($PM10$) has a positive effect on the total number of hospital visits and total costs. Specifically, each extra standard deviation of exposure to $PM10$ costs the city of Leicester £5.7 million to treat older adults and children.

Declaration

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Chapter 1

Introduction

In this thesis I explore two main Health Economics topics, the economics of antibiotic resistance and the effects of pollution on health care costs, both of which are current public health concerns. In recent years, there has been an increase in bacteria resistance to antibiotics, especially those considered as the last line of defence. Whenever an antibiotic is used, bacteria are given the opportunity to develop resistance to the drug. This shows that resistance is a natural consequence of treatment therefore some level of resistance is inevitable in any optimal treatment policy. Words such as "unnecessary" and "overuse" are commonly used to describe contemporary antibiotic consumption. To understand increasing resistance as a public health problem, we need to formally define optimal antibiotic use and study the factors that lead to deviations from this optimum.

In Chapter 2 we define antibiotic overuse as any free market or uncoordinated use in excess of the social optimum which would prevail in a coordinated market. Using this definition, we model humans' utility maximising behaviour with regards to antibiotic use in the presence of a bacterial infection in contrast to a social planner's welfare maximising behaviour. In our simple two individual model, each individual takes an antibiotic if the probability of being cured is greater than the cost–benefit ratio of antibiotic use. We show that an individual's antibiotic use results in positive externalities (a decrease in the spreading of microbes that are susceptible to antibiotic use) and negative externalities (an increase in the spreading of microbes that are resistant to antibiotic use). Furthermore, overuse depends on the infection transmission rate and

the cost of antibiotic. Specifically, when the transmission rate is 0 the market case coincide with the social optimum. Additionally, for sufficiently high costs associated with antibiotic use we see under use of antibiotics while sufficiently low costs result in overuse.

It is evident that increased public awareness about antibiotic consumption and resistance could lead to behavioural changes which would help slow the pace of antibiotic resistance. One such behavioural change is a higher demand for goods produced without antibiotics or with antibiotics only when necessary. This could incentivize farmers to reduce or stop using antibiotics for disease prevention and as growth inducers. I explore whether such incentives exist in Chapter 3 by examining the effect of knowledge about antibiotic consumption and resistance, on people's stated willingness–to–pay for antibiotic–free products. I designed a survey instrument to collect primary data since no secondary dataset exists with the required information. The survey includes a choice experiment using the sequential bid Contingent Valuation Method to collect the willingness–to–pay data. Using the sequential bid approach respondents are presented with a sequence of hypothetical market scenarios to ascertain the interval which contains their true willingness–to–pay. I find that on average respondents are willing to pay 57% more for the antibiotic free product they purchase the most and 52% more for the product they purchase the least, compared to the regular option of the good. Furthermore, for the product most purchased, a one standard deviation increase in knowledge, increases the willingness–to–pay for the antibiotic free product by £0.085 over the price of the regular option of the good.

In the final chapter, I explore the second health topic, pollution and its effect on health and health care costs. Despite the ample literature that establishes that chronic exposure of children and older adults to air pollution results in worsening of health conditions, there is little empirical evidence that evaluates the immediate effects of nitrogen dioxide (NO_2) and particulate matter with an aerodynamic diameter less than 10 μm ($PM10$) on healthcare costs for the most vulnerable groups, i.e. children and seniors. In Chapter 4 we evaluate this immediate impact by quantifying the effect of NO_2 and $PM10$ on the economic costs of Emergency Department visits and their subsequent admission to the hospital. We use proprietary data from the University Hospitals of Leicester NHS Trust and pollution data from the Air Quality Management Area monitors provided by Leicester City Council. Our study exploits the spatial and temporal variation of pollution as well as temporal variation in wind speed and direction. We

find that each extra standard deviation of exposure to $PM10$ costs the city of Leicester a total of £5.7 million treating children and older adults (£4.4 million for older adults and £1.3 million for children). We do not find clear effects of changes in daily average exposure to NO_2 on hospital visits and their costs. Nonetheless, we find that larger daily ranges of exposure to NO_2 increase total number of hospital visits per day and postcode sector, increase the total costs per visit of discharged patients, and increases the total costs per visit of admitted older adults only when controlling for fiscal year fixed effects.

Chapter 2

Are we overusing antibiotics? Defining and analyzing optimal antibiotic consumption

> *"A post-antibiotic era—in which common infections and minor injuries can kill—far from being an apocalyptic fantasy, is a very real possibility for the 21st century."*
>
> World Health Organisation (2014) *"Antimicrobial resistance: global report on surveillance."*

2.1 Introduction

The discovery and successful use of antibiotics revolutionized the treatment of infectious diseases. Before the 20th century infectious diseases were virtually incurable accounting for high proportion of human morbidity and mortality worldwide (Aminov, 2010). Today we rely heavily on antibiotics for treatment of infectious diseases and routine medical procedures. However, this reliance comes with a cost as increased antibiotic use is associated with increased resistance (Austin et al., 1997, 1999; Goossens et al., 2005). The World Health Organisation (WHO) declared antimicrobial resistance as "a problem so serious it threatens the achievements of modern medicine" (WHO, 2014).

Antimicrobial agents are drugs used to treat illnesses caused by micro–organisms/microbes such as bacteria, viruses, and fungi. Antimicrobial resistance arises when the targeted micro-organisms survive exposure to the antimicrobial drug unaffected. Some level

of resistance will always be present, potentially through random mutations in micro-organisms. Studies such as D'Costa et al. (2011) and Bhullar et al. (2012) have found evidence that antibiotic resistance pre-dates the clinical use of antibiotics. Additionally, penicillin resistant bacteria were identified before widespread use of the drug (Stuart, 1992; Walsh et al., 2003; Alanis, 2005; Davies and Davies, 2010).

Within a single infected individual, antibiotic use may exacerbate the presence of a small number of resistant micro-organisms. By killing off susceptible microbes, the antibiotics lessen the competition between mutant resistant microbes and susceptible microbes for scarce resources, allowing the resistant population to grow. In addition to increasing the presence of these resistant microbes within one individual, this also increases the probability that resistant microbes are spread between individuals. Through this process, antibiotic use may increase the presence of resistant microbes in a human population.

In this paper we use a simple two-agent model to analyse this process of bacteria resistance and consider the following question: What factors lead to the free market—the *uncoordinated* scenario—use of antibiotics deviating from *optimal* antibiotic use? We focus specifically on three factors, the known initial distribution of resistant bacteria, the cost-versus-benefits for the individual user of antibiotics, and the rate of microbial transmission between individuals. *Optimal use* is defined by the solution to a social planner's problem—the *coordinated* scenario—in which antibiotics are used to maximize social welfare.

The model consists of two agents and two periods. In the first period, individual 1 realises an infection and makes a utility-maximizing treatment decision. In the second period, with some probability there is a microbial transmission from individual 1 to individual 2, and individual 2 makes a utility-maximizing treatment decision based on: a) whether an infection is realised, and b) the likelihood that a realised infection is susceptible or resistant. Both individuals have complete knowledge except they do not know whether an untreated infection contains only susceptible microbes, and is therefore treatable with antibiotic technology, or also contains resistant microbes.

While simple, our model captures the important features of microbial dynamics described above. First, microbial dynamics are modelled using a Lotka–Volterra two species competition model, modified to include the effects of antibiotics on bacteria populations. Second, and most important, it captures the externality that comes from

individual antibiotic use: individual 1's decision impacts both the likelihood individual 2 becomes infected, and the type of infection individual 2 is likely to realise.

The initial distribution of susceptible and resistant microbes is important in determining antibiotic use. We consider a simple distribution where with probability p individual 1's initial infection is entirely composed of susceptible microbes, with probability $1 - p$ individual 1's initial infection is composed of resistant microbes. When $p = 1$ antibiotics are always effective and when $p = 0$ antibiotics are never effective. For $0 < p < 1$ there will be uncertainty about the antibiotics effectiveness.

We compare antibiotic use in different scenarios by determining the minimum value of p for which individuals 1 and 2 take antibiotics, given the other parameters of the model. When the value of this minimum p is greater in the coordinated scenario versus the uncoordinated scenario, we say that antibiotics have the potential to be overused. When the value of this minimum p is less in the coordinated scenario versus the uncoordinated scenario, we say that antibiotics have the potential to be underused.

Whether antibiotics are overused or underused, relative to the optimal solution, depends on two critical parameters. The first is the private costs versus benefits of antibiotic use. All else equal, when the cost is low relative to benefits, the likelihood of overuse is high. However, when the cost is high relative to the benefits, antibiotics are underused relative to the optimum.

The second critical parameter is the rate of between-individual microbe transmission. To see this, consider the special case where the transmission rate is zero. In this case there is no externality, and therefore no over or under use; the uncoordinated decisions are always optimal. As the transmission rate increases, there is a monotonic divergence between coordinated and uncoordinated use. A higher transmission rate increases the social cost of greater antibiotic use.

Words such as "unnecessary" and "overuse" are commonly used to describe contemporary antibiotic consumption. It does not follow from our model that individuals always overuse antibiotics. This is because, while antibiotic use increases resistance, it also decreases the likelihood of spreading resistant microbes. This suggests that we face a trade-off between treating current illnesses and treating future illnesses. Antimicrobial infection has two properties that make it economically interesting. First, antimicrobial illnesses are communicable, meaning that there may be externalities to individual

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decisions. Second, since resistance is a consequence of treatment, the efficacy of an antimicrobial should be treated as a finite resource.

This paper contributes to the literature by explicitly modelling the behavioural mechanisms through which antibiotic resistance will increase (or decrease). In this model, an individual's antibiotic use results in positive externalities (a decrease in the spreading of microbes that are susceptible to antibiotic use) and negative externalities (an increase in the spreading of microbes that are resistant to antibiotic use). The relative size of these externalities determine whether uncoordinated antibiotic use is above or below the social optimum. Further, the propensity to deviate from optimal antibiotic use depends crucially on the rate of bacterial transmission between individuals. In contrast to the literature which model optimal drug use as a resource extraction problem (Laxminarayan et al., 2001; Wilen and Msangi, 2003; Rowthorn and Brown, 2003; Laxminarayan and Weitzman, 2002), we focus on the question of why uncoordinated antibiotic use deviates from the social optimum. Additionally, our model explicitly links the evolution of bacteria within an individual with the spread of resistance between individuals. We conclude that geographic areas and diseases for which transmission rates are high are particularly susceptible to over-use.

The remainder of the paper is organised as follows. In Section 2.2 we provide an overview of the literature on optimal antibiotic use and modelling antibiotic resistance. In Section 2.3 we discuss bacteria dynamics and the outcomes of competition between susceptible and resistant strains. We present the model with transmission between humans in Section 2.4 and closing remarks in Section 2.5.

2.2 Literature Review

This paper contributes to two strands of literature, optimal antibiotic use and modelling antibiotic resistance evolution. Firstly, by looking at how optimal antibiotic use/overuse is defined and applied, we contribute by providing a new way of defining optimal antibiotic use. Secondly, we focus on modelling the evolution of antibiotic resistance. Given the unique properties of antibiotic resistance, in addition to the economic literature, we explore a wide range of literature from other disciplines such as biology, mathematics, and epidemiology—collectively called the epidemiology literature.

Optimal antibiotic therapy/prescription strategy includes choosing when to use an antibiotic, and how to best use the available antibiotic options.[1] If the decision to use an antibiotic is based on preventing resistance, then the optimal choice would be to withhold treatment. However, since treatment is necessary, the optimal choice should minimize resistance. Then, the optimal treatment strategy is the option that reduces the total number of infected or colonised individuals—individuals who experience a growth of illness–causing bacteria but are not infected—over a specific time period (Bonhoeffer et al., 1997; Blanquart, 2019).

In this context, there are several definitions of overuse in the literature, Chang et al. (2019) define appropriate antibiotic use in primary healthcare, such as hospitals, as any use that is based on the diagnosis of probable bacterial infection. Antibiotic overuse is defined as either incorrect spectrum of antibiotic, escalated use of extended spectrum antibiotics, or combined use of antibiotics.[2] Similarly, Kardos (2017) indicates that overuse includes the use of broad–spectrum antibiotics in healthcare when the bacteria that cause the infection is unknown along with widespread antibiotic consumption in agriculture. Sulis et al. (2020) defines overuse as the proportion of standardized patients–healthcare provider interactions that resulted in prescription or dispensing of at least one antibiotic where the condition does not require antibiotics.[3] Karakonstantis and Kalemaki (2019) highlights that in addition to over prescription, self-medication—administration of antibiotics by parents or pharmacists without consultation from a physician— is another factor of overuse.

In contrast, our definition of overuse focuses on the externalities to antibiotic use. That is, over/under use is framed relative to the decision that a total welfare maximizing social planner would make. Therefore, appropriate antibiotic use as defined by these papers might be seen as overuse in our model, since our definition hinges on the relative size of the positive and negative externalities associated with uncoordinated individual use.

To prevent overuse, a key decision is whether or not the optimal treatment decision

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[1]The discussion in this paper on optimal antibiotic use does not include optimal treatment duration or optimal drug dosage. A discussion on the literature of these topics can be found in Tetteh et al. (2020).

[2]Extended spectrum antibiotics are those that affect additional types of bacteria as a result of chemical modification while combined use of antibiotics is defined as use of more than one antibiotic group per patient visit without any indications.

[3]Standardized patients are healthy individuals recruited from local communities and extensively trained to portray a standardised clinical condition to a healthcare provider (Sulis et al., 2020).

is to forgo antibiotic use. In economics, it has been found that when fitness costs are taken into account, ecological/infection control methods may be more economical than aggressive antibiotic treatment (Wilen and Msangi, 2003).[4] Additionally, the choice of policy—antibiotics vs infection control methods—depends on cost considerations and on the probability of success when the infection control strategy is used (Batabyal and Nijkamp, 2005).

Another key decision is how best to use a single antibiotic. In epidemiology, it has been found that the long term treatment benefit does not depend on the pattern of use however, the benefit increases slightly if the drug is used heavily at first (Bonhoeffer et al., 1997). In economics, it is found that the optimal treatment is for all patients to be treated with the antibiotic that is effective against the more prevalent strain (Rowthorn and Brown, 2003).

The pattern of use/treatment strategies for using multiple antibiotics is one of the key debates in the optimal use literature. Strategies such as mixing—treating infected individuals with different antibiotics at any point in time—and cycling—treating infected individuals with a sequence of different antibiotics where the sequence is repeated—form a key part of such debates (Masterton, 2010; Brown and Nathwani, 2005; Bonhoeffer et al., 1997).[5] The key in cycling antibiotics is that the predominant class is reintroduced which, if not accurately timed, could increase resistance to it given the change in the frequency of resistance overtime (Austin et al., 1997, 1999).

In epidemiology, it has been found that in most cases the optimal treatment is the mixing strategy, combination therapy where both drugs are simultaneously administered to each infected host (Bonhoeffer et al., 1997). In economics, it is recommended that the most effective drug be used first until the resistance level is the same then each drug should be used in precise proportion to the rate that use deteriorates their effectiveness (Laxminarayan et al., 2001).[6] Additionally, the optimal treatment strategy

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[4]Fitness costs are a biological cost to the resistant strain that is reflected in increased mortality in the absence of treatment, which arises from the possession of genes that allow it to survive under drug treatment (Wilen and Msangi, 2003).

[5]Mixing involves strategies such as 50–50 treatment—the administration of each drug to equal proportions of the infected population; and combination therapy—the simultaneous administration of both drugs to each infected host (Bonhoeffer et al., 1997). The antibiotics used in cycling have a comparable spectrum of activity (the range of microorganisms it can kill or inhibit) but do not share a common mechanism of resistance (Brown and Nathwani, 2005).

[6]The difference in recommendation between Bonhoeffer et al. (1997) and Laxminarayan et al. (2001) highlights the contrast in the results obtained for the optimum treatment strategy derived from an

should include a variety of drugs, including some less cost effective ones, and to minimize the increase in resistance, the choice of drug should be randomized over patients (Laxminarayan and Weitzman, 2002).

Generally, studies that have evaluated the effectiveness of cycling vs mixing generally finds that mixing provides better results than cycling in both hospitals and the community (Blanquart, 2019; Tetteh et al., 2020). However, there no clear empirical evidence to support the efficacy either strategy (Blanquart, 2019). Studies have found that there is no difference in outcomes such as mortality, colonization by resistance strain or the incidence of infection when cycling is compared to normal practice or mixing, despite the theoretical support for mixing (Toltzis et al., 2002; van Duijn et al., 2018).

Antibiotic resistance evolution is modelled both at the within-individual level and the between-individual level. The models found in the economic literature are between-individual models which describe the spread of resistance in the population. One of the key features of economic models is that resistance is modelled as an externality to antibiotic use. Coast et al. (1998) discusses resistance as an externality and as well as policy options for addressing it. Phelps (1989) is one of the earliest papers to quantify the negative externality associated with antimicrobial resistance.[7] Phelp's model has been adapted and expanded to determine whether assumptions about antibiotic effectiveness are important when modelling resistance as an externality and to calculate the net welfare deadweight loss to society from resistance (Kaier, 2012; Elbasha, 2003).[8]

Optimal antibiotic use is also modelled in the economic literature as a resource extraction problem. Laxminarayan et al. (2001) explores optimal antibiotic treatment policy. Specifically, they examine the use of two antibiotics in a hospital setting in which antibiotic effectiveness is treated as a non–renewable resource.[9] This strand of

economic formulation of the problem and epidemiological formulation. This is mainly due to the 0 discount rate assumption by epidemiologists, that is they attribute the same value to a successful treatment today as they do a successful treatment in the future (Rowthorn and Brown, 2003).

[7]Using estimates from the literature, Phelps (1989) reports that for the estimated 150 million annual antibiotic prescriptions, the cost of the externality is at least US$0.1 billion, and may exceed US$30 billion in the worst case.

[8]Using hospital data Kaier (2012) concludes that the relative fitness of resistant bacteria is one driving factor for the size of the externality and Elbasha (2003) finds that the annual deadweight loss associated with outpatient prescriptions for amoxicillin in the United States is estimated at $225 million.

[9]The methodology modifies the Kermack–McKendrick Susceptible-Infected-Susceptible (SIS) model to include the dynamics of resistance. The SIS model describes the transition of people from susceptible (to an infection) to infection states. There are other variations of the model to account for the characteristics of different illnesses. Another popular version is the SIR- Susceptible Infected Recovered-

the literature expands the model developed by Laxminarayan et al. (2001) to explore the case where resistance is renewable, and include fitness cost with and without uncertainty (Rowthorn and Brown, 2003; Batabyal and Nijkamp, 2005; Wilen and Msangi, 2003).

Brown and Layton (1996) model the utility maximizing behaviour of individuals and farmers with regards to antibiotic use in comparison to a social planner who aims to maximize the net benefit to society. Their results show that privately optimizing individuals and farmers will ignore the social-cost component of antibiotic use which leads to a fast depletion of the antibiotic effectiveness. In contrast to them, we explicitly model the behavioural mechanisms through which antibiotic resistance will increase (or decrease) and we focus on the question of why uncoordinated antibiotic use deviates from a social optimum.

Another methodological difference between our work and the previous economics work is the inclusion of within–individual resistance evolution in our model. One of the gaps in the economic literature on optimal antibiotic use is that the evolution of resistance within individuals is not explicitly modelled. Within-individual models describe resistance evolution, how antibiotic treatment affects it, and how resistance can be prevented within an individual. The type of model used in Laxminarayan et al. (2001); Rowthorn and Brown (2003); Batabyal and Nijkamp (2005); Wilen and Msangi (2003) divides the infected population into two subgroups depending on the strain causing the infection: resistant or susceptible. While the choice of compartment is determined by competition between strains, this is not explicitly modelled. However, competition between resistant and sensitive strains —referred to in this paper as susceptible strains— is a key feature of models of antibiotic resistant evolution (Blanquart, 2019; Tetteh et al., 2020). As such, unlike the other models in the economics literature, we explicitly model the within–individual bacteria dynamics and explicitly link this to the between–individual dynamics.

While the economics models have not focussed on within-individual resistance evolution, it has been a feature of epidemiology models since the 1970s (Blanquart, 2019). However, only a few studies have developed models of resistance dynamics which link

model. Other variations include moving between two states such as susceptible to infected— SI model, see Spicknall et al. (2013) for a discussion on state transmissions. The version of the SIS model used in Laxminarayan et al. (2001) describes the dynamics of infection when antibiotics are used. This modified SIS model is combined with an economic modelling of natural resource extraction.

both within–individual and between–individual models. Massad et al. (1993) uses bacteria competition to determine the proportion of treated patients which provides the resistant strains a competitive advantage over the susceptible strain.

Webb et al. (2005); D'Agata et al. (2007); D'Agata et al. (2008); Caudill and Lawson (2017) have also developed models of resistance dynamics which link these two types of models. Webb et al. (2005) models resistance evolution by connecting the dynamics of bacteria within infected individuals, and patients interacting in the hospital. Later versions of the model account for variations in treatment–timing, length, and prescription strategies mentioned previously, and the individual's immune response to bacteria invasion (D'Agata et al., 2007; D'Agata et al., 2008). Finally, Caudill and Lawson (2017) presents a detailed model linking an agent-based structure at the patient–health care worker interaction level with a very detailed model at the within-individual level. We contribute to this strand of literature by linking the within–individual model of bacteria competition with and without antibiotic use with a between–individual model of antibiotic resistance transmission to answer a new question: what factors lead to a deviation of uncoordinated antibiotic use from the optimal antibiotic use?

2.3 Within-Individual Bacteria Dynamics and Resistance

Here we consider the dynamics of heterogeneous microbial population, within the body of a single host, in the presence of an antibiotic. This will establish the mechanism through which antibiotic use increases the density of resistant bacteria within a host. It is the microfoundation which motivates how we build the model in Section 2.4.

Consider the growth of a single bacteria species with two interacting strains, susceptible and resistant, denoted by subscripts $\{r, s\}$. Bacteria are referred to as susceptible if when exposed to an antibiotic the antibiotic is able to alter or kill the bacteria cell, and resistant otherwise. We model the growth of the bacteria species using a modified version of the Lotka–Volterra two–species competition framework to include the effect of antibiotics on population growth.

First we consider the dynamics without the introduction of antibiotics. The growth of

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each strain is described by the set of equations:

$$\dot{N}_s(t) = \rho_s N_s(t) \left(\frac{K - N_s(t) - \beta_{sr} N_r(t)}{K} \right) \tag{2.1}$$

$$\dot{N}_r(t) = \rho_r N_r(t) \left(\frac{K - N_r(t) - \beta_{rs} N_s(t)}{K} \right) \tag{2.2}$$

Where $\dot{N}_k(t) = \dfrac{dN_k(t)}{dt}$ and $N_k(t)$, for $k \in \{r, s\}$, denote the population size of bacteria type k at time t. We assume that the initial number of susceptible bacteria is higher than the initial number of resistant bacteria, i.e. $N_s(0) > N_r(0)$, this is consistent with r bacteria being a rare mutation of s bacteria. For cell division to be possible we assume that $N_s(0) > 1; N_r(0) \geq 1$. K is the carrying capacity, or maximum size, of a bacteria colony. K captures the fact that there are resource constraints to bacterial growth (we assume for now that resource availability replenishes in every period). As the resource requirements for the r and s bacteria are the same, K does not vary between them. β_{sr} and β_{rs} are the *competition coefficients*, measuring the per unit effect of one strain on the population growth of the other, relative to the effect of competition between members of the same strain (Begon et al., 1996). The effect of competition between members of the same strain (intra–specific competition) on its own population growth, β_{ss} and β_{rr}, is 1. Now, $\beta_{sr} < 1$ implies that the effect of competition between members of the susceptible strain is more harmful to the growth of the susceptible bacteria than the per unit effect of competition with the resistant strain. We allow for different inherent per-unit growth-rates, $\rho_s > 0$ and $\rho_r > 0$, and population sizes $N_s(t)$ and $N_r(t)$.

Now consider the introduction of an antibiotic. The antibiotic kills a fraction of the susceptible bacteria population $\delta_s N_s(t)$. By definition, the highest concentration of the antibiotic the body can tolerate has no effect on the resistant strain of the bacteria. The antibiotic therefore changes the proportion of susceptible and resistant bacteria in the colony.

The growth of each strain will now be described by:

$$\dot{N}_s(t) = \rho_s N_s(t) \left(\frac{K - N_s(t) - \beta_{sr} N_r(t)}{K} \right) - \delta_s N_s(t) \tag{2.3}$$

$$\dot{N}_r(t) = \rho_r N_r(t) \left(\frac{K - N_r(t) - \beta_{rs} N_s(t)}{K} \right) \tag{2.4}$$

following Nikolaou and Tam (2006). We assume that $\rho_s \geq \rho_r > \delta_s$. Notice that when $\delta_s = 1$ the antibiotic kills all susceptible bacteria.

Using these growth equations we calculate the equilibrium population size (steady state solutions) and analyse the outcomes of competitive interaction. The equilibrium population size is dependent on the relative size of the species competitive coefficients (β_{sr} and β_{rs}) and the initial population values ($N_s(0)$ and $N_r(0)$). The steady state solutions are detailed in Appendices 2.A.1 and 2.A.2 and summarised in Table 2.1.

There are four possible steady states as depicted in Table 2.1, no infection steady state (SS1), resistant infection steady state (SS2), susceptible infection steady state (SS3), or mixed infection steady state (SS4). In an antibiotic–free environment we can rule out a resistant infection steady state as resistant bacteria are at a disadvantage in this environment. The initial size of the population is below the susceptible bacteria ($N_s(0) > N_r(0)$) and the susceptible bacteria grows at least as fast as the resistant ones ($\rho_s \geq \rho_r$). These conditions rule out *SS2* therefore we will only have a susceptible or mixed infection steady state.

When antibiotics are introduced only *SS3* and *SS4* changes, as expected, since only the susceptible bacteria population is affected by the introduction of antibiotics. In the case where the antibiotic only kills a fraction of the susceptible bacteria ($\delta_s \neq 1$), the outcome of competition now also depend on the ratio $\dfrac{\delta_s}{\rho_s}$, the efficacy of the antibiotic. If the effect of the antibiotic is sufficiently large it gives the resistant bacteria a competitive advantage leading to the extinction of susceptible bacteria in the steady state (SS2). Otherwise we have the extinction of resistant bacteria in the steady state (SS3). This may be due to an ineffective antibiotic or a very large $N_s(0)$ compared to $N_r(0)$. The resulting equilibrium number of susceptible strain is $\dfrac{\delta_s}{\rho_s}$ lower than the no–antibiotic case. In the case where the bacteria are able to coexist peacefully (*SS4*), antibiotic use reduces the equilibrium population of the susceptible strain while increasing the population of the resistant bacteria strains. Appendix 2.B provides

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a more detailed discussion on the dynamics of competitive interaction and expected steady state outcomes both with and without antibiotic use. Where antibiotic use is detrimental to the entire susceptible bacteria population ($\delta_s = 1$), then in equilibrium there will either be no bacteria (*SS1*) or only resistant bacteria (*SS2*).

Using the steady state solutions we now turn to how the outcome of bacteria competition determines the probability of getting an infection from resistant bacteria. In the antibiotic case, the steady state population is either comprised of only susceptible bacteria or a mixed population with some probability. Let p be the probability that the population is comprised only of susceptible bacteria. The mixed population contains some proportion, θ of resistant bacteria. Therefore, in the case where no antibiotics are used the probability of being infected with a resistant bacteria is $(1-p)\theta$, conditional on the bacteria being in the mixed steady state, and $(1-p)$ otherwise (see Figure 2.1). When antibiotics are used then in the case where $\delta_s = 1$, the infection is solely caused by a resistant infection ($p = 0$). We explore these probabilities further in the following section through a two person model with bacteria transmission in order to define optimal antibiotic treatment.

2.4 Between-Individual Antibiotic Use and Resistance

Following the insight from the microfoundation of the model that antibiotic use leads to a possible increase in resistance within a host, we look at how antibiotic use can affect the transmission of different bacteria between different hosts.

2.4.1 Timing and transmission

Individual 1 has realised a bacterial infection. With probability p the infection is entirely due to a susceptible strain of bacteria. With probability $1-p$ the infection is composed (in part) of bacteria which is resistant to existing antibiotics. The infection will be passed to individual 2 with probability λ (the transmission rate). We denote with θ the conditional probability that bacteria are composed of the resistant strain, when

bacteria are transmitted from individual 1 to individual 2 (see Figure 2.1).[10] In this simple model, individual 1 is the only source of infection for individual 2.

The timing of events is as follows. Individual 1 realises an infection and makes a treatment decision. After the treatment takes effect (possibly changing the composition of individual 1's bacteria flora) individual 1 interacts with individual 2, and there is a possible transmission of bacteria.[11]

2.4.2 Utility

Individual utility is made up of two components. The first is the utility an individual receives from his or her health status. This is a function of the individual's bacterial composition and the use of antibiotics. We denote this by $H(B_i, A_i)$ where $B_i = B^n, B^s, B^r$ is the bacterial composition to which individual i is exposed (no infection, susceptible, resistant) and $A_i = \{0, 1\}$ is an indicator for whether i uses the existing antibiotic treatment (of which there is only one). We make the following assumption:

Assumption 1:

$$H(B^r, 1) = H(B^r, 0) = H(B^s, 0) < H(B^s, 1) < H(B^n, 0)$$

Intuitively, this simplifying assumption means that 1) the use of antibiotics does not affect utility beyond what is captured by the additively separable cost (C described below), and 2) the negative utility from antibiotic use does not differ dependent on the type of infection (B^r versus B^s).[12] This implies that left untreated, a B^s bacteria will have the same health-utility consequence as a B^r bacteria.

The other component of utility, as mentioned above, is the cost (pecuniary, health, or other) associated with taking the antibiotic, which we denote by $C > 0$. To simplify

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[10]Notice that this could also be relaxed to say that there is a mass of the resistant bacteria that needs to be passed from individual 1 to individual 2 before it is problematic. θ then reflects the probability that the transmission involves some amount of the resistant strain that is less than this critical mass.

[11]Notice that the timing of individual 1 and individual 2's interaction, after individual 1's treatment decision, is important. If transmission takes place before the treatment decision then there is no mechanism for which treatment will lead to an externality.

[12]A more general version of this assumption is that $H(B^r, 1) \leq H(B^r, 0) \leq H(B^s, 0) < H(B^s, 1) < H(B^n, 1)$. Assumption 1 simplifies the analysis considerably.

the analysis we assume that these two components of utility are additive such that:

$$U_i = H(B_i, A_i) - C \times A_i \tag{2.5}$$

Both agents choose antibiotic use to maximise their expected utility. Individuals know if they have contracted an infection when the decision is made but do not know the composition of the bacteria of which they have been infected. In the second period, when individual 2 realises an infection, the antibiotic use and health status of individual 1 is observable.

2.4.3 Antibiotic use

Here we examine the uncoordinated use of antibiotics for the two individuals. We start by looking at individual 1's decision and then we turn our attention to individual 2.

Individual 1

Individual 1 is exogenously infected with a bacteria of an unknown composition. Individual 1 takes an antibiotic if and only if the expected utility from doing so exceeds the expected utility from forgoing antibiotic use. That is:

$$pH(B^s, 0) + (1 - p)H(B^r, 0) < pH(B^s, 1) + (1 - p)H(B^r, 1) - C$$

rearranging we get

$$p(H(B^s, 1) - H(B^s, 0)) + (1 - p)(H(B^r, 1) - H(B^r, 0)) > C$$

Given Assumption 1, $H(B^r, 1) = H(B^r, 0)$, the condition simplifies to:

$$p > \frac{C}{(H(B^s, 1) - H(B^s, 0))}, \tag{2.6}$$

Individual 1 only uses antibiotics if the ratio of the cost, C, to the benefit of antibiotic use with a susceptible bacteria, $H(B^s, 1) - H(B^s, 0)$, is less than the probability of

realising the benefit (i.e. curing the infection). We refer to the right hand side of this inequality as the cost-benefit ratio, $\left(CBR = \dfrac{C}{(H(B^s, 1) - H(B^s, 0))} \right)$.

Define the critical value of p to be p^u such that

$$p^u = \frac{C}{(H(B^s, 1) - H(B^s, 0))}. \tag{2.7}$$

Individual 1 will only choose to take an antibiotic if the probability of B^s infection is sufficiently high, $p > p^u$.

Individual 2

In the next period individual 2 makes an antibiotic use decision. There are two states under which individual 2 will make this decision. The first is the healthy state, $B_2 = B^n$. In this state there is no benefit to taking the antibiotic, so $A_2 = 0$, and realised utility is $U_2 = H(B^n, 0)$.

The second possible state is that individual 2 has an infection. In this state the antibiotic decision is less trivial and depends on individual 1's antibiotic use. First consider when individual 1 does not use an antibiotic. This means that there is no information about the composition of the bacteria, and individual 2 must infer the probability of a resistant infection from the known parameters. Individual 2's infection will be susceptible if either individual 1's infection is susceptible, or individual 1's infection is resistant but only susceptible bacteria are transmitted:

$$P(B^s | A_1 = 0, B_2 \neq B^n) = p + (1 - p)(1 - \theta) = (1 - (1 - p)\theta)$$

Individual 2's infection will be resistant if individual 1's infection is resistant and resistant bacteria are transmitted:

$$P(B^r | A_1 = 0, B_2 \neq B^n) = (1 - p)\theta$$

As with individual 1, individual 2 will take an antibiotic only if the expected benefits

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to doing so exceed the cost:

$$(1 - (1-p)\theta)(H(B^s, 1) - H(B^s, 0)) + (1-p)\theta(H(B^r, 1) - H(B^r, 0)) > C \quad (2.8)$$

Again, when $H(B^r, 1) = H(B^r, 0)$ this simplifies to

$$(1 - (1-p)\theta) > \frac{C}{(H(B^s, 1) - H(B^s, 0))}. \quad (2.9)$$

Notice that it is always the case that $p < (1 - (1-p)\theta)$, therefore the range of values for the cost–benefit ratio which individual 1 takes an antibiotic is smaller than that for which individual 2 takes an antibiotic.

From inequality 2.9 we define the critical probability, p^{uu}, for individual 2's decision as

$$p^{uu} = \left(1 - \frac{1}{\theta}\right) + \frac{1}{\theta}\frac{C}{(H(B^s, 1) - H(B^s, 0))}. \quad (2.10)$$

For individual 2 to use an antibiotic, it is necessary (but not sufficient) that $p > p^{uu}$.

Now consider if individual 1 does use an antibiotic. In this case the bacteria type of individual 1 can be inferred from his health level. If individual 1's health is $H(B^r, 1)$, then individual 2 knows that his infection is the B^r type. In this case there is no point in taking the antibiotic. If individual 1's health is $H(B^s, 1)$, then there will not be a bacterial transmission, as the antibiotic kills off all the susceptible bacteria. In this case the information provided by individual 1's use of the antibiotic perfectly informs individual 2's decision, and it will never be optimal for individual 2 to take an antibiotic.

2.4.4   Uncoordinated equilibrium

Here we summarize the Nash equilibrium for the case of uncoordinated antibiotic use, using the cost–benefit ratio of taking the antibiotic with a susceptible bacteria $\left(CBR = \frac{C}{(H(B^s, 1) - H(B^s, 0))} \right)$. The Nash equilibrium for each realised state of individual 2's health status will be as follows:

Uncoordinated equilibrium when $B_2 = B^n$

$$\text{If} \quad p \leq CBR, \qquad \text{then} \quad A_1 = 0, A_2 = 0$$

$$\text{If} \quad p > CBR, \qquad \text{then} \quad A_1 = 1, A_2 = 0$$

Uncoordinated equilibrium when $B_2 \neq B^n$

$$\text{If} \quad CBR > (1 - (1 - p)\theta), \qquad \text{then} \quad A_1 = 0, A_2 = 0$$

$$\text{If} \quad (1 - (1 - p)\theta) > CBR > p, \qquad \text{then} \quad A_1 = 0, A_2 = 1$$

$$\text{If} \quad p > CBR, \qquad \text{then} \quad A_1 = 1, A_2 = 0$$

This equilibrium is depicted across different values of p and CBR in Figure 2.2. The timing and information in this game is important. If individual 2 gets sick when individual 1 takes the antibiotic, then individual 2 can perfectly infer that he has the resistant strain. Therefore, individual 1 and individual 2 never both take the antibiotic. Also, the probability that an infected individual 2 has a susceptible strain $(1 - (1 - p)\theta)$ is strictly less than the probability that individual 1 has a susceptible strain (p). Therefore, individual 2 will use the antibiotic when the CBR is relatively high.

2.4.5 A social planner's choice

***A priori* infection probabilities**

The social planner will make decisions regarding antibiotic use in the first stage. Therefore, we must know the *a priori* probability of the type of infection that individual 2 is expected to experience.

Consider first what happens if individual 1 does not use antibiotics. There are three possible outcomes for individual 2's infection status (B^n, B^s, and B^r), each of which

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will be realised with the following probability:

$$P(B^n|A_1 = 0) = 1 - \lambda$$

$$P(B^s|A_1 = 0) = \lambda(p + (1-p)(1-\theta))$$

$$P(B^r|A_1 = 0) = \lambda(1-p)\theta$$

Now consider what happens if individual 1 takes an antibiotic. We assume that the antibiotic kills all susceptible bacteria, but not the resistant ones. In this case individual 1 only passes bacteria on to individual 2 if individual 1 has a resistant strain.

$$P(B^n|A_1 = 1) = 1 - \lambda + \lambda p$$

$$P(B^s|A_1 = 1) = 0$$

$$P(B^r|A_1 = 1) = \lambda(1-p)$$

Therefore individual 1 taking an antibiotic has a positive and a negative externality. The positive externality is that the probability of individual 2 remaining healthy increases by λp. The negative externality is that the probability that 2 is infected with the resistant strain increases by $\lambda(1-p)(1-\theta)$

Optimal antibiotic use

Given that individual 1 has an infection, when will the social planner choose to give individual 1 antibiotics? The social planner uses antibiotics such that the total welfare (the summed utility of individual 1 and individual 2) is maximized. In this simple model there is no externality associated with individual 2's antibiotic use; for individual 2 the social planer's choice will always coincide with the uncoordinated solution above. Therefore, we can use backwards induction to solve for the welfare maximizing antibiotic use for individual 1, given that individual 2 uses antibiotics when infected based on the critical probability defined by condition (2.10).

Consider if condition (2.9) holds, so that when $A_1 = 0$, an infected individual 2 always

takes the antibiotic. Total welfare can be written as:

$$pH(B^s, 0) + (1 - p)H(B^r, 0) + P(B^n|0)H(B^n, 0) + P(B^s|0)H(B^s, 1)$$

$$+P(B^r|0)H(B^r, 1) - (1 - P(B^n|0))C$$

When $A_1 = 1$ then individual 2 never takes the antibiotic, because an infection can only be the result of a resistant bacteria. In this case, total welfare can be written as:

$$pH(B^s, 1) + (1 - p)H(B^r, 1) - C + P(B^n|1)H(B^n, 0) + P(B^r|1)H(B^r, 0)$$

The social planner sets $A_1 = 1$ if and only if it provides greater welfare than $A_1 = 0$:

$$p(H(B^s, 1) - H(B^s, 0)) + (P(B^n|1) - P(B^n|0))H(B^n, 0) - P(B^s|0)H(B^s, 1)$$

$$+(P(B^r|1) - P(B^r|0))H(B^r, 0) - P(B^n|0)C > 0$$

Notice that $P(B^n|0) + P(B^s|0) + P(B^r|0) = 1$ and $P(B^n|1) + P(B^r|1) = 1$. It follows that $P(B^s|0) = (P(B^n|1) - P(B^n|0)) + (P(B^r|1) - P(B^r|0))$. Therefore, we can rewrite the above inequality as:

$$p(H(B^s, 1) - H(B^s, 0)) + (P(B^n|1) - P(B^n|0))(H(B^n, 0) - H(B^s, 1))$$

$$+(P(B^r|1) - P(B^r|0))(H(B^r, 0) - H(B^s, 1)) - P(B^n|0)C > 0$$

From this inequality the costs and benefits from individual 1's antibiotic use are clear. The first term reflects a private benefit to individual 1, realised only if individual 1's infection does not include B^r. The social benefit includes a reduction in the probability of transmitting an infection $P(B^n|1) - P(B^n|0) > 0$, times the benefit of no infection over a treatable infection $H(B^n, 0) - H(B^s, 1)$. The social cost is reflected by the increase in the probability of the resistant infection $P(B^r|1) - P(B^r|0) > 0$ times the loss of health due to a resistant over a treatable infection $H(B^r, 0) - H(B^s, 1)$.

Substituting in the values for the *a priori* probabilities derived in Section 2.4.5, and noting that $H(B^s, 1) - H(B^s, 0) = -(H(B^r, 0) - H(B^s, 1))$ (from Assumption 1), the

social planner sets $A_1 = 1$ if and only if the following condition is satisfied:

$$p > \frac{\lambda(1 - \theta)}{(1 + \lambda Z + \lambda(1 - \theta))} + \frac{(1 - \lambda)}{(1 + \lambda Z + \lambda(1 - \theta))} CBR,$$

where $Z = \frac{H(B^n, 0) - H(B^s, 1)}{H(B^s, 1) - H(B^s, 0)}$. Z is the ratio of the incremental health benefit of no infection over a treated susceptible infection and a treated susceptible infection over an untreated infection.

Now consider if condition (2.9) does not hold ($p < p^{uu}$). In this case, individual 2 always chooses $A_2 = 0$. Social welfare when $A_1 = 1$ will remain unchanged from above (as individual 2 never take the antibiotic when $A_1 = 1$). When $A_1 = 0$ social welfare will now be:

$$pH(B^s, 0) + (1 - p)H(B^r, 0) + P(B^n|0)H(B^n, 0) + P(B^s|0)H(B^s, 0).$$

Given this, the social planner only gives individual 1 the antibiotic when the following condition holds:

$$p(H(B^s, 1) - H(B^s, 0)) + (P(B^n|1) - P(B^n|0))H(B^n, 0)$$

$$-(1 - P(B^r|1) - P(B^n|0))H(B^r, 0) > C$$

Substituting in the values for $P(B^r|1)$, $P(B^n|0)$ and $P(B^n|1)$ from Section 2.4.5:

$$p(H(B^s, 1) - H(B^s, 0)) + \lambda p(H(B^n, 0) - H(B^r, 0)) > C$$

A final collection of terms and we find that this condition can be written as

$$p > \frac{1}{1 + \lambda Z'} CBR$$

where $Z' = \frac{H(B^n, 0) - H(B^r, 0)}{H(B^s, 1) - H(B^s, 0)}$, so the term $1 + \lambda Z' > 1$.[13]

Define the social planner's critical value of p, denoted $p^\star$, for given values of λ, θ, Z,

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[13]It follows from Assumption 1 that $Z' > Z$.

Z', and CBR as

$$p^\star = \begin{cases} \frac{\lambda(1-\theta)}{1+\lambda Z+\lambda(1-\theta)} + \frac{(1-\lambda)}{1+\lambda Z+\lambda(1-\theta)}CBR & \text{if } p > p^{uu} \\ \frac{1}{1+\lambda Z'}CBR & \text{if } p \leq p^{uu} \end{cases} \tag{2.11}$$

The social planner will only prescribe an antibiotic to individual 1 for values of $p > p^\star$. The delineation of optimal allocations in (CBR, p) space is shown in Figure 2.3.

There are a couple of things to notice about (2.11). First, when $\lambda = 0$ (no transmission) then $p^\star = p^u$; no transmission between individuals means that uncoordinated individual use always coincides with the social optimum. Second, consider $\lambda = 1$ (transmission is guaranteed) then $p^\star$ depends on the health utility difference $H(B^n, 0) - H(B^s, 0)$. Notice, as $H(B^n, 0) - H(B^s, 0)$ increases, the positive externality from 1's antibiotic use (curing a susceptible infection) increases, therefore $p^\star$ decreases.

The other important distributional parameter is θ, which determines the concentration of resistant bacteria in an untreated infection (conditional on a mixed microbial population), and therefore plays a role in determining the rate of transmission of resistant microbes absent treatment. At one extreme of $\theta = 1$, individual 1 taking an antibiotic will influence the overall probability of infection, but not the probability of a resistant infection (conditional on an infection). Therefore, there is only a positive externality to taking the antibiotic (a reduction in transmitting a susceptible infection). At the other extreme of $\theta = 0$, again there is only a positive externality (although larger this time) as the antibiotic reduces the probability of individual 2 being infected to 0. However, the for values of θ a little bit larger than 0, the potential negative consequences of individual 1 taking the antibiotic increase dramatically. When θ is very close to 0, the chances of passing resistant bacteria to individual 2 are very low, absent treatment. However, if an antibiotic is taken by individual 1, the chances of passing resistant bacteria to individual 2 increase dramatically. For θ values closer to 1 this negative component of the externality decreases.

Figure 2.3b highlights the combination values of p and CBR for which individual 1 overuses (solid blue area) and under-uses (textured red area) antibiotics. Overuse occurs when both the cost to antibiotic use and the probability of a susceptible infection are relatively low. Intuitively, this makes sense: there the private cost (CBR) to antibiotic use is low, but the social cost (increased transmission of resistant microbes) is relatively

high. In contrast, when the personal cost to antibiotic use is high, but the probability of susceptible infection is also high, then under-use of antibiotics relative to the social optimum is more likely.

The health benefits to the patient are an important part of determining over/under use. Both the individuals and the social planner take this into account. For example, in the social planner's critical value p^* (Equation 2.11), the cost-benefit ratio enters. Consider the case where a patient will receive infinite utility (i.e. avoid a painful death), and incur a finite cost, from using the antibiotic. In this case CBR approaches 0 and the social planner's p^* falls (possibly to 0), relative to a larger value of CBR. Holding all else equal, this will also result in the "overuse" (blue) area in Figure 2.3 to disappear.

The model may give rise to the "problematic" scenario where a patient may die without treatment but the size of the positive externality is smaller than the negative externality. For example, consider a situation in which: a) the benefit to not having or curing an infection is very high, b) the probability that an infection is entirely susceptible is very low (low p), and c) the proportion of bacteria that are resistant in a non-susceptible infection is very low (low θ). There is a low chance that the antibiotic will cure individual 1, but it will significantly increase the probability that a resistant microbe is passed on to individual 2. In such a case it may be optimal to not give individual 1 the antibiotic, even though it may mean a very bad outcome with certainty. While this conclusion may seem problematic, it nicely highlights the importance of understanding both the positive and negative externalities. To ensure that a model does not result in this scenario, would require adding in additional parameters to the social planner's problem, such as a limit on how bad an outcome can be when treatment is withheld.

2.5   Discussion & Conclusion

The use of antibiotics creates a selection pressure leading to increased proportions of resistant bacteria in an individual and the environment. The increase in the frequency of resistant organisms diminishes the effectiveness of antibiotics in treating future infections. Therefore, the long-term value of the antimicrobial resource is reduced. The problem is exacerbated when antibiotics are misused resulting in increased resistance with little or no compensating benefit. This effect is not taken into consideration when individuals decide to take antibiotics but would be taken into consideration by a so-

cial planner. In this paper we define antibiotic overuse as free market (uncoordinated) antibiotic use in excess of the social optimum which would prevail in a coordinated market.

We demonstrate that uncoordinated individuals use antibiotics if the expected benefits exceed the individual cost (pecuniary, health, or other). Given that the social planner considers total welfare, the conditions under which the first individual who becomes ill will be treated is smaller than the market case. The difference between the market optimum and the social optimum depends on the transmission rate and the cost of antibiotic use to the first individual who becomes ill.

We show that when the transmission rate is 0 there is no overuse of antibiotics and uncoordinated decisions are always optimal. As the transmission rate increases, there is a monotonic divergence between coordinated and uncoordinated use. Moreover, a higher transmission rate increases the social cost of greater antibiotic use. We also find a negative relationship between individual costs and overuse. For sufficiently high costs associated with antibiotic use we see underuse of antibiotics while sufficiently low costs results in overuse.

In this paper we provide guidance for how we should approach the empirical analysis of antibiotic overuse. In particular, analysing transmission rates should be a determining factor for antibiotic consumption. It is key to note that areas and diseases for which transmission rates are high are particularly susceptible to overuse. While data on transmission rates in the absence of an infection outbreak is relatively scarce there are several factors that could increase transmission rates. These include poor infection control in health care settings, and poor hygiene and sanitation.

The model used here is a starting point for us to think about optimal antibiotic use. As such, there are some simplifications to the analysis which limits its applicability. Our analysis uses a simple two-agent model where the source of the infection is known and there is only one antibiotic treatment option. By using this simple model, we can understand the importance of transmission rates in a small, enclosed area such as a hospital setting where transmission can be traced. We say hospital setting, as we have seen with the COVID-19 pandemic that even with the best technology, tracking transmission of infections in the community setting is often difficult and imprecise. However, we are aware that should we relax any one of these assumptions, we will be able to apply the model more widely but the results may not hold. We discuss these

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assumptions—the population, treatment option, and timing— below along with some ideas for relaxing them in future research.

Firstly, having only two people in the model might seem unrealistic for obvious reasons. However, we can think of the two people as two subsets of the population where one subset is infected while the other subset is susceptible to infection (this would be in line with the SIS models in the literature, see Section 2.2). Secondly, our model has one treatment option, which while being another simplification, is not an unrealistic one. It is true that treating an infection is complicated, even if two people have the same infection they may be offered different treatment options depending on several factors including their age, gender, and medical history. However, we can think of the antibiotic treatment in the model as a generalization of the first line therapy antibiotics. That is, for each antibacterial infection, this antibiotic/antibiotic class is most effective and less expensive (in terms of less side effects, and cost) of all the options.

Thirdly, one of the key assumptions of our model is that there is perfect information. Individual 2 knows the type of infection, the source of infection, and if the infection is treatable since individual 1's antibiotic use is observable, and the timing is such that the treatment would have taken effect before their interaction. This may be problematic as there are several uncertainties here, all of which cannot realistically be known. For example an individual could know the type of infection or whether it is treatable but not the source. Therefore, we can introduce some uncertainties here in the source of the infection, the timing of the interaction, and the effect of the antibiotic on the susceptible population. Suppose individual 2 could get an infection from the environment or Individual 1. In this case, individual 1's health status only provides imperfect information about the type of bacterial infection that individual 2 has. Notice also that due to the uncertainty of the source of the infection, the timing of the interaction between the individuals is not important. In this case, there is a possibility that individual 2 takes an antibiotic when individual 1 does.

The timing of the interaction between the individuals is also key to the model, here we assumed that the interaction between the two individuals occur after the treatment takes effect. We have also assumed that antibiotic treatment kills all susceptible bacteria and therefore any transmission between the individuals will only be resistant bacteria, that is $\theta = 1$. Both of these assumptions result in individual 1 only transmitting resistant bacteria to individual 2 and therefore individual 2 never takes an antibiotic.

We can modify either of these assumptions by allowing the interaction to take place before the treatment takes effect and/or allowing for varying effects of the antibiotic on the susceptible bacteria population. Either of these options will provide the possibility of susceptible bacteria being transmitted. Therefore there would be no way to know whether the infection is treatable and could result in higher antibiotic use than in the simple case.

To see this more clearly, suppose the treatment takes 5 days to be fully effective. If we allow for interaction within a window starting from the first day of treatment to the final day, then individual 2's illness could be treatable. In the case where the antibiotic kills all susceptible bacteria, whether or not the treatment is effective depends on the day of the interaction. Any contact before the end of the 5 days will only imperfectly inform individual 2's antibiotic decision. In this case the probability that the illness is untreatable will be higher the closer the interaction is to the end of the treatment window. That is, θ gets closer to 1 the closer the interaction is to Day 5 —the end of treatment. And, as we have assumed in the model presented, any interaction after treatment takes effect (5 days or later) will result in only resistant bacteria being transmitted, $\theta = 1$.

Now let us consider the case where when exposed to an antibiotic only a fraction of the susceptible bacteria will be killed.[14] In this case there is the possibility that individual 2 has a treatable infection even if the interaction takes place after the treatment takes effect. That is, the timing of the interaction is not important here. Here once again, individual 1's health state only provides imperfect information about the type of bacterial infection that individual 2 has and therefore does not determine individual 2's antibiotic use.

For future developments, we will first introduce another source of infection, the environment. This will allow us to study optimal antibiotic use in the simple case giving us a starting point for the analysis. Here individual 1's decision making will be unaffected and it is individual 2 who will have to make a decision under uncertainty. We will then expand the current model to a population of people and study infection from human transmission. This will also introduce uncertainty in the source of infection, instead of the source of infection being individual 1, it would be any of the infected persons who had contact with the susceptible person. Also now the timing of the interaction will

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[14]This case, $\delta_s \neq 1$, is discussed in Sections 2.3 and Appendix 2.B.2.

not be as important as in the simple case since there is uncertainty in the source of the infection. In a final instalment, we will introduce the possibility of two different sources of infection in the population of people. In all of these we will consider the varying the effectiveness of the antibiotic. In the current model, we have a strong antibiotic which completely eradicates the susceptible bacteria population. We can modify this to allow for different effects, however the key effect of the antibiotic use will remain unchanged, that is, it increases the probability of having and transmitting resistant bacteria.

Tables

Table 2.1: Lotka–Volterra Steady State Solutions

Steady State & Infection Type	Population size $(\bar{N}_s, \bar{N}_r) =$
No antibiotic use	
SS1: No infection steady state	$(0,0)$
SS2: Resistant infection steady state	$(0,K)$
SS3: Susceptible infection steady state	$(K,0)$
SS4: Mixed infection steady state	$\left(\dfrac{1-\beta_{sr}}{1-\beta_{sr}\beta_{rs}}K, \dfrac{1-\beta_{rs}}{1-\beta_{sr}\beta_{rs}}K \right)$
Antibiotic use, $\delta_s \neq 1$	
SS1: No infection steady state	$(0,0)$
SS2: Resistant infection steady state	$(0,K)$
SS3: Susceptible infection steady state	$\left(\left(1-\dfrac{\delta_s}{\rho_s}\right)K, 0 \right)$
SS4: Mixed infection steady state	$\left(\left(\dfrac{1-\dfrac{\delta_s}{\rho_s}-\beta_{sr}}{1-\beta_{sr}\beta_{rs}}\right)K, \left(\dfrac{1-\beta_{rs}\left(1-\dfrac{\delta_s}{\rho_s}\right)}{1-\beta_{sr}\beta_{rs}}\right)K \right)$
Antibiotic use, $\delta_s = 1$	
SS1: No infection steady state	$(0,0)$
SS2: Resistant infection steady state	$(0,K)$

This table shows the equilibrium population size (steady state solutions) with and without antibiotic use. In the case where antibiotics are used, we show the results when the antibiotic kills only a fraction of the susceptible bacteria ($\delta_s \neq 1$) and the case where the antibiotic kills the entire susceptible bacteria population ($\delta_s = 1$). The equilibrium population size is dependent on the relative size of the species competitive coefficients (β_{sr} and β_{rs}) and the initial population values ($N_s(0)$ and $N_r(0)$). Steady State 4 (SS4) is only feasible when either: (1) $\beta_{sr} > 1$ and $\beta_{sr}\beta_{rs} > 1$; OR $\beta_{sr} < 1$, and $\beta_{sr}\beta_{rs} < 1$. See Appendices 2.A.1 and 2.A.2 for more details.

Figures

Figure 2.1: Bacteria Competition and Resulting Infection
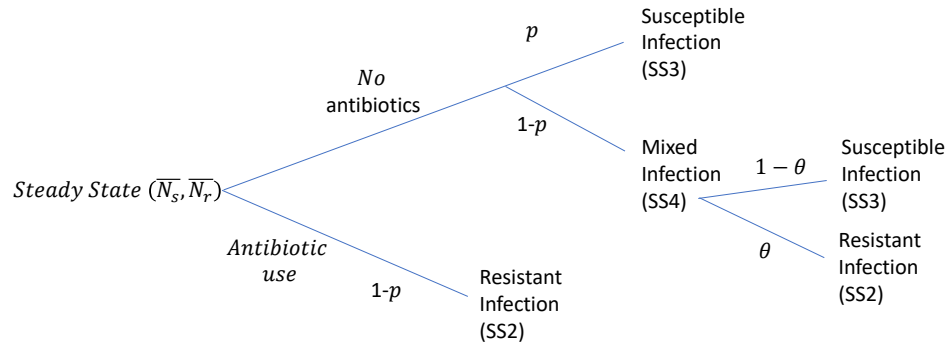
This figure shows how the outcome of bacteria competition, determines the probability of getting an infection from resistant bacteria. In the antibiotic case, the steady state population is either comprised of only susceptible bacteria or a mixed population. p is the probability that the population is comprised only of susceptible bacteria. The mixed population contains some proportion, θ of resistant bacteria. When antibiotics are used then in the case where the antibiotic kills all susceptible bacteria, the infection is solely caused by a resistant infection ($p = 0$).

Figure 2.2: Uncoordinated equilibrium when $B_2 \neq B^n$
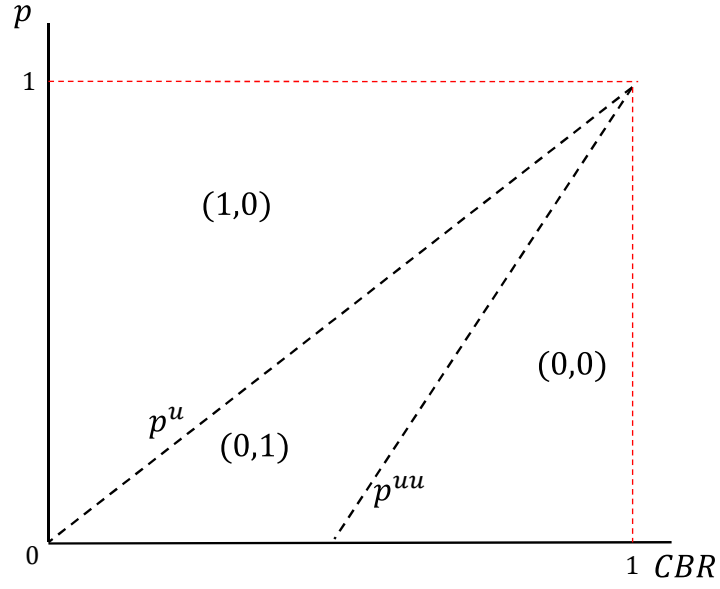
Notes: This figure depicts the uncoordinated equilibrium when individual 2 has a bacterial infection. The figure delineates the different uncoordinated antibiotic use equilibrium in p, CBR space. p^u and p^{uu} are the critical values for p, as defined in the main text. Equilibrium for the different areas in the figure are shown in parenthesis as (A_1, A_2).

Figure 2.3: Social optimum antibiotic use

(a) Social optimum allocations

(b) Areas of deadweight loss
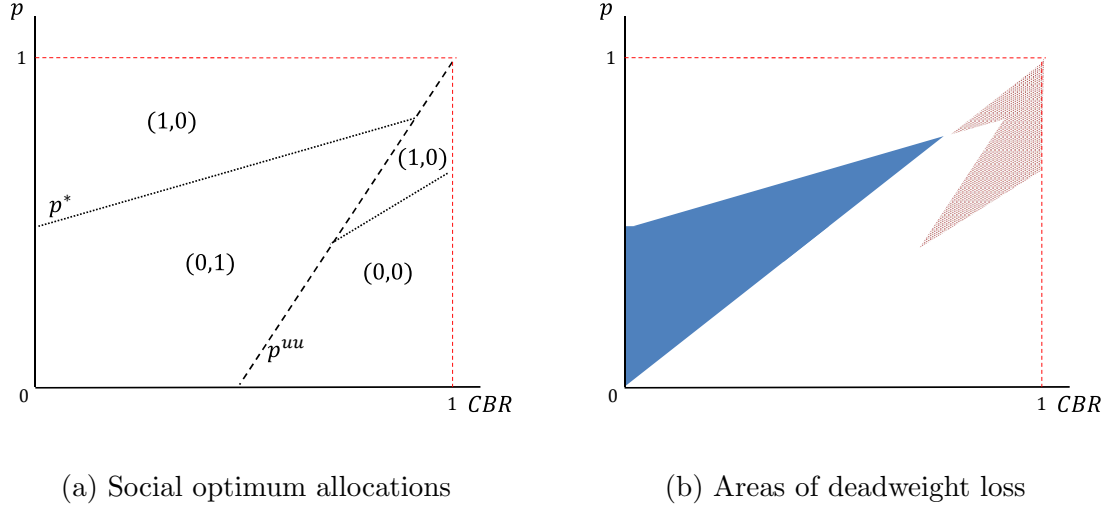
Notes: Figure (a) delineates the socially optimal antibiotic use in p, CBR space. $p^\star$ is the social planner's critical p value for individual 1's antibiotic use. p^{uu} is the critical values for p, defining individual 2's antibiotic use (conditional on $A_1 = 0$). Equilibrium for the different areas in the figure are shown in parenthesis as (A_1, A_2). Figure (b) shows combinations of p and CBR where the uncoordinated equilibrium deviates from optimal antibiotic use. The blue area shows uncoordinated over-use, the textured red area shows uncoordinated under-use.

Appendix 2.A   Proof of Results in Table 2.1

2.A.1   No Antibiotic use

As stated before, without antibiotic use, the growth of each strain is given by:

$$\dot{N_s}(t) = \rho_s N_s(t) \left(\frac{K - N_s(t) - \beta_{sr} N_r(t)}{K} \right) \tag{2.A.1}$$

$$\dot{N_r}(t) = \rho_r N_r(t) \left(\frac{K - N_r(t) - \beta_{rs} N_s(t)}{K} \right) \tag{2.A.2}$$

The steady state solution to Equations (2.A.1) and (2.A.2) is the pair of values $\bar{N}_s$ and $\bar{N}_r$ at which $\dot{N}_s(t)$ and $\dot{N}_r(t)$ both equal 0.

For the susceptible bacteria $\dot{N}_s(t) = 0$ can be satisfied with:

$$\bar{N}_s = 0^{15} \tag{2.A.3}$$

or

$$\frac{K - \bar{N}_s - \beta_{sr}\bar{N}_r}{K} = 0$$

$$\bar{N}_s = K - \beta_{sr}\bar{N}_r{}^{16} \tag{2.A.4}$$

or both. Similarly for the resistant bacteria $\dot{N}_r(t) = 0$ can be satisfied with

$$\bar{N}_r = 0 \tag{2.A.5}$$

or

$$\frac{K - \bar{N}_r - \beta_{rs}\bar{N}_s}{K} = 0$$

$$\bar{N}_r = K - \beta_{rs}\bar{N}_s \qquad (2.A.6)$$

or both. Equations 2.A.3–2.A.6 are the zero–growth equations for each strain from which the zero–growth isoclines are constructed.

Corner Solution

The corner solutions are:

1. Both the susceptible and resistant strains are extinct (Equations 2.A.3 and 2.A.5 are true). In the steady state the equilibrium population is $(\bar{N}_s, \bar{N}_r) = (0,0)$.

2. The susceptible bacteria are extinct, Equations 2.A.3 and 2.A.6 are true. Substituting $\bar{N}_s = 0$ (Equation 2.A.3) into 2.A.6 gives the equilibrium population for the resistant bacteria. In this case the steady state population is $(\bar{N}_s, \bar{N}_r) = (0, K)$.

3. The resistant bacteria are extinct, Equations 2.A.4 and 2.A.5 are true. Similar to the previous case, substituting $\bar{N}_r = 0$ (Equation 2.A.5) into 2.A.4 gives the equilibrium population for the susceptible bacteria. In this case the steady state population is $(\bar{N}_s, \bar{N}_r) = (K, 0)$.

Interior Solution

In the previous steady state solutions we have the extinction of either one or both strains. The final steady state solution is found at the intersection of Equations 2.A.4 and 2.A.6. We obtain this equilibrium solution by substitution as follows:

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[15]Equations 2.A.3 and 2.A.5 are possible given our assumption that $\rho_s > 0$ and $\rho_r > 0$.

[16]Equations 2.A.4 and 2.A.6 are possible using the assumptions $K > 0$, $\bar{N}_s > 0$, and $\bar{N}_r > 0$.

$$\bar{N}_s = K - \beta_{sr}\bar{N}_r$$

$$\bar{N}_s = K - \beta_{sr}(K_r - \beta_{rs}\bar{N}_s)$$

$$\bar{N}_s = \frac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}K \qquad (2.A.7)$$

and

$$\bar{N}_r = K - \beta_{rs}\bar{N}_s$$

$$\bar{N}_r = K - \beta_{rs}\left(\frac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}K\right)$$

$$\bar{N}_r = \frac{1 - \beta_{rs}}{1 - \beta_{sr}\beta_{rs}}K \qquad (2.A.8)$$

Therefore the coexistence steady state, is $\left(\dfrac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}K, \dfrac{1 - \beta_{rs}}{1 - \beta_{sr}\beta_{rs}}K\right)$. A necessary condition for coexistence is for either: (1) $\beta_{sr} < 1, \beta_{rs} < 1$ and $\beta_{sr}\beta_{rs} < 1$, or (2) $\beta_{sr} > 1, \beta_{rs} > 1$ and $\beta_{sr}\beta_{rs} > 1$.

2.A.2   Antibiotic use

Now consider the introduction of an antibiotic. The growth of each strain will now be described by:

$$\dot{N}_s(t) = \rho_s N_s(t)\left(\frac{K - N_s(t) - \beta_{sr}N_r(t)}{K}\right) - \delta_s N_s(t) \qquad (2.A.9)$$

$$\dot{N}_r(t) = \rho_r N_r(t)\left(\frac{K - N_r(t) - \beta_{rs}N_s(t)}{K}\right) \qquad (2.A.10)$$

following Nikolaou and Tam (2006). We assume that $\rho_s \geq \rho_r > \delta_s$. Notice that when $\delta_s = 1$, the susceptible bacteria will be extinct and there would be no competition.[17] Therefore we focus on the case where $\delta_s \neq 1$.

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[17]The steady state solutions would collapse to $(\bar{N}_s, \bar{N}_r) = (0, 0)$ or $(\bar{N}_s, \bar{N}_r) = (0, K)$ in this case.

Once again, the solution to Equations (2.A.9) and (2.A.10) are the pair of values $\bar{N}_s$ and $\bar{N}_r$ at which $\dot{N}_s(t)$ and $\dot{N}_r(t)$ both equal 0.

$$\bar{N}_s = 0 \tag{2.A.11}$$

or

$$\rho_s \left(\frac{K - \bar{N}_s - \beta_{sr}\bar{N}_r}{K} \right) - \delta_s = 0$$

$$\bar{N}_s = \left(1 - \frac{\delta_s}{\rho_s} \right) K - \beta_{sr}\bar{N}_r \tag{2.A.12}$$

or both. The conditions for $\dot{N}_r(t) = 0$ is the same as the no antibiotic case:

$$\bar{N}_r = 0 \tag{2.A.13}$$

or

$$\bar{N}_r = K - \beta_{rs}\bar{N}_s \tag{2.A.14}$$

or both.

Corner Solutions

As in the case with no antibiotic use, we have three steady state solutions with one or both of the strains becoming extinct. The corner solutions remain the same except for the case where the resistant bacteria are extinct. In this case, Equations 2.A.12 and 2.A.13 are true. Substituting $\bar{N}_r = 0$ (Equation 2.A.13) into 2.A.12 gives the equilibrium population for the susceptible bacteria. The steady state population is now: $(\bar{N}_s, \bar{N}_r) = \left(\left(1 - \frac{\delta_s}{\rho_s} \right) K, 0 \right)$.

Interior Solution

The fourth steady state solution, the interior solution, is be found at the intersection of Equations 2.A.12 and 2.A.14. Substitution yields:

$$\bar{N}_s = \left(1 - \frac{\delta_s}{\rho_s}\right)K - \beta_{sr}\bar{N}_r$$

$$\bar{N}_s = \left(1 - \frac{\delta_s}{\rho_s}\right)K - \beta_{sr}\left(K - \beta_{rs}\bar{N}_s\right)$$

$$\bar{N}_s = \left(\frac{1 - \frac{\delta_s}{\rho_s} - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}\right)K \tag{2.A.15}$$

and

$$\bar{N}_r = K - \beta_{rs}\bar{N}_s$$

$$\bar{N}_r = K - \beta_{rs}\left(\frac{1 - \frac{\delta_s}{\rho_s} - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}\right)K$$

$$\bar{N}_r = \left(\frac{1 - \beta_{rs}\left(1 - \frac{\delta_s}{\rho_s}\right)}{1 - \beta_{sr}\beta_{rs}}\right)K$$

$$\tag{2.A.16}$$

As before, a necessary condition for coexistence is for either: (1) $\beta_{sr} + \frac{\delta_s}{\rho_s} < 1$; $\beta_{rs}(1 - \frac{\delta_s}{\rho_s}) < 1$ and $\beta_{sr}\beta_{rs} < 1$; or (2) $\beta_{sr} + \frac{\delta_s}{\rho_s} > 1$; $\beta_{rs}(1 - \frac{\delta_s}{\rho_s}) > 1$ and $\beta_{sr}\beta_{rs} > 1$.

Appendix 2.B   Dynamics of Competitive Interactions

2.B.1   No Antibiotics

There are four possible steady state outcomes when no antibiotics are used leading to 4 types of infections. These are:

SS1: No infection steady state $(\bar{N}_s, \bar{N}_r) = (0, 0)$

SS2: Resistant infection steady state $(\bar{N}_s, \bar{N}_r) = (0, K)$

SS3: Susceptible infection steady state $(\bar{N}_s, \bar{N}_r) = (K, 0)$

SS4: Mixed infection steady state $(\bar{N}_s, \bar{N}_r)) = \left(\dfrac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}} K, \dfrac{1 - \beta_{rs}}{1 - \beta_{sr}\beta_{rs}} K \right),$
which is only feasible when either: (1) $\beta_{sr} > 1, \beta_{rs} > 1$ and $\beta_{sr}\beta_{rs} > 1$; or (2) $\beta_{sr} < 1.\beta_{rs} < 1$, and $\beta_{sr}\beta_{rs} < 1$.

The steady state outcome that occurs highly depends on the initial values of N_r and N_s, $N_s(0)$ and $N_r(0)$. First we will analyse initial values on the boundary using the typical Lokta–Volterra model solutions then apply it to the case of bacteria. There are three possible starting points on the boundary, $N_s(0) = 0, N_r(0) = 0$; $N_s(0) = 0, N_r(0) > 0$; and $N_s(0) > 0, N_r(0) = 0$. The Lokta–Volterra model is a form of the Kolmogorov system of equations. This gives two results that we will use, first trajectories starting on the axes stay on the axes and, second interior trajectories cannot reach the axes in finite time (Dobrushkin, 2017). When $N_s(0) = 0$ and $N_r(0) = 0$ this results in a steady state, *SS1*. This steady state is unstable as any unexpected shock to population of either or both bacteria strains will cause the populations to grow away from this steady state.

When either $N_s(t) = 0$ while $N_r(t) > 0$ or $N_s(t) > 0$ while $N_r(t) = 0$ competition will result in one species dominating the other. The species with the positive initial value always drives the other to extinction resulting in steady state *SS2* or *SS3*. Given the assumption that the initial value of N_s and N_r is at least 1, we do not have a case where the pair of initial values fall the boundaries.

Let us now consider initial population values where $N_s(0) > 0, N_r(0) > 0$. There are four distinguishable cases corresponding to the four possible sign combinations of β_{sr} and β_{rs} as shown in Figure 2.B.1. The growth trajectories depend on the relationship between the initial value of each strain and its zero–growth isocline. Generally, when a strain's population is below its zero–growth isocline the population will increase and when the population is above its zero–growth isocline the population will decline.

For Case 1 and 2, inter-specific competition always leads to the extinction of one species by the other. The species with the strongest competition always drives the other to

Figure 2.B.1: Possible Isocline Crossings for the Lokta-Volterra Model
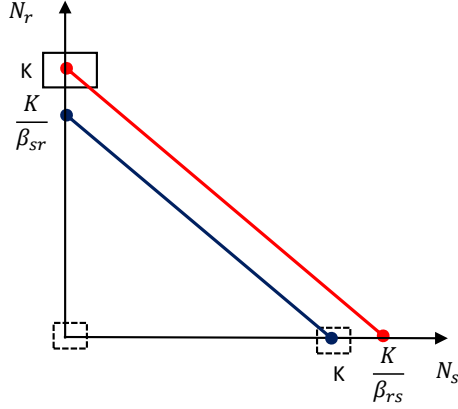
(a) Case 1: $\beta_{sr} > 1$ and $\beta_{rs} < 1$
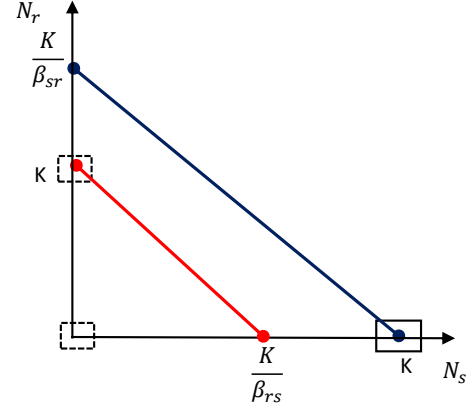
(b) Case 2: $\beta_{sr} < 1$ and $\beta_{rs} > 1$
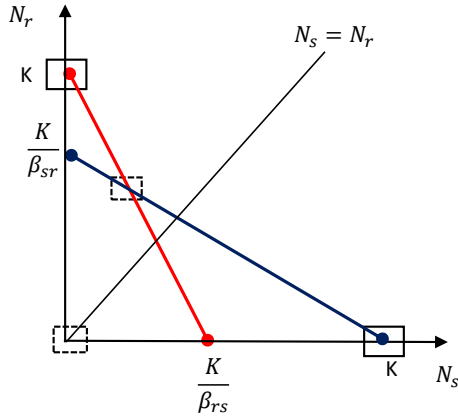
(c) Case 3: $\beta_{sr} > 1$ and $\beta_{rs} > 1$
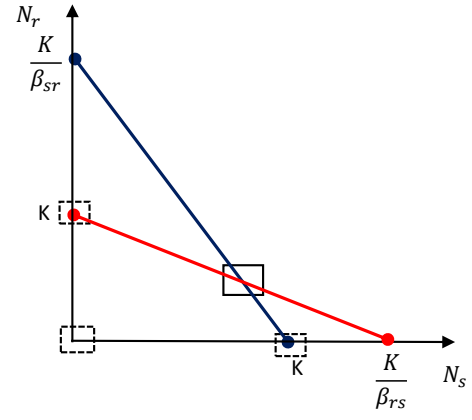
(d) Case 4: $\beta_{sr} < 1$ and $\beta_{rs} < 1$

The zero–growth isocline describes expected equilibrium population sizes of one strain's growth if the growth of the other is held constant. Using Equation 2.A.4: $\bar{N}_s = K - \beta_{sr}\bar{N}_r$ the coordinates are are when $\bar{N}_r = 0$, $\bar{N}_s = K$ and when $\bar{N}_s = 0$, $\bar{N}_r = \frac{K}{\beta_{sr}}$. The coordinates for the susceptible bacteria isolcline are: $(N_s(t), N_r(t)) = (K, 0)$ and $\left(0, \frac{K}{\beta_{sr}}\right)$. Similarly from Equation 2.A.6 the coordinates for the resistant bacteria isolcline are $(N_s(t), N_r(t)) = (0, K)$ and $\left(\frac{K}{\beta_{sr}}, 0\right)$.

A stable equilibrium is shown by a solid–line box while an unstable equilibrium is shown by a broken–line box.

extinction. We can rule out Case 1 as we assumed $\rho_s \geq \rho_r$ therefore the zero growth line for resistant bacteria cannot be above the susceptible bacteria. In Case 2 (refer Figure 2.B.1b) we have $\beta_{rs} > 1$ meaning the competition with the susceptible bacteria is more

harmful to the resistant strain's growth than competition within the resistant strain. Also competition with the resistant strain is less harmful to the susceptible bacteria growth than competition between the members of the susceptible strain, $\beta_{sr} < 1$. Together this means the susceptible bacteria are the better competitors. As such for all interior initial values, competition will lead to the outcome $(K, 0)$, the extinction of the resistant bacteria by the susceptible ones. The other two steady states *SS1* and *SS3* are unstable.

For Case 3, presented in Figure 2.B.1c, all four steady states are possible outcomes. However, only two of these, *SS2*: $(0, K)$ and *SS3*: $(K, 0)$, are stable. From Figure 2.B.1c we have $\beta_{sr} > 1$, and $\beta_{rs} > 1$. Where $\beta_{sr} > 1$ means that the effect of resistant bacteria on the susceptible is greater than the effect of susceptible bacteria on its own growth. In other words, each species limits the other growth more than it's own. In this case the species cannot coexist peacefully and the outcome will be that one population wins, while the other is driven to extinction. The winner depends on which species has the starting advantage. The $45°$ line shows all the points where $N_s(t) = N_r(t)$, as such all points above the line we have $N_r(t) > N_s(t)$ and for the points below $N_s(t) > N_r(t)$. Given our assumption about the initial values of each strain $N_s(0) > N_r(0)$, all possible initial population values will be below the $45°$ line. Therefore the outcome of Case 3 will be the same as Case 2 unless the trajectory of the strains growth is directly in line with the unstable equilibrium, SS4.

As in the previous case, for Case 4 all four steady states are possible outcomes however only *SS4*: $\left(\dfrac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}} K, \dfrac{1 - \beta_{rs}}{1 - \beta_{sr}\beta_{rs}} K \right)$ is stable and all interior initial points leads to the stable steady state. From Figure 2.B.1d we have that each strain limits it's own growth more than that of its competitor $\beta_{sr} < 1$, and $\beta_{rs} < 1$. Therefore there will be stable coexistence even though the strains compete with each other.

2.B.2 With Antibiotics

When antibiotics are used we have the same four types of infection from the steady state outcomes. These are:

SS1: No infection steady state $(\bar{N}_s, \bar{N}_r) = (0, 0)$

SS2: Resistant infection steady state $(\bar{N}_s, \bar{N}_r) = (0, K)$

SS3: Susceptible infection steady state $(\bar{N}_s, \bar{N}_r) = \left(\left(1 - \dfrac{\delta_s}{\rho_s}\right)K, 0\right)$

SS4: Mixed infection steady state $(\bar{N}_s, \bar{N}_r) = \left(\left(\dfrac{1 - \dfrac{\delta_s}{\rho_s} - \beta_{sr}}{1 - \beta_{sr}\beta_{rs}}\right)K, \left(\dfrac{1 - \beta_{rs}\left(1 - \dfrac{\delta_s}{\rho_s}\right)}{1 - \beta_{sr}\beta_{rs}}\right)K\right),$

and as before is only feasible when either: (1) $\beta_{sr} > 1$ and $\beta_{sr}\beta_{rs} > 1$; OR $\beta_{sr} < 1$, and $\beta_{sr}\beta_{rs} < 1$.

There are a few obvious changes to the competitive interactions when antibiotics are introduced. First, only *SS3* and *SS4* changes which is expected, as only susceptible bacteria population is affected by the introduction of antibiotics. Second, the outcome of competitive interactions now also depend on the ratio $\dfrac{\delta_s}{\rho_s}$, the efficacy of the antibiotic. Third, we can no longer rule out Case 1 or *SS3*. Finally the susceptible bacteria is now affected by the efficacy of the antibiotic in addition to competition with the resistant bacteria (β_{sr}).

We will analyse the outcomes of competitive interactions when antibiotics are introduced building on the previous section (Section 2.B.1). In an antibiotic–free environment we ruled out a resistant infection steady state. This is because our assumption of $\rho_s \geq \rho_r$ ruled out Case 1 and $N_s(0) > N_r(0)$ makes it impossible for the bacteria population to arrive at *SS3* in Case 3. As stated before, the use of antibiotics affects the ratio of susceptible to resistant bacteria and therefore the outcome of competitive interaction.

There are now two ways in which competitive interaction results in the extinction of susceptible bacteria. To see this, let us assume that each strain's growth rate is such that the zero-growth isoclines do not cross (Case 1 and 2). In the absence of antibiotics the susceptible bacteria's zero–growth iscoline is above the resistant bacteria as depicted in Figure 2.B.1a. Now we will introduce an antibiotic into the bacteria's environment. The antibiotic reduces the susceptible population by $\delta_s N_s$ and the zero growth line decreases by $\dfrac{\delta_s}{\rho_s}$. It is clear that the magnitude of $\dfrac{\delta_s}{\rho_s}$ determines the relationship of the zero growth lines. If the effect of the antibiotic is sufficiently large it gives the resistant bacteria a competitive advantage leading to the extinction of susceptible bacteria in the steady state, depicted in Case 1, Figure 2.B.2a. Otherwise we have the extinction of resistant bacteria in the steady state (Case 2 Figure 2.B.2b).

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In Case 1 (Figure 2.B.2a) the use of antibiotic is detrimental to the susceptible bacteria population in two ways. Firstly, the antibiotic assists the resistant bacteria so that the competition between the susceptible and resistant bacteria is more harmful than competition among the susceptible strain ($\beta_{sr} + \frac{\delta_s}{\rho_s} > 1$). Secondly, the antibiotic reduces the susceptible bacteria population such that the effect on the susceptible bacteria, post–antibiotic use, is less harmful to the growth of the resistant bacteria than the effect of competition between the members of the resistant strain $\left(\left(1 - \frac{\delta_s}{\rho_s} \right) \beta_{rs} < 1 \right)$. These two effects combined result in a steady state equilibrium where the susceptible bacteria are driven to extinction (SS2).

For Case 2 (Figure 2.B.2b) notice that even with the antibiotic reducing the zero–growth line for the susceptible bacteria, the susceptible bacteria are still able to out–compete the resistant bacteria. This may be due to an ineffective antibiotic or a very large $N_s(0)$ compared to $N_r(0)$. The resulting equilibrium number of the susceptible strain is $\frac{\delta_s}{\rho_s}$ lower than the no antibiotics case.

The second way in which competition leads to the extinction of the susceptible bacteria is where the isoclines cross and each strain limit each other's growth more than its own. This situation, Case 3 is depicted in Figure 2.B.2c. Let us focus on the stable equilibria represented by solid boxes, these are: $(\bar{N}_s, \bar{N}_r) = (0, K)$ and $(\bar{N}_s, \bar{N}_r) = \left(\left(1 - \frac{\delta_s}{\rho_s} \right) K, 0 \right)$. In the no antibiotics case the initial values are all below the 45° line since we assumed $N_s(0) > N_r(0)$. As mentioned before, antibiotic use reduces the population of susceptible bacteria by $\delta_s N_s$. If the remaining population $(1 - \delta_s)N_s$ falls below N_r the result will be $SS2$ $(0, K)$ the extinction of the susceptible bacteria. Otherwise we have the extinction of the resistant bacteria ($SS3$: $(0, K)$).

Finally, both species are able to coexist peacefully as before in Case 4. Notice that the outcome doesn't change however, antibiotic use changes the equilibrium population of susceptible and resistant bacteria strains by $\left(-\frac{\frac{\delta_s}{\rho_s}}{1 - \beta_{sr}\beta_{sr}} K, \frac{\frac{\delta_s}{\rho_s}\beta_{rs}}{1 - \beta_{sr}\beta_{sr}} K \right)$ as shown below.

for $\bar{N}_s$

$$\bar{N}_s{}^{antibiotic} - \bar{N}_s =$$

$$= \left(\frac{1 - \beta_{sr} - \dfrac{\delta_s}{\rho_s}}{1 - \beta_{rs}\beta_{rs}} \right) K - \frac{1 - \beta_{sr}}{1 - \beta_{sr}\beta_{sr}} K$$

$$= \frac{1 - \beta_{sr} - \dfrac{\delta_s}{\rho_s} - 1 + \beta_{sr}}{1 - \beta_{sr}\beta_{sr}} K$$

$$= -\frac{\dfrac{\delta_s}{\rho_s}}{1 - \beta_{sr}\beta_{sr}} K$$

for $\bar{N}_r$

$$\bar{N}_r{}^{antibiotic} - \bar{N}_r =$$

$$= \left(\frac{1 - \beta_{rs} + \dfrac{\delta_s}{\rho_s}\beta_{rs}}{1 - \beta_{rs}\beta_{rs}} \right) K - \frac{1 - \beta_{rs}}{1 - \beta_{sr}\beta_{sr}} K$$

$$= \frac{1 - \beta_{rs} + \dfrac{\delta_s}{\rho_s}\beta_{rs} - 1 + \beta_{rs}}{1 - \beta_{sr}\beta_{sr}} K$$

$$= \frac{\dfrac{\delta_s}{\rho_s}\beta_{rs}}{1 - \beta_{sr}\beta_{sr}} K$$

Figure 2.B.2: Possible Isocline Crossings for the Lokta-Volterra Model with Antibiotic Use
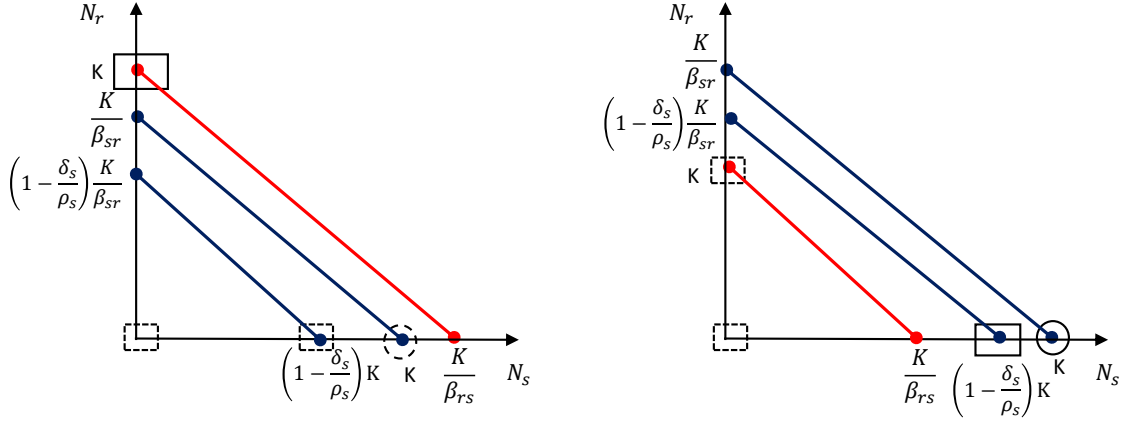
(a) Case 1: $\beta_{sr} + \frac{\delta_s}{\rho_s} > 1$ and $(1 - \frac{\delta_s}{\rho_s})\beta_{rs} < 1$ (b) Case 2: $\beta_{sr} + \frac{\delta_s}{\rho_s} < 1$ and $(1 - \frac{\delta_s}{\rho_s})\beta_{rs} > 1$
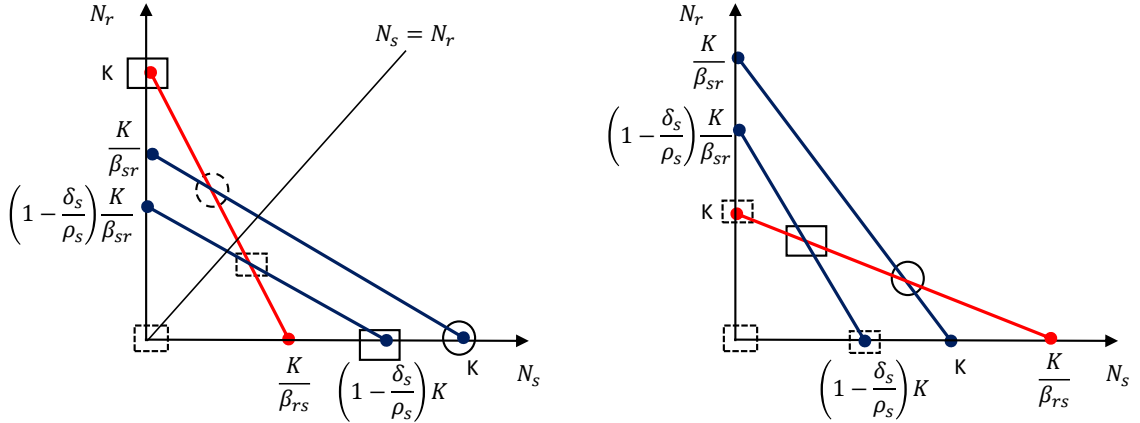
(c) Case 3: $\beta_{sr} + \frac{\delta_s}{\rho_s} > 1$ and $(1 - \frac{\delta_s}{\rho_s})\beta_{rs} > 1$ (d) Case 4: $\beta_{sr} + \frac{\delta_s}{\rho_s} < 1$ and $(1 - \frac{\delta_s}{\rho_s})\beta_{rs} < 1$

The zero–growth isocline describes expected equilibrium population sizes of one strain's growth if the growth of the other is held constant and an antibiotic is introduced. Since the antibiotic only affects the susceptible bacteria the coordinates for the susceptible bacteria isocline are different from 2.B.1.

Using Equation (2.A.12): $\bar{N}_s = \left(1 - \frac{\delta_s}{\rho_s}\right)K - \beta_{sr}\bar{N}_r)$, when $\bar{N}_r = 0$, $\bar{N}_s = \left(1 - \frac{\delta_s}{\rho_s}\right)K$ and when

$\bar{N}_s = 0$, $\bar{N}_r = \left(1 - \frac{\delta_s}{\rho_s}\right)\frac{K}{\beta_{sr}}$. Therefore points for the zero–growth line for susceptible bacteria are

$(N_s(t), N_r(t)) = \left(\left(1 - \frac{\delta_s}{\rho_s}\right)K, 0\right)$ and $\left(0, \left(1 - \frac{\delta_s}{\rho_s}\right)\frac{K}{\beta_{sr}}\right)$ for susceptible bacteria and as in Figure

2.B.1 for resistant bacteria the points are $(N_s(t), N_r(t)) = (0, K)$ and $\left(\frac{K}{\beta_{sr}}, 0\right)$.

A stable equilibrium is shown by a solid–line while an unstable equilibrium is shown by a broken–line. The boxes represent the equilibrium in the antibiotic–use case while the no antibiotic equilibrium is represent by a circle.

Chapter 3

Does Knowledge Affect Willingness–to–Pay for Antibiotic–free Goods?

3.1 Introduction

Public health authorities have been placing more emphasis on controlling antimicrobial resistance in light of the lack of innovation in new antibiotic classes.[18]   Controlling resistance includes ensuring optimal use of antibiotics in both humans and agriculture. Globally antibiotics are used in food production for disease treatment, prevention of diseases (prophylaxis), and growth promotion. A joint report by the European Centre for Disease Prevention and Control (ECDC), European Food Safety Authority (EFSA), and European Medicines Agency (EMA) found that in 2014 the average antimicrobial consumption was higher in animals than in humans (ECDC and EMA, 2017).   In addition, antibiotics deemed medically important to humans are used in agriculture.

There is a general consensus that the use of antibiotics in agriculture has an impact on its effectiveness in treating humans even though there is no evidence of a direct link (O'Neill et al., 2015; Scott et al., 2018; Tang et al., 2017). Despite this consensus, there is a lack of public awareness regarding antibiotic resistance which must be addressed as

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[18]Antimicrobial agents are drugs used to treat illnesses caused by micro–organisms such as bacteria, viruses, and fungi. I use antibiotics in this chapter to refer to agents used to treat bacterial infections.

a part of broader strategy to reduce resistance (WHO et al., 2015; O'Neill et al., 2016). The implication being that increasing the general public's knowledge about antibiotic consumption and resistance could lead to behavioural changes. In health care, this includes patients only requesting or purchasing antibiotics when there is a genuine need, and proper antibiotic prescribing techniques.[19] In terms of agriculture, farmers would reduce unnecessary antibiotic use and receive additional incentives through higher demand for goods produced using appropriate antibiotic methods. In this paper I explore whether such incentives exist by examining the effect of knowledge about antibiotic consumption and resistance, on people's stated willingness–to–pay for antibiotic–free products.

This paper has two main purposes: (1) to estimate respondents' willingness–to–pay to forgo antibiotic use in the food they consume and (2) to identify how this willingness–to–pay is affected by knowledge. To estimate the key effects, I designed a survey instrument to collect primary data since no secondary dataset exists with the required information. Knowledge is measured directly by six questions in the survey based on antibiotic use, antibiotic resistance, the use of antibiotics in food production, and indirectly through the respondent's area(s) of work. The survey also includes a choice experiment using the sequential bid Contingent Valuation Method to collect the willingness–to–pay data. Using the sequential bid approach, respondents are presented with a sequence of hypothetical market scenarios In each market scenario the respondent chooses either the regular option (Option 1), the antibiotic–free option (Option 2) or neither of these options (Option 3). The choice made in each scenario is used to ascertain the interval which contains their true willingness–to–pay. The method applied to estimating the willingness–to–pay has up to six scenarios which is the highest in the willingness–to–pay literature. This results in tighter willingness–to–pay intervals and therefore more precise bounds for the respondents' true willingness–to–pay.

The experiment is comprised of two parts, the first part has market scenarios for the product the respondent purchases the most (Frame 1), and the second for the least purchased product (Frame 2). I use these two frames to test whether willingness–to–pay varies not only by protein of choice but also by frequency of purchase, i.e. whether the protein is most or least commonly bought. This gives some idea about what preferences may be driving willingness–to–pay. The results indicate that there is variation in both

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[19]Genuine need for antibiotics here refer to the case where the individual has a bacterial infection or most likely has a bacterial infection. In Chapter 2 Section 2.2 we cover the various definitions of optimal antibiotic use.

these cases, but this is more evident when comparing willingness–to–pay by protein. I find that on average the willingness–to–pay for the antibiotic–free option compared to the regular option is 57% higher for Frame 1 and 52% higher for Frame 2. Furthermore, willingness–to–pay is higher for antibiotic–free chicken and antibiotic–free chickpeas than for antibiotic–free sea bass.

I estimate the effect of knowledge on willingness–to–pay with both the maximum likelihood method using interval regression, and OLS. Both methods give similar results indicating a positive and significant effect of knowledge on willingness–to–pay for Frame 1, and positive but non–significant effect for Frame 2. Using my preferred specification, the interval regression estimates suggest that the willingness–to–pay for the antibiotic–free good increases by approximately £0.085 for each one standard deviation increase in *Knowledge*. For Frame 2, the willingness–to–pay for the antibiotic–free good increases by £0.056 over the price of the regular good, in response to a one standard deviation increase in knowledge. The positive effect of knowledge is robust to various specifications and is consistent with the literature on organic products (see Díaz et al., 2012; Owusu and Owusu Anifori, 2013).

This paper adds to the literature by directly estimating the effect of knowledge about antibiotic consumption and resistance on willingness–to–pay for antibiotic free goods. Moreover, this is the first study to explore willingness–to–pay for antibiotic–free goods in the UK. A previous study Lusk et al. (2006) estimates the willingness–to–pay for antibiotic free products in the U.S.A. However in contrast to Lusk et al. (2006) I provide no information about the use of antibiotics in food production to the respondents before the choice experiment, and I test the respondent's knowledge level directly and estimate its effect on willingness–to–pay. I essentially capture the respondent's preferences for antibiotic–free goods by providing no information, and by asking questions further in the survey about antibiotic use and resistance, I am able to test directly whether the respondent's knowledge had any effect on the choices made.

The remainder of this paper is organised as follows. In Section 3.2, I highlight the previous literature on willingness–to–pay, the effect of knowledge, and the Contingent Valuation Method. In Section 3.3, I describe the survey instrument, how I calculate willingness–to–pay, and provide summary statistics. I detail the interval and OLS regression techniques in Section 3.4 and report the resulting estimates in Section 3.5. In Section 3.6, I test the robustness of the main results, and present final remarks in

Section 3.7.

3.2 Literature Review

Willingness–to–pay can be estimated from existing markets using the revealed prefer-
ences method, or from hypothetical markets using the stated preferences method such as
the Contingent Valuation Method, and Choice Experiment. There are three approaches
to Contingent Valuation Method: open–ended, sequential bids and closed–ended ques-
tions. The sequential bid approach, applied in this paper, asks an individual if he/she
would pay some given amount for an improvement in some good followed by a second
question with another dollar amount, higher or lower depending on the response to
the first question (Hanemann et al., 1991; Alberini, 1995; Scarpa and Bateman, 2000).
This double–bounded method to estimate willingness–to–pay is utilised by Hutchinson
et al. (2001); Jin et al. (2006); Cairns and van der Pol (2000). Less prevalent is the
repeated follow–up method, an extension of the double-bounded method. The high-
est bounded method used in the willingness–to–pay literature is triple–bounded used
in Scarpa and Bateman (2000). However, there is no one set rule to determining the
number of bounds to use. Scott et al. (2003) notes that usually, people are presented
with additional follow-up choices until an indifference point is identified.

One or a combination of these methods are often used to determine the willingness–to–pay
for the valuation of environmental resources including clean air, food and water safety,
and reduction in waiting times for health services (Dupont, 2004; Bateman, 1996; Huang
et al., 2018; Andersson et al., 2016; Bishai and Lang, 2000). There is also a sizeable
literature that explores the willingness–to–pay for organic products, which is in some
way similar to antibiotic–free goods. Some of these studies finds that an increase in
consumer knowledge results in an increase in the willingness–to–pay for these healthier
food alternatives (Bonti-Ankomah and Yiridoe, 2006; Díaz et al., 2012; Owusu and
Owusu Anifori, 2013).

The literature on willingness–to–pay for antibiotic free products on the other hand is
relatively scarce, limited to two studies Lusk et al. (2006) and Lusk et al. (2007). Lusk
et al. (2007) investigates the effect of altruism and free riding on demand for pork chops
with public good attributes including certified free of antibiotic.[20] The results indicate

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[20]Lusk et al. (2007) defines altruism as the extent to which an individual derives satisfaction from

a negative willingness–to–pay which is interpreted as some people preferring the use of sub-therapeutic antibiotics because this keeps animals healthy and promotes animal welfare.

Lusk et al. (2006) takes a more detailed look at the topic using a Choice Experiment to estimate consumers' willingness–to–pay for pork produced without sub–therapeutic antibiotics (antibiotics used indiscriminately), and consumers' willingness to contribute to a reduction in antibiotic resistance. The respondents were randomly given information sheets on the use of antibiotics from the WHO, or the industry, or were given no information.[21] After reading the information they were asked to choose between one free antibiotic–friendly product and one free regular product plus a coupon for $X off their total grocery bill, or a coupon for $X+ $Y off their total grocery bill.[22] His estimates indicate that on average, willingness–to–pay for antibiotic-friendly product over regular product was US$1.86 per choice, a 76.7% premium for antibiotic–friendly product over regular product. Lusk et al. (2006) notes that while the premium seems high it may be due to low knowledge levels as there is very little evidence to suggest that consumers in the U.S.A. know that most pork is produced with subtherapeutic antibiotics.

There are two key differences between this study and the previous in the willingness–to–pay for antibiotic–free food literature. First, unlike Lusk et al. (2006), the respondents were not provided any information about the use of antibiotics in food production prior to the choice experiment. Lusk et al. (2006) found that the choice behaviour of those with no information was similar to those with some information. This was attributed to either the consumers having strong 'priors' or that the underlying message for all the information groups was that the antibiotic use in pig production may be harmful to human health. This leads to the second key difference, I directly estimate the effect of knowledge on WTP. While, Lusk et al. (2006) identifies the need to estimate the effect of consumers' knowledge on willingness–to–pay, this was not done. The consumers may have had 'priors' resulting in similar choice regardless of the information provided however, there was no direct measure for what the consumers knew

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the utility of others and free-riding is the extent to which an individual is a purely selfish utility maximizer.

[21]Specifically, the WHO perspective compiled using information from the National Academy of Science (National Research Council 1999) and World Health Organization (2002), and the industry perspective compiled in consultation with representatives from pork producer organizations.

[22]Antibiotic–friendly refers to products from pigs that were only administered antibiotics when the animal was sick.

prior to participation in the survey.

This paper contributes by filling the gap in the literature. I estimate the effect of consumer knowledge and perception about antibiotics and antibiotic resistance on willingness–to–pay for antibiotic free food. By providing no information to the respondents before the choice experiment, I essentially capture the respondent's preferences for antibiotic–free goods. Additionally, using responses from the knowledge section of the survey—which is done after the choice experiment—I test directly whether knowledge had any effect on the choices made. Furthermore this is first study to estimate the willingness–to–pay for antibiotic free products in the UK.

3.3   Data Description

Given the absence of a secondary data source containing information on willingness–to–pay and knowledge about antibiotic use and resistance, I designed a survey instrument to collect primary data. The survey was designed to collect data from a representative sample of the UK population as such a survey company was approached to conduct the survey. I applied for both ethical approval and funding from the University of Leicester prior to disseminating the survey. Once ethical approval was granted, funding for the survey was sought and received from the College of Social Science Research Development Fund.[23] The sample size was entirely determined by the funding received, with the funding only 500 persons could have been recruited for the survey. However, at the end of the survey I received 23 extra responses at no extra cost.

Given the limitations of funding, the pilot study was conducted using a convenience sample. The survey was developed on an online platform, which was used to conduct the pilot testing. In total the pilot testing was done by 10 persons who were other PhD students, as well as some Economics and Science faculty members. Persons who agreed to assist with the testing were provided with a link to survey which they completed online and then shared their feedback on the survey. No preliminary econometric analysis was conducted with the data from the pilot testing, the purpose of the testing was

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[23]Ethical approval was granted by the Chair of the University Ethics Sub-Committee of School of Business Dr. Chris Grocott in June 2019, Ethics Reference: 20851-mmw18-ss/bu:economics. The funding totalled £2000 and the survey company charged £4 per person to disseminate the survey, therefore the sample size would be 500.

to ensure that the choice experiment and the knowledge questions were sound and in no way misleading. The survey instrument was edited after these tests were completed based on the feedback from the sessions. The notes from the sessions were written and used to update the instrument. One of the changes made following the focus group was for example, asking persons to rank the proteins instead of choosing the most often purchased.[24]

Once the survey instrument was finalised, the survey company was employed to recruit respondents and deploy the survey online. There was no pilot testing of the current instrument however, the administration of the survey in October 2019 included a soft launch, that is, the survey was launched and a fraction of the data was collected (30 responses) then the survey was paused for analysis. As no problems were found with the data from the soft launch, the data collection resumed until the full sample was collected. This resulted in 523 respondents, all of whom are U.K. residents aged $25 - 50$.[25]

The survey consists of three distinct sections, the demographic information, the choice experiment, and the knowledge section. These sections were not randomised for a few reasons. Firstly, since there was an age criteria, the Demographic information was collected first. Furthermore, the survey company indicated that research and experience show that demographic questions enhance data quality when they are at the beginning of the survey. Secondly, the method and research question required that the Choice Experiment is done before the Knowledge Section to ensure validity of the responses from choice experiment. The knowledge questions had information that could have influence the choices made such as Question 137 "Which of the following is true about the use of antibiotics in food production (such as poultry, beef, swine, fish and crop)?" with responses like: "Antibiotics are used to enhance growth." and "The same antibiotics used in humans are also used in food production." (see Appendix 3.A for the survey instrument). This question could signal to the respondent that these responses are true and therefore influence their willingness–to–pay. As such, it was important that the Choice Experiment be done before the Knowledge section so that the respondent's current knowledge and preferences are what drive the choices made. Each of the survey sections is discussed below.

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[24]None of the changes made here required any updates to the ethics committee or further approval being sought.

[25]I chose to restrict the age to $25 - 50$ because I wanted the respondents to be persons who most likely did their own shopping and I believe this age group best captures that population.

3.3.1 Socio–demographic Statistics

Table 3.1 summarizes the descriptive statistics of the 523 UK residents who completed the survey in October 2019. While the age group is restricted, the sample is otherwise representative of the UK population. The age was restricted to $25 - 50$ years old, as such the average age of the respondents 37 years. Males constitute 46.3% of the sample and the largest ethnic group, White constitutes 88.9%. More than 80% of the sample reside in England with the regions South East and London having the highest number of respondents while North East and Yorkshire and the Humber have the least. Only 45.7% of the sample has higher education as their highest level of education while the remaining 54.5% has GCSE or A–Levels as the highest level of education.

3.3.2 The Choice Experiment

The choice experiment is best described as a sequential bid Contingent Valuation Experiment with up to six rounds of bidding. Going forward, this will be referred to as *the Experiment.* The experiment proceeds as follows. First, respondents rank three sets of proteins—chicken, seafood, and legumes—by frequency of purchase (1 being most purchased). This ranking is used to frame the experiment. For each respondent, the experiment is run with two frames, the most commonly purchased protein (*Frame 1*) and the least commonly purchased protein (*Frame 2*). I use these two frames to test whether willingness–to–pay varies both by protein of choice and by the frequency of purchase. The frames are expected to provide some information about individual preferences, as it may be the case that persons care more about antibiotic use in the foods they consume the most but may be less concerned about its use in foods they consume the least.

Each frame starts by presenting the subject with a hypothetical context in which the choices are to be made, for example:

> *This section of the survey comprises questions exploring whether antibiotic use in poultry production affects the demand for chicken.*

> *In this hypothetical situation there are two farmers producing chicken. The first farmer uses antibiotics to treat and prevent diseases. The second farmer*

does not use antibiotics in chicken production, utilising organic methods instead. Your local supermarket sells both types of chicken and labels the second type Antibiotic free. Both types of chicken are safe for consumption.

For each of the following questions, please carefully consider each option and indicate your choice. Even though this is a hypothetical situation, it is important that you make your selections as you would if you were facing these choices in your retail purchase decisions. Therefore, allocating funds to the purchase of any of these products means there will be less money available for other goods. Please note that the objective of this research is to learn about decision making, it is not meant to persuade your decisions in any way.

For each frame, the respondent is presented with up to six choice *Scenarios*. Each choice scenario consists of 2 options of the good: a regular option, a good not specifically labelled as antibiotic–free (*Option 1*), and the antibiotic–free option (*Option 2*). Options are described by price, special label, and the use of antibiotics (see Table 3.2 for further information and Table 3.3 for the initial scenario in the chickpeas frame). Scenarios within a frame differ only in variation of the relative price between Option 1 and Option 2. The price is varied in such a way that a price threshold can be established where the respondent changes their choice from the no–label option to the antibiotic–free option (or vice versa).

The initial scenario within a frame is the same for all respondents. The subsequent scenarios depend on the option each respondent chooses. If Option 1 is chosen in the initial scenario, then subsequent scenario has a lower relative price as the price of Option 1 increases while Option 2's price is unchanged. The Frame ends whenever the respondent chooses Option 3.[26] Figure 3.B.1 presents the experiment Frame for a respondent who never chooses Option 3 in the first 5 scenarios.

The price for Option 1 in the initial scenario is based on the actual price of the corresponding product during February 2018. Using mySupermarket, I collected the price

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[26]In the survey design, whenever a respondent chooses Option 3 they receive a final choice scenario (except the case where Option 3 is chosen in the sixth scenario). The final choice scenario is designed to keep the relative price constant at the previous level. Given that the focus here is on the relative price, this final choice scenario does not add any new information and therefore is not used in this paper. If the nominal prices were used to inform the willingness to pay then this final choice scenario would be relevant.

for the products selected from major supermarkets over a one month period.[27] For ease of comparison, only the supermarkets that sold the product of the same weight were included in the comparison. The median price at the end of the month was used as the initial price for Option 1. The initial price of the antibiotic–free product was set $20\% - 65\%$ higher than the regular good, depending on the product. Each additional price level was $20\% - 25\%$ higher than the previous price to provide a unique relative price for each question. The highest price for each option is a 100% increase of the initial price.

The data from the ranking of the proteins at the beginning of the choice experiment shows that chicken is the most common purchase among the respondents while chickpeas is the least common (see Table 3.4). In Frame 1, approximately 76% of the respondents identified chicken as the most frequent purchase, while only 18% indicated it as their least frequent purchase. Of the proteins least purchased (Frame 2), chickpeas is the most common as it is selected by 47% of the respondents. The chicken frame therefore has the largest number of respondents in Frame 1 and the chickpeas frame in Frame 2.

3.3.3 Calculating Willingness–to–Pay

I define each respondent's willingness–to–pay (WTP_i) for the antibiotic–free option as the maximum relative price (RP) for which they select Option 2 in each frame. Relative price is calculated as the ratio of the Option 2 price to Option 1 price for a given scenario. With an infinite number of scenarios in continuous increments of RP, the calculation of willingness–to–pay would be straightforward. However, there are no more than six scenarios, in discrete increments, from which we can gather information. For this reason I consider my calculations to provide bounds on the true willingness-to-pay. Here I explain the bounds in three cases, upper, lower, and interior bounds.

1. An upper bound is calculated in cases where the respondent never selects Option 2. This suggests that valuation of the antibiotic–free option lies below the lowest relative price the respondent faced, RP_{min}. Since no lower bound is observed, I set the lower bound equal to 0. In this case, for respondent i, $WTP_i = [0, RP_{min})$

2. A lower bound is calculated when the respondent only chooses Option 2 or chooses Option 2 at the highest relative price in the Frame. In this case the respondent's valuation of the antibiotic–free good is at least the highest relative price they faced, RP_{max}. Therefore for respondent i, $WTP_i = [RP_{max}, \infty)$.

3. Interior bounds are calculated for the cases where the respondent switches from Option 2 at least once. The lower bound is defined as the highest observed relative price at which Option 2 is chosen (RP_{k-1}). The upper bound ($= RP_k$) is the next highest relative price at which the respondent indicated an unwillingness–to–pay for Option 2. In this case for respondent i, $WTP_i = [RP_{k-1}, RP_k)$, where $RP_{min} < RP_{k-1} < RP_k \leq RP_{max}$.[28]

For the analysis I will be using OLS estimation which requires a point estimate for WTP_i, as such I need to replace the unobservable bounds with a measurable value. As indicated before, in the case where the respondent never chooses Option 2, I set the lower bound equal to 0. For the case where only Option 2 is chosen I consider two alternatives: (1) setting WTP_i equal to the lower bound, and (2) using the relative price from a hypothetical 7th choice scenario as the upper bound. By setting, the WTP_i equal to the lower bound, the assumption is that the highest relative price in the frame (RP_{max}) is the respondent's willingness–to–pay for the antibiotic–free option. While this is a feasible assumption, some respondents may have a higher valuation. As such, I created a hypothetical 7th choice scenario for the individuals who only choose Option 2. The new choice scenario consists of the initial price Option 1 and the price for Option 2 increasing the corresponding base price for the antibiotic–good by 120%.[29] The relative price from this choice scenario is used as the upper bound. There is a special case where there is no upper bound but the respondent chooses Option 1 as well. In this case, the upper bound RP_k, is selected from the other relative prices in the frame.

The observed willingness–to–pay falls into 3 data categories: left–censored (no lower bound is observed); right–censored (no upper bound is observed); and interval censored (see Table 3.5). Majority of the willingness–to–pay observations is interval data in both frames. For Frame 2 a larger number of the observations are left–censored which suggests that the respondents are less likely to select Option 2 for the protein they

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[28]Notice that the upper bound is never truly observed in this case, I can only conclude that the upper bound is less than the observed maximum.

[29]This is consistent with each additional price level being $20\% - 25\%$ higher than the previous price to provide a unique RPs.

consume the least (see Table 3.5 for more information and Table 3.C.1 for a breakdown by protein).

One of the key indicators of the reliability of willingness–to–pay data is the bounds (the number of bids or questions used to elicit willingness–to–pay) in a Contingent Valuation experiment. In this case the bounds refer to the number of relative prices used in the calculation of willingness–to–pay. Generally, the higher the number of bounds the more precise the estimated willingness–to–pay.[30] In Table 3.6, I present the number of bounds used in calculating the willingness–to–pay (for the number of bounds by protein see Table 3.C.2). Over 90% of the estimates are at least double–bounded (2 RPs are used to estimate WTP_i) in Frame 1 and approximately 80% in Frame 2. Of this, majority of the willingness–to–pay estimates results from all 6 relative prices being used (approximately 69% in Frame 1 and 60% in Frame 2).

Table 3.7 depicts a summary of the willingness–to–pay estimates using the interval midpoint as a proxy for the true willingness–to–pay. The estimates in Frame 1 are extremely close. On average using only the observed values, respondents are willing to pay 57% more for the antibiotic–free option compared to the regular option. When a lower bound of 0 is imposed and using the lower bound as the WTP_i estimate when only Option 2 is chosen, the average the willingness–to–pay for antibiotic–free product remains the same. Finally using a 7th choice scenario results in a slight increase in the willingness–to–pay to 58% above the price of the regular product.

In Frame 2, using only the observed relative prices, on average respondents are willing to pay 52% more than the price of the regular product for antibiotic–free product. Making assumptions for the unobserved bounds reduces the willingness–to–pay in this frame. The average willingness–to–pay decreases to 47% more than the price of the regular product when a lower bound of 0 is imposed and WTP_i is equal to the lower bound ($WTP_i = LB$) when only Option 2 is chosen. When the upper bound is increased using a 7th choice scenario, the average willingness–to–pay for antibiotic–free good becomes 49% more than the price of the regular option. Overall, respondents are willing to pay more for Option 2 for the protein they purchase most frequently. Notice that on average, the estimated willingness–to–pay is similar to the observed values. This suggests that the methods employed to deal with unobserved bounds are consistent with the observed

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[30]There are discussions in the literature regarding bounds and the efficiency of higher order bounding, this is not addressed here. See Hanemann et al. (1991); Scarpa and Bateman (2000); Alberini (1995) for a discussion on this topic.

data.

The willingness–to–pay summary statistics is presented by product in Table 3.C.3. Antibiotic–free chicken and chickpeas have a higher willingness–to–pay than antibiotic–free sea bass. This could be due to the fact that the nominal price for sea bass is much higher than the price of the other two proteins, or that people are more worried about antibiotics use in chicken than in sea bass.

3.3.4   Knowledge

Knowledge is measured directly through six questions in the survey based on antibiotic use, antibiotic resistance and the use of antibiotics in food production, and indirectly through the respondent's area(s) of work. The survey tests whether the respondent has heard of antibiotic resistance and other related terms such as drug resistance and superbugs; whether the respondent knows that antibiotics are only effective against bacterial infection; and knows the use of antibiotics in food production. The questions were drawn from the WHO resources on antimicrobial resistance including a multi-country awareness survey, quizzes, and other topical information, and questions relating to antibiotic use is agriculture were developed from the UK review on antimicrobial resistance.[31]

Each respondent receives a score for the number of correct answers selected in each question, which is then summed to provide the knowledge index, however the overall score presented here ranges from 0 to 1.[32] The survey asks respondents to report if they work in Farming, Food production, and/ or Health care. Only 94 respondents (roughly 18%) worked in at least 1 of these areas. These areas were chosen because they provide a level of exposure to issues related to antibiotic use and resistance.

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[31]The sources are: The WHO Antibiotic Resistance: Multi-Country Public Awareness Survey https://www.who.int/news/item/16-11-2015-who-multi-country-survey-reveals-widespread-public-misunderstanding-about-antibiotic-resistance, WHO Quiz: How much do you know about antibiotic resistance? (this has been removed from the website); the Antimicrobial and Antibiotic Resistance from the WHO health Topics pages https://www.who.int/health-topics/antimicrobial-resistance; and the UK's review on antimicrobial resistance report: Antimicrobials in Agriculture and the Environment: Reducing Unnecessary use and Waste https://amr-review.org/Publications.html

[32]For the six questions, the maximum scores are as follows: (1) 1 for *Knows the impact of antibiotic resistance; Knows antibiotics treat bacterial infections; and Knows illnesses treated by antibiotics*; (2) 2 for *Knows common antibiotics*; (3) 4 for *Knows the use of antibiotics in food production*; and 5 for *Heard of antibiotic resistance or any related terms*. Therefore the knowledge index has a maximum score of 15.

Table 3.8 presents a summary of the respondents' knowledge level and gives a breakdown by field of work. In Panel (A) I depict the percentage of the population having at least some level of knowledge for each area (identifying at least 1 correct answer for each question where applicable), as well as the percentage identifying all the correct answers. Panel (B) contains the average score across the sample for each question and the average knowledge index. Majority of the respondents (87.5%) heard of antibiotic resistance or one of the related terms. One of the key knowledge variables is the use of antibiotics in food production. Of the sample, 80% knows at least one use of antibiotics in food production, however, only 1.3% could identify all the uses (Table 3.8 Panel A). As such, the respondents scored 27% on average for this question.

In terms of the average score, overall, knowledge levels are below average (respondents receive below 50%) in all areas except the respondents knowledge about antibiotics treating bacterial infection (see Table 3.8 Panel B). Knowledge by work fields gives a different picture. Knowledge is below average in all areas for respondents working in Farming and Food production (this relationship holds even when I control for individual characteristics such as education). This goes against the expectation that these respondents would know the use of antibiotics in food production. Respondents working in the Health care sector, show above average knowledge in one area, identifying some illnesses that can be treated with antibiotics. Overall the knowledge index is slightly higher for respondents who work in the healthcare sector compared to the other sectors.

3.4   Econometric Model

I assume that each respondent's willingness–to–pay for the antibiotic free good is determined by:

$$WTP_i^* = \boldsymbol{x_i'\beta} + \varepsilon_i \qquad (3.4.1)$$

where $E(\varepsilon_i \mid \boldsymbol{x_i}) = 0; Var(\varepsilon_i \mid \boldsymbol{x_i}) = \sigma^2,$

WTP_i^* is the unobserved willingness–to–pay for individual i, for which only the interval bounds containing it is observed using the responses given in the Experiment. As

such the intervals are completely exogenously determined. $\boldsymbol{x_i}$ is a vector of individual characteristics, $\boldsymbol{\beta}$ is a vector of coefficients to be estimated, and ε_i is the error term which is assumed to have zero conditional mean. For simplicity I also assume constant variance, $Var(\varepsilon_i \mid \boldsymbol{x_i}) = \sigma^2$, and in practice I use robust standard errors.

I assume that each respondent has a single willingness–to–pay value, and that the responses to the initial and follow–up questions are driven by this single value. I estimate Equation 3.4.1 using two methods: maximum likelihood estimation (MLE) using Interval Regression, and OLS estimation. The rationale for using each of these methods as well as the assumptions made in each are discussed below.

Interval Regression

Interval regression is apt to estimate Equation 3.4.1 as it can fit models for data where each observation is either censored, as is the case in this paper (see Table 3.5), or is a point estimate (see Colombo et al., 2009).[33] The single WTP value assumption makes the interval regression more appropriate than other bivariate binary response models such as probit.[34] Other advantages of using interval regression is that the estimates are easily interpreted compared to tobit or probit estimates and perhaps most importantly, there is no need to make any assumption about the unobserved bounds for the WTP unlike the OLS case.

I assume normality of the error term, $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$, to get consistent $\boldsymbol{\beta}$ estimates for Equation 3.4.1. The conditional distribution of the unobserved willingness–to–pay is therefore $WTP_i^* \mid \boldsymbol{x_i} \sim \mathcal{N}(\boldsymbol{x_i\beta}, \sigma^2)$, where $\sigma^2 = Var(y_i \mid \boldsymbol{x_i})$ is assumed independent of $\boldsymbol{x_i}$ (see Wooldridge, 2010). Using the observed data on willingness–to–pay in Section 3.3.3, all the possible realizations of WTP_i^* were divided in K intervals in each frame. The intervals were designed using the relative prices from each choice scenario with the

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[33]Generally, when the data is censored a naïve estimation using OLS would provide inconsistent results (Davidson et al., 1993; Long, 1997). There are two options for estimation: the tobit regression or the interval regression. However, the tobit model can only fit data where the dependent variable is either left–censored, right–censored or both, but not interval censored. Interval regression is a generalisation of the tobit model.

[34]The estimates from interval regression has been found robust even if this assumption is incorrect (see Cameron and Quiggin, 1994; Alberini, 1995, for a detailed discussion).

boundaries being RP_k, $k = 0, 1, ..., K$. $WTP_i = k$ is observed if

$$RP_{k-1} \leq WTP_i^* < RP_k$$

and probability that WTP_i^* falls into the kth interval is

$$P(WTP_i = k \mid \boldsymbol{x_i}) = P(RP_{k-1} \leq WTP_i^* < RP_k \mid \boldsymbol{x_i})$$

$$= P(RP_{k-1} - \boldsymbol{x_i}\boldsymbol{\beta} \leq \varepsilon_i < RP_k - \boldsymbol{x_i}\boldsymbol{\beta})$$

$$= \Phi\left(\frac{RP_k - \boldsymbol{x_i}\boldsymbol{\beta}}{\sigma}\right) - \Phi\left(\frac{RP_{k-1} - \boldsymbol{x_i}\boldsymbol{\beta}}{\sigma}\right)$$

where Φ denotes the standard normal distribution function.

The probability that WTP_i^* is left censored, that is falls in the 1st interval, is:

$$P(WTP_i = 1 \mid \boldsymbol{x_i}) = P(WTP_i^* < RP_1 \mid \boldsymbol{x_i})$$

$$= P(WTP_i^* - \boldsymbol{x_i}\boldsymbol{\beta} < RP_1 - \boldsymbol{x_i}\boldsymbol{\beta})$$

$$= \Phi\left(\frac{RP_1 - \boldsymbol{x_i}\boldsymbol{\beta}}{\sigma}\right)$$

For right censored observations, the probability that WTP_i^* falls in the Kth interval is:

$$P(WTP_i = K \mid \boldsymbol{x_i}) = P(RP_{K-1} \leq WTP_i^* \mid \boldsymbol{x_i})$$

$$= P(RP_{K-1} - \boldsymbol{x_i}\boldsymbol{\beta} \leq WTP_i^* - \boldsymbol{x_i}\boldsymbol{\beta})$$

$$= 1 - \Phi\left(\frac{RP_{K-1} - \boldsymbol{x_i}\boldsymbol{\beta}}{\sigma}\right)$$

The log likelihood function is:

$$\mathcal{L}(\beta;\sigma) = \sum_{i=1}^{n}\sum_{k}\left\{\mathbb{1}(RP_{k-1} \leq WTP_i^* < RP_k)\log\left[\Phi\left(\frac{RP_k - x_i\beta}{\sigma}\right) - \Phi\left(\frac{RP_{k-1} - x_i\beta}{\sigma}\right)\right] + \right.$$

$$(3.4.2)$$

$$\left.\mathbb{1}(WTP_i^* < RP_1)\log\Phi\left(\frac{RP_1 - x_i\beta}{\sigma}\right) + \mathbb{1}(RP_{K-1} \leq WTP_i^*)\log\left[1 - \Phi\left(\frac{RP_{k-1} - x_i\beta}{\sigma}\right)\right]\right\}$$

where $\mathbb{1}(\cdot)$ is an indicator function which is equal to 1 where the argument in brackets is true and 0 otherwise. Maximum likelihood estimates for β and σ are found by maximizing Equation 3.4.2 using interval regression with robust standard errors.

Using this method, I estimate the effect of knowledge on willingness–to–pay for individual i in each frame with the following equation:

$$WTP_i^* = \beta_0 + \beta_1 Knowledge_i + \tilde{x}_i'\gamma + \varepsilon_i \qquad (3.4.3)$$

where $(\varepsilon_i \mid Knowledge_i, \tilde{x}_i) \sim \mathcal{N}(0, \sigma^2)$

and $Knowledge_i$, the variable of interest, is the knowledge index for individual i calculated as the sum of the correct answers given in the Perceptions on Antibiotic Resistance section of the survey (see Section 3.3.4) which is then standardized. I also control for other individual characteristics in $\tilde{x}_i$ including age, highest level of education, ethnicity, household income, and protein choice. In order to identify β_1, $Knowlege_i$ and the other controls $\tilde{x}_i$, are assumed to be uncorrelated with the error term ε_i.

Additionally, I perform the estimation in Equation 3.4.3 controlling for the respondent's field of work using a binary variable $Work_i$ which is 1 if the respondent works in farming, food production and/ or health care.

Linear Regression

If each respondent's true willingness–to–pay was observable then OLS could be used to estimate Equation 3.4.1. However, given that it is unobserved, in order to estimate

Equation 3.4.1 using OLS I assume WTP_i^* is equal to the midpoint of the interval $[RP_{k-1}, RP_k]$. I recognize that using the midpoints may produce biased estimates however, since the intervals used in this paper are sufficiently fine/ small this minimizes the potential bias (see Cameron, 1987; Cameron and Huppert, 1989).[35] The main advantage of using OLS is there is no need to make a functional assumption about the error term. To address observations in the tails, I assume that the unobserved lower bound is 0 and define the upper bound using the relative prices in the Frame or a hypothetical 7th choice scenario as described in Section 3.3.3.[36]

Using these adjustments I estimate the effect of knowledge on willingness–to–pay for the antibiotic–free good as follows:

$$WTP_i = \beta_0 + \beta_1 Knowledge_i + \tilde{\boldsymbol{x}}_{\boldsymbol{i}}'\boldsymbol{\gamma} + v_i \tag{3.4.4}$$

where $v_i = \varepsilon_i + (WTP_i^* - WTP_i)$,

and WTP_i is individual $i's$ willingness–to–pay in each Frame calculated as the midpoint of the interval containing WTP_i^*. The error term v_i captures the true error term ε_i and the measurement error which results from using the midpoint as a proxy for WTP_i^*. Identification of β_1 now requires two error assumptions. First, as in the interval regression case, $Knowledge_i$ is assumed to be uncorrelated with the true error term ε_i. Second, I assume that the $Knowledge$ is also uncorrelated with the error introduced by using the midpoint as a proxy for the unobserved willingness to pay $(WTP_i^* - WTPi)$. The same assumptions are made for the other regressors $\tilde{\boldsymbol{x}}_{\boldsymbol{i}}$. As with the interval regression, I also estimate the marginal effect of $Knowledge_i$ controlling for the individual's field of work.

The direction of the effect of $Knowledge$ on willingness–to–pay depends on the be-

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[35]There is no standard definition in the literature for what 'sufficiently fine/small' means. However, Cameron (1987) and Cameron and Huppert (1989) included intervals that were classified as fine, these intervals are: $0 - 5, 5 - 10$ etc in Cameron and Huppert (1989) and $< 3000, 3000 - 3999, 4000 - 4999$ etc in Cameron (1987). The intervals used in this paper are much smaller, using Figure 3.B.1 these are as small as $1.70 - 1.71$ and the bigger intervals are $1.47 - 1.83$ and $2.64 - 2.93$, therefore I can say that the intervals used here are sufficiently fine/small.

[36]The assumptions made about the respondent's true WTP is the main disadvantage of using this method. For interval censored data, assuming the WTP is equal to the midpoint may provide biased estimates as the true WTP may fall in the tails, however, given that the intervals used in my work is fine this potential bias is significantly reduced.

haviour of the respondents who are less knowledgeable. A positive β_1 indicates that the less knowledgeable respondents have a lower valuation of antibiotic–free goods as they are unaware of the threat of antibiotic resistance. It is also possible that respondents who are less knowledgeable perceive antibiotic resistance as a much bigger problem than it is and therefore have a higher WTP_i. Respondents who work in Health care, Farming and/ or Food production are expected to be more exposed to information about antibiotics and resistance than those who work in other fields. Therefore the inclusion of $Work$ in the regression could also yield a positive or negative coefficient. It may be the case that these respondents know that the problem is not a large one and therefore have a lower WTP_i using similar arguments.

3.5 Results

In Table 3.9, I present the results for the effect of individual characteristics on willingness–to–pay. Willingness–to–pay is defined as the price of the antibiotic free option over the price of the regular option (the incremental value for the antibiotic free good). My preferred estimation method is the MLE using interval regression. The results for OLS are very similar as such I will discuss the interval regression estimates throughout as it is the preferred method for fitting censored data (see section 3.4 for more information).

The estimates show that knowledge has a positive effect on willingness–to–pay in both frames however the effect is only significant for Frame 1. In Frame 1, using the base specification presented in Column 1, the results indicate that a one standard deviation increase in *Knowledge* increases the *WTP* for the antibiotic free good by £0.080. In Column 3, I estimate the effect of *Knowledge* with the added control *Work*. *Work* is a binary variable which takes a value of 1 for respondents working in: farming, food production and/or health care. In this specification we see a small increase in the effect of *Knowledge*. This indicates that when we account for the effect of work fields, the willingness to pay for the antibiotic free option increases by £0.085 for each standard deviation increase in *Knowledge*. As it relates to the sectors identified, the incremental value for the antibiotic free option is 0.334 higher for the respondents working in those fields compared to all other fields.

For Frame 2, *Knowledge* is non–significant in both specifications and the effect is smaller than in Frame 1. Using the base specification, a one standard deviation increase in

Knowledge increases the *WTP* for antibiotic free good by £0.051. When *Work* is included, the estimate for *Knowledge* increases to £0.056. The effect of *Work* is dampened compared to Frame 1. Respondents who work in farming, food production and/or health care are willing to pay 0.188 more than those who work in neither of those fields.

This result of a positive effect of knowledge is consistent with the literature on organic products. Díaz et al. (2012) found that the maximum willingness–to–pay for organic tomatoes was slightly higher among informed consumers. Owusu and Owusu Anifori (2013) report that consumer awareness of chemical residues in conventional food products has a significant positive effect on their willingness–to–pay premiums for organic lettuce and watermelon compared to conventional watermelon and lettuce.

The results in Table 3.9 indicate that women have a higher willingness–to–pay than men in all specifications for both frames, but the effect is only significant for Frame 1. In Frame 1 using the base specification, I find that the willingness–to–pay for the antibiotic–free good for men is 0.204 less than women (Column 1). When I include the added control for field of work, I find that men are willing to pay 0.219 less than women for the antibiotic free good (Column 3). Other studies have also shown that women are more willing to pay higher premiums for safe foods (Owusu and Owusu Anifori, 2013; Williams and Hammitt, 2001). Some studies have found that women have a higher risk perception than men for food safety hazards and are more concerned with health, nourishment, and the environment (Williams and Hammitt, 2001; Ureña et al., 2008). Furthermore, being the primary grocery shoppers in most households, women would have more knowledge about food safety and various farming practices.[37] On the contrary, Haghiri et al. (2009) and Wandel and Bugge (1997) found that men have a higher willingness to pay.

I also find a significant effect of education on willingness–to–pay in both frames. Specifically, respondents with higher education have a higher willingness–to–pay than those with lower levels of education. Of the education variables included, only *A levels* is significant in Frame 1. The estimates show that respondents with *A levels* are willing to pay an increment of 0.220 less than those with higher education, using the base specification (Column 1). The willingness–to–pay for the antibiotic free good is 0.211 less for respondents with *A levels* compared to those with higher education, when I add the

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[37]Bonti-Ankomah and Yiridoe (2006), Williams and Hammitt (2001), and Díaz et al. (2012) have indicated that women are the primary grocery shoppers either directly or by sampling only primary grocery shoppers and the sample contains a higher proportion of women than men.

control for work areas (Column 3). In Frame 2, *A levels* is non–significant but *GCSE* becomes significant in both specifications. The willingness to pay for GCSE holders is 0.224 and 0.174 lower than those with higher education, in the base specification and the specification with work areas included as a control.

This education effect is also present in the literature. Studies such as Owusu and Owusu Anifori (2013) and Magnusson and Cranfield (2005), have found that higher educated customers are more likely to purchase foods produced in an environmentally sound manner such as organic food, and pay more for these products. The argument being that higher educated consumers tend to understand issues regarding consumption of chemically free food better than other consumers (Haghiri et al., 2009). This argument easily extends to the issue of antibiotic use in food production.

In terms of the specific proteins used in the experiment, I find that the willingness–to–pay for chicken is higher than both fish and chickpeas. However, only the fish framing has a significant effect on willingness–to–pay in both frames. Respondents are willing to pay an increment of 0.395 less for antibiotic–free fish than antibiotic–free chicken. This incremental value increases to 0.429 less than the price for antibiotic free chicken when I control for work areas. In Frame 2, the willingness to pay for antibiotic–free fish is 0.687 and 0.683 lower than antibiotic–free chicken, for the base specification and the addition of *Work*, respectively. It is not surprising that there is product differentiation in willingness to pay as Rodriguez et al. (2008) and Magnusson and Cranfield (2005) also find that willingness–to–pay varies by product.

There is no significant effect of age, ethnicity, or household income on *WTP* in any of the specifications for both frames. This is not an anomaly as other studies have also found no significant effect of age and that the household income effect on *WTP* is small and/ or not statistically significant (see Goldman and Clancy, 1991; Buzby and Skees, 1994; Darby et al., 2008).

Overall, the estimates of both regression methods are close which suggests that the midpoint technique used for OLS is close to the true WTP_i^*. My preferred specification for explaining the effect of *Knowledge* on the respondent's true willingness to pay, WTP_i^* is presented Columns 3 and 7 of Table 3.9. This specification includes work areas as added controls as these provide an insight into the issues surrounding antibiotic use and resistance, and into food safety and production. These issues influence willingness–to–pay, therefore it is important to include in the regression analysis. Given

that *Work* is also correlated with *Knowledge*, including *Work* could introduce multi–collinearity. However, we can rule that out since the standard error for the knowledge coefficient did not change between the two specifications.

To summarize, my main result is that knowledge has a positive effect on willingness–to–pay, which is significant for Frame 1. Using the preferred specification, for Frame 1, the willingness–to–pay for the antibiotic–free good increases by £0.085 for each standard deviation increase in *Knowledge*. For Frame 2, the increase in willingness–to–pay for the antibiotic–free good in response to a one standard deviation increase in *Knowledge* is £0.056, however *Knowledge* is not a significant determining factor for changes in willingness–to–pay. As mentioned before, this positive effect is consistent with the literature which explores knowledge/ consumer awareness on organic products.

3.6   Robustness Checks

To test the robustness of the interval regression estimates in the main results (Table 3.9), I report several estimates in Table 3.10 and Table 3.11 corresponding to changes in the preferred specification.

In Column 1 of Tables 3.10 and 3.11, I present the preferred specification. I redefine household income using dummy variables for each household income group in Column 2. I replace the work dummy variable with dummies for each work area in Column 3. The knowledge variable is redefined in Columns $4-7$ using various dummy variables, key knowledge variables and a principal component analysis index.

Starting with Frame 1, *Knowledge* remains significant though slightly lower when the household income groups: below $10,000$, £$10,001-$£$20,000$, £$20,001-$£$30,000$ are included, and over £$40,000$ is excluded (Column 2). When work areas are included (Column 3), *Knowledge* remains significant but reduces slightly compared to the preferred specification (Column 1). Of the work areas included, only *Health care* is significant, those who work in the health care sector are willing to pay 0.360 more than those who do not, to avoid the use of antibiotics in the food they consume.

In Column 4 two knowledge dummy variables are included, below average knowledge (=1 if knowledge is $< 50\%$), and average knowledge (=1 if $50\% \leq knowledge < 70\%$),

while above average knowledge (=1 if knowledge> 70%) is excluded. Only below average knowledge is significant. Respondents with below average knowledge are willing to pay 0.238 less than those with above average knowledge for antibiotic–free food. I use *Knowledgeable*, a dummy variable which is 1 if the respondent has at least average level knowledge (*Knowledge* $\geq 50\%$) in Column 5. In this specification knowledge is not significant in explaining variations in willingness to pay. The result from using these knowledge binary variables is consistent with the positive effect found in the main results, and shows that the higher the level of knowledge the higher the willingness–to–pay.

Column 6 includes the use of the key knowledge variables. These are: (1) knows the impact of antibiotic resistance, (2) knows that antibiotics treat bacterial infections, (3) knows how antibiotics are used in food production. The variables *knows the implication of antibiotic resistance* and *knows antibiotic use in food production* are higher for the respondents who know compared to those who do not. Only *knows antibiotic use in food production* has a significant effect on willingness–to–pay. The respondents who know how antibiotics are used in food production are willing to pay 0.397 more than those who do not to avoid antibiotics use in the food they consume. Interestingly, the respondents who knows antibiotics treat bacterial infection are willing to pay less than those who do not know this.

In Column 7, a standardized knowledge index is created using a Principal Component Analysis (PCA) of all the knowledge variables. This index reports the most important knowledge variable for each individual.[38] The Knowledge PCA index also has significant effect on willingness to pay though slightly smaller than the preferred specification. In this specification, a one standard deviation increase in *Knowledge*, using the PCA index increases willingness–to–pay for the antibiotic–free good by £0.084.

For Frame 2, the effect of *Knowledge* remains unchanged when the household income groups are included individually (Column 2). In Column 3, using the work areas in the regression slightly increases the effect of *Knowledge* compared to the preferred specification (Column 1) though it remains non–significant. In Frame 2, *Farming & Food production* now has a significant effect on willingness–to–pay. Respondents who work in the Farming and or Food Production are willing to pay 0.482 more than those who work in other fields, to avoid the use of antibiotics in the food they consume.

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[38]The index was created using a Principal Component Analysis method developed by Anderson (2008).

Using *Average* and *Below average* knowledge dummies (Column 4) while non–significant, the direction of the effect is as expected. Respondents with average and below average knowledge are willing to pay less than those with above average knowledge to avoid antibiotics use in their food. When *Knowledgeable*, is included (Column 5), the effect of knowledge is stronger than the preferred specification, however it remains non–significant in explaining variations in willingness to pay. The effect of the binary variables is similar to that of Frame 1.

In Column 6, key antibiotic knowledge variables are included the results are similar to Frame 1. As in Frame 1 the variable *knows antibiotic use in food production* has a significant effect on willingness–to–pay. The willingness to pay for respondents who know how antibiotics are used in food production is 0.396 higher than the other respondents. Column 7 presents the results using the Knowledge PCA index, this specification gives a much smaller estimate than the preferred specification.

In addition to the tests done for interval regression, I also test the robustness of the OLS results to changes in the calculation of the willingness–to–pay when the upper bound is unobserved (only Option 2 is chosen). The robustness checks for the OLS estimates are presented in Appendix 3.D. In the preferred specification, I use the relative price from hypothetical 7th choice scenario as the upper bound when only Option 2 is chosen. In Column 2, I use the other option for dealing with unobserved upper bounds, setting WTP_i equal to the lower bound (see Section 3.3.3). The results indicate only a slight decrease in the effect of knowledge in both Frames compared to the preferred specification in Column 1 (see Table 3.D.1 and 3.D.2). Therefore the chosen method to estimate the willingness–to–pay in the presence of unobserved upper bounds does not distort the effect of knowledge on willingness–to–pay. The other robustness checks give similar results as in the interval regression case. The only exception being that *Knowledge* becomes significant in Frame 2 when the work areas are included in the regression (Table 3.D.2, Column 4). For the product least purchased, each standard deviation increase in knowledge increases the willingness–to–pay for the antibiotic–free product by 0.064.

Overall the results are largely unchanged using these alternative specifications. However since the alternative specifications mostly involved including more variables, given the sample size, this suggests that the estimation of the key effect with less power.

3.7   Summary and Concluding Remarks

This paper investigates the effect of knowledge of antibiotic use and resistance on will-ingness to pay for antibiotic free goods. I designed a survey for the study which was disseminated to 523 respondents. Using the survey, I tested the respondents' knowledge levels and conducted a choice experiment using the sequential bid contingent valuation method to estimate willingness to pay. On average, only approximately 34% of the respondents were able to correctly identify the potential impact of antibiotic resistance. The average scores across the knowledge variables are below 50% in almost all areas, including the respondents knowledge of the use of antibiotics in food production. This level is below average for all the work areas specified, however the respondents in the health care sector were slightly more knowledgeable about this issue. This highlights the fact that the issues relating to antibiotic resistance is still largely misunderstood. I find that on average, willingness–to–pay for the antibiotic free product is over 50% more than the price of regular good. A one standard deviation increase in knowledge leads to 0.085 and 0.056 increase in the willingness–to–pay for the protein most purchased and the protein least purchased. This result is fairly robust to changes in the preferred specification.

One of the limitations of this paper is that the sample size is small which may mean that the power of the estimates is low. Generally, a larger sample size would increase the power of the test and provide stronger evidence for whether or not the relationships estimated exist. Another limitation is the measurement of the knowledge index. While I maintain that this overall measure of knowledge provides a good understanding of the respondent's knowledge about antibiotic consumption and resistance, there are other ways the questions could have been weighted, which may have provided a more accurate description of knowledge. For example, low levels of knowledge could be redefined to mean that the respondent has at most heard of one antibiotic resistance related term, or has selected at least one correct answer for each of the knowledge questions. Another option could be to weight the three key knowledge variables included in the robustness checks more than the other three variables. This is due to the fact that being aware of a term does not mean the respondent knows what the term means or its implications.

One limitation of the survey instrument is that the choice experiment does not collect any information about the maximum willingness for respondents. As such the max-imum willingness to pay was estimated making some assumptions. While this was

not a significant issue as only approximately 13% of the sample was right–censored, including an open ended question to collect this data would provide more accurate willingness–to–pay data. A minimum WTP question was not included either but this is trivial as the minimum can be assumed to be 0.

Two main policy implications arise from this study: first there is room for improving public awareness campaigns regarding antibiotic resistance. The low levels of public awareness regarding antibiotic resistance needs to be addressed. Public awareness campaigns may need to be more tailored to addressing the general audience. Second, there is evidence that individuals are concerned about the food they consume. The willingness–to–pay is over 50% higher than the price of the regular good even for the protein identified as the least purchased. This suggests that while knowledge about antibiotics use in food production is low the respondents would still prefer food produced without antibiotics. This may be of interest to agriculture companies or food safety regulators.

This paper serves as evidence that there is a link between consumer knowledge and willingness to pay for antibiotic–free goods. There are two directions that future work on this topic could take. The first route involves utilizing the current dataset. I plan to explore other ways to measure knowledge using the current data, including: using different weights for each question, and measuring different levels of knowledge as discussed above. Additionally, in a future study I will explore the relationship between respondents attitudes towards issues relating to antibiotics and resistance and their willingness–to–pay for antibiotic free goods.

The second route is to rerun the survey which would require further funding. A natural extension of this paper is to replicate it with a larger sample to improve the power of the estimates. I plan to use this study as a concept paper as the findings regarding willingness–to–pay for antibiotic free food are relevant for agricultural and food safety groups, and to some extent public health authorities. The survey could be redesigned to provide data on the possible pricing for future antibiotic–free products, whether people are interested in such products, and the concerns people have with antibiotic resistance and/or its use in the food they consume.

Tables

Table 3.1: Survey Participants Summary Statistics

Variable	Mean	Std. Dev.
Age	37.201	7.401
Male	0.463	0.499
Higher Education	0.457	0.499
Household Income		
below £10,000	0.08	0.272
£10, 001 - £20, 000	0.17	0.376
£20, 001 - £30, 000	0.226	0.418
£30, 001 - £40, 000	0.226	0.418
above £40, 000	0.298	0.458
White	0.889	0.314
Country		
England	0.843	0.364
North East	0.04	0.197
North West	0.115	0.319
Yorkshire and the Humber	0.08	0.272
East Midlands	0.067	0.25
West Midlands	0.092	0.289
East of England	0.092	0.289
London	0.134	0.341
South East	0.145	0.353
South West	0.078	0.269
Wales	0.048	0.213
Scotland	0.082	0.275
Northern Ireland	0.027	0.161
N	**523**	

This table shows the descriptive statistics of the 523 UK residents who completed the survey in October 2019.

Table 3.2: Informational Attributes Used in the Choice Scenarios

Attributes	Number of Levels	Description
Price (Chicken)	17	Price expressed in £per 1kg
Price (Chickpeas)	16	Price expressed in £per 500g
Price (Sea bass)	17	Price expressed in £per 300g
Special Label	2	If special label (Antibiotic–free) is present, organic methods were used in food production instead of antibiotics
Antibiotic Use	2	If used, the use of antibiotics occur frequently for disease treatment and prevention

This table depicts the attributes used to describe each option of the good in presented in each choice scenario.

Table 3.3: Chickpeas Frame Initial Choice Scenario

Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

Table 3.4: Number of Respondents by Experiment Frame and Protein

	Frame 1		Frame 2	
	N	%	N	%
Chicken	385	76.31	95	18.16
Sea bass	55	10.52	181	34.61
Chickpeas	83	15.87	247	47.23
Total	**523**	**100**	**523**	**100**

Table 3.5: Willingness–to–Pay Observations by Data Type and Experiment Frame

Data Type	Frame 1	Frame 2
Left censored $[0, RP_{min})$	86	139
Interval censored $[RP_{k-1}, RP_k)$	367	317
Right censored $[RP_{max}, \infty)$	70	67
N	**523**	

This table shows the willingness–to–pay observations by data type and experiment frame. RP_{min} is the lowest relative price in each Frame, while RP_{max} is the highest. RP_{k-1} is the highest observed relative price at which Option 2 is chosen and RP_k is the next highest relative price at which the respondent indicated an unwillingness–to–pay. I use 0 to represent the unobserved lower bounds and ∞ for the unobserved upper bounds.

Table 3.6: Number of Unique Relative Prices (Bounds) Used in Estimating Willingness–to–Pay

Bounds	Frame 1	Frame 2
1	42	103
2	23	34
3	40	33
4	28	25
5	28	16
6	362	312
N	**523**	

Table 3.7: Willingness–to–Pay Summary Statistics

	Willingness–to–pay	Mean	Std. Dev.	Min.	Max.	N
	Observed Interval Data	1.572	0.554	0.774	2.793	367
Frame 1	*Unobserved UB: $WTP_i = LB$*	1.567	0.763	0.307	3.286	523
	Unobserved UB= RP from 7th CS	1.582	0.790	0.307	3.450	523
	Observed Interval Data	1.518	0.539	0.865	3.121	317
Frame 2	*Unobserved UB: $WTP_i = LB$*	1.470	0.816	0.307	3.286	523
	Unobserved UB= RP from 7th CS	1.487	0.851	0.307	3.450	523

This table provides a summary of the willingness–to–pay estimates, by frame, using the interval midpoint as a proxy for the true willingness–to–pay. I use 0 for unobserved lower bounds, that is the case where Option 2 is not chosen. For the case where only Option 2 is chosen I present two alternatives: (1)$WTP_i = LB$: setting the WTP_i equal to the lower bound, and (2) UB= RP from 7th CS: using the relative price from a hypothetical 7th choice scenario as the upper bound.

Table 3.8: Knowledge Summary Statistics by Field of Work

Variable	All	Farming & Food production	Health care	Neither Field
(A) % of N				
Heard of antibiotic resistance *or* *any* related terms	0.875	0.875	0.892	0.851
Heard of antibiotic resistance *and* *all* related terms	0.057	0.000	0.015	0.068
Knows the impact of antibiotic resistance	0.338	0.156	0.338	0.350
Knows antibiotics treat bacterial infections	0.532	0.313	0.462	0.555
Knows *at least one* use of antibiotics in food production	0.803	0.844	0.862	0.793
Knows *all* the use of antibiotics in food production	0.013	0.000	0.015	0.014
Knows illnesses treated by antibiotics	0.478	0.125	0.523	0.494
Knows *at least* one common antibiotic	0.700	0.406	0.723	0.716
Knows *all* the common antibiotics	0.199	0.125	0.200	0.205
(B) Average Scores				
Heard of antibiotic resistance and related terms	0.437	0.292	0.485	0.441
Knows the impact of antibiotic resistance	0.338	0.156	0.338	0.350
Knows antibiotics treat bacterial infections	0.532	0.313	0.462	0.555
Knows the use of antibiotics in food production	0.271	0.242	0.300	0.269
Knows illnesses treated by antibiotics	0.478	0.125	0.523	0.494
Knows common antibiotics	0.449	0.266	0.462	0.460
Knowledge index	0.397	0.256	0.424	0.403
Std. Dev.	(0.206)	(0.127)	(0.203)	(0.208)
N	**523**	**32**	**65**	**429**

This table shows the Knowledge summary statistics by field of work. Three of the respondents worked in all three fields identified, as such the sample totals do not add up to 523. The variables relate directly to the survey questions. In Panel (A) I present the percentage of the population who identifies at least one correct answer/heard of at least one of the terms. In Panel (B) I present the average knowledge scores for each question, the overall average knowledge score (knowledge index) and its standard deviation.

Table 3.9: Interval and OLS Regression Estimates

	Frame 1				Frame 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Int. Reg	OLS	Int. Reg	OLS	Int. Reg	OLS	Int. Reg	OLS
Knowledge	0.080**	0.080**	0.085**	0.085**	0.051	0.052	0.056	0.055
	(0.040)	(0.035)	(0.040)	(0.035)	(0.045)	(0.037)	(0.045)	(0.037)
Work			0.334***	0.272***			0.188	0.141
			(0.109)	(0.092)			(0.123)	(0.101)
Age	0.003	0.001	0.004	0.002	0.010	0.008	0.010	0.008
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Education (Higher education excluded)								
GCSE	-0.093	-0.066	-0.088	-0.062	-0.228**	-0.176**	-0.224**	-0.174**
	(0.108)	(0.093)	(0.108)	(0.093)	(0.113)	(0.088)	(0.113)	(0.088)
A Levels	-0.220**	-0.188**	-0.211**	-0.183**	-0.052	-0.043	-0.048	-0.040
	(0.093)	(0.081)	(0.092)	(0.079)	(0.109)	(0.089)	(0.108)	(0.089)
Ethnicity (White excluded)								
Mixed	-0.050	-0.058	-0.071	-0.080	-0.220	-0.225	-0.236	-0.237
	(0.197)	(0.169)	(0.203)	(0.176)	(0.235)	(0.176)	(0.235)	(0.177)
Asian	0.199	0.165	0.185	0.149	-0.098	-0.060	-0.112	-0.070
	(0.193)	(0.167)	(0.191)	(0.166)	(0.197)	(0.160)	(0.190)	(0.155)
Black	-0.213	-0.164	-0.265	-0.211	0.105	0.124	0.071	0.099
	(0.187)	(0.180)	(0.167)	(0.166)	(0.165)	(0.159)	(0.152)	(0.148)
Male	-0.204**	-0.178**	-0.219***	-0.190***	-0.037	-0.029	-0.044	-0.035
	(0.083)	(0.072)	(0.082)	(0.071)	(0.091)	(0.074)	(0.091)	(0.074)
Income (Low income ≤ £20,000 excluded)								
Average Income (£20,001 − £40,000)	0.074	0.057	0.076	0.061	0.175	0.135	0.176	0.137
	(0.103)	(0.089)	(0.101)	(0.088)	(0.111)	(0.087)	(0.111)	(0.087)
High Income (over £40,000)	0.024	0.017	0.031	0.024	0.128	0.093	0.131	0.097
	(0.115)	(0.100)	(0.113)	(0.099)	(0.128)	(0.102)	(0.128)	(0.102)
Protein (Chicken excluded)								
Chickpeas	-0.131	-0.116	-0.141	-0.122	-0.033	-0.006	-0.024	0.002
	(0.122)	(0.107)	(0.120)	(0.104)	(0.128)	(0.107)	(0.128)	(0.107)
Fish	-0.395***	-0.350***	-0.429***	-0.379***	-0.687***	-0.561***	-0.683***	-0.554***
	(0.111)	(0.089)	(0.112)	(0.090)	(0.129)	(0.100)	(0.129)	(0.100)
Constant	1.702***	1.708***	1.633***	1.653***	1.359***	1.375***	1.315***	1.338***
	(0.214)	(0.192)	(0.211)	(0.189)	(0.259)	(0.204)	(0.256)	(0.203)
N	523	523	523	523	523	523	523	523

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the estimation of the effect of knowledge on willingness to pay using both Interval regression and OLS. Columns (1) to (4) present the corresponding estimates for Frame 1 and Columns (5) to (8) that of Frame 2. *Work* is a binary variable which is 1 if the respondent works in Food Production, Farming and/ or Health care. Income refers to household income.

Table 3.10: Interval Regression Robustness Checks Frame 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Knowledge	0.085**	0.082**	0.084**				
	(0.040)	(0.040)	(0.040)				
Work	0.334***	0.326***		0.325***	0.334***	0.319***	0.336***
	(0.109)	(0.109)		(0.110)	(0.111)	(0.111)	(0.109)
Work Fields							
Farming			0.271				
Food production			(0.182)				
Health care			0.360***				
			(0.124)				
Knowledge Dummy Variables							
Average Knowledge levels							
(Above Average Excluded)							
Below average				-0.238*			
knowledge				(0.136)			
Average				-0.210			
knowledge				(0.150)			
Knowledgeable					0.095		
					(0.088)		
Key Knowledge Variables							
Knows the impact						0.085	
of antibiotic resistance						(0.086)	
Knows antibiotics treat						-0.020	
bacterial infections						(0.081)	
Knows the use of antibiotics						0.397**	
in food production						(0.197)	
Knowledge PCA							0.084**
							(0.038)
N	523	523	523	523	523	523	523
Age Control	✓	✓	✓	✓	✓	✓	✓
Gender Control	✓	✓	✓	✓	✓	✓	✓
Ethnicity Control	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓
Protein Control	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays the robustness checks for the interval regression estimates for willingness–to–pay in Frame 1. The results presented for each column is: (1) preferred specification, (2) household income groups below $10,000$, $£10,001 − £20,000$, $£20,001 − £30,000$, $£30,001 − £40,000$ and over $£40,000$ (this is the excluded group), (4) below average and average knowledge compared to above average knowledge, (5) binary knowledge variable $= 1$ if $Knowledge \geq 50\%$, (6) key knowledge variables, (7) knowledge principal component analysis index.

Table 3.11: Interval Regression Robustness Checks Frame 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Knowledge	0.056	0.056	0.067				
	(0.045)	(0.045)	(0.045)				
Work	0.188	0.186		0.181	0.184	0.170	0.184
	(0.123)	(0.123)		(0.123)	(0.123)	(0.124)	(0.123)
Work Fields							
Farming &			0.482**				
Food production			(0.211)				
Health care			0.091				
			(0.140)				
Knowledge Dummy Variables							
Average Knowledge levels							
(Above Average Excluded)							
Below average				-0.098			
knowledge				(0.150)			
Average				-0.090			
Knowledge				(0.164)			
Knowledgeable					0.037		
					(0.101)		
Key Knowledge Variables							
Knows the impact						0.048	
of antibiotic resistance						(0.100)	
Knows antibiotics treat						-0.054	
bacterial infections						(0.092)	
Knows the use of antibiotics						0.396*	
in food production						(0.227)	
Knowledge PCA							0.025
							(0.044)
N	523	523	523	523	523	523	523
Age Control	✓	✓	✓	✓	✓	✓	✓
Gender Control	✓	✓	✓	✓	✓	✓	✓
Ethnicity Control	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓
Protein Control	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays the robustness checks for the interval regression estimates for willingness–to–pay in Frame 2. The results presented for each column is: (1) preferred specification, (2) household income groups below $10,000$, £$10,001 -$ £$20,000$, £$20,001 -$ £$30,000$, £$30,001 -$ £$40,000$ and over £$40,000$ (this is the excluded group), (4) below average and average knowledge compared to above average knowledge, (5) binary knowledge variable $= 1$ if $Knowledge \geq 50\%$, (6) key knowledge variables, (7) knowledge principal component analysis index.

Appendix 3.A   The Survey

3.A.1   Consent Form

Introduction

You are being invited to take part in a research project on antibiotic use in food production. Before you decide on whether to take part, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully before you decide whether you wish to take part.

Purpose of Research This is a research project being conducted by Melisa Williams, a PhD student at the University of Leicester. The aim of the project is to measure preferences and beliefs with respect to antibiotic use. The data for the project will be collected from this online survey.

Participation

Your participation in this survey is voluntary. You may refuse to take part in the research or exit the survey at any time without penalty. You are free to decline to answer any question you do not wish to answer for any reason. The survey should take approximately 15 minutes to complete.

Benefits

There are no benefits relating to your answers to any question in the survey, however, you will receive an incentive based on the length of the survey. You will be able to choose the specific type of reward which includes cash, airline miles, gift cards, redeemable points, sweepstakes entrance and vouchers.

Risks

There are no foreseeable risks involved in participating in this study.

Confidentiality

The information provided by you in this questionnaire will be used for research purposes. It will not be used in any manner which would allow identification of your individual responses. Your survey answers will be sent to a link at Qualtrics where data will be stored in a password protected electronic format. Qualtrics will not collect identifying information such as your name, email address, or IP address. Anonymised research data will be archived to make them available to other researchers in line with current data sharing practices.

Contact
If you have questions at any time about the study or the procedures, you may contact Melisa Williams (mmw18@leicester.ac.uk) or her supervisors Dr Arkadiusz Szydlowski (ams102@leicester.ac.uk) or Dr Jesse Matheson (j.matheson@sheffield.ac.uk).

Thank you for taking the time out to read the information sheet. Please select your choice below. Clicking on the "Agree" button indicates that:

○ You have read the above information

○ You voluntarily agree to participate

○ You are 18 years of age or older

○ Agree

○ Disagree

3.A.2 Survey Questionnaire

Part 1: Demographics

PART 1 This part of the survey consists of some demographic questions. As previously stated, the questions will not be used in a manner which would allow identification of you or your individual responses. Please answer as many of the following questions as you feel comfortable.

1. Please enter your age ——————————————————

2. Sex:

   ○ Female

   ○ Male

   ○ Other

   ○ Prefer not to say

3. In which of the following regions do you live?

   ○ North East

   ○ North West

   ○ Yorkshire and the Humber

   ○ East Midlands

   ○ West Midlands

   ○ East of England

   ○ London

   ○ South East

   ○ South West

   ○ Wales

   ○ Scotland

   ○ Northern Ireland

4. What is your highest level of qualification?

   ○ GCSE or lower

   ○ A Levels

   ○ Higher Education

5. Are you currently working in any of the following areas?
   Choose all that apply

   ☐ Farming

   ☐ Food production

   ☐ Health care

   ☐ None of the above

6. Please indicate the total annual income of your household (before tax and deductions, but including benefits/allowances)?

   ○ Below £10,000

   ○ £10,001–£20, 000

   ○ £20,001–£30, 000

   ○ £30,001–£40, 000

   ○ Above £40,000

7. To which of the following ethnic groups do you belong??

   ○ White

   ○ Mixed / multiple ethnic groups

   ○ Asian / Asian British

   ○ Black / African / Caribbean / Black British

   ○ Another ethnic group ―――――――――――――――――――――

End of Part 1: Demographics

Part 2: Choice Experiment- Background

Part 2 This part of the survey consists a series of questions exploring whether antibiotic use in the production of meats and other proteins for human consumption has an effect on your purchasing choices.

8. Which of the following proteins do you most often purchase? Rank the choices 1-3 (1 being the most often purchased).

_____ Chicken

_____ Seafood

_____ Beans, Lentils, Chickpeas

Note: The respondent faces a choice experiment for the protein ranked 1 then 3.

Part 2: Choice Experiment- Chicken

This section of the survey comprises questions exploring whether antibiotic use in poultry production affects the demand for chicken.

In this hypothetical situation there are two farmers producing chicken. The first farmer uses antibiotics to treat and prevent diseases. The second farmer does not use antibiotics in chicken production, utilising organic methods instead. Your local supermarket sells both types of chicken and labels the second type Antibiotic free. Both types of chicken are safe for consumption.

For each of the following questions, please carefully consider each option and indicate your choice. Even though this is a hypothetical situation, it is important that you make your selections as you would if you were facing these choices in your retail purchase decisions. Therefore, allocating funds to the purchase of any of these products means there will be less money available for other goods. Please note that the objective of this research is to learn about decision making, it is not meant to persuade your decisions in any way.

9. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of these options

If Option 1 is selected move to Question 10, if Option 2 move to Question 11, if Option 3 move to Question 30

10. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 12, if Option 2 move to Question 13, if Option 3 move to Question 31

11. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 13, if Option 2 move to Question 14, if Option 3 move to Question 32

12. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 15, if Option 2 move to Question 16, if Option 3 move to Question 33

13. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 16, if Option 2 move to Question 17. If Option is 3 is selected then: move to Question 34 if Option 1 was selected in Question 11, move to Question 35 if Option 2 was selected in Question 10.

14. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 17, if Option 2 move to Question 18, if Option 3 move to Question 36

15. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.40	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 19, if Option 2 move to Question 20, if Option 3 move to Question 37

16. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 20, if Option 2 move to Question 21.
If Option is 3 is selected then: move to Question 38 if Option 1 was selected in Question 13, move to Question 39 if Option 2 was selected in Question 12.

17. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

*If Option 1 is selected move to Question 21, if Option 2 move to Question 22.
If Option is 3 is selected then: move to Question 40 if Option 1 was selected in
Question 14, move to Question 41 if Option 2 was selected in Question 13.*

18. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£3.52
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

*If Option 1 is selected move to Question 22, if Option 2 move to Question 23, if
Option 3 move to Question 42*

19. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.70	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

*If Option 1 is selected move to Question , if Option 2 move to Question , if Option
3 move to Question 43.*

20. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.40	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 25, if Option 2 move to Question 26.

If Option is 3 is selected then: move to Question 44 if Option 1 was selected in Question 16, move to Question 45 if Option 2 was selected in Question 15.

21. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 26, if Option 2 move to Question 27.

If Option is 3 is selected then: move to Question 46 if Option 1 was selected in Question 17, move to Question 47 if Option 2 was selected in Question 16.

22. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£3.52
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 27, if Option 2 move to Question 28. If Option is 3 is selected then: move to Question 48 if Option 1 was selected in Question 18, move to Question 49 if Option 2 was selected in Question 17.

23. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£3.96
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 28, if Option 2 move to Question 29, if Option 3 move to Question 50

24. Please choose the option that you would prefer

	Option 1	Option 2
Price	£3.00	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

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25. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.70	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

26. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.40	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

27. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£3.52
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

28. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£3.96
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

29. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£4.40
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

30. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.20	£1.76
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

31. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£1.83
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

32. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.20	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

33. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£1.89
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

34. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£2.29
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

35. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.44	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

36. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

37. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£1.93
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

38. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£2.36
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

39. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.68	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

40. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£2.66
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

41. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.55	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

42. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.36	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

43. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.40	£1.96
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

44. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£2.10	£2.41
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

45. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.92	£2.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

46. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.80	£2.73
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

47. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.81	£2.75
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

48. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.50	£2.93
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

49. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.63	£3.19
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

50. Please choose the option that you would prefer

Chicken (1 kg)	Option 1	Option 2
Price	£1.33	£3.52
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2: Choice Experiment- Chicken

Part 2: Choice Experiment -Fish

This section of the survey consists a series of questions exploring whether antibiotic use in fish production affects the demand for sea bass.

In this hypothetical situation there are two farmers producing sea bass. The first farmer uses antibiotics to treat and prevent diseases. The second farmer does not use antibiotics in the production of sea bass, utilising organic methods instead. Your local supermarket sells both types of sea bass and labels the second type Antibiotic free. Both types of products are safe for consumption.

For each of the following questions, please carefully consider each option and indicate your choice. Even though this is a hypothetical situation, it is important that you make your selections as you would if you were facing these choices in your retail purchase decisions. Therefore, allocating funds to the purchase of any of these products means there will be less money available for other goods. Please note that the objective of this research is to learn about decision making, it is not meant to persuade your decisions in any way.

51. Please choose the option that you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 52, if Option 2 move to Question 53, if Option 3 move to Question 72.

52. Please choose the option that you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 54, if Option 2 move to Question 55, if Option 3 move to Question 73.

53. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 55, if Option 2 move to Question 56, if Option 3 move to Question 74.

54. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 58, if Option 2 move to Question 59. If Option is 3 is selected and Option 1 was selected in Question 53 then move to Question 76, otherwise move to Question 77.

55. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 59, if Option 2 move to Question 60, if Option 3 move to Question 78.

56. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 61, if Option 2 move to Question 62, if Option 3 move to Question 79.

57. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£5.60	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 62, if Option 2 move to Question 63.
If Option is 3 is selected and Option 1 was selected in Question 55 then move to
Question 80, otherwise move to Question 81.

58. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 63, if Option 2 move to Question 64.
If Option is 3 is selected and Option 1 was selected in Question 56 then move to
Question 82, otherwise move to Question 83.

59. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 64, if Option 2 move to Question 65, if Option 3 move to Question 84.

60. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£6.88
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 57, if Option 2 move to Question 58, if Option 3 move to Question 75.

61. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£6.30	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 66, if Option 2 move to Question 67, if Option 3 move to Question 85.

62. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£5.60	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 67, if Option 2 move to Question 68.
If Option is 3 is selected then: move to Question 86 if Option 1 was selected in
Question 58, move to Question 87 if Option 2 was selected in Question 57.

63. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 68, if Option 2 move to Question 69.
If Option is 3 is selected then: move to Question 88 if Option 1 was selected in
Question 59, move to Question 89 if Option 2 was selected in Question 58.

64. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£6.88
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

111

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 69, if Option 2 move to Question 70. If Option is 3 is selected then: move to Question 90 if Option 1 was selected in Question 60, move to Question 91 if Option 2 was selected in Question 59.

65. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£7.74
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 70, if Option 2 move to Question 71, if Option 3 move to Question 92.

66. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£7.00	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

67. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£6.30	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

68. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£5.60	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

69. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£6.88
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

70. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£7.74
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

71. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£8.60
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

72. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£2.80	£3.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

73. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£3.58
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

74. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£2.80	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

75. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£3.69
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

76. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£4.48
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

77. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.36	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

78. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.02	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

79. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£3.76
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

80. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£4.61
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

81. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.92	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

82. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£5.20
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

83. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.62	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

84. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.17	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

85. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£5.60	£3.82
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

119

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

86. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.90	£4.70
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

87. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.48	£4.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

88. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.20	£5.34
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

89. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£4.22	£5.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

90. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.50	£5.73
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

91. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.81	£6.24
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

92. Please choose the option you would prefer

Sea bass (300 g)	Option 1	Option 2
Price	£3.11	£6.88
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Fish

Part 2: Choice Experiment- Chickpeas

This section of the survey consists a series of questions exploring whether antibiotic use in crop production affects the demand for chickpeas.

In this hypothetical situation there are two farmers producing chickpeas. The first farmer uses antibiotics to treat and prevent diseases. The second farmer does not use antibiotics in crop production, utilising organic methods instead. Your local supermarket sells both types of chickpeas and labels the second type Antibiotic free. Both types of chickpeas are safe for consumption.

For each of the following questions, please carefully consider each option and indicate your choice. Even though this is a hypothetical situation, it is important that you make your selections as you would if you were facing these choices in your retail purchase decisions. Therefore, allocating funds to the purchase of any of these products means there will be less money available for other goods. Please note that the objective of this research is to learn about decision making, it is not meant to persuade your decisions in any way.

93. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 94, if Option 2 move to Question 95, if Option 3 move to Question 114.

94. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 96, if Option 2 move to Question 97, if Option 3 move to Question 115.

95. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 97, if Option 2 move to Question 98, if Option 3 move to Question 116.

96. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 99, if Option 2 move to Question 100, if Option 3 move to Question 117.

97. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 100, if Option 2 move to Question 101. If Option is 3 is selected then: move to Question 118 if Option 1 was selected in Question 95, move to Question 119 if Option 2 was selected in Question 94.

98. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.67
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 101, if Option 2 move to Question 102, if Option 3 move to Question 120.

99. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.12	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 103, if Option 2 move to Question 104, if Option 3 move to Question 121.

100. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 104, if Option 2 move to Question 105. If Option is 3 is selected then: move to Question 122 if Option 1 was selected in Question 97, move to Question 123 if Option 2 was selected in Question 96.

101. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.67
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 105, if Option 2 move to Question 106. If Option is 3 is selected then: move to Question 124 if Option 1 was selected in Question 98, move to Question 125 if Option 2 was selected in Question 97.

102. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.84
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 106, if Option 2 move to Question 107, if Option 3 move to Question 126.

103. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.26	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 108, if Option 2 move to Question 109, if Option 3 move to Question 127.

104. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.12	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 109, if Option 2 move to Question 110. If Option is 3 is selected then: move to Question 128 if Option 1 was selected in Question 100, move to Question 129 if Option 2 was selected in Question 99.

105. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.67
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 110, if Option 2 move to Question 111, if Option 3 move to Question 130.

106. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.84
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 111, if Option 2 move to Question 112. If Option is 3 is selected then: move to Question 131 if Option 1 was selected in Question 102, move to Question 132 if Option 2 was selected in Question 101.

107. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£2.07
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

If Option 1 is selected move to Question 112, if Option 2 move to Question 113, if Option 3 move to Question 133.

108. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.40	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

109. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.26	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

110. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.12	£1.67
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

111. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.84
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

112. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£2.07
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

113. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£2.30
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

114. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.56	£1.64
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

115. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.37
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

116. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.56	£2.05
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

117. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.17
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

118. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.71
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

119. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.67	£1.71
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

120. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.60	£2.38
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

121. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.03
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

122. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.47
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

123. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.78	£1.47
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

124. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.99
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

125. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.72	£1.99
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

126. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.63	£2.63
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

127. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£1.12	£0.91
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

128. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.98	£1.28
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

129. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.90	£1.15
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

130. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.84	£1.44
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

131. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.70	£1.53
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

132. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.76	£1.67
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

133. Please choose the option you would prefer

Chickpeas (500 g)	Option 1	Option 2
Price	£0.62	£1.84
Special label	None	Antibiotic free
Antibiotics use	Frequently used for disease treatment, prevention and to enhance growth	Not used

○ I would like Option 1

○ I would like Option 2

○ I wouldn't choose any of the options

End of Part 2:Choice Experiment- Chickpeas

Part 3: Perceptions on Antibiotic Resistance

This part of the survey consists of questions regarding your current knowledge of antibiotics and antibiotic resistance. We therefore ask that you do not look for answers on Google or any other source, online or otherwise.

134. **Before taking this survey**, which of the following terms have you heard of?
     Choose all that apply

     ☐ Antibiotic resistance

     ☐ Superbugs

     ☐ Antimicrobial resistance

     ☐ Drug resistance

     ☐ Antibiotic–resistant bacteria

     ☐ I haven't heard of any of these terms

135. Antibiotics are medicines use to fight ———————— that cause infections.
     Choose all that apply

     ☐ Bacteria

     ☐ Fungi

     ☐ Parasites

     ☐ Viruses

     ☐ Don't know

136. Which of the following is true about antibiotic resistance?

     ○ Antibiotic resistance is only a problem for people who take antibiotics regularly

     ○ Using antibacterial cleaning products and soap will reduce the chances of having an antibiotic resistant infection

     ○ Antibiotic–resistant infections could make routine medical procedures much more dangerous

     ○ Don't know

137. Which of the following is true about the use of antibiotics in food production (such as poultry, beef, swine, fish and crop)? *Choose all that apply*

☐ Antibiotics are used to treat diseases.

☐ Antibiotics are used to prevent diseases.

☐ Antibiotics are used to enhance growth.

☐ The same antibiotics used in humans are also used in food production.

☐ Don't know

138. Which of the following do you think an antibiotic should be used for? *Choose all that apply*

☐ Cold

☐ Flu (influenza)

☐ Sore throat

☐ Urinary tract infections

☐ Don't know

139. Which of the following are common antibiotics? *Choose all that apply*

☐ aspirin

☐ penicillin

☐ paracetamol

☐ tetracycline

☐ Don't know

End of Part 3: Perceptions on Antibiotic Resistance

Part 4: Attitudes Regarding Antibiotic Usage and Resistance

This part of the survey consists of questions regarding your beliefs about antibiotic usage and resistance.

140. Do you think antibiotics will be less effective in the future?

    ○ Yes, in the next year

    ○ Yes, in less than 5 years

    ○ Yes, in 5 - 10 years

    ○ Yes, in 10 - 15 years

    ○ Yes, in over 20 years

    ○ No

141. Among 1,000 persons, how many of them do you think will have an infection/illness that cannot be treated by the standard antibiotic?

    _____

142. Among 1,000 persons, how many of them do you think will die due to an infection/illness that cannot be treated by the standard antibiotic?

    _____

143. **Which of the following statements describe your attitude towards antibiotic use in agriculture?**

    Use the following statements to share your views by indicating whether you Strongly Agree, Agree Slightly, Neither Agree nor Disagree, Disagree Slightly, or Strongly Disagree with each statement.

	Strongly Agree	Agree slightly	Neither Agree nor Disagree	Disagree Slightly	Disagree Strongly
Using antibiotics in food-producing animals is a main contributor to antibiotic resistance	○	○	○	○	○
It is OK to use antibiotics to treat sick animals	○	○	○	○	○
Antibiotic use in food–producing animals is too small to be a problem for humans	○	○	○	○	○
Only antibiotics that are not used to treat humans should be used to treat sick animals	○	○	○	○	○

144. **How do you view antibiotic resistance?**

Use the following statements to share your views by indicating whether you Strongly Agree, Agree Slightly, Neither Agree nor Disagree, Disagree Slightly, or Strongly Disagree with each statement.

	Strongly Agree	Agree slightly	Neither Agree nor Disagree	Disagree Slightly	Disagree Strongly
Antibiotic resistance is one of the biggest problems the world faces	○	○	○	○	○
I am worried about the impact that antibiotic resistance will have on my health, and that of my family	○	○	○	○	○
I am not at risk of getting an antibiotic-resistant infection	○	○	○	○	○

145. **How do you think antibiotic resistance can be reduced?**

Use the following phrases to share your views by indicating whether you Strongly Agree, Agree Slightly, Neither Agree nor Disagree, Disagree Slightly, or Strongly

143

Disagree with each statement.

	Strongly Agree	Agree slightly	Neither Agree nor Disagree	Disagree Slightly	Disagree Strongly
Parents ensuring all their children's vaccinations are up-to-date	○	○	○	○	○
Doctors prescribing antibiotics only when they are needed	○	○	○	○	○
Governments providing financial assistance for the development of new antibiotics	○	○	○	○	○
Everyone taking antibiotics responsibly	○	○	○	○	○

End of Part 4: Attitudes Regarding Antibiotic Usage and Resistance

We thank you for your time spent taking this survey. Your response has been recorded.

End of Survey

Appendix 3.B   The Experiment Flow

Figure 3.B.1: Experiment Frame - Chicken Framing Choice Scenarios
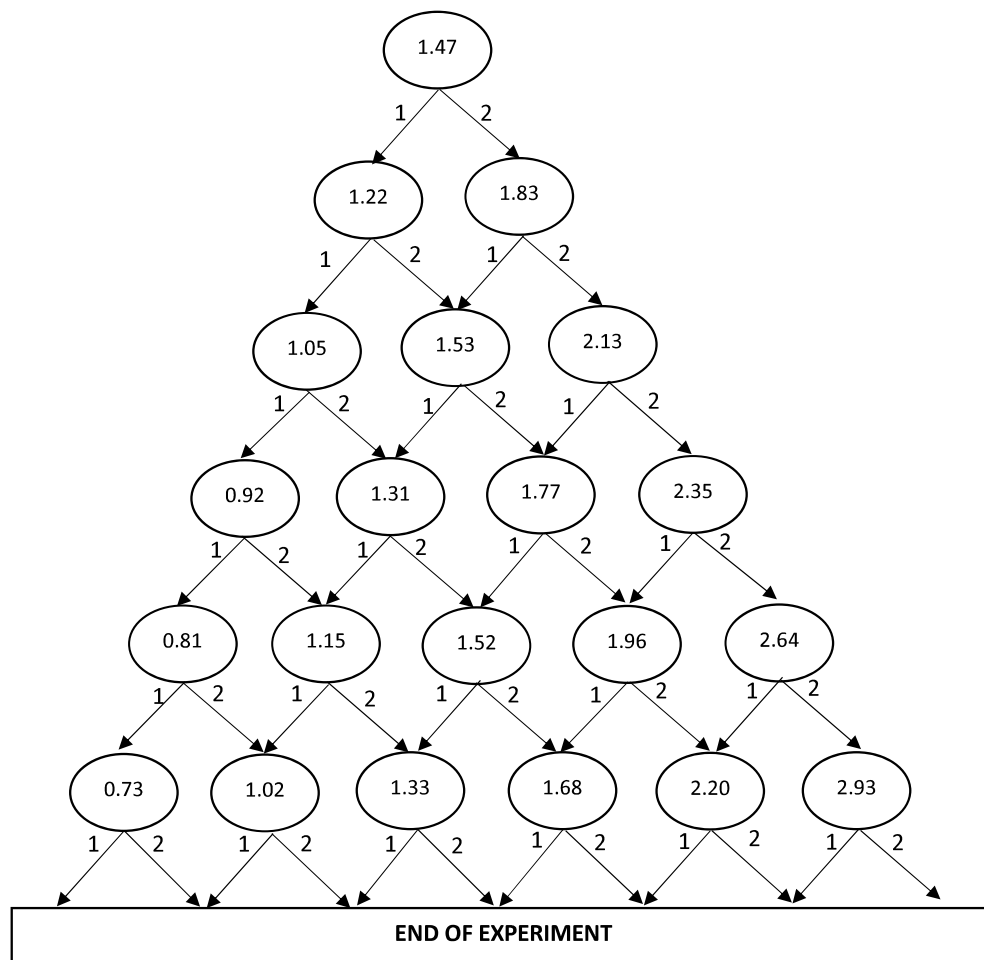
The figure presents the Frame for the chicken option. The flow of choice scenarios does not include Option 3— the frame ends once Option 3 is chosen. The number in each circle represent the relative price for that choice scenario. The number beside each arrow represent the option selected (1: Option 1 and 2: Option 2) which takes the respondent to the next choice scenario or the end of the experiment.

Appendix 3.C   Willingness–to–Pay

Table 3.C.1: Willingness–to–Pay Observations by Data Type, Experiment Frame, and Protein

Data Type	N	Chicken	Fish	Chickpeas
Left censored $[0, RP_{min})$	**86**	53	11	22
Interval censored $[RP_{k-1}, RP_k)$	**367**	277	38	52
Right censored $[RP_{max}, \infty)$	**70**	55	6	9
N	**523**	385	55	83
Left censored $[0, RP_{min})$	**139**	17	62	60
Interval censored $[RP_{k-1}, RP_k)$	**317**	65	114	159
Right censored $[RP_{max}, \infty)$	**67**	18	13	36
N	**523**	60	106	151

RP_{min} is the lowest relative price in each Frame, while RP_{max} is the highest. RP_{k-1} is the highest observed relative price at which Option 2 is chosen and RP_k is the next highest relative price at which the respondent indicated an unwillingness–to–pay. I use 0 to represent the unobserved lower bounds and ∞ for the unobserved upper bounds.

Table 3.C.2: Number of Unique Relative Prices (Bounds) Used in Estimating Willingness –to–Pay by Frame, and Protein

Bounds	Frame 1				Frame 2			
	All	Chicken	Fish	Chickpeas	All	Chicken	Fish	Chickpeas
1	**42**	29	5	8	**103**	10	48	45
2	**23**	15	5	3	**34**	7	16	11
3	**40**	31	5	4	**33**	6	14	13
4	**28**	14	6	8	**25**	1	11	13
5	**28**	23	3	2	**16**	2	4	10
6	**362**	273	31	58	**312**	69	88	155
N	**523**	**385**	**55**	**83**	**523**	**95**	**181**	**247**

In this table I present the number of unique relative prices (bounds) used in calculating the willingness–to–pay by protein.

Table 3.C.3: Willingness–to–Pay Summary Statistics by Frame and Protein

	Willingness–to–pay	Mean	Std. Dev.	Min.	Max.	N
Frame 1	*Observed Interval Data*	1.555	0.551	0.774	3.386	405
	Unobserved UB: $WTP_i = LB$	1.566	0.745	0.307	3.386	523
	Unobserved UB= RP from 7th CS	1.581	0.773	0.307	3.450	523
	Observed Interval Data	1.565	0.545	0.774	2.785	306
Chicken	*Unobserved UB: $WTP_i = LB$*	1.613	0.731	0.367	2.933	385
	Unobserved UB= RP from 7th CS	1.629	0.760	0.367	3.080	385
	Observed Interval Data	1.316	0.347	0.878	2.334	41
Sea bass	*Unobserved UB: $WTP_i = LB$*	1.279	0.580	0.307	2.457	55
	Unobserved UB= RP from 7th CS	1.290	0.603	0.307	2.580	55
	Observed Interval Data	1.672	0.652	0.970	3.386	58
Chickpeas	*Unobserved UB: $WTP_i = LB$*	1.539	0.866	0.411	3.386	83
	Unobserved UB= RP from 7th CS	1.551	0.891	0.411	3.450	83
Frame 2	Observed Interval Data	1.534	0.583	0.865	3.386	338
	Unobserved UB: $WTP_i = LB$	1.494	0.828	0.307	3.386	523
	Unobserved UB= RP from 7th CS	1.511	0.862	0.307	3.450	523
	Observed Interval Data	1.519	0.510	0.866	2.787	65
Chicken	*Unobserved UB: $WTP_i = LB$*	1.625	0.793	0.367	2.933	95
	Unobserved UB= RP from 7th CS	1.650	0.835	0.367	3.080	95
	Observed Interval Data	1.297	0.317	0.865	2.334	114
Sea bass	*Unobserved UB: $WTP_i = LB$*	1.143	0.537	0.307	2.457	181
	Unobserved UB= RP from 7th CS	1.150	0.556	0.307	2.580	181
	Observed relative prices	1.710	0.690	0.867	3.386	159
Chickpeas	*Unobserved UB: $WTP_i = LB$*	1.701	0.929	0.411	3.386	247
	Unobserved UB= RP from 7th CS	1.723	0.967	0.411	3.450	247

This table provides a summary of the willingness–to–pay estimates, by frame and protein, using the interval midpoint as a proxy for the true willingness–to–pay. I use 0 for unobserved lower bounds, that is the case where Option 2 is not chosen. For the case where only Option 2 is chosen I present two alternatives: (1)$WTP_i = LB$: setting the WTP_i equal to the lower bound, and (2) UB= RP from 7th CS: using the relative price from a hypothetical 7th choice scenario as the upper bound.

Appendix 3.D   OLS Estimates Robustness Checks

In this Appendix I test the robustness of the OLS estimates presented in Table 3.9. The resulting estimates are presented in Table 3.D.1 and Table 3.D.2. For both tables, in Column 1 I present the preferred specification. In Column 2, willingness–to–pay is equal to the lower bound ($WTP_i = LB$) when only Option 2 is chosen. I redefine household income using dummy variables for each income group in Column 3. I replace the work dummy variable with dummies for each work area in Column 4. The knowledge variable is redefined in Columns $5-8$. In Column 5 two knowledge dummy variables are included, below average knowledge (=1 if knowledge is $< 50\%$), and average knowledge (=1 if $50\% \leq knowledge < 70\%$), while above average knowledge (=1 if knowledge$>$ 70%) is excluded. I use *Knowledgeable*, a dummy variable which is 1 if the respondent has at least average level knowledge (*Knowledge* $\geq$ 50%) in Column 6. Column 7 includes the use of the following key knowledge variables: (1) knows the impact of antibiotic resistance, (2) knows that antibiotics treat bacterial infections, (3) knows how antibiotics are used in food production. In Column 8 a knowledge index is created, using a Principal Component Analysis (PCA) of all the knowledge variables, which reports the most important knowledge variable for each individual.

Table 3.D.1: OLS Regression Robustness Checks Frame 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Knowledge	0.085**	0.084**	0.083**	0.082**				
	(0.035)	(0.034)	(0.035)	(0.035)				
Work	0.272***	0.262***	0.266***		0.263***	0.272***	0.259***	0.274***
	(0.092)	(0.089)	(0.092)		(0.094)	(0.094)	(0.093)	(0.092)
Work Fields								
Farming &				0.182				
Food Production				(0.146)				
Health care				0.315***				
				(0.107)				
Knowledge Dummy Variables								
Average Knowledge levels								
(Above Average Excluded)								
Below average					-0.245**			
knowledge					(0.123)			
Average					-0.209			
knowledge					(0.136)			
Knowledgeable						0.102		
						(0.077)		
Key Knowledge Variables								
Knows the impact							0.070	
of antibiotic resistance							(0.075)	
Knows antibiotics treat							-0.025	
bacterial infection							(0.071)	
Knows the use of antibiotics							0.375**	
in food production							(0.170)	
Knowledge PCA								0.079**
								(0.033)
N	523	523	523	523	523	523	523	523
Age Control	✓	✓	✓	✓	✓	✓	✓	✓
Gender Control	✓	✓	✓	✓	✓	✓	✓	✓
Ethnicity Control	✓	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓	✓
Protein Control	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays the robustness checks for the OLS regression estimates for willingness–to–pay in Frame 1. The results presented for each column is: (1) preferred specification, (2) willingness–to–pay is equal to the lower bound $WTP_i = LB$ when only Option 2 is chosen (3) household income groups below $10,000$, £$10,001-$£$20,000$, £$20,001-$£$30,000$, and over £$40,000$ (this is the excluded group), (4) work areas, (5) below average and average knowledge compared to above average knowledge, (6) binary knowledge variable $= 1$ if $Knowledge \geq 50\%$, (7) key knowledge variables, (8) knowledge principal component analysis index.

Table 3.D.2: OLS Regression Robustness Checks Frame 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Knowledge	0.055	0.054	0.055	0.064*				
	(0.037)	(0.035)	(0.037)	(0.037)				
Work	0.141	0.131	0.139		0.137	0.140	0.130	0.139
	(0.101)	(0.097)	(0.101)		(0.101)	(0.101)	(0.102)	(0.101)
Work Fields								
Farming &				0.373**				
Food production				(0.167)				
Health care				0.064				
				(0.117)				
Knowledge Dummy Variables								
Average Knowledge levels								
(Above Average Excluded)								
Below average					-0.096			
knowledge					(0.129)			
Average					-0.064			
knowledge					(0.141)			
Knowledgeable						0.052		
						(0.083)		
Key Knowledge Variables								
Knows the impact							0.059	
of antibiotic resistance							(0.082)	
Knows antibiotics treat							-0.038	
bacterial infection							(0.075)	
Knows the use of antibiotics							0.317*	
in food production							(0.184)	
Knowledge PCA								0.029
								(0.036)
N	523	523	523	523	523	523	523	523
Age Control	✓	✓	✓	✓	✓	✓	✓	✓
Gender Control	✓	✓	✓	✓	✓	✓	✓	✓
Ethnicity Control	✓	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓	✓
Protein Control	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays the robustness checks for the OLS regression estimates for willingness–to–pay in Frame 2. The results presented for each column is: (1) preferred specification, (2) willingness–to–pay is equal to the lower bound $WTP_i = LB$ when only Option 2 is chosen (3) household income groups below 10,000, £10,001 − £20,000, £20,001 − £30,000, and over £40,000 (this is the excluded group), (4) work areas, (5) below average and average knowledge compared to above average knowledge, (6) binary knowledge variable = 1 if $Knowledge \geq 50\%$, (7) key knowledge variables, (8) knowledge principal component analysis index.

Chapter 4

Pollution and Health: The allocation of resources dilemma. Evidence from the University Hospitals of Leicester NHS Trust.

4.1 Introduction

The Great Smog of London of 1952 was a five day event that is estimated to have killed up to 12,000 people (Bell and Davis, 2001). Since then, air pollution has dropped greatly. However, it still poses a major health threat. The UK Government identified poor air quality as the largest environmental risk to public health (Smith, 2017). According to the Royal College, 40,000 deaths annually in the UK are attributable to air pollution costing more than £20 billion in 2016 (Holgate et al., 2016).

There is ample literature that establishes that chronic exposure of children and older adults to air pollution results in decreased development and lung function, increased number of respiratory and coronary diseases, diabetes and dementia (Brunekreef and Holgate, 2002; Margaryan, 2019). These effects are usually associated with nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), and particulate matter with an aero-

dynamic diameter less than 2.5 μm and 10 μm ($PM2.5$ and $PM10$).[39]

This paper analyses the impact of pollution on the economic costs of public health-care. We quantify the effect of different types of air pollution on the economic costs of Emergency Department (ED) visits and subsequent admission to hospital using proprietary data from the University Hospitals of Leicester NHS Trust and pollution data from the Air Quality Management Area (AQMA) monitors provided by the Leicester City Council. We focus on two air pollutants: nitrogen dioxide (NO_2) and particulate matter with an aerodynamic diameter less than 10 μm ($PM10$).

We find that days that exhibit higher average levels of $PM10$ also exhibit higher total numbers of hospital visits by children and seniors. Among children, these results are driven by higher numbers of ED visits leading to discharge while, among seniors, these results hold for both hospital admitted patients as well as patients discharged from ED. In addition, we analyse the effects of $PM10$ among hospital admitted patients by diagnosis and find that an increase in exposure to $PM10$ increases the total numbers of children and seniors admitted to the hospital due to cerebrovascular conditions.

We then quantify the costs of higher pollution for the healthcare system to see whether the above results reflect in the healthcare system costs. Consistent with our previous findings, we show that higher exposure to $PM10$ has a positive effect on total costs. In the case of older adults, even when this higher exposure to $PM10$ does not generate higher average costs of visits for discharged older adults, our results of more costly hospital visits are driven by higher numbers of hospital visits in general—both visits ending in admission to hospital and discharge from ED— due to higher exposure to $PM10$. Our results allow us to quantify the the economic costs of pollution due to $PM10$ for hospital admitted older adults in Leicester. We find that each standard deviation of increase of exposure to $PM10$ increases daily cost for hospital admitted

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[39]According to the American Lung Association, NO_2 causes a range of harmful effects on the lungs, including: increased inflammation of the airways, worsened cough and wheezing, reduced lung function, increased asthma attacks, greater likelihood of emergency department and hospital admissions, in addition to be likely a cause of asthma in children, see lung.org acceded on July 21st 2021. Similarly, short-term increases in particle pollution have been linked to: increased mortality in infants, increased hospital admissions for cardiovascular disease (including heart attacks and ischemic heart disease), increased hospital admissions and emergency department visits for chronic obstructive pulmonary disease (COPD), increased hospitalization for asthma among children and increased severity of asthma attacks in children. In addition to this, they present that year-round exposure to particle pollution is linked to: development of asthma in children, worsening of COPD in adults, slowed lung function growth in children and teenagers, increased risk of death from cardiovascular disease, and increased risk of heart attacks and strokes, see lung.org acceded on July 21st 2021.

seniors by £273.90 which translates to £4, 398, 834 on a yearly basis.

In the case of children, a higher average daily exposure to $PM10$ implies higher levels of hospital admissions and average and total costs of children hospital admissions are higher when children are more exposed to $PM10$. Similar to our results for older adults, we find that each standard deviation of increase of exposure to $PM10$ increases daily cost for hospital admitted children and children discharged from ED by £74.71 and £4.08 which translates to £1, 199, 843 and £65, 525 on a yearly basis, respectively. In total, each extra standard deviation of exposure to $PM10$ costs the Leicester Clinical Commissioning Groups (CCGs) £4, 398, 834 a year treating older adults and £1, 265, 368 treating children adding up to £5, 664, 202.[40,41]

We find that a larger daily range of exposure to NO2 increases the total number of hospital visits per day and postcode sector, increases the total costs per visit of discharged patients, and increases the total costs per visit of admitted older adults. However, NO2 results are not as strong as PM10, and are sensitive to the specification used.

There are several methodological challenges present in the literature involved with quantifying the effects of pollution on health outcomes and their subsequent healthcare costs, such as omitted variable bias, measurement error, and avoidance behaviour (see Neidell, 2006; Deryugina et al., 2019).[42] We overcome these by using a novel dataset which combines air pollution and meteorological readings with individual level data on Emergency Department attendance at the University Hospitals of Leicester (UHL), NHS Trust between 2006 and 2011. In addition, we restrict our analysis to children and older adults for two reasons. Firstly, to address concerns of omitted variables and measurement

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[40]For consistency purposes, these calculations are based in specification without any type of fixed effects, which does not allow us to quantify the costs for discharged older adults since the corresponding coefficient are non-significant. Given this, the results presented should be interpreted as a lower bound in costs as the total costs for discharged older adults are positive and significant in the remaining three specifications where fixed effects are included.

[41]The Leicester CCGs (NHS East Leicestershire and Rutland CCG, NHS Leicester City CCG, and NHS West Leicestershire CCG) determine what health services their local population require then purchase these services from health providers. Using data from the University Hospitals of Leicester NHS Trust annual reports we find that the average total expenditure from fiscal years 2007/08 to 2011/12 is £667.4 million, see Leicester Hospitals Annual Reports (2007-2012). The total cost to the Leicester CCGs of each standard deviation of exposure to $PM10$ is 0.85% of this average total expenditure. See Section 4.3 for further explanation on how the health services in the NHS are funded.

[42]In general, avoidance behaviors are defined as any actions a person takes to escape from difficult thoughts and feelings. In environmental economics, this term has been translated to behavioural adjustments in response to pollution, such as people respond to pollution by staying indoors instead of outdoors, see Neidell (2006).

error, our data allows us to geo–locate each individual given their home address. Since children go to school close to home and older adults are predominantly retired and spent most of their time at home we are able to assign to each individual the most accurate hourly pollution readings.[43,44] Secondly, and to address concerns about the potential presence of avoidance behaviour where individuals avoid outings on days/areas of higher pollution (see Neidell, 2006, 2009; Moretti and Neidell, 2011; Janke, 2014), we use a level of disaggregation of pollution data that is not publicly/easily available and, most importantly, our target population for this analysis has very little to no possibilities of avoidance behaviour. Individuals could check air quality in Leicester as a whole, then avoidance behaviour could potentially be present only in the time dimension but not in the geographical dimension we use for our analysis and, in addition, our target population is children (schools are close to their residence) and older adults (whom are retired). This allowed us to better impute pollution using their residence postcode and, in addition, should alleviate any concerns about avoidance behaviour.

To quantify these causal effects, we employ a novel identification strategy. We define Inverse Distance Weighted (IDW) as the weighted average inverse distance from a pollution monitor to the centroid of a postcode sector. A fundamental premise of this paper's analysis is the exogeneity of our pollution measure. We weigh the different available monitors by accounting for wind direction and speed. The motivation for the use of wind direction and speed is not only as a source of exogenous variation—as the variation of pollution readings over time also are—but a more accurate calculation of its impact. Our measure combines elements of the ones used in Boggiano (2019) and

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[43]For more details on how schools are assigned in Leicester, see 4.A.

[44]The average age of retirement has increased over the past two decades. The average age of retirement for men is 65.1, while for women it is 63.9 years old and with retirement one could argue that there is a reduction in mobility due to the lack of the commute to work both in terms of distance and frequency, see "Later Life in the United Kingdom 2019", Accessed on July 21st 2021 from ageuk.org.uk. Nontheless, it could also be argued that we are overstating the likelihood of 60 and over spending all their time at home. However, the emergence of organisations, such as ageuk.org.uk which aim to tackle issues associated with older adults staying at home for long periods of time, for instance isolation and loneliness should alleviate this concern. Moreover, in line of the emergence of this type of organisations, it is reported that 41% of people aged 65 and over in the UK feel out of touch with the pace of modern life and 12% say they feel cut off from society, see "Evidence Review: Loneliness in Later Life", Accessed on July 21st 2021 from ageuk.org.uk. This does not mean that all older adults spent all their time at home but, as this report shows, a significant number of older adults are detached from social life (20 % detached from 3 or more domains, 50 % detached from civic participation and leisure activities and 5 % detached from social networks) which, in the context of our paper, means that they end up spending most of their time at home and much more time than adults economically active or below 60. In this context, older adults who live alone are more likely to attend ED, see "Later Life in the United Kingdom 2019", Accessed on July 21st 2021 from ageuk.org.uk.

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Deryugina et al. (2019). However, it differs from the measure in Boggiano (2019) since each monitor has a time varying weight due to wind direction and speed. It also differs from the measure used in Deryugina et al. (2019) since we build a pollution measure contingent on the *strength* of the effect of each monitor on each postcode sector based on wind direction and wind speed directly.[45]

In order to test for the robustness of our results, we perform a series of additional analyses. Firstly, we perform the same analysis with daily ranges of exposure to pollution—NO_2 and $PM10$—instead of using the daily averages. Secondly, we perform our main analysis replacing our key explanatory variable—IDW—with the pollution reading from the nearest monitor and find that our results are largely unaltered. Thirdly, since we only have average daily air pressure data from 2009 and 2011, we have excluded this control from our main analysis. We find that including air pressure as a control for the available years does not alter our main findings. In addition, we also examine the robustness of our results by restricting our sample to weekdays only and we find that our results still hold on the restricted sample. Finally, we run a falsification test replacing our main explanatory variable—IDW—by its 7 day lagged and lead versions and we find that the coefficients associated with both changes are non-significant when analysing the effects of IDW_{PM10}.

The findings presented in this paper contribute to two strands of literature. Firstly, we contribute to the pollution effects on health literature by documenting the short term effects of pollution in health and its immediate consequences for the healthcare system in terms of healthcare costs. In particular, while most studies look at the relationship between air pollution and health focus on infant and child health, our paper expands this analysis by also looking at the effects on the older adults population and quantifying the economic costs of these effects for both groups. Children are of particular interest because of their susceptibility to respiratory conditions while older adults are of particular interest because of their susceptibility to cardiovascular conditions. Secondly, we contribute to the public policy literature by identifying and quantifying the direct NHS costs associated with treatments and services for specific health conditions that are associated with more polluted environments and covered by public funds. By quantifying these higher economic costs, we can inform the debate on how to allocate resources in Leicester.

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[45]Since our measure of pollution is computed hourly and our ED visits data is recorded daily, in our main analysis we use the daily average. However, we also examine these effects using alternative measures in Section 4.7.

The remainder of this paper is structured as follows. In Section 4.2, we review the related literature. Section 4.3 describes the institutional framework for environmental and health care policies in the UK in the period 2006-2011. In Section 4.4, we discuss the data. In Section 4.5, we present a description of the IDW measure and the empirical methodology, respectively. Section 4.6 and Section 4.7 present the results and robustness checks, respectively. We conclude with final remarks in Section 4.8.

4.2 Literature Review

There is a wealth of literature exploring the relationship between air quality, meteorological conditions and human health outcomes. Pintarić et al. (2012) shows that higher ED visits are positively associated with higher concentration of NO_2 and higher temperatures, but negatively associated with the average daily moisture and the average daily atmospheric pressure.

A sizeable part of this literature focuses in particular on the effects of worse air quality on children's health. Chay and Greenstone (2003) estimates the effects of particulates pollution on infant mortality and find that about 2,500 fewer infants died than would have died in the absence of the dramatic reductions in pollution during a recession. Currie and Neidell (2005) quantifies the number of infant lives—1,000—saved by the reductions in CO. Similarly, Knittel et al. (2016) quantifies the number of infant lives—18 lives per 100,000 live births—saved by a one-unit decrease in $PM10$.

Another important strand of this literature focuses on the pollution effects on respiratory illnesses such as asthma, bronchitis, and pneumonia. This strand of literature focuses on the general population but usually finds more severe effects for children and older adults. Samoli et al. (2006) shows a positive relationship between NO_2 and cardiovascular and respiratory mortality with larger effects in cities with higher proportions of older adults and higher levels of $PM10$.[46] Coneus and Spiess (2012) finds that high exposure to CO prior to birth causes lower birth weight, and that O_3 exposure leads to higher probability of respiratory diseases and impairment for toddlers. Neidell (2004) finds that CO has an effect on hospitalizations for asthma among children and that public alerts of pollution levels predicted to exceed certain limits decreases asthma

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[46]These effects are stronger on cause-specific mortality in cities participating in the Air Pollution on Health: a European Approach (APHEA)-2 project.

hospitalizations by approximately 1%.

There is ample literature that exploits the effect of the new pollution policies, aimed at reduction of air pollution, on health outcomes. Currie and Walker (2011) show that the introduction of electronic toll collection (E-ZPass) had a positive effect on the health of infants born to mothers living near toll plazas. They show that E-ZPass reduced the incidence of prematurity and low birth-weight of mothers within 2 kilometres (km) of a toll plaza relative to mothers 2–10 km away. In another study, Simeonova et al. (2018) show that the introduction of congestion pricing in an urban area significantly reduced NO_2 and $PM10$ levels and reduced the rate of acute asthma visits. Margaryan (2019) shows that low emission zones (LEZs)—designated areas that restrict cars' access based on their emission class—reduce monthly $PM10$ concentrations and reduces cardiovascular disease with this effect being more pronounced in older adults (aged over 65 years). Beatty and Shimshack (2011) finds that school bus emissions reductions induced statistically significant and large reductions in bronchitis, asthma, and pneumonia incidence for children and adults with chronic conditions.

Schlenker and Walker (2016) and Deryugina et al. (2019) explore the effect of pollution on health care costs. Schlenker and Walker (2016) estimates how daily variation in ground level airport congestion due to network delays affects local measures of health. They find that a one standard deviation increase in daily pollution explains roughly one third of average daily admissions for asthma problems. As it relates to the cost, Schlenker and Walker (2016) finds that this increase in daily pollution leads to an additional US$540 thousand per day in hospitalization costs for respiratory and heart related admissions of individuals within 10 km of one of the twelve largest airports in California. Unlike Schlenker and Walker (2016) we do not restrict our cost evaluations to admissions only or specific illnesses.

Deryugina et al. (2019) estimates the effect of fine particulate matter $PM2.5$ exposure on older adults' mortality, health care use, and medical cost over a three–day window that spans the day of the increase and the following two days. The study combines administrative data on Medicare beneficiaries of the US population aged 65 and over with daily pollution data for the United States from 1999 to 2013. Using changes in wind direction as an IV for pollution, they found that increases in daily $PM2.5$ is found to have a positive effect on mortality, hospitalizations and inpatient spending (mainly due to admissions that originate in ER). Our study differs from Deryugina et al. (2019)

in one key way. We build a pollution measure directly accounting for wind direction and speed, instead of using them as part of an instrumental variable approach to identify pollution variation.

Some studies have found that avoidance behaviour is an important aspect in estimating effect of pollution on hospitalizations and health care costs. Janke (2014) finds a 10% increase in NO_2 or O_3 increases the rate of hospital emergency admissions for respiratory diseases and symptoms in children by around 1%. However, when he controls for avoidance behaviour, he finds an 8% reduction in asthma admissions (a subset of respiratory diseases) in response to a pollution warning the day before.[47] Neidell (2009) also finds that individuals respond to smog alert announcements by reducing daily outdoor activities, and that this avoidance behaviour significantly impacts asthma hospitalizations for children and older adults. Specifically, the pollution standard index increases estimates of the effect of ozone on children by roughly 160 percent for children and 40 percent for older adults, when smog alerts are included. Moretti and Neidell (2011) quantifies the effect of pollution avoidance behaviour reporting that respiratory related hospitalizations due to ozone exposure costs at least $44 million annually in Los Angeles and that the cost of avoidance behaviour is at least $11 million.

The literature also provides some insight as to how the effect of pollution, and hospital attendance and admissions vary by day of the week. Green et al. (2016) shows that despite the introduction of congestion charge in London, the monthly traffic accident counts did not increase for weekend days which were exempt from charges. This suggests that pollution levels may be lower on weekends given the level of activity in the weekday. Meacock et al. (2017) reports differences in admissions and mortality on weekends compared to weekdays. Specifically, they find that proportionally fewer patients who attended ED on weekends were admitted to hospital, and the probability of dying was higher among ED attendants who were subsequently admitted on the weekend. Furthermore, they find that there were fewer deaths (in numbers) following direct admission (admissions from services in the community/ GPs) on weekends than weekdays. However, they also find that the mortality rate was significantly higher because there was a greater reduction in admissions compared to deaths on weekends. Additionally, Green et al. (2020) examine the effect of the London Congestion Charge introduced in 2003 and found varied but substantial reductions in three pollutants (including $PM10$)

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[47]Janke (2014) also notes that ignoring avoidance behaviour, does not result in statistically significant underestimation of the effects of nitrogen dioxide and ozone.

but a sharp increase in NO_2. This suggests that when $PM10$ decreases NO_2 increases due to their sources (petrol based cars vs. diesel) which is consistent with our results.

Another set of literature focuses on the effect of air quality on non-health outcomes such as labour supply and crime. Holub et al. (2016) uses the air quality at an individual's residence and finds a positve effect of $PM10$ levels on the probability that a worker takes a sick leave from work due to cardiovascular or respiratory disease. Bondy et al. (2018) estimate the impact of short–term exposure to elevated levels of air pollution on crime levels in London. They show that an additional 10 Air Quality Index points increase the crime rate by 0.9%.

4.3   Institutional Framework

Air Quality Standards   In order to protect human health the first European level air quality standards have been implemented by the European Union in the 1970s, obliging member states to assure adequate air quality for their citizens. These standards have significantly evolved over the years. Since 2008, the Ambient Air Quality Directive (AAQD) provides the current framework for the control of ambient concentrations of air pollution in the EU.[48] In Table 4.1, we present the current air quality standards (AQS) for the relevant high priority air pollutants for this paper, NO_2 and $PM10$.

One particular aspect of the AAQD is that the NO_2 limits set were to be achieved by all EU members by 1st January 2010. By the 2010 deadline, the UK was in breach of regulations in 93% of its designated zones and agglomerations and applied for a Time Extension Notification (TEN) of five years for 60% of its exceeding zones and agglomerations in September 2011. Moreover, by 2011 the UK Government also required the local authorities to comply with the AAQD, despite local authorities not having any say over which zones or agglomerations were included in the TEN application. By 2015, the UK government reported that 37 out of the 43 areas were in breach of the NO_2 limits set by the AAQD. Failing to meet the AAQD in 2017, the European Commission issued a warning to the UK, escalating the potential for fines if the UK government cannot produce plans to meet the AAQD as soon as possible. For more details about the evolution of air quality standards in the UK, see Barnes et al. (2018).

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[48]In this paper's period of analysis (2006-2011), the UK was obliged to abide by these standards.

Public Funding and the NHS Majority of the NHS funding comes from general taxation while a small proportion comes from patient charges, such as prescription charges and dental treatment. The level of NHS funding in a given year is set by the central government through the Spending Review process. This process estimates how much income the NHS will receive from sources such as user charges, National Insurance and general taxation. If National Insurance or patient charges raise less funding for the NHS than estimated, funds from general taxation are used to ensure that the NHS receives the original level of funding it was allocated.

NHS England is responsible for allocating funding to the CCGs. The CCGs assess the health needs of their local population to make decisions about the health and care services they need. They then buy those services, given their budget constraints, from providers such as hospitals. During the period 2006-2011, the funding for hospital services in NHS England was under a system of Payment by Results (PbR). Under PbR, CCGs pay healthcare providers a nationally determined price for each patient seen or treated. Where there is no fixed price for a service, the price the CCG pays is determined locally between the CCG and the hospital. Funding from the CCGs covers over 60% of the healthcare costs. Hospitals can generate additional income through parking charges, land sales and treating private patients.[49]

4.4 Data

To identify direct NHS costs for services that are associated with higher levels of air pollution we combine data from multiple sources to create our final dataset. Each of these and the notation we use to address them are discussed below. For details about these data sources, see Table 4.2.

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[49]Please see A Simple Guide to Payment by Results at https://www.gov.uk/government/publications/simple-guide-to-payment-by-results, and How the NHS is Funded at https://www.kingsfund.org.uk/projects/nhs-in-a-nutshell/how-nhs-funded for more information. The limitations of using HRGs and National Tariffs to calculate the cost of hospital use are discussed in section 4.C.

4.4.1 Pollution, Meteorological Data, and Additional Controls

Pollution and Meteorological data were provided by the Leicester City Council. Leicester City Council collects hourly data on an array of pollution variables among which are NO_2 and $PM10$. The monitors used for this data collection are: St Matthews Way, Vaughan Way, Melton Road, Abbey Lane, Glenhills Way, Imperial Ave, London Road, and Uppingham Road. NO_2 data is collected in all the monitors while $PM10$ data is only collected in Vaughan Way, Melton Road, Abbey Lane, Glenhills Way, Imperial Ave, and London Road. In Map 4.1 we show the locations of these monitors.

Similarly, these monitors collect hourly data on climate variables such as wind direction and speed, air pressure, rainfall, and temperature. In the case of air pressure, we only have data for the period 2009-2011. Therefore we exclude air pressure data from the main analysis and use it as a robustness check later in the paper. In Table 4.3 we present the summary statistics of the hourly pollution measures of each monitor and the climate measures over the period 2006-2011.

In addition, and to control for socio-economic characteristics in our analysis we use the Deprivation Indices of 2004, 2007 and 2010. These data—provided by the Office of the Deputy Prime Minister (ODPM)—is at the Lower Layer Super Output Areas (LSOAs) which we translated into their respective postcode sectors. These provide us an understanding of the level of deprivation of the population in each postcode sector of the following characteristics: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environment. We use the deprivation indices of the year 2004 for the year 2006, of the year 2007 for the years 2007 to 2009 and of the year 2010 for the years 2010 and 2011.

4.4.2 Health Data

The Health Data consists of individual level data for all patients who attended the Emergency Department at Leicester Royal Infirmary or the Clinical Decisions Unit at Glenfield Hospital (ED) from January 1, 2006 to December 31, 2011. The data is restricted to individuals aged from birth up to the 18th birthday and from the 60th birthday upwards at the time of ED attendance, and whose registered address postcode is within the following Postcode Districts: LE1, LE2, LE3, LE4, LE5, and LE19. Other

demographic information includes ethnicity, and gender. The health–related data include the date of attendance, reason for visit, and the healthcare resource group (HRG) code.

In Table 4.4, we present some summary statistics for the patients who attended ED from $2006 - 2011$. For this period, 272,757 individuals of the specified age group visited the ED. Of this number, 56% are children (153,937) and the remaining 44% (118,820) are older adults. Our sample consists of slightly more males (143,839 or 53%) than females (128,918 or 47%). In terms of ethnic groups, White constitute majority of the sample (168,036 or 62%), next in size is Asian (64,576 or 24%), while Black is the smallest ethnic group (11,764 or 4%). The remaining 10% of individuals are either of other ethnic groups or chose not to indicate their ethnicity.

A total of 87,400 individuals were admitted to the hospital following a visit to the ED, representing 32% of total visits. Older adults were more likely to be admitted than children (56% compared to 13%). Length of stay varies widely for the two broad age groups. The average length of stay for children is approximately 2 days while older adults spend 9 days on average. We present a breakdown of these statistics by Postcode Districts in Table 4.B.2.

We have HRG codes for 93% of the sample (254,203 ED attendants). The HRG code is a combination of all the intervention and diagnoses of hospital attendants from attendance to discharge into a single code. As such, each code is a standard grouping of clinically similar treatments which use similar levels of resources.[50] The HRG code determines the cost of the hospital visit for ED attendants and admitted patients. We complement the individual level data with the National Tariff Data to get the cost of attendance. We obtain the National Tariff Data for the fiscal years 2005/06 to 2011/12 from the National Archives. The National Tariff Data provides: the price for each HRG code (tariff); whether the price can be increased when predetermined specialised services are done; and where relevant, the expected length of stay; the price per day above the expected length of stay; and the price for short length of stay (< 2 days). We are able to match 98% (248,572) of the HRG codes in the sample to the cost information from the National Tariff data.

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[50]Please see A Simple Guide to Payment by Results at https://www.gov.uk/government/publications/simple-guide-to-payment-by-results for more information.

4.5 Empirical Specification

The main contribution of this paper is to quantify the immediate effects of pollution on hospital visits, obtained diagnoses, and its subsequent economic costs. We link NO_2 and $PM10$ variation with administrative records of hospital visits, their mode of disposal, the obtained diagnosis, and economic costs of the overall visit. We classify this analysis into two groups of models. We begin by examining the effects of pollution on the total number of hospital visits, and obtained diagnoses by age group—children and older adults—and postcode sector. We then analyse the effects of pollution on the costs of attendance at the individual level. We refer to these groups as *non-cost analysis* and *cost analysis*, respectively.

Firstly, we examine the effects of pollution—NO_2 and $PM10$—on the total number of visits by age group and postcode sector as follows:

$$HospitalVisits_{ct}^a = \beta_0 + \beta_1 \, Pollution_{ct}^p + \beta_2 \, WC_t + \beta_3 \, DI_{ct} + \gamma_d + \delta_{wy} + \omega_c + \epsilon_{ct},$$

$$(4.5.1)$$

where $HospitalVisits_{ct}^a$ is the number of hospital visits on day t by age group $a \in$ {children, older adults}, and postcode sector c, $Pollution_{ct}^p$ is each measure of pollution used for postcode sector c day t, $p \in \{daily\ NO_2,\ daily\ PM_{10}\}$. Each postcode sector has a unique centroid therefore both centroids and postcode sectors are identified by the subscript c.[51] WC_t are the weather controls, such as average daily temperature, and average daily rainfall, and ϵ_{ct} are the error terms. DI_{ct} are the postcode sector controls. We use the deprivation indices of the year 2004 for the year 2006, of the year 2007 for the years 2007 to 2009 and of the year 2010 for the years 2010 and 2011. These indices provide us an understanding of the level of deprivation of the population in each postcode sector of the following characteristics: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environment. This specification also includes γ_d, δ_{wy} and ω_c which are day of the week, week/year and postdistrict fixed effects, respectively. The day of the week fixed effects account for differences in hospital attendance by day of the week while the week/year fixed effects account for seasonal effects that can vary across years, such as influenza, asthma, and

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[51]The Postcode sector identifier is composed by the Postcode district plus one digit.

urinary tract infection prevalence.[52] We include these in a staggered way. We also perform the same analysis with $Pollution_{ct}^{p}$ lagged by seven days.

To perform the analysis presented we would need a monitor per postcode sector, ideally on their centroids. However, Leicester only has 8 monitors between 2006 and 2011 while in the Postcode Districts of analysis there are 48 postcode sectors. Furthermore, a postcode sector's pollution may not be adequately measured by a simple average pollution exposure for residents based on the closest monitor readings due to the sparse placement of monitors within postcode sectors. As we show in Map 4.2, these monitors are not only less than the number of postcode sectors we are analysing but are also placed on the border of some postcode sectors. To impute pollution to the centroid of each postcode sector more accurately, we build a pollution measure based on wind direction and wind speed in addition to the geographic coordinates of the centroid and monitors. We refer to this measure as the inverse distance weighted (IDW).

We calculate the weights of each monitor's pollution based on two main factors, strength and distance. *Strength* refers to the exposure of the centroid of each postcode sector to the pollution readings of each monitor using the wind speed and direction. We denote each monitor with the subscript k. We calculate the hourly strength of a monitor to a centroid as follows:

$$Strength_{ckt} = \text{abs}\left(cos\ \theta_{ckt}\right) * WindSpeed_{t} \tag{4.5.2}$$

where θ_{ckt} is the angle difference between the wind direction and the projected line that connects the monitor k and the centroid c at time t, and $WindSpeed$ is the wind speed at time t. Additionally, we take the absolute value of the *cos* of the angle difference to capture the case where a centroid is behind a monitor in terms of the wind direction. This use of wind speed and direction assumes two things. Firstly, the higher the wind speed the further away pollution particles travel. Secondly, if the monitor and centroid of the postcode sector are aligned in terms of wind direction then the exposure of that centroid with respect to that monitor is high, the converse also holds. For a graphical representation of this calculation, see Figure 4.2. We also use the *distance* in kilometres from each monitor to each centroid.

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[52]See Johnston et al. (1996); Rosello et al. (2018) for discussions on seasonality in hospital admissions. See https://www.bbc.com/news/health-45783005 for more details on differences of hospital attendance by day of the week.

IDW is defined as the weighted average inverse distance from a pollution monitor to the centroid of a postcode sector at the hourly level:

$$IDW_{ckt} = \frac{\sum_k \frac{Strength_{ckt}}{Distance_{ck}} * Pollution_{kt}}{\sum_k \frac{Strength_{ckt}}{Distance_{ck}}} \qquad (4.5.3)$$

where $Strength$ is the projected proportion of the effect of monitor k at time t on centroid c conditional on wind speed and direction at time t, $Distance$ is the distance in kilometres from centroid c to the monitor k, and $Pollution$ is the mean of the 24 hourly measures of NO_2 or $PM10$ of monitor k at time t. Figure 4.1 depicts the distribution of $IDW\ NO_2$ and $IDW\ PM10$ from 2006 to 2011.

A potential concern is the well established fact that lower wind speeds are correlated with higher concentrations of pollution (Grundstrom et al., 2015; Czernecki et al., 2017).[53] Since the monitors simultaneously capture both measures, the resulting pollution measure already accounts for this relationship. An additional concern is the endogeneity of pollution monitors locations. Map 4.3 should alleviate this concerns since Leicester Industrial workers' work place is relatively evenly distributed in the outskirts of Leicester City. However, to address this concern in a systematic way our measure construction approach exploits variation in wind speed and direction—both considered to be exogenous with respect to health—by weighting the impact of each monitor's pollution measure by the wind direction and speed. Moreover, our measure exploits hourly pollution that is independent of monitor placement, therefore our estimates should not be biased by changes in monitor composition due to wind direction and speed. For more details on wind direction and speed in Leicester from 2006 to 2011, see Figure 4.3.

In addition to analysing the effects of daily pollution on the total number of hospital visit, we examine whether daily pollution has an effect on the total number of visits by mode of disposal, i.e. discharged from ED and admitted to hospital.[54] To do so, we use the following empirical specification:

$$MOD^b_{ct} = \beta_0 + \beta_1\,IDW_{ct} + \beta_2\,WC_t + \beta_3\,DI_{ct} + \gamma_d + \delta_{wy} + \omega_c + \epsilon_{ct}, \qquad (4.5.4)$$

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[53]This result also holds in Leicester in the analysed period, see Table 4.B.3.

[54]We exclude from this analysis the individuals that died on arrival at the Emergency Department.

where MOD is the total number of visits from individuals residing in postcode sector c at time t, resulting in $b \in \{$admitted to hospital, discharged from ED$\}$. Since individuals more severely ill are more likely to be admitted to hospital, a potential interpretation of these specifications is the severity of the immediate effects of pollution. While a positive coefficient of total number of discharged from ED visits would increase the total costs of healthcare in Leicester due to pollution, an increase of the total number of hospital admitted patients would increase the total costs of healthcare in Leicester more since the differences in average costs by mode of disposal are substantial even when assuming the average cost per visit is fixed.

To further explore the immediate effects of daily pollution among more severe conditions, we additionally examine the effects of daily pollution on the total number of hospital admitted patients by diagnosis. We exploit diagnosis data at the individual level and classify the hospital admitted patients into respiratory, cardiovascular, and cerebrovascular diagnosis. We then regress:

$$Diagnosis_{ct}^e = \beta_0 + \beta_1\, IDW_{ct} + \beta_2\, WC_t + \beta_3\, DI_{ct} + \gamma_d + \delta_{wy} + \omega_c + \epsilon_{ct}, \quad (4.5.5)$$

where $Diagnosis$ is the total number of visits from individuals residing in postcode sector c at time t, and $e \in \{$respiratory, cardiovascular, and cerebrovascular$\}$. There is ample literature that establishes the short and long term effects of pollution among respiratory, cardiovascular, and cerebrovascular conditions. In this context, we expect to find effects of NO_2 on respiratory and cardiovascular diseases and effects of $PM10$ on cerebrovascular diseases similar to the ones documented by Samoli et al. (2006), Beatty and Shimshack (2011), Simeonova et al. (2018), among many others.

The second part of our analysis focuses on examining whether and to what extent daily pollution affects healthcare costs to inform the debate of resource allocation in Leicester. We firstly use OLS to estimate the effect of pollution on hospital costs at the individual level. Since the individual costs of hospital attendance vary greatly by mode of disposal, we examine these effects on discharged from ED patients and hospital admitted patients separately, see Section 4.C for a detailed account of how we compute the individual level costs per hospital visit. Since this analysis is at the individual level, variables at the level of an individual attending the ED are denoted by subscript i. We then estimate the following specifications:

$$Cost_{ict}^b = \beta_0 + \beta_1\, IDW_{ct} + \beta_2\, WC_t + \beta_3\, DI_{ct} + \gamma_d + \Delta_{wy} + \omega_c + \epsilon_{ct}, \quad (4.5.6)$$

where $Cost$ is the cost of attendance for individual i residing in postcode sector c at time t, $b \in \{$admitted to hospital, discharged from ED$\}$, and Δ are the interacted week of the year, fiscal year fixed effects.[55] β_1 can be interpreted as the changes in the average cost per visit by mode of disposal due to spatial and daily changes in pollution and we expect it to be positive. Although average cost per visit is an informative indicator of the effects of pollution on healthcare costs, the goal of this paper is to quantify the immediate total costs of pollution in terms of emergency department visits. We therefore further examine the effects of pollution on the total costs. To do so, we aggregate the individual level costs by mode of disposal, day, and postcode sector. This allows us to estimate the changes in the total costs by mode of disposal due to spatial and daily changes in pollution as follows:

$$TotalCost_{ct}^{b} = \beta_0 + \beta_1 \, IDW_{ct} + \beta_2 \, WC_t + \beta_3 \, DI_{ct} + \gamma_d + \Delta_{wy} + \omega_c + \epsilon_{ct}, \quad (4.5.7)$$

where $TotalCost$ is the total costs of all hospital visits of individuals residing in postcode sector c at time t, $b \in \{$admitted to hospital, discharged from ED$\}$, and β_1 can be interpreted as the changes in total costs due to spatial and daily changes in pollution. It is noteworthy that these estimates are composed by the effects presented in Equations (4.5.4) and (4.5.6). Nonetheless, by estimating β_1, we are quantifying the amount of resources that are being allocated to remedy the immediate daily costs of pollution.

4.6   Results

Figure 4.4 depicts the relationship between the IDW_{NO2} and IDW_{PM10} daily demeaned average and the hospital visits' count demeaned average by age group—children and older adults—during the 6 year period from 2006 to 2011. From this, we observe a positive relationship between IDW_{NO2} and IDW_{PM10} daily demeaned average and the hospital visits' count demeaned average for older adults and between IDW_{PM10} daily demeaned average and the hospital visits' count demeaned average for children. These relationships are more pronounced for older adults than for children. In addition, we find a negative relationship between IDW_{NO2} daily demeaned average and the hospital visits' count demeaned average for children. It is noteworthy that all of these

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[55]We use fiscal year fixed effects and its interaction with week of the year instead of calendar year since they are not equivalent and costs are updated each fiscal year in the Payment by Results system, see Section 4.C.

descriptive relationships hold when observing a plot with all observations and a plot where all observations are grouped by 100 pollution level bins. Nonetheless, since these descriptive relationships do not control for any of the relevant characteristic described in Section 4.5, in Table 4.5 we examine the relationship between daily IDW_{NO2} and IDW_{PM10} and hospital visits by postcode sector from Equation (4.5.1) where we replace *Pollution* by *IDW*. In this analysis, we make a distinction between the ED visits by population age group, i.e. children (age 17 or less) and older adults (age 60 and above).

In Columns (1) to (4), we show the estimates of the effects of pollution—IDW_{NO2} and IDW_{PM10}—on the total number of children attending hospital by day and postcode sector. We find that all estimates associated with the effect of IDW_{PM10} on the total number of children attending hospital per day and postcode sector are positive, significant and robust to the inclusion of day of the week, week times year, and post districts fixed effects. An increase of one standard deviation of the average daily exposure to $PM10$ increases the total number of children attending hospital by 0.091 or 4.87 percentage points (p.p.) with respect to the dependent variable mean, see Column (3). Once we include post district fixed effects, a one standard deviation increase of the average daily exposure to $PM10$ translates into 0.069 more children attending hospital or 6.69 p.p. with respect to the variable mean. In addition, and consistent with the relationship presented in Figure 4.4, we find that the coefficient related to the effect of IDW_{NO2} on the total number of children attending hospital by day and postcode sector is negative and significant.

Analogously, in Columns (5) to (8), we present the estimates of the effects of pollution—IDW_{NO2} and IDW_{PM10}—on the total number of older adults attending hospital by day and postcode sector. We find that all estimates associated with the effect of IDW_{PM10} on the total number of older adults attending the ED per day and postcode sector are positive, significant and largely unaltered by the inclusion of day of the week fixed effects, week times year fixed effects, and post district fixed effects. An increase of one standard deviation of average daily exposure to $PM10$ increases the total number of older adults attending hospital by 0.081 or 5.8 p.p. with respect to the dependent variable mean, see Column (7). Once including controls that by construction were not included in Figure 4.4, we find a stronger effect of IDW_{PM10} on the total number of children attending hospital per day and postcode sector than in the total number of older adults. Additionally, we find that the coefficient related to the effect IDW_{NO2} on the total number of older adults attending hospital by day and postcode sector is

positive and significant. However, this coefficient is not robust to the inclusion of day of the week fixed effects, week times year fixed effects, and post district fixed effects since its sign is reversed by the inclusion of these.

We then further investigate the effects of pollution, in particular, the effects of IDW_{NO2} on hospital visits decomposing the effects by mode of disposal. In Table 4.6, we present the estimates corresponding to Equation (4.5.4). We find that the results presented hold irrespective of the classification by mode of disposal. In the case of children, each standard deviation increase of average daily exposure to $PM10$ increases the total number of children being discharged by 0.084 (4.94 p.p. with respect to the mean) and the total number of admitted children to hospital by 0.012 (4.63 p.p. with respect to the mean), see Column (3). Meanwhile, and consistent with the relationship presented in Figure 4.4, we find that the coefficient related to the effect of IDW_{NO2} on the total number of children attending hospital by day and postcode sector is negative and significant irrespective to the mode of disposal. Similarly, in the case of older adults, an increase of one standard deviation of average daily exposure to $PM10$ increases the total number of older adults being admitted to hospital by 0.042 (4.91 p.p. with respect to the mean) and the total number of older adults being discharged from hospital by 0.050 (7.69 p.p. with respect to the mean), see Column (7). Similar to our main specification, we find that the coefficient related to the effect IDW_{NO2} on the total number of older adults attending hospital by day and postcode sector is positive and significant irrespective to the mode of disposal. However, as with our main specification, this coefficient is not robust to the inclusion of day of the week fixed effects, week times year fixed effects, and post district fixed effects since its sign is reversed by the inclusion of these.

In addition, we analyse the effects of pollution on hospital admissions by diagnosis. We focus on three types of diagnoses of hospital admitted patients:(1) respiratory conditions, (2) cardiovascular conditions, and (3) cerebrovascular conditions. When analysing all conditions together, we find that all estimates associated with the effect of IDW_{PM10} on these conditions hospital admitted patients are positive and largely unaltered by the addition of day of the week fixed effects, week times year fixed effects, and post district fixed effects. However, almost all are non-significant. When analysing the conditions separately for older adults, we find that estimates associated with the effect of IDW_{PM10} on cardiovascular and cerebrovascular conditions for older adults admitted patients are positive, significant and robust to the inclusion of fixed effects. However,

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the robustness mentioned does not hold in the case for respiratory diseases where the inclusion of week of the year times year fixed effects make the results non-significant. When analysing the conditions separately for children, we find that estimates associated with the effect of IDW_{PM10} on cerebrovascular conditions for admitted children are positive, significant and robust to the inclusion of fixed effects. However, this result does not hold for respiratory and cardiovascular conditions on children.

Meanwhile, when analysing all conditions together, we find that estimates associated with the effect of IDW_{NO2} on these conditions for older adults hospital admitted patients are positive, significant but non-robust to the inclusion week of the year times year fixed effects. Moreover, when we examine the effects of IDW_{NO2} separately by condition, we find that these results are mainly driven by respiratory conditions. However, these are non-robust to the inclusion of day of the week fixed effects and week times year fixed effects.

In Table 4.8, we present the effect of daily IDW_{NO2} and IDW_{PM10} on hospital costs at the individual level following Equation (4.5.6). Similar to the specification presented in Table 4.6, we distinguish between the hospital visits by mode of disposal, hospital admission or discharged from ED. In Panel (A), we present the results for hospital admitted patients. In the case of hospital admitted children, we find that changes in IDW_{PM10} have a positive and significant effect on individual level costs of visit when controlling for postcode sector characteristics and weather conditions. This effect is non-robust to the inclusion of week of the year times fiscal year fixed effects. Nonetheless, an increase of one standard deviation of average daily exposure to $PM10$ increases the average cost per hospital admitted child by £60.40 or 7.15 p.p. with respect to the dependent variable mean, see Column (1). In the case of hospital admitted older adults, we find that in IDW_{PM10} have a positive and significant effect on individual level costs of visit, however, this effect is not robust to the inclusion of day of the week fixed effects. An increase of one standard deviation of average daily exposure to $PM10$ increases the average cost per hospital admitted older adults by £179.89 or 9.81 p.p. with respect to the dependent variable mean, see Column (5). Likewise, the effects of IDW_{NO2} on costs at the individual level for admitted children and older adults are negative and significant but non-robust to the inclusion of day of the week fixed effects.

In Panel (B), we present results corresponding to Equation (4.5.6) for patients discharged from ED. We find that IDW_{PM10} have a positive and significant effect on in-

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dividual level costs of discharged children's visits when including day of the week fixed effects fiscal year fixed effects and week times year fixed effects. For each standard deviation of increase on IDW_{PM10} and IDW_{NO2} the individual costs of discharged hospital visits by children increase by £0.31 and £0.27. These magnitudes might seem small, however, these coefficients can be interpreted as the average costs of visit which for 132,895 individuals can add up to £41,197 (or 546 extra discharged visits) and £35,882 (or 478 extra discharged visits), respectively. Meanwhile, we find that IDW_{PM10} has negative effect and IDW_{NO2} has a positive effect on individual level costs of discharged older adults' visits. However, these are not robust to the inclusion of any fixed effects, the coefficient associated with IDW_{PM10} becomes non-significant while the coefficients' sign associated with IDW_{NO2} becomes negative.

To further investigate the effects of pollution—IDW_{PM10} and IDW_{NO2}—on healthcare costs we analyse its effects on total costs by day and postcode sector following Equation (4.5.7). In Table 4.9, we present the estimates for the hospital admitted patients in Panel A and in Panel B that of the discharged from ED patients. In the case of the hospital admitted children, we find that changes in IDW_{PM10} have positive and significant effects on total costs that are robust to the inclusion of day of the week fixed effects but non-robust to the addition of week times fiscal year fixed effects. An increase of one standard deviation of average daily exposure to $PM10$ increases the total costs for hospital admitted children by £74.71 (or 7.98 p.p. with respect to the mean) and £39.79 (or 4.25 p.p. with respect to the mean) per day and postcode sector if we do not include and include day of the week fixed effects, respectively, see Columns (1) and (2). Meanwhile, in the case of hospital admitted older adults, we find that changes in IDW_{PM10} have positive and significant effects on total costs for older adults hospital admitted patients. However, these are non-robust to the inclusion of day of the week fixed effects. An increase of one standard deviation of average daily exposure to $PM10$ increases the total costs for older adults hospital admitted patients by £273.90 (or 10.70 p.p. with respect to the mean) per day and postcode sector if we include postcode sector and weather controls but do not include fixed effects, respectively, see Columns (5). In addition, we find that changes in IDW_{NO2} have negative and significant effects on total costs for children and older adults hospital admitted patients that are non-robust to the inclusion of day of the week fixed effects.

When analysing total costs for discharged patients, we find that coefficients associated with changes in IDW_{NO2} are non-robust to the inclusion of day of the week fixed effects

are included irrespective of the age group. Meanwhile, when analysing the effects of IDW_{PM10} on total costs for children, we find that an increase of one standard deviation of exposure to $PM10$ increases the total costs of ED visits by children by £4.08 and £3.94 on average per day per postcode sector if we do not include and include day of the week fixed effects, respectively, see Columns (1) and (2). Likewise, increased exposure to $PM10$ has a positive effect and significant effect of £0.78 on total costs for older adults on average per day and postcode sector when including day of the week fixed effects and £2.06 when including in addition week of the year times fiscal year and post district fixed effects, respectively.

The combination of these results suggest that a higher exposure to $PM10$ increases healthcare costs since it causes more, and more costly hospital visits, see Tables 4.5, 4.6, and 4.9. In the case of older adults, even when this higher exposure to $PM10$ does not generate higher average costs of visits for discharged older adults, our results of more costly hospital visits are driven by higher numbers of hospital visits in general— admitted to hospital and discharged from ED— due to higher exposure to $PM10$. Our results allow us to quantify the economic costs of pollution due to $PM10$ for hospital admitted older adults in Leicester. An increase in one standard deviation of exposure to $PM10$ increases the total costs by £273.90 per day per postcode sector on average and by £4,398,834 in the whole city in a year only accounting for the higher total costs of older adults hospital admitted patients.[56] When making the same calculations for older adults discharged from ED, we find non-significant results when we do not include fixed effects, see Table 4.9, Columns (5) to (8). In the case of children, higher exposure to $PM10$ generates higher hospital admissions and both average and total costs of children hospital admissions are higher when children are more exposed to $PM10$. Similar to our results for the hospital admitted older adults, we find that each standard deviation of increase of exposure to $PM10$ increases daily cost for hospital admitted children and discharged from ED children by £74.71 and £4.08 which translates to £1,199,843 and £65,525 on a yearly basis, respectively. In total, each extra standard deviation of exposure to $PM10$ costs the Leicester CCGs £4,398,834 a year treating older adults and £1,265,368 treating children adding up to £5,664,202.[57]

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[56]This result is accounting for years of 365 days and 44 postcode sectors for which we have their local characteristics (deprivation indices).

[57]For consistency purposes, these calculations are based in specification without any type of fixed effects, which does not allow us to quantify the costs for discharged older adults since the corresponding coefficient are non-significant. Given this, the results presented should be interpreted as a lower bound in costs as the total costs for discharged older adults are positive and significant in the remaining three

Our results with respect to NO_2 are mixed which prevent us from fully quantifying the economic costs of pollution due to NO_2. We find negative, often non-significant and very small in magnitude effects of positive changes in NO_2 on total number of hospital visits irrespective of the age group and mode of disposal. In addition, we find that only the average costs for children discharged from ED consistently increases when NO_2 increases. As a consequence, these mixed results are also reflected in our estimates of the effects of changes in NO_2 on total costs by day and postcode sector. In line with these mixed findings, our results for children discharged from ED associated with positive changes in NO_2 are negative and the only ones robust to the inclusion of controls and fixed effects.

4.7 Robustness Checks

A potential concern regarding our main analysis is the use of average daily exposure to pollution. In order to alleviate this concern, we also perform all our analyses using the range of exposure to pollution within a day, i.e. maximum minus minimum daily exposure. The daily range is a relevant indicator since big changes in pollution in a short period of time can trigger health conditions for people to attend hospital. In Table 4.10, we find that larger daily ranges of exposure to $PM10$ do not have a consistent effect on total number of hospital visits, do not have a consistent effect on total costs for hospital admitted patients; and by and large do not consistently have an effect on total costs for discharged patients. Additionally, whenever these results are consistent with our main results they are not robust to the inclusion of controls. Notably, we find that larger daily ranges of exposure to NO_2 increase the total number of hospital visits per day and postcode sector—since almost all coefficients are positive, significant and robust to the inclusion of controls— increase the total costs per visit of discharged patients, and increase the total costs per visit of older adult admitted patients only when fixed effects are included.

Another potential concern about our results is the possible presence of avoidance behaviour where individuals avoid outings on days/areas of higher pollution (see Janke, 2014; Neidell, 2009; Moretti and Neidell, 2011). There are two reasons why avoidance behaviour should not be of concern. Firstly, since the level of disaggregation of pollution

specifications where fixed effects are included.

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data we work with is not publicly/easily available. Individuals could check air quality in Leicester as a whole, then avoidance behaviour could potentially be present only in the time dimension but not in the geographical dimension we use for our analysis. Secondly, and most importantly, our target population for this analysis has very little to no possibilities of avoidance behaviour by our design. Our target population is children (schools are close to their residence) and the older adults (whom are retired). This allowed us to better impute pollution using their residence postcode and, in addition, should alleviate any concerns about avoidance behaviour.

An additional concern regarding our results is the way we incorporate wind speed and direction to our measure of pollution. To alleviate those concerns, we perform the same analysis presented in Table 4.5 using the nearest monitor as our pollution measure. We know these estimates are prone to bias since exposure to monitors is not necessarily randomly assigned. However, since we are analysing pollution within a very small area—a city—we can assume that the limits to consider the centroid of the postcode sector closer to one monitor are random. In Table 4.11, we show that our results are largely unaltered by the change in the pollution measure.

Another potential concern is the exclusion of air pressure as a weather control. The inclusion of air pressure is relevant, as pressure of the air affects whether pollution levels build up. During high pressure systems, the air is usually still which allows pollution to accumulate. Conversely, during low pressure systems the weather is often windy and rainy, leading to pollutants to disperse or be washed out of the atmosphere. Since we only have average daily pressure data for 2009 to 2011, we excluded it from the main analysis. When we include air pressure as a control in Table 4.12, the results from the main analysis still hold when we restrict the sample to 2009-2011 and include the air pressure control.

In addition, a potential concern is the fact that weekdays might present different pollution patterns and hospital admissions than weekends. As a robustness check, we examine the effects of IDW_{PM10} and IDW_{NO_2} on total hospital visits and total costs for admitted and discharged patients. In Table 4.13, we show that our results still hold when we restrict the sample to weekdays only.

Finally, another concern regarding our main result is the potential cumulative effects of pollution on individuals' health and therefore the likelihood of a hospital visit. To address this concern, we perform the same analysis than the one presented in Table 4.5

but including seven day lags. In Table 4.14, we include seven day lags to check whether there are cumulative effects. By and large we find that when analysing the effects of IDW_{PM10} the lags included are associated with negative coefficients when significant. To the contrary, when analysing the effects of IDW_{NO_2} the inclusion of lags present some positive and significant coefficients. Our results suggest that there is positive and significant cumulative effects of NO_2. In addition, we also run a falsification test, replacing our main explanatory variables with its corresponding seven day lag and lead, see Table 4.15. When analysing the effects of IDW_{PM10}, we find that none of these replacements have an effect on of total number hospital visits. However, this is not the case when analysing the effects of IDW_{NO_2}.

4.8   Final Remarks

This paper investigates the impact of pollution on the economic costs of public healthcare using proprietary data from the University Hospitals of Leicester NHS Trust. Our study exploits the spatial and temporal variation of pollution—nitrogen dioxide (NO_2) and particulate matter with an aerodynamic diameter less than 10 μm ($PM10$)—as well as temporal variation in wind speed and direction.

Despite the ample literature that establishes that chronic exposure of children and older adults to air pollution results in decreased development and lung function, increased number of respiratory and coronary conditions, diabetes and dementia, there is little empirical evidence that evaluates the immediate effects of NO_2 and $PM10$ on healthcare costs for the most vulnerable groups, i.e. children and seniors.

In this paper, we have shown each extra standard deviation of exposure to $PM10$ costs the Leicester CCGs £4, 398, 834 per year treating older adults and £1, 265, 368 treating children which sums to £5, 664, 202 in total costs per year, 0.85% of the average total expenditure for UHL NHS Trust (from fiscal year 2007/08 to 2011/12). The cost may seem small compared to the budget but we maintain that the pollution cost is a substantial burden on the Leicester CCGs. We do not find clear effects of changes in daily average exposure to NO_2 on hospital visits and their costs. Nonetheless, we find that larger daily ranges of exposure to NO_2 increase total number of hospital visits per day and postcode sector, increase the total costs per visit of discharged patients, and increases the total costs per visit of admitted older adults only when controlling

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by fiscal year fixed effects.

Our findings quantify the resources that could potentially be reallocated from NHS treating immediate consequences of pollution, in particular consequences of $PM10$, on pollution reduction programs while improving Leicester residents' health. By overcoming the usual challenges to identify the causal effects of pollution—such as endogeneity, measurement error and avoidance behaviour—we shed light on how air pollution affects medical costs, which is in turn critical for crafting efficient environment policies.

Tables

Table 4.1: EU Standards

Pollutant	Averaging period	Concentration	Limit value to be met as of	Permitted exceedences each year
NO_2	1 hour	200 $\mu g/m3$	1.1.2010	18
	1 year	40 $\mu g/m3$	1.1.2010	-
$PM10$	24 hours	50 $\mu g/m3$	1.1.2005	35
	1 year	40 $\mu g/m3$	1.1.2005	-

Source: European Commission, Environment. https://ec.europa.eu/environment/air/quality/standards.htm

*Under Directive 2008/50/EU, the Member State could apply for an extension of up to five years (i.e. maximum up to 2015) in a specific zone. The request is subject to an assessment by the Commission. In such cases within the time extension period the limit value applies at the level of the limit value + maximum margin of tolerance (48 $\mu g/m3$ for annual NO_2 limit value).

**Under Directive 2008/50/EU, the Member State was able to apply for an extension until three years after the date of entry into force of the new Directive (i.e. May 2011) in a specific zone. The request was subject to assessment by the Commission. In such cases within the time extension period the limit value applies at the level of the limit value + maximum margin of tolerance (35 days at $75\mu g/m3$ for daily $PM10$ limit value, $48\mu g/m3$ for annual $PM10$ limit value).

Table 4.2: Data Description and Sources

Type	Date	Freq.	Level	Description	Source
(I) Pollution					
NO2	2006 to 2011	Hourly	Monitor	Micrograms per m3	Leicester City Coucil (AQMA)
PM10	2006 to 2011	Hourly	Monitor	TEOM 1.3 measure	Leicester City Coucil (AQMA)
(II) Meteorological					
Temperature	2006 to 2011	Hourly	Monitor	Degree Celcius (degree C)	Leicester City Coucil (AQMA)
Rainfall	2006 to 2011	Hourly	Monitor	Millimiter per hour (mm/h)	Leicester City Coucil (AQMA)
Air Pressure	2009 to 2011	Hourly	Monitor	Millibar (mbar)	Leicester City Coucil (AQMA)
(III) Health					
Age	2006 to 2011	-	ED visit	Age Groups: Children (<18), **Older Adults**(>60)	UHL, NHS Trust
Gender	2006 to 2011	-	ED visit	Female, Male	UHL, NHS Trust
Ethnicity	2006 to 2011	-	ED visit	Asian, Black, White and Other Ethnicities	UHL, NHS Trust
Postcode Sector	2006 to 2011	-	ED visit	Postcode District plus one digit	UHL, NHS Trust
Admission Date	2006 to 2011	-	ED visit	Date the individual enters ED	UHL, NHS Trust
Episode End Date	2006 to 2011	-	ED visit	Date the individual is released from ED or hospital	UHL, NHS Trust
Mode of Disposal	2006 to 2011	-	ED visit	Discharged, Admitted, Dead	UHL, NHS Trust
ICD	2006 to 2011	-	ED visit	International Classification of Diseases	UHL, NHS Trust
HRG	2006 to 2011	-	ED visit	Healthcare Resource Group	UHL, NHS Trust
Fiscal Year	2006 to 2011	-	ED visit	Necessary to merge with the National Tariff Data	UHL, NHS Trust
(IV) Administrative					
National Tariff	2005/6 to 2011/2	Yearly		Fiscal Year Data	National Archives
Census 2011	2011	-		Whole population by age, gender and postcode sector	Consumer Data Research Centre
Maps		-		Postcode Sectors in LE1, LE2, LE3, LE4, LE5, and LE19	Own elaboration, EDINA Digimap
Deprivation Indices	2004,2007,2010	Yearly		Originally in Lower Layer Super Output Areas (LSOAs) but translated into Postcode Sectors	(ODPM) Office of the Deputy Prime Minister

Note: ED stands for Emergency Department at Leicester Royal Infirmary or the Clinical Decisions Unit at Glenfield Hospital

Table 4.3: Pollution Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
St Matthews Way NO2	56.37	28.024	0.191	225.571	1942272
St Matthews Way PM10	-	-	-	-	-
Vaughan Way NO2	60.641	34.539	4.393	1076.094	2453616
Vaughan Way PM10	24.729	18.456	0.6	1010.6	2503920
Melton Road NO2	52.571	26.352	2.483	474.444	2454528
Melton Road PM10	22.7	14.016	0.5	792.6	2286672
Abbey Lane NO2	50.439	34.534	0.764	436.626	1246032
Abbey Lane PM10	18.842	12.113	1.1	1022.8	1174608
Glenhills Way NO2	69.387	36.669	1.91	280.388	2495280
Glenhills Way PM10	26.063	12.959	0.9	291.6	2470656
Imperial Ave NO2	35.011	17.901	0.573	148.407	2456208
Imperial Ave PM10	17.021	10.796	0.8	723.2	2402352
London Road NO2	31.145	22.205	0.191	159.485	2382192
London Road PM10	16.222	10.673	0.6	714.4	2328288
Uppingham Road NO2	35.819	22.449	0.191	286.882	2347056
Uppingham Road PM10	-	-	-	-	-
Wind Speed	2.829	1.674	0	39.99	2522112
Wind Direction	191.95	97.874	0	360	2522112
Temperature	10.178	6.251	-9.859	34.54	2522112
Rainfall	0.053	0.306	0	14.96	2513424
Air Pressure	1004.008	10.919	957	1032	1245696

Table 4.4: Health Statistics, 2006 to 2011.

| | | | Visits | Admissions | | Length of Stay* | | Number of Doctors* | |
			Total	Total	% of Visits	Mean	St. Dev.	Mean	St. Dev.
Gender									
	Female		128918	45158	35.03%	7.64	13.30	1.61	0.82
	Male		143839	42242	29.37%	6.33	11.71	1.57	0.81
Age									
	Children		153937	20349	13.22%	1.55	4.16	1.04	0.22
		0 to 4	62383	11,409	18.29%	1.50	4.51	1.02	0.15
		5 to 9	29737	2887	9.74%	1.40	2.91	1.02	0.13
		10 to 17	61817	6053	9.79%	1.71	3.97	1.09	0.33
	Older Adults		118820	67051	56.43%	8.66	13.75	1.76	0.86
		60 to 64	21537	8029	37.28%	5.57	10.79	1.64	0.81
		65 to 69	17398	7936	45.61%	6.71	12.86	1.68	0.83
		70 to 74	19087	10211	53.50%	7.63	12.54	1.72	0.84
		75 to 79	19169	11599	60.51%	8.86	14.30	1.79	0.88
		80 to 84	18391	12181	66.23%	9.94	14.82	1.81	0.87
		85 to 89	14203	10214	71.91%	10.53	14.27	1.83	0.89
		90+	9035	6881	76.16%	10.71	14.73	1.78	0.85
Ethnicities									
	White		168036	61333	36.50%	7.53	12.91	1.63	0.83
	Black		11764	2697	22.93%	4.64	11.79	1.34	0.67
	Asian		64576	17954	27.80%	5.82	11.33	1.53	0.80
	Other		28381	5416	19.08%	6.22	12.62	1.46	0.77
Total			272757	87400	32.04%	–	–	–	–

*Admitted to Hospital sample only.

Table 4.5: Standardized IDW on Hospital Visits with Weather Controls and Time Fixed Effects

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
daily $IDW\ PM10$	0.080***	0.077***	0.091***	0.069***	0.030***	0.035***	0.081***	0.087***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)	(0.008)
daily $IDW\ NO_2$	-0.081***	-0.059***	-0.059***	-0.053***	0.027***	-0.006	-0.019**	-0.006
	(0.007)	(0.008)	(0.011)	(0.011)	(0.006)	(0.006)	(0.009)	(0.009)
Observations	78219	78219	78219	78219	78219	78219	78219	78219
Adjusted R^2	.1818	.1836	.2128	.2315	.0359	.0403	.0457	.0827
Dep. var. mean	1.868	1.868	1.868	1.868	1.395	1.395	1.395	1.395
Dep. var. st. dev.	1.549	1.549	1.549	1.549	1.170	1.170	1.170	1.170
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates corresponding to Equation (4.5.1) where we replace *Pollution* by *IDW*. Our dependent variable is total number of visits by age group. Our main independent variables are the daily average IDW_{PM10} and IDW_{NO_2}. Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our unit of observation is day/postcode sector. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.6: Standardized IDW on Hospital Visits with Weather Controls and Time Fixed Effects by Mode of Disposal

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Admitted								
daily $IDW\ PM10$	0.011***	0.009***	0.012***	0.011***	0.013***	0.015***	0.042***	0.047***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)
daily $IDW\ NO_2$	-0.018***	-0.008***	-0.012***	-0.013***	0.012**	-0.001	-0.008	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.008)
Observations	78219	78219	78219	78219	78219	78219	78219	78219
Adjusted R^2	.0357	.037	.0514	.0543	.0288	.0297	.0347	.058
Dep. var. mean	0.259	0.259	0.259	0.259	0.854	0.854	0.854	0.854
Dep. var. st. dev.	0.530	0.530	0.530	0.530	0.967	0.967	0.967	0.967
(B) Discharged								
daily $IDW\ PM10$	0.073***	0.071***	0.084***	0.060***	0.021***	0.025***	0.050***	0.051***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.004)	(0.004)	(0.005)	(0.005)
daily $IDW\ NO_2$	-0.071***	-0.053***	-0.050***	-0.043***	0.018***	-0.007	-0.015**	-0.005
	(0.007)	(0.008)	(0.011)	(0.011)	(0.004)	(0.005)	(0.007)	(0.007)
Observations	78219	78219	78219	78219	78219	78219	78219	78219
Adjusted R^2	.1661	.1676	.1939	.2111	.0139	.0193	.023	.0398
Dep. var. mean	1.699	1.699	1.699	1.699	0.650	0.650	0.650	0.650
Dep. var. st. dev.	1.529	1.529	1.529	1.529	0.841	0.841	0.841	0.841
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.4). Our dependent variable is total number of visits by age group. Our main independent variables are the daily average IDW_{PM10} and IDW_{NO_2}. In Panel (A), we present estimates for the hospital admitted patients sub-sample while, in Panel (B), we present that of discharged from ED patients. Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our unit of observation is day/postcode sector. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.7: Standardized IDW on Hospital Admissions with Weather Controls and Time Fixed Effects by Diagnosis

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Respiratory, Caridiovascular, and Cerebrovascular Diagnosis.								
daily $IDW\ PM10$	0.002	0.001	0.002	0.002	0.001	0.001	0.010*	0.008
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
daily $IDW\ NO_2$	-0.002	0.004*	-0.001	-0.001	0.013***	0.011**	0.006	0.007
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.007)
Observations	51584	51584	51584	51584	51584	51584	51584	51584
Adjusted R^2	.0203	.0214	.0323	.0327	.0189	.0205	.0243	.0338
Dep. var. mean	0.164	0.164	0.164	0.164	1.081	1.081	1.081	1.081
Dep. var. st. dev.	0.403	0.403	0.403	0.403	0.874	0.874	0.874	0.874
(B) Respiratory Diagnosis.								
daily $IDW\ PM10$	-0.002	0.004*	-0.001	-0.001	0.013***	0.011**	0.006	0.007
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.007)
daily $IDW\ NO_2$	0.002	0.001	0.002	0.002	0.001	0.001	0.010*	0.008
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	51584	51584	51584	51584	51584	51584	51584	51584
Adjusted R^2	.0174	.0185	.0308	.031	.0162	.0163	.02	.0238
Dep. var. mean ymean	0.125	0.125	0.125	0.125	0.525	0.525	0.525	0.525
Dep. var. st. dev.	0.353	0.353	0.353	0.353	0.677	0.677	0.677	0.677
(C) Cardiovascular Diagnosis.								
daily $IDW\ PM10$	-0.000	-0.000	-0.000	0.000	0.010**	0.013**	0.030***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.006)	(0.007)
daily $IDW\ NO_2$	0.000	0.001	-0.001	-0.001	0.025***	0.009	-0.005	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.008)	(0.008)
Observations	51584	51584	51584	51584	51584	51584	51584	51584
Adjusted R^2	.0018	.0018	.0021	.0022	.0138	.0155	.0207	.0286
Dep. var. mean	0.015	0.015	0.015	0.015	0.904	0.904	0.904	0.904
Dep. var. st. dev.	0.123	0.123	0.123	0.123	0.824	0.824	0.824	0.824
(D) Cerebrovascular Diagnosis.								
daily $IDW\ PM10$	0.004***	0.003***	0.003**	0.003*	0.004*	0.004*	0.007**	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
daily $IDW\ NO_2$	-0.004***	-0.002*	-0.002	-0.002	0.003	0.001	-0.006	-0.006
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Observations	51584	51584	51584	51584	51584	51584	51584	51584
Adjusted R^2	.005	.0052	.0061	.0063	.0059	.0059	.0073	.0085
Dep. var. mean	0.036	0.036	0.036	0.036	0.159	0.159	0.159	0.159
Dep. var. st. dev.	0.188	0.188	0.188	0.188	0.393	0.393	0.393	0.393
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.5). Our dependent variable is total number of admitted patients by age group. Our unit of observation is day/postcode sector for the hospital admitted patients sub-sample. Our main independent variables are the daily average IDW_{PM10} and IDW_{NO_2}. In Panel (A), we present estimates for respiratory, cardiovascular and cerebrovascular diagnosis together while, in Panels (B), (C) and (D), we present that of the same diagnosis separately. Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.8: Standardized IDW on Costs, 2006 to 2011.

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Admitted								
IDW PM10	60.396***	27.927*	-5.758	-7.622	179.886***	-2.237	-17.522	-14.209
	(14.596)	(15.090)	(22.462)	(21.342)	(12.152)	(10.895)	(14.380)	(14.953)
IDW NO$_2$	-62.453***	-17.148	6.342	5.559	-264.802***	16.260	8.420	7.062
	(13.071)	(14.886)	(29.249)	(28.697)	(13.180)	(11.787)	(15.228)	(15.231)
Observations	12378	12378	12378	12378	50751	50751	50751	50751
Adjusted R^2	.0041	.0519	.0617	.0616	.047	.28	.2825	.2825
Dep. var. mean	845.152	845.152	845.152	845.152	1833.388	1833.388	1833.388	1833.388
Dep. var. st. dev.	932.832	932.832	932.832	932.832	2078.593	2078.593	2078.593	2078.593
(B) Discharged								
IDW PM10	-0.019	0.311***	-0.170	-0.355***	-0.560***	-0.070	0.069	0.006
	(0.090)	(0.089)	(0.111)	(0.115)	(0.147)	(0.144)	(0.183)	(0.189)
IDW NO$_2$	1.221***	0.274***	0.970***	0.977***	0.674***	-0.317*	-0.715***	-0.726***
	(0.101)	(0.103)	(0.131)	(0.131)	(0.169)	(0.170)	(0.217)	(0.218)
Observations	132895	132895	132895	132895	50871	50871	50871	50871
Adjusted R^2	.0285	.0602	.0673	.0676	.03	.0835	.0868	.087
Dep. var. mean	75.053	75.053	75.053	75.053	76.421	76.421	76.421	76.421
Dep. var. st. dev.	25.288	25.288	25.288	25.288	25.579	25.579	25.579	25.579
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.6) at the individual level. Our dependent variable is individual costs of hospital attendance for individual i in postcode sector c at time t. Our main independent variables are the daily average IDW_{PM10} and IDW_{NO_2}. In Panel (A), we present estimates for the hospital admitted patients sub-sample while, in Panel (B), we present that of patients discharged from ED. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our unit of observation is day/postcode sector. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.9: Standardized IDW on Total Costs, 2006 to 2011.

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Admitted								
$IDW\,PM10$	74.713***	39.786**	7.289	6.989	273.896***	29.996	36.346	35.851
	(17.344)	(17.916)	(25.636)	(24.923)	(20.423)	(18.578)	(24.480)	(25.306)
$IDW\,NO_2$	-76.336***	-25.053	-8.203	-9.618	-361.405***	20.114	2.644	4.138
	(15.379)	(17.413)	(32.421)	(31.826)	(21.842)	(19.859)	(25.710)	(25.712)
Observations	11172	11172	11172	11172	36370	36370	36370	36370
Adjusted R^2	.0049	.0485	.0583	.0584	.0428	.2528	.2561	.2578
Dep. var. mean	936.385	936.385	936.385	936.385	2558.325	2558.325	2558.325	2558.325
Dep. var. st. dev.	1018.666	1018.666	1018.666	1018.666	2932.164	2932.164	2932.164	2932.164
(B) Discharged								
$IDW\,PM10$	4.076***	3.938***	4.710***	2.722***	-0.014	0.776*	2.310***	2.064***
	(0.558)	(0.565)	(0.716)	(0.737)	(0.421)	(0.423)	(0.532)	(0.550)
$IDW\,NO_2$	-1.438**	-1.008	-2.817***	-2.483***	1.572***	0.422	-0.007	0.382
	(0.616)	(0.645)	(0.817)	(0.813)	(0.479)	(0.498)	(0.621)	(0.621)
Observations	61189	61189	61189	61189	36465	36465	36465	36465
Adjusted R^2	.1443	.148	.1659	.1798	.0233	.0436	.0474	.0546
Dep. var. mean ymean	163.006	163.006	163.006	163.006	106.612	106.612	106.612	106.612
Dep. var. st. dev.	111.945	111.945	111.945	111.945	61.550	61.550	61.550	61.550
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.7) at the day/postcode sector level. Our dependent variable is total costs of hospital attendance in postcode sector c at time t. Our main independent variables are the daily average IDW_{PM10} and IDW_{NO_2}. In Panel (A), we present estimates for the hospital admitted patients sub-sample while, in Panel (B), we present that of patients discharged from ED. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our unit of observation is day/postcode sector. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.10: Standardized IDW on Total Hospital Visits and Total Costs Using Exposure Range (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Total Number of Hospital Visits								
$IDW\,PM10\,(Range)$	0.016***	0.016***	0.006	0.008	0.001	0.003	0.012**	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
$IDW\,NO_2\,(Range)$	0.002	0.022***	0.025***	0.023***	0.058***	0.025***	0.034***	0.043***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.005)	(0.005)	(0.006)	(0.006)
Observations	78219	78219	78219	78219	78219	78219	78219	78219
Adjusted R^2	.1802	.1825	.2118	.231	.0366	.04	.0444	.0814
Dep. var. mean ymean	1.868	1.868	1.868	1.868	1.395	1.395	1.395	1.395
Dep. var. st. dev.	1.549	1.549	1.549	1.549	1.170	1.170	1.170	1.170
(B) Total Costs for Admitted Patients								
$IDW\,PM10\,(Range)$	34.535***	16.911	11.152	11.730	101.089***	-4.829	-14.867	-11.750
	(11.160)	(11.025)	(13.404)	(13.406)	(16.945)	(15.241)	(17.229)	(17.237)
$IDW\,NO_2\,(Range)$	-31.667***	3.702	2.261	1.587	-180.053***	40.538***	50.394***	52.522***
	(11.910)	(13.170)	(18.215)	(18.837)	(16.378)	(14.614)	(17.015)	(17.109)
Observations	11172	11172	11172	11172	36370	36370	36370	36370
Adjusted R^2	.0027	.048	.0584	.0585	.0382	.2528	.2561	.2579
Dep. var. mean	936.385	936.385	936.385	936.385	2558.325	2558.325	2558.325	2558.325
Dep. var. st. dev.	1018.666	1018.666	1018.666	1018.666	2932.164	2932.164	2932.164	2932.164
(C) Total Costs for Discharged Patients								
$IDW\,PM10\,(Range)$	1.034**	0.720	0.090	0.051	0.074	0.186	0.491	0.467
	(0.495)	(0.497)	(0.550)	(0.553)	(0.355)	(0.346)	(0.382)	(0.381)
$IDW\,NO_2\,(Range)$	2.860***	3.015***	2.027***	1.660***	1.167***	0.700*	1.170***	1.356***
	(0.490)	(0.497)	(0.555)	(0.553)	(0.380)	(0.384)	(0.424)	(0.424)
Observations	61189	61189	61189	61189	36465	36465	36465	36465
Adjusted R^2	.1443	.1479	.1655	.1797	.0231	.0435	.047	.0544
Dep. var. mean	163.006	163.006	163.006	163.006	106.612	106.612	106.612	106.612
Dep. var. st. dev.	111.945	111.945	111.945	111.945	61.550	61.550	61.550	61.550
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Panel (A) reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by $IDW(Range)$. Panels (B) and (C) report the OLS estimates obtained from performing Equation (4.5.7) replacing IDW by $IDW(Range)$ at the day/postcode sector level for hospital admitted and discharged from ED patients, respectively. Our unit of observation is day/postcode sector. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.11: Standardized IDW on Total Hospital Visits and Total Costs Using Nearest Monitor (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Total Number of Hospital Visits								
$IDW\,PM10\,(Near)$	0.125***	0.122***	0.112***	0.128***	0.118***	0.122***	0.143***	0.173***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.007)	(0.007)	(0.008)
$IDW\,NO2\,(Near)$	-0.113***	-0.105***	-0.099***	-0.113***	-0.007	-0.021***	-0.026***	-0.040***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.007)	(0.007)	(0.008)	(0.008)
Observations	78219	78219	78219	78219	78219	78219	78219	78219
Adjusted R^2	.1832	.1851	.2139	.2335	.0425	.047	.0528	.0916
Dep. var. mean	1.868	1.868	1.868	1.868	1.395	1.395	1.395	1.395
Dep. var. st. dev	1.549	1.549	1.549	1.549	1.170	1.170	1.170	1.170
(B) Total Costs for Admitted Patients								
$IDW\,PM10\,(Near)$	36.489**	17.548	0.504	6.937	264.043***	86.325***	89.365***	126.534***
	(17.214)	(17.331)	(20.801)	(20.397)	(25.989)	(21.287)	(22.582)	(24.520)
$IDW\,NO2\,(Near)$	-45.074***	-20.635	-7.779	-12.091	-224.089***	-16.649	-19.162	-40.582**
	(14.169)	(12.990)	(13.889)	(14.447)	(25.904)	(18.407)	(19.473)	(20.330)
Observations	11172	11172	11172	11172	36370	36370	36370	36370
Adjusted R^2	.0024	.0479	.0584	.0585	.0386	.2532	.2565	.2585
Dep. var. mean	936.385	936.385	936.385	936.385	2558.325	2558.325	2558.325	2558.325
Dep. var. st. dev.	1018.666	1018.666	1018.666	1018.666	2932.164	2932.164	2932.164	2932.164
(C) Total Costs for Discharged Patients								
$IDW\,PM10\,(Near)$	6.692***	7.006***	7.166***	7.905***	2.073***	3.258***	4.064***	4.122***
	(0.660)	(0.663)	(0.704)	(0.787)	(0.504)	(0.510)	(0.538)	(0.578)
$IDW\,NO2\,(Near)$	-5.370***	-5.405***	-6.151***	-7.077***	0.510	-0.588	-1.193**	-0.974*
	(0.775)	(0.772)	(0.838)	(0.932)	(0.525)	(0.533)	(0.563)	(0.580)
Observations	61189	61189	61189	61189	36465	36465	36465	36465
Adjusted R^2	.1452	.149	.167	.1815	.0243	.0454	.0492	.0565
Dep. var. mean	163.006	163.006	163.006	163.006	106.612	106.612	106.612	106.612
Dep. var. st. dev.	111.945	111.945	111.945	111.945	61.550	61.550	61.550	61.550
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Panel (A) reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by $IDW(Near)$. Panels (B) and (C) report the OLS estimates obtained from performing Equation (4.5.7) replacing IDW by $IDW(Near)$ at the day/postcode sector level for hospital admitted and patients discharged from ED, respectively. Our unit of observation is day/postcode sector. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.12: Standardized IDW on Total Hospital Visits and Total Costs with Air Pressure Controls, 2009 to 2011 (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A.1) Total Number of Hospital Visits - No Air Pressure Control								
IDW PM10	0.076***	0.073***	0.089***	0.066***	0.042***	0.046***	0.100***	0.105***
	(0.011)	(0.011)	(0.013)	(0.014)	(0.009)	(0.009)	(0.012)	(0.012)
IDW NO2	-0.038***	-0.017	-0.038**	-0.028*	0.013	-0.019**	-0.039***	-0.024*
	(0.010)	(0.011)	(0.015)	(0.015)	(0.009)	(0.009)	(0.013)	(0.013)
Observations	39365	39365	39365	39365	39365	39365	39365	39365
Adjusted R^2	.1951	.1969	.2174	.2328	.041	.0456	.0497	.088
Dep. var. mean	1.833	1.833	1.833	1.833	1.426	1.426	1.426	1.426
Dep. var. st. dev.	1.530	1.530	1.530	1.530	1.182	1.182	1.182	1.182
(A.2) Total Number of Hospital Visits - With Air Pressure Control								
IDW PM10	0.072***	0.070***	0.086***	0.062***	0.045***	0.048***	0.101***	0.107***
	(0.011)	(0.011)	(0.013)	(0.014)	(0.009)	(0.009)	(0.012)	(0.012)
IDW NO2	-0.040***	-0.020*	-0.045***	-0.034**	0.015*	-0.018*	-0.035***	-0.020
	(0.010)	(0.011)	(0.015)	(0.015)	(0.009)	(0.009)	(0.013)	(0.013)
Observations	39365	39365	39365	39365	39365	39365	39365	39365
Adjusted R^2	.1954	.1971	.2177	.2331	.0412	.0457	.0498	.0882
Dep. var. mean	1.833	1.833	1.833	1.833	1.426	1.426	1.426	1.426
Dep. var. st. dev.	1.530	1.530	1.530	1.530	1.182	1.182	1.182	1.182
(B.1) Total Costs for Admitted Patients - No Air Pressure Control								
IDW PM10	81.944***	44.357	-9.013	6.762	215.351***	40.950*	61.477**	59.547**
	(31.188)	(31.637)	(47.939)	(43.923)	(26.011)	(21.650)	(27.108)	(27.979)
IDW NO2	-84.275***	-13.401	27.170	19.908	-375.955***	10.920	6.139	10.218
	(23.678)	(27.930)	(57.312)	(55.335)	(23.539)	(20.001)	(24.501)	(24.587)
Observations	5936	5936	5936	5936	19537	19537	19537	19537
Adjusted R^2	.0074	.0633	.0771	.0774	.0371	.3678	.3718	.3737
Dep. var. mean	847.393	847.393	847.393	847.393	1624.430	1624.430	1624.430	1624.430
Dep. var. st. dev.	1082.147	1082.147	1082.147	1082.147	2350.277	2350.277	2350.277	2350.277
(B.2) Total Costs for Admitted Patients - With Air Pressure Control								
IDW PM10	78.660***	40.509	-11.887	3.571	214.046***	41.682*	63.828**	62.457**
	(30.479)	(30.997)	(48.038)	(43.950)	(26.382)	(21.920)	(27.257)	(28.141)
IDW NO2	-86.538***	-16.079	24.078	16.950	-376.704***	11.360	8.644	12.812
	(24.192)	(28.377)	(57.174)	(55.250)	(23.572)	(20.050)	(24.574)	(24.652)
Observations	5936	5936	5936	5936	19537	19537	19537	19537
Adjusted R^2	.0075	.0636	.0773	.0775	.037	.3678	.3718	.3737
Dep. var. mean	847.393	847.393	847.393	847.393	1624.430	1624.430	1624.430	1624.430
Dep. var. st. dev.	1082.147	1082.147	1082.147	1082.147	2350.277	2350.277	2350.277	2350.277
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4.12: Standardized IDW on Total Hospital Visits and Total Costs with Air Pressure Controls, 2009 to 2011 (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(C.1) Total Costs for Discharged Patients - No Air Pressure Control								
IDW PM10	5.978***	6.223***	5.780***	3.313***	0.000	-0.518	1.804*	1.403
	(0.965)	(0.975)	(1.228)	(1.274)	(0.761)	(0.763)	(0.958)	(0.989)
IDW NO2	0.260	-0.474	-1.445	-0.744	0.445	0.657	0.107	0.576
	(0.910)	(0.968)	(1.224)	(1.219)	(0.738)	(0.779)	(0.969)	(0.969)
Observations	30677	30677	30677	30677	18660	18660	18660	18660
Adjusted R^2	.1472	.1476	.1624	.1748	.014	.0239	.0281	.0354
Dep. var. mean	170.045	170.045	170.045	170.045	115.388	115.388	115.388	115.388
Dep. var. st. dev.	117.460	117.460	117.460	117.460	67.466	67.466	67.466	67.466
(C.2) Total Costs for Discharged Patients - With Air Pressure Control								
IDW PM10	5.772***	6.009***	5.620***	3.105**	0.259	-0.291	1.898**	1.528
	(0.974)	(0.982)	(1.230)	(1.277)	(0.764)	(0.765)	(0.959)	(0.991)
IDW NO2	0.133	-0.621	-1.710	-1.022	0.616	0.822	0.241	0.713
	(0.909)	(0.967)	(1.228)	(1.222)	(0.739)	(0.780)	(0.973)	(0.972)
Observations	30677	30677	30677	30677	18660	18660	18660	18660
Adjusted R^2	.1473	.1477	.1625	.175	.0146	.0244	.0282	.0355
Dep. var. mean	170.045	170.045	170.045	170.045	115.388	115.388	115.388	115.388
Dep. var. st. dev.	117.460	117.460	117.460	117.460	67.466	67.466	67.466	67.466
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Panels (A.1) and (A.2) report the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by *IDW* for the years 2009 to 2011 without and including an Air Pressure Control, respectively. Panels (B.1) and (B.2) report the OLS estimates obtained from performing Equation (4.5.7) at the day/postcode sector level for hospital admitted for the years 2009 to 2011 without and including an Air Pressure Control, respectively. Panels (C.1) and (C.2) report the same OLS estimates of the patients discharged from ED sub-sample. Our unit of observation is day/postcode sector. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for older adults. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.13: Standardized IDW on Total Hospital Visits and Total Costs Using Weekdays Only (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Children	(5) Older Adults	(6) Older Adults	(7) Older Adults	(8) Older Adults
(A) Total Number of Hospital Visits								
$daily\ IDW\ PM10$	0.077***	0.075***	0.096***	0.071***	0.039***	0.038***	0.097***	0.108***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.007)	(0.007)	(0.010)	(0.010)
$daily\ IDW\ NO_2$	-0.059***	-0.049***	-0.063***	-0.057***	-0.013*	-0.009	-0.020*	-0.009
	(0.009)	(0.009)	(0.013)	(0.013)	(0.008)	(0.008)	(0.011)	(0.011)
Observations	55935	55935	55935	55935	55935	55935	55935	55935
Adjusted R^2	.184	.1857	.2162	.235	.0346	.0351	.0406	.0788
Dep. var. mean	1.850	1.850	1.850	1.850	1.445	1.445	1.445	1.445
Dep. var. st. dev.	1.551	1.551	1.551	1.551	1.190	1.190	1.190	1.190
(B) Total Costs for Admitted Patients								
$daily\ IDW\ PM10$	54.875***	18.756	5.137	9.881	292.549***	24.954	60.014*	59.927*
	(12.794)	(13.428)	(19.663)	(19.021)	(24.687)	(22.554)	(31.873)	(33.284)
$daily\ IDW\ NO_2$	-65.465***	-6.739	19.692	16.454	-402.342***	13.218	-31.616	-29.793
	(13.705)	(16.285)	(34.431)	(33.349)	(26.938)	(24.305)	(33.966)	(33.929)
Observations	7645	7645	7645	7645	26362	26362	26362	26362
Adjusted R^2	.0035	.0437	.0642	.0638	.0422	.2519	.2568	.2589
Dep. var. mean	934.035	934.035	934.035	934.035	2574.580	2574.580	2574.580	2574.580
Dep. var. st. dev.	1031.931	1031.931	1031.931	1031.931	2966.699	2966.699	2966.699	2966.699
(C) Total Costs for Discharged Patients								
$daily\ IDW\ PM10$	3.961***	3.798***	6.070***	3.508***	-0.026	0.733	2.850***	2.682***
	(0.674)	(0.684)	(0.913)	(0.951)	(0.510)	(0.513)	(0.685)	(0.715)
$daily\ IDW\ NO_2$	-1.345*	-0.824	-4.644***	-4.468***	1.176**	-0.084	-0.899	-0.324
	(0.763)	(0.806)	(1.104)	(1.103)	(0.585)	(0.617)	(0.826)	(0.828)
Observations	43531	43531	43531	43531	27152	27152	27152	27152
Adjusted R^2	.1476	.1514	.172	.1858	.0234	.0428	.0462	.0536
Dep. var. mean	164.485	164.485	164.485	164.485	106.946	106.946	106.946	106.946
Dep. var. st. dev.	113.235	113.235	113.235	113.235	62.528	62.528	62.528	62.528
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE		✓	✓	✓		✓	✓	✓
Week × Fiscal Year FE			✓	✓			✓	✓
Post District FE				✓				✓

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Panel (A) reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by *dailyIDW* using weekdays only. Panels (B) and (C) report the OLS estimates obtained from performing Equation (4.5.7) using weekdays only at the day/postcode sector level for hospital admitted and discharged from ED patients, respectively. Our unit of observation is day/postcode sector. Additionally, Columns (1) to (4) present the corresponding estimates for children while Columns (5) to (8) present the corresponding results for the older adults. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.14: Standardized IDW on Total Number of Hospital Visits with 7 Day Lags (Robustness Check)

	(1) Children	(2) Children	(3) Older Adults	(4) Older Adults	(5) Children	(6) Children	(7) Older Adults	(8) Older Adults
IDW PM10								
$t = 0$	0.080***	0.264***	0.030***	0.170***	0.091***	0.242***	0.081***	0.186***
	(0.007)	(0.015)	(0.006)	(0.012)	(0.009)	(0.015)	(0.007)	(0.012)
$t = -1$		-0.043***		-0.025**		-0.039***		-0.018*
		(0.013)		(0.011)		(0.013)		(0.010)
$t = -2$		-0.056***		-0.043***		-0.056***		-0.040***
		(0.013)		(0.011)		(0.013)		(0.011)
$t = -3$		-0.031**		-0.032***		-0.028**		-0.029***
		(0.013)		(0.010)		(0.013)		(0.010)
$t = -4$		-0.039***		-0.020*		-0.035***		-0.017
		(0.013)		(0.010)		(0.013)		(0.010)
$t = -5$		-0.039***		-0.021**		-0.038***		-0.020*
		(0.013)		(0.010)		(0.013)		(0.010)
$t = -6$		0.000		-0.030***		-0.000		-0.028***
		(0.013)		(0.010)		(0.013)		(0.010)
$t = -7$		-0.017		-0.003		-0.018		-0.001
		(0.012)		(0.010)		(0.012)		(0.010)
IDW NO2								
$t = 0$	-0.081***	-0.235***	0.027***	-0.065***	-0.059***	-0.178***	-0.019**	-0.087***
	(0.007)	(0.020)	(0.006)	(0.017)	(0.011)	(0.020)	(0.009)	(0.017)
$t = -1$		0.059***		0.036**		0.051***		0.020
		(0.020)		(0.016)		(0.019)		(0.016)
$t = -2$		0.011		0.019		0.009		0.010
		(0.020)		(0.017)		(0.019)		(0.016)
$t = -3$		0.053***		0.031*		0.047**		0.027
		(0.020)		(0.017)		(0.020)		(0.016)
$t = -4$		0.052**		0.028*		0.048**		0.023
		(0.020)		(0.017)		(0.020)		(0.017)
$t = -5$		0.010		-0.020		0.008		-0.018
		(0.020)		(0.016)		(0.020)		(0.016)
$t = -6$		-0.026		0.032*		-0.025		0.037**
		(0.020)		(0.016)		(0.019)		(0.016)
$t = -7$		0.020		-0.018		0.017		-0.008
		(0.019)		(0.015)		(0.018)		(0.015)
Observations	78219	78213	78219	78213	78219	78213	78219	78213
Adjusted R^2	.1818	.1841	.0359	.0384	.2128	.2147	.0457	.0473
Dep. var. mean ymean	1.868	1.868	1.395	1.395	1.868	1.868	1.395	
Dep. var. st. dev.	1.549	1.549	1.170	1.170	1.549	1.549	1.170	
Postcode Sector Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Day of the week FE					✓	✓	✓	✓
Week × Year FE					✓	✓	✓	✓

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by *IDW* and control for its 7 day lagged version. Our unit of observation is day/postcode sector. Additionally, Columns (1) to (4) present the corresponding estimates for children—Columns (1) and (2) and older adults—Columns (3) and (4)—using postcode sector controls and weather controls. Meanwhile, Columns (5) to (8) present the corresponding results when adding day of the week fixed effects, and week times year fixed effects. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.

Table 4.15: Standardized IDW on Total Number of Hospital Visits with 10–, 7–, and 3–Day Lags and Leads (Robustness Check)

	(1) Children	(2) Children	(3) Children	(4) Older Adults	(5) Older Adults	(6) Older Adults
(A) 10 day differences						
IDW PM10						
$t = 0$	0.091***			0.074***		
	(0.009)			(0.007)		
$t = -10$		-0.002			0.005	
		(0.008)			(0.007)	
$t = 10$			-0.007			0.000
			(0.008)			(0.007)
IDW NO2						
$t = 0$	-0.059***			0.020**		
	(0.011)			(0.008)		
$t = -10$		-0.008			0.030***	
		(0.010)			(0.008)	
$t = 10$			0.012			0.033***
			(0.010)			(0.008)
Observations	78219	78211	78212	78219	78211	78212
Adjusted R^2	.2128	.2116	.2117	.0442	.0419	.0419
Dep. var. mean	1.868	1.868	1.868	1.395	1.395	1.395
ysd Dep. var. st. dev.	1.549	1.549	1.549	1.170	1.170	1.170
(B) 7 day differences						
IDW PM10						
$t = 0$	0.091***			0.074***		
	(0.009)			(0.007)		
$t = -7$		0.002			0.007	
		(0.008)			(0.007)	
$t = 7$			-0.006			-0.007
			(0.008)			(0.007)
IDW NO2						
$t = 0$	-0.059***			0.020**		
	(0.011)			(0.008)		
$t = -7$		-0.006			0.037***	
		(0.010)			(0.008)	
$t = 7$			0.019*			0.045***
			(0.010)			(0.008)
Observations	78219	78213	78213	78219	78213	78213
Adjusted R^2	.2128	.2116	.2117	.0442	.0421	.042
Dep. var. mean	1.868	1.868	1.868	1.395	1.395	1.395
Dep. var. st. dev.	1.549	1.549	1.549	1.170	1.170	1.170
Postcode Sector Controls	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓
Day of the week FE	✓	✓	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses, $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4.15: Standardized IDW on Total Number of Hospital Visits with 10–, 7–, and 3–Day Lags and Leads (Robustness Check)

|	(1) Children	(2) Children	(3) Children	(4) Older Adults	(5) Older Adults	(6) Older Adults
(C) 3 day differences						
IDW PM10						
$t = 0$	0.091***			0.074***		
	(0.009)			(0.007)		
$t = -3$		0.003			0.002	
		(0.008)			(0.007)	
$t = 3$			0.001			0.010
			(0.008)			(0.007)
IDW NO2						
$t = 0$	-0.059***			0.020**		
	(0.011)			(0.008)		
$t = -3$		-0.001			0.048***	
		(0.011)			(0.008)	
$t = 3$			0.002			0.039***
			(0.010)			(0.008)
Observations	78219	78216	78217	78219	78216	78217
Adjusted R^2	.2128	.2117	.2117	.0442	.0422	.0422
Dep. var. mean	1.868	1.868	1.868	1.395	1.395	1.395
Dep. var. st. dev.	1.549	1.549	1.549	1.170	1.170	1.170
Postcode Sector Controls	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓
Day of the week FE	✓	✓	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses, $*p < 0.10, **p < 0.05, ***p < 0.01$

This table reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by *IDW* and control for its lagged and leaded versions. Our unit of observation is day/postcode sector. This table reports the OLS estimates obtained from performing Equation (4.5.1) where we replace *Pollution* by *IDW*. Our unit of observation is day/postcode sector. Panel (A) presents results for 10 day differences while Panels (B) and (C) present results for 7 and 3 days, respectively. Columns (1) to (3) present the corresponding estimates for children without any fixed effects while Columns (4) to (6) present the corresponding results for older adults including postcode sector and weather controls, day of the week and week/year fixed effects. Our postcode sector controls are the deprivation indices for the years 2004 (used for 2006), 2007 (used for 2007 to 2009) and 2010 (used for 2010 and 2011) corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average minimum and maximum daily temperature, daily rainfall.
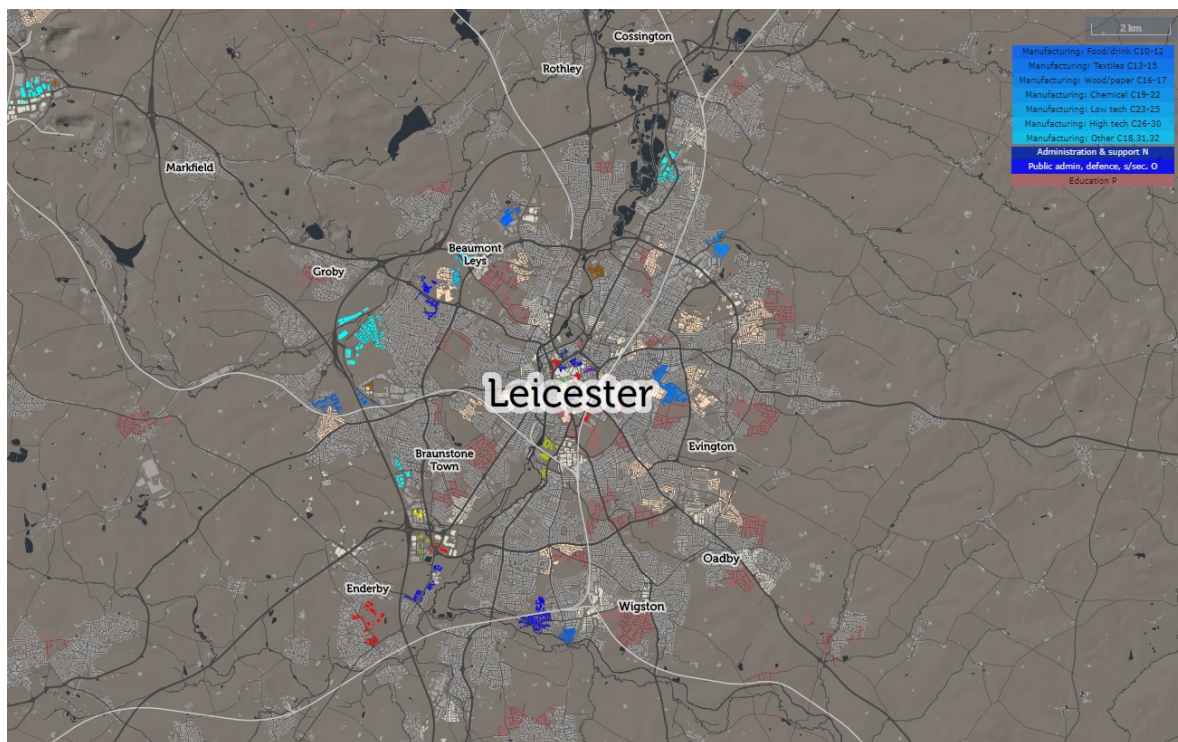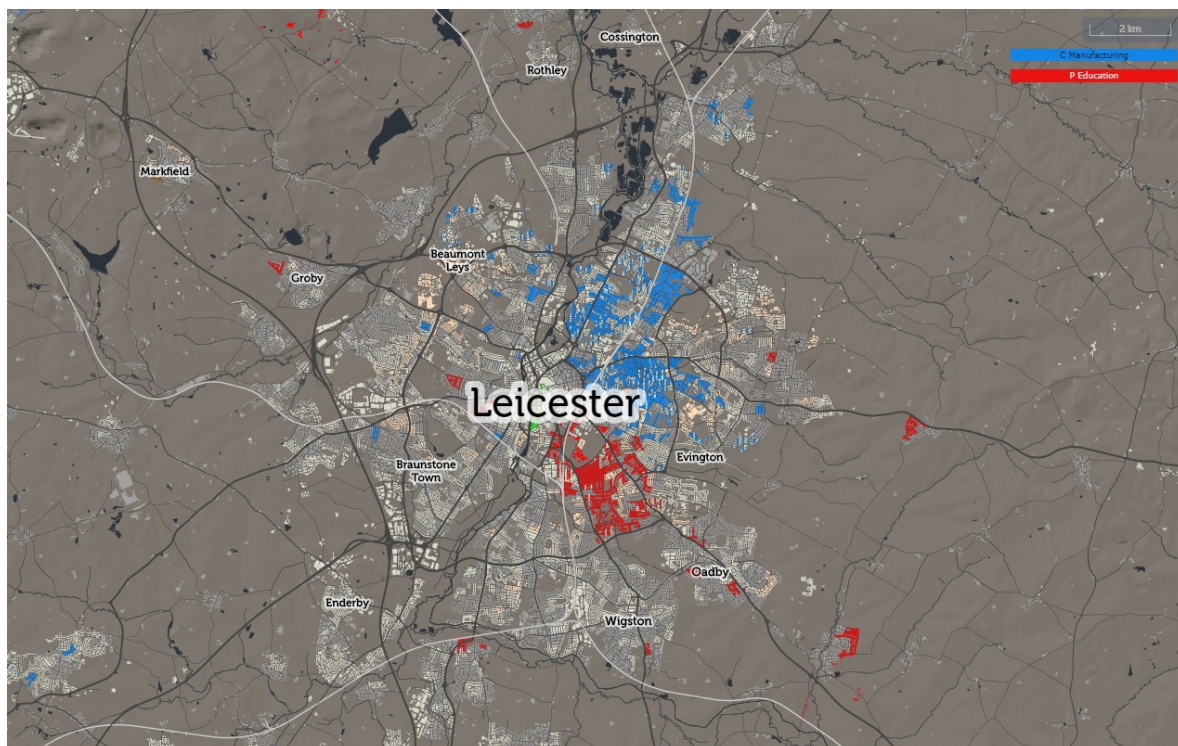
Maps

Map 4.1: Monitors

(a) Leicester Map, Postcode Sectors with Centroids
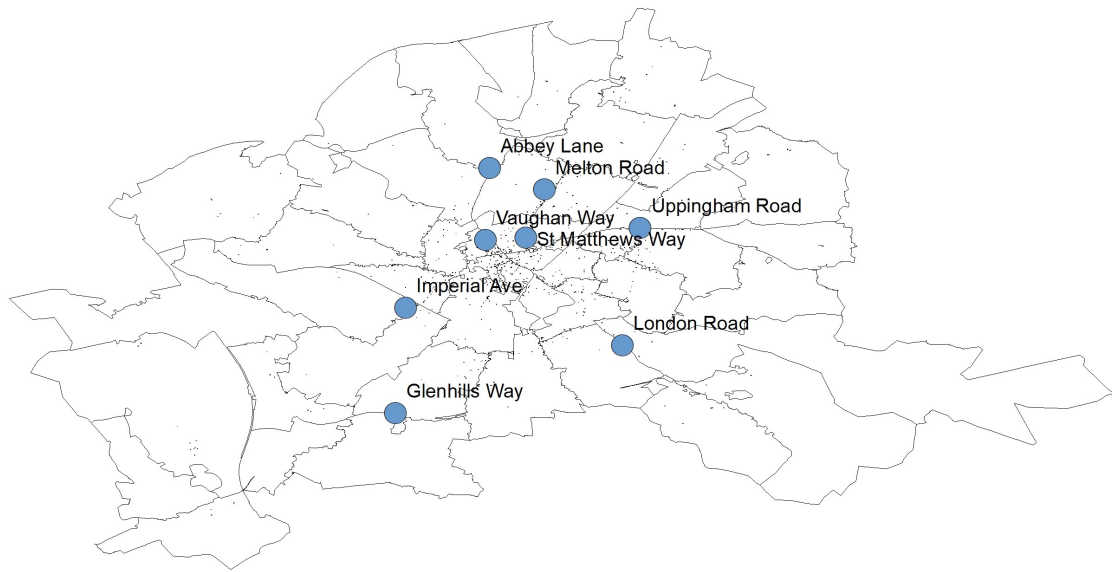
(b) Leicester Map, Postcode Sectors
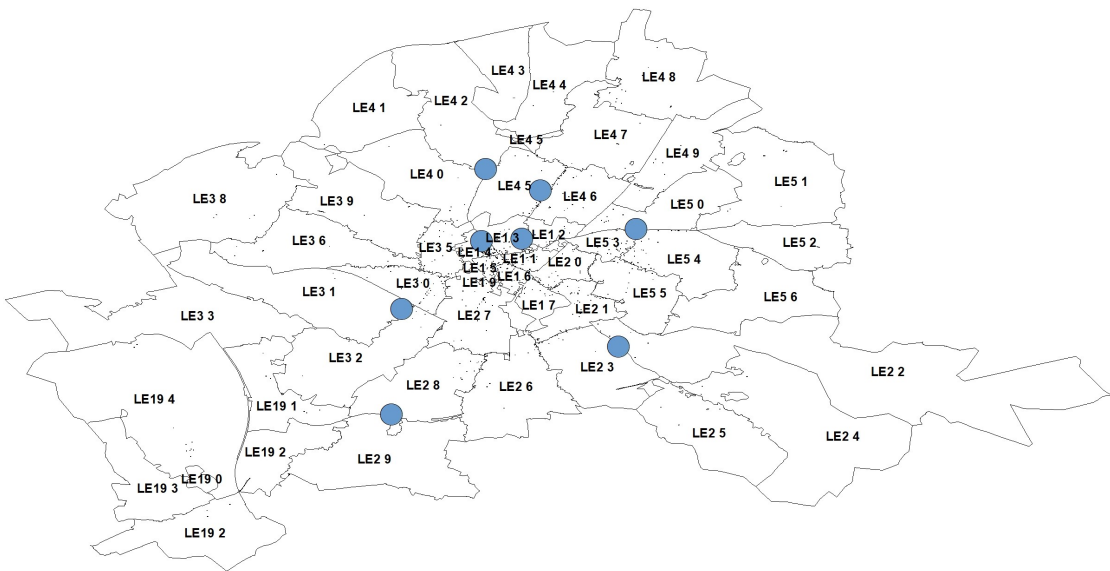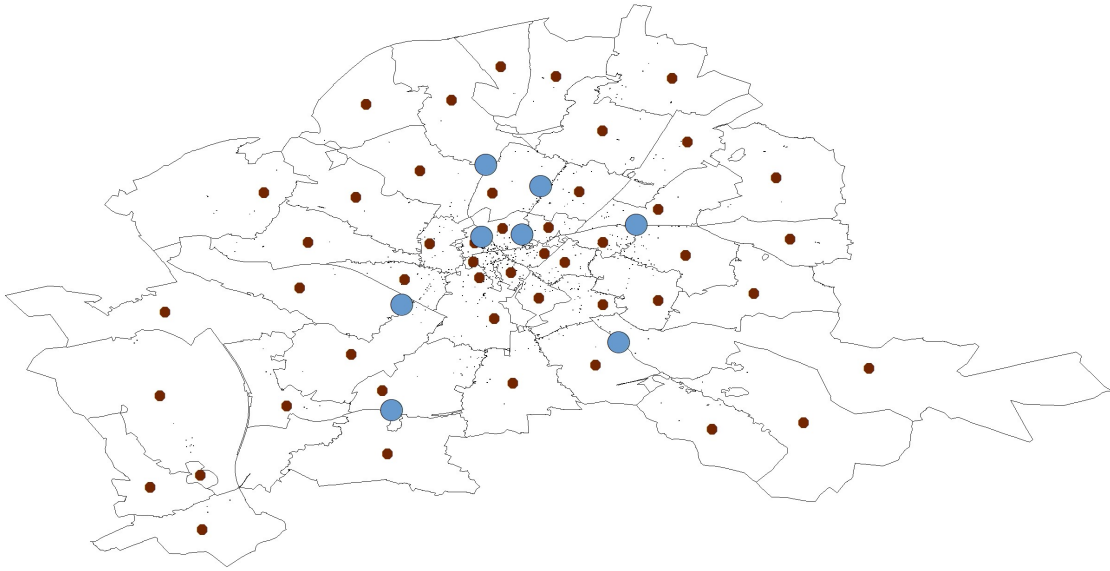
Map 4.2: Leicester Map, Postcode Sectors

(a) Where workers work.

(b) Where workers live.

Map 4.3: Population Distribution by Industry.
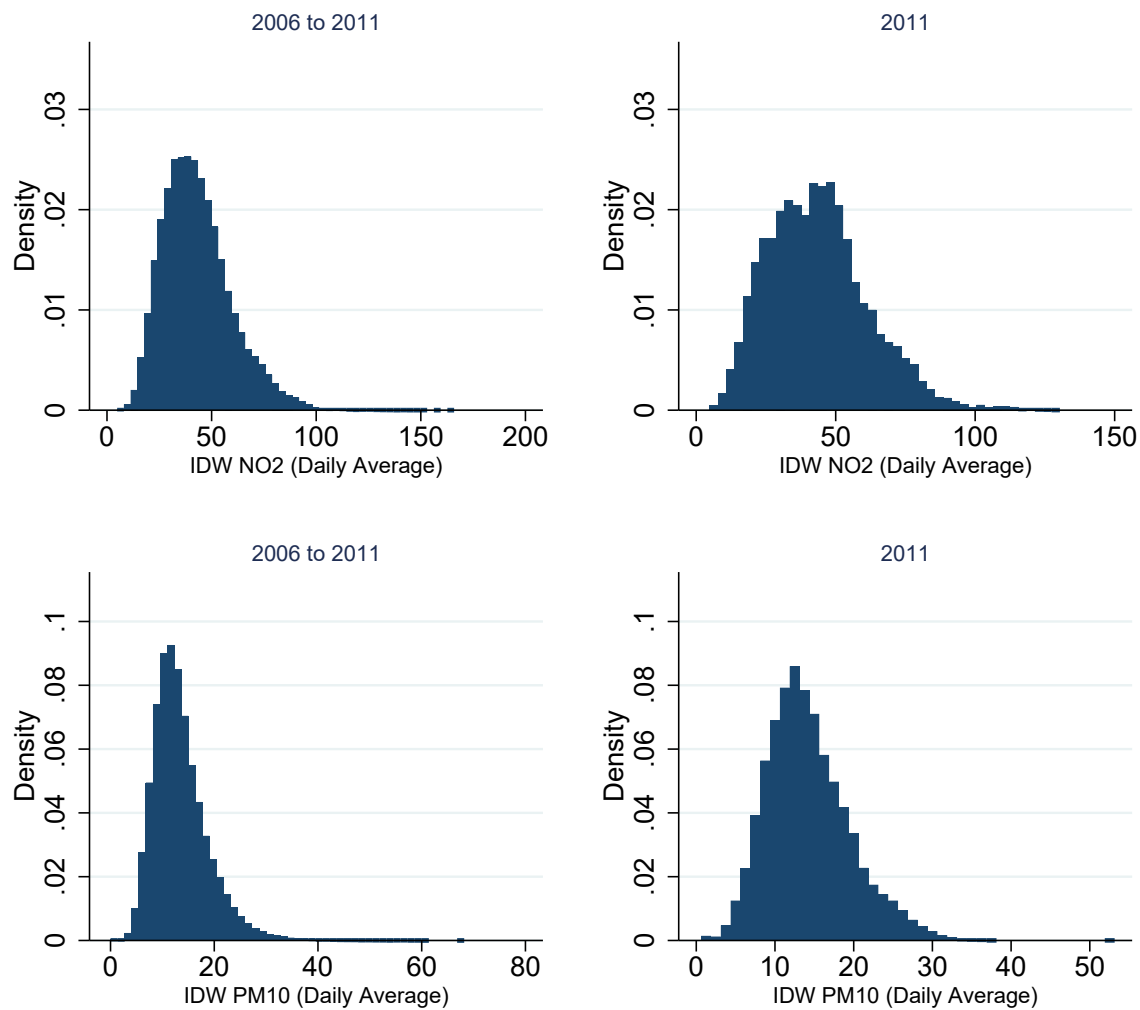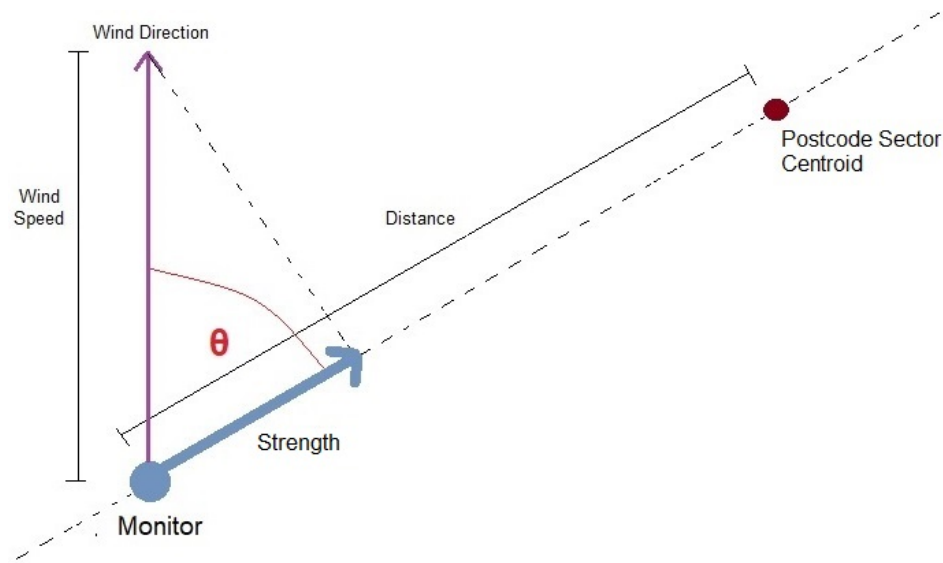
Figures
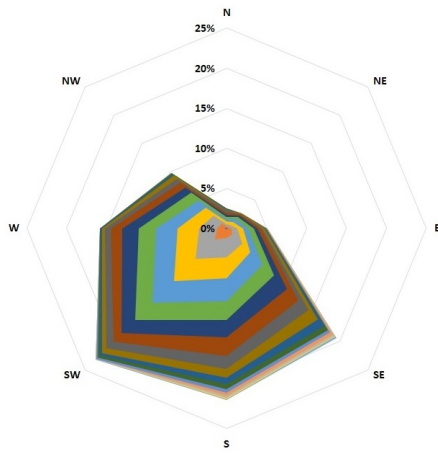
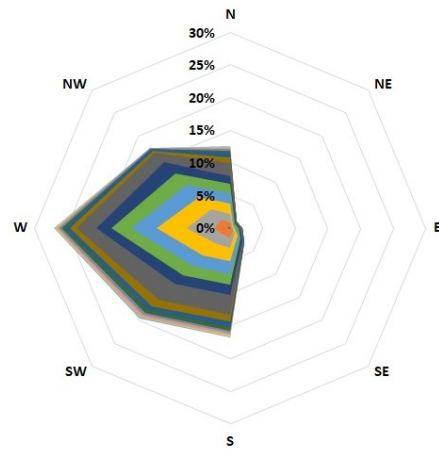Figure 4.1: Inverse Distance Weighted, IDW
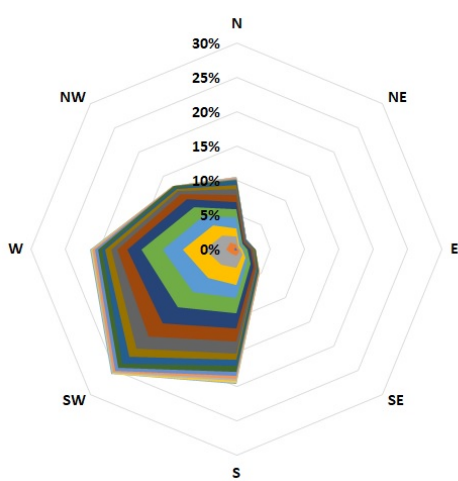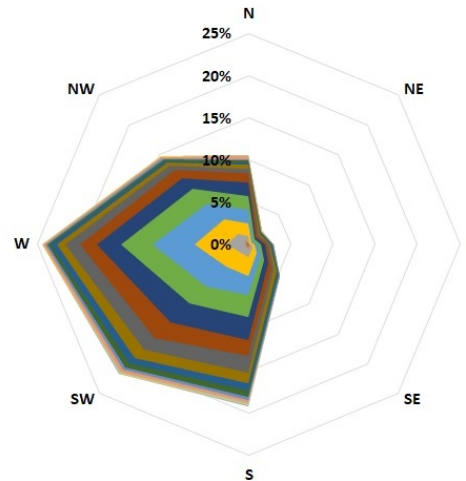
Figure 4.2: Strength
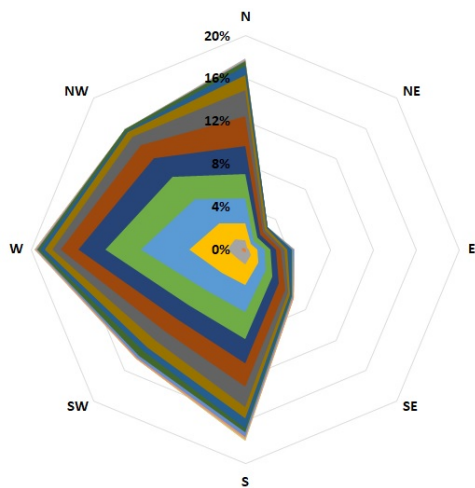
Figure 4.3: Wind-roses, 2006-2011

(a) 2006

(b) 2007

(c) 2008

(d) 2009

(e) 2010
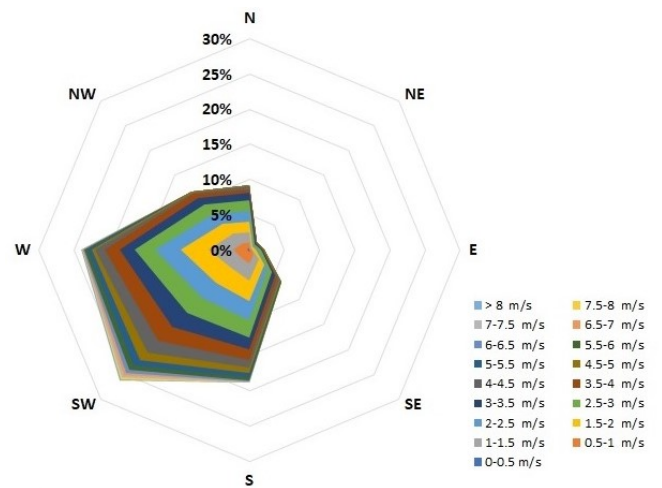
(f) 2011
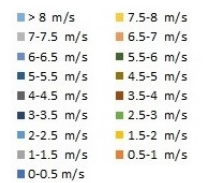
Figure 4.4: IDW on Hospital Visits by Age Group, 2006 to 2011.

All Observations

All Observations Grouped by 100 Pollution Level Bins
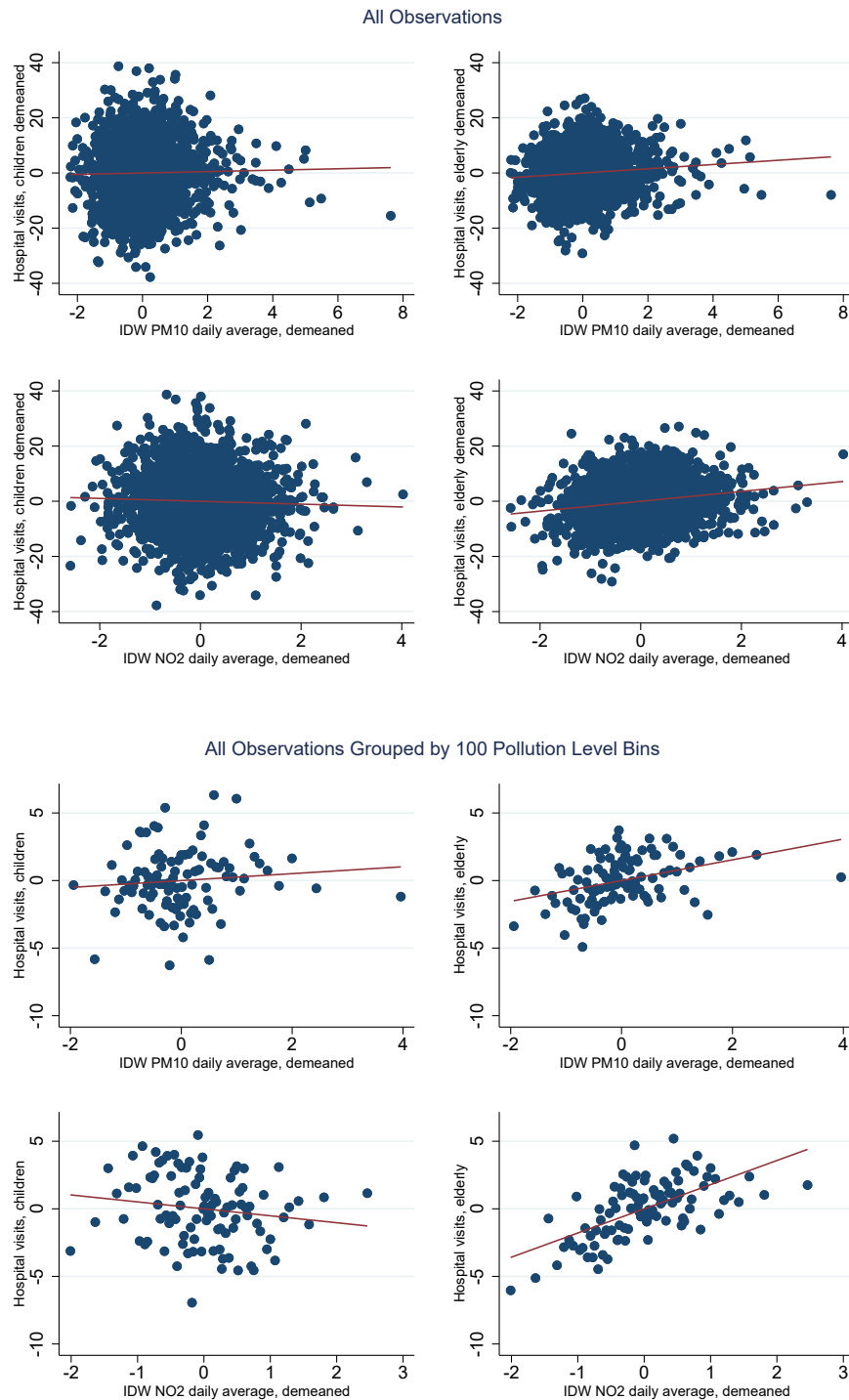
<u>Notes:</u>
(1) The top four figures are performed with all observations and no grouping.
(2) The bottom four figures are created using binscatter. The command groups the x-variable into 100 equal-sized bins, computed the mean of the x-variable and y-variable within each bin, and created a scatterplot of these 100 data points. Each dot shows the average "Hospital Visits" for a given level of "IDW, demeaned". Finally, binscatter plots the best linear fit line, constructed from an OLS regression of the y-observations on the x-observations.

Appendix 4.A   School Catchment Areas

Figure 4.A.1: School Catchment Areas
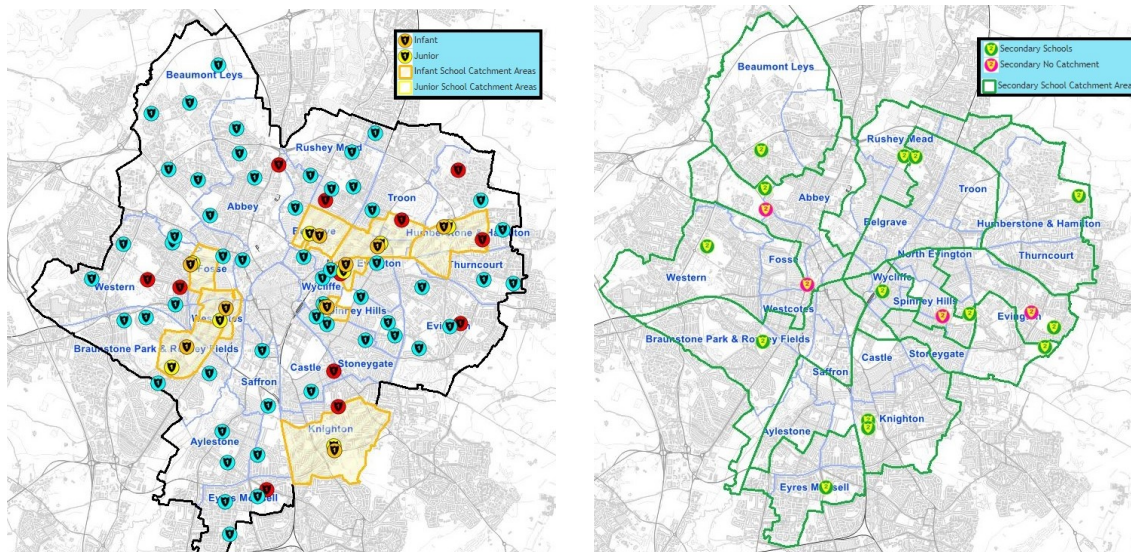
(a) Infant and Junior Schools Catchment Areas

(b) Secondary Schools Catchment Areas
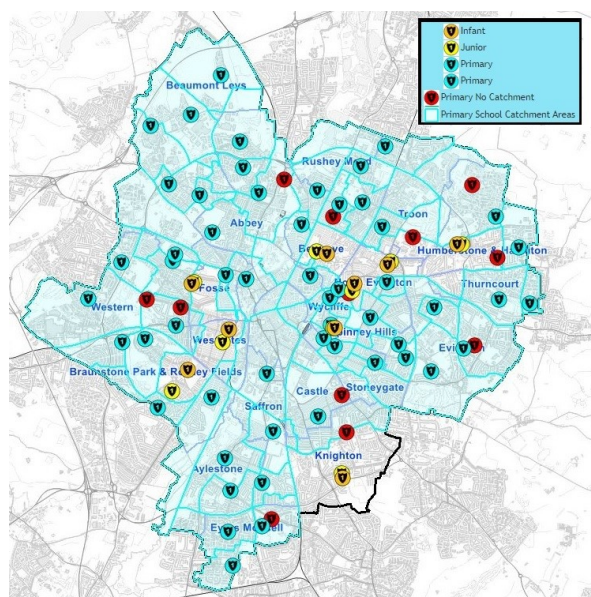
(c) Primary Schools Catchment Areas

Appendix 4.B Extra Descriptive Statistics

4.B.1 Health and Population Data

Table 4.B.1: Census 2011, Population Totals by Postcode District

| | | | Population Totals | | | | | |
			LE1	LE2	LE3	LE4	LE5	LE19
Gender								
	Female		1514	23524	20973	21075	18827	3317
	Male		1480	21999	19964	20201	18275	3221
Age								
	Children							
		0 to 4	910	7191	7526	6601	6809	865
		5 to 9	627	6614	6110	5916	6081	874
		10 to 17	655	11325	9438	10140	10048	1539
	Older Adults							
		60 to 64	240	5226	4840	5297	3725	974
		65 to 69	157	3935	3494	3710	2746	715
		70 to 74	147	3452	3132	3316	2440	528
		75 to 79	92	3001	2644	2786	2085	428
		80 to 84	94	2416	1877	1912	1685	341
		85 to 89	40	1546	1279	1101	1011	191
		90+	32	817	597	497	472	83
Total			2994	45523	40937	41276	37102	6538

Table 4.B.2: Health Statistics, 2006 to 2011 by Postcode District.

Postcode District			Visits Total	Admissions Total	Admissions % of Visits	Length of Stay* Mean	Length of Stay* St. Dev.	Number of Doctors* Mean	Number of Doctors* St. Dev.
LE1									
Gender									
	Female		2231	635	28.46%	6.50	14.28	1.43	0.70
	Male		3002	703	23.42%	4.86	8.77	1.41	0.70
Age									
	Children								
		0 to 4	1905	337	17.69%	1.74	5.88	1.01	0.12
		5 to 9	592	57	9.63%	0.91	1.06	1.00	0.00
		10 to 17	1157	133	11.50%	1.71	3.11	1.08	0.29
	Older Adults								
		60 to 64	488	200	40.98%	5.78	9.11	1.61	0.80
		65 to 69	289	121	41.87%	6.61	12.89	1.65	0.81
		70 to 74	244	122	50.00%	5.91	10.39	1.59	0.72
		75 to 79	193	102	52.85%	10.79	20.83	1.79	0.81
		80 to 84	165	120	72.73%	10.47	14.64	1.65	0.73
		85 to 89	114	84	73.68%	10.20	11.63	1.77	0.86
		90+	86	62	72.09%	12.73	19.09	1.79	0.81
Ethnicities									
	White		1807	702	38.85%	7.65	13.98	1.59	0.78
	Black		1124	220	19.57%	2.37	6.27	1.13	0.41
	Asian		1232	281	22.81%	4.82	9.85	1.34	0.65
	Other		1070	135	12.62%	2.23	5.69	1.14	0.43
Total			5233	1338	25.57%	–	–	–	–
LE2									
Gender									
	Female		34431	12517	36.35%	7.68	12.71	1.63	0.83
	Male		37095	11191	30.17%	6.63	12.26	1.59	0.83
Age									
	Children								
		0 to 4	14831	2627	17.71%	1.43	3.57	1.02	0.18
		5 to 9	7503	741	9.88%	1.43	2.33	1.02	0.15
		10 to 17	16063	1612	10.04%	1.72	4.67	1.10	0.36
	Older Adults								
		60 to 64	5536	2098	37.90%	5.71	10.40	1.65	0.83
		65 to 69	4606	2036	44.20%	6.97	13.14	1.71	0.86
		70 to 74	5176	2718	52.51%	7.12	11.85	1.71	0.84
		75 to 79	5389	3218	59.71%	8.71	13.95	1.77	0.88
		80 to 84	5236	3434	65.58%	9.91	14.33	1.80	0.86
		85 to 89	4209	2982	70.85%	10.55	14.39	1.85	0.90
		90+	2978	2242	75.29%	10.51	14.58	1.78	0.85
Ethnicities									
	White		46311	17547	37.89%	7.73	13.00	1.65	0.84
	Black		3040	716	23.55%	5.13	10.42	1.44	0.74
	Asian		14864	3979	26.77%	5.24	10.23	1.53	0.79
	Other		7312	1466	20.05%	6.86	12.56	1.51	0.80
Total			71527	23708	33.15%	–	–	–	–
LE3									
Gender									
	Female		34456	11901	34.54%	7.58	13.51	1.59	0.81
	Male		37055	10970	29.60%	6.43	11.89	1.57	0.81
Age									
	Children								
		0 to 4	17311	3114	17.99%	1.50	4.98	1.02	0.14
		5 to 9	7603	697	9.17%	1.39	3.36	1.01	0.11
		10 to 17	16224	1586	9.78%	1.68	4.34	1.07	0.28
	Older Adults								
		60 to 64	4935	1931	39.13%	5.55	12.57	1.60	0.79
		65 to 69	4285	1962	45.79%	6.55	11.07	1.66	0.83
		70 to 74	5097	2708	53.13%	7.68	11.98	1.72	0.84
		75 to 79	4848	2955	60.95%	8.93	15.48	1.78	0.87
		80 to 84	4834	3201	66.22%	10.32	15.63	1.82	0.88
		85 to 89	3908	2795	71.52%	10.27	13.98	1.80	0.87
		90+	2468	1922	77.88%	10.41	14.07	1.77	0.83
Ethnicities									
	White		56704	19402	34.22%	7.23	12.86	1.60	0.82
	Black		2150	474	22.05%	4.90	13.50	1.30	0.64
	Asian		5882	1647	28.00%	5.83	10.95	1.54	0.79
	Other		6777	1348	19.89%	6.37	13.19	1.45	0.77
Total			71513	22871	31.98%	–	–	–	–

*Admitted to Hospital sample only.

Table 4.B.2: Health Statistics, 2006 to 2011 by Postcode District.

Postcode District			Visits Total	Admissions Total	% of Visits	Length of Stay* Mean	St. Dev.	Number of Doctors* Mean	St. Dev.
LE4									
Gender									
	Female		28932	9685	33.48%	7.42	12.84	1.61	0.83
	Male		33153	9330	28.14%	6.09	11.22	1.57	0.81
Age									
	Children								
		0 to 4	14104	2548	18.07%	1.43	3.48	1.02	0.15
		5 to 9	6748	639	9.47%	1.41	3.16	1.01	0.10
		10 to 17	14295	1366	9.56%	1.61	2.97	1.10	0.36
	Older Adults								
		60 to 64	5925	2083	35.16%	5.28	9.75	1.64	0.80
		65 to 69	4270	1874	43.89%	6.55	13.56	1.68	0.83
		70 to 74	4334	2294	52.93%	7.62	12.41	1.74	0.87
		75 to 79	4334	2559	59.04%	8.85	13.61	1.80	0.87
		80 to 84	3835	2530	65.97%	9.61	13.24	1.82	0.88
		85 to 89	2750	2012	73.16%	10.67	13.96	1.87	0.91
		90+	1492	1110	74.40%	11.48	16.54	1.79	0.85
Ethnicities									
	White		33423	11201	33.51%	7.15	12.08	1.62	0.83
	Black		2721	590	21.68%	4.00	11.48	1.27	0.61
	Asian		19679	6131	31.16%	6.58	12.27	1.60	0.83
	Other		6264	1093	17.45%	5.34	11.17	1.41	0.72
Total			62087	19015	30.63%	–	–	–	–
LE5									
Gender									
	Female		25485	9220	36.18%	8.11	14.43	1.61	0.83
	Male		29944	8924	29.80%	6.22	11.58	1.55	0.80
Age									
	Children								
		0 to 4	12911	2522	19.53%	1.61	5.54	1.01	0.13
		5 to 9	6600	671	10.17%	1.43	2.92	1.02	0.14
		10 to 17	12407	1203	9.70%	1.88	3.65	1.08	0.30
	Older Adults								
		60 to 64	4029	1502	37.28%	5.72	10.65	1.64	0.81
		65 to 69	3426	1709	49.88%	6.80	13.78	1.66	0.81
		70 to 74	3759	2106	56.03%	8.50	14.49	1.75	0.85
		75 to 79	3879	2446	63.06%	9.10	13.84	1.78	0.87
		80 to 84	3817	2576	67.49%	9.91	15.99	1.80	0.87
		85 to 89	2868	2085	72.70%	10.67	14.94	1.80	0.89
		90+	1734	1324	76.36%	11.22	14.71	1.79	0.85
Ethnicities									
	White		23303	10286	44.14%	8.39	13.97	1.67	0.84
	Black		2700	693	25.67%	5.22	13.32	1.39	0.70
	Asian		22815	5892	25.83%	5.48	11.17	1.47	0.77
	Other		6612	1273	19.25%	6.39	13.49	1.47	0.77
Total			55430	18144	32.73%	–	–	–	–
LE19									
Gender									
	Female		3377	1200	35.53%	6.73	10.77	1.63	0.86
	Male		3590	1124	31.31%	6.05	10.92	1.59	0.82
Age									
	Children								
		0 to 4	1321	261	19.76%	1.51	2.46	1.02	0.12
		5 to 9	691	82	11.87%	1.35	2.28	1.01	0.11
		10 to 17	1671	153	9.16%	1.51	1.95	1.05	0.28
	Older Adults								
		60 to 64	624	215	34.46%	5.81	8.99	1.67	0.88
		65 to 69	522	234	44.83%	6.52	11.47	1.72	0.90
		70 to 74	477	263	55.14%	6.42	9.59	1.67	0.79
		75 to 79	526	319	60.65%	7.34	12.78	1.82	0.91
		80 to 84	504	320	63.49%	8.97	13.72	1.81	0.84
		85 to 89	354	256	72.32%	10.75	13.72	1.86	0.90
		90+	277	221	79.78%	7.74	9.27	1.81	0.94
Ethnicities									
	White		6488	2195	33.83%	6.38	10.70	1.61	0.84
	Black		29	4	13.79%	2.25	3.86	1.25	0.50
	Asian		104	24	23.08%	3.00	4.86	1.75	0.99
	Other		346	101	29.19%	7.86	14.47	1.60	0.88
Total			6967	2324	33.36%	–	–	–	–

*Admitted to Hospital sample only.

4.B.2 Pollution Data

Table 4.B.3: Correlation Between Hourly Pollution and Wind Speed (2006-2011)

Monitor	Pollutant	Wind Speed (Correlation)
St Matthews Way	NO2	-0.2127
	PM10	-
Vaughan Way	NO2	-0.1757
	PM10	-0.0835
Melton Road	NO2	-0.1773
	PM10	-0.117
Abbey Lane	NO2	-0.165
	PM10	-0.0966
Glenhills Way	NO2	-0.1803
	PM10	-0.1679
Imperial Ave	NO2	-0.2429
	PM10	-0.1249
London Road	NO2	-0.2578
	PM10	-0.1204
Uppingham Road	NO2	-0.2327
	PM10	-

Appendix 4.C Cost Calculations

We estimate healthcare costs using the Payment by Results system as follows:

$$Cost_{it} = \text{AETariff}_{hy} \tag{4.C.1}$$

for ED attendants, and

$$Cost_{it} = \text{Tariff}_{hy} + \text{topup}_{idy} * \text{NSTariff}_{hy} \tag{4.C.2}$$

where

$$\text{Tariff}_{hy} = \begin{cases} \text{SSTariff}_{hy} & \text{if LOS}_{it} < 2 \\ \text{NSTariff}_{hy} & \text{if } 2 \leq \text{LOS}_{it} \leq \text{TP}_{hy} \\ \text{LSTariff}_{hy} = \text{NSTariff}_{hy} + \text{ppd}_{hy} * (\text{LOS}_{it} - \text{TP}_{hy}) & \text{if LOS}_{it} > \text{TP}_{hy} \\ \text{LocalTariff}_{hy} \end{cases}$$

$$\tag{4.C.3}$$

for admitted patients, where the HRG code does not have a short stay tariff we use the normal stay tariff. $Cost_{it}$ is the cost of hospital attendance for individual i at attendance date t, AETariff_{hy} is the price for the HRG code h in fiscal year y for ED attendants, LOS_{it} is the length of stay for individual i measured in days, $SSTariff_{hy}$ is the price for short length of stay ($LOS < 2$) corresponding to HRG code h in fiscal year y, TP_{hy} is the expected length of stay in days for HRG code h in fiscal year y, $NSTariff_{hy}$ is the price for HRG code h in fiscal year y for normal stay ($LOS \leq TP$), $LSTariff_{hy}$ is the price for long length of stay ($LOS > TP$) or HRG code h in fiscal year y, ppd_{hy} is the price per day above the expected length of stay for HRG code h in fiscal year y, LocalTariff_{hy} is the locally determined price for for HRG code h in fiscal year y, and $topup_{idy}$ is the extra cost of treating individual i when disease d is predetermined as specialised service for fiscal year y.

The cost for admitted patients is a sum of the tariff and top up. For nationally determined costs, the applicable tariff depends on the length of stay, both actual and

expected. For some HRGs there is a short stay tariff (SSTariff) that is payable whenever the patient spend less than 2 days in the hospital. Where the patient's length of stay is at most the expected length of stay, the normal stay tariff (NSTariff) is applicable. For length of stay exceeding the expected length of stay, the long stay tariff (LSTariff) is applicable which includes the normal stay tariff in addition to per day price for the days above the expected length of stay. Finally, the price for some HRG codes is locally (LocalTariff) determined through negotiation between the hospital and the CCGs which is not dependent on length of stay. Top up payments are made to compensate for specialised services and is triggered when a predetermined ICD code is present. These top up payments are a percent increase of the normal stay tariff. Some top ups are limited to eligible providers.

There are some limitations with using the PbR system such as the range of services covered and the methodology for cost calculation. While it is stated that the hospital is paid for each person seen or treated, not all services are included in the system. Some services are added to the system gradually and when introduced either does not have an HRG code or does not have a national tariff. We encountered both of these issues in our sample. There were no HRG codes for 18,554 ED attendants (7% of the sample), and of the ED attendants with an HRG code, there were no cost information for 5,631 (or 2%). Another limitation is that the national tariff is calculated as the average of cost of services submitted by NHS organisations.[58] This means that the cost we calculated for Leicester reflect the national average rather than the actual cost for services provided by the hospital. This is because PbR is meant to incentivise providers with higher levels of cost to improve their efficiency in order to make savings on services. This suggests further that the cost calculations we have provided are a lower bound for the total costs of providing health services in Leicester. Despite the limitations, as the health care costs in England during 2006-2011 were covered by PbR, using this method is the most accurate cost calculation that can be provided.

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[58]Please see A Simple Guide to Payment by Results at gov.uk accessed July 30th 2021.

Bibliography

ALANIS, A. J., "Resistance to antibiotics: are we in the post-antibiotic era?," *Archives of Medical Research* 36 (2005), 697–705.

ALBERINI, A., "Efficiency vs bias of willingness-to-pay estimates: bivariate and interval-data models," *Journal of Environmental Economics and Management* 29 (1995), 169–180.

AMINOV, R. I., "A brief history of the antibiotic era: lessons learned and challenges for the future," *Frontiers in Microbiology* 1 (2010), 134.

ANDERSON, M. L., "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American statistical Association* 103 (2008), 1481–1495.

ANDERSSON, H., A. R. HOLE AND M. SVENSSON, "Valuation of small and multiple health risks: A critical analysis of SP data applied to food and water safety," *Journal of Environmental Economics and Management* 75 (2016), 41–53.

AUSTIN, D., M. KAKEHASHI AND R. ANDERSON, "The transmission dynamics of antibiotic–resistant bacteria: the relationship between resistance in commensal organisms and antibiotic consumption," *Proceedings of the Royal Society of London B: Biological Sciences* 264 (1997), 1629–1638.

AUSTIN, D. J., K. G. KRISTINSSON AND R. M. ANDERSON, "The relationship between the volume of antimicrobial consumption in human communities and the frequency of resistance," *Proceedings of the National Academy of Sciences* 96 (1999), 1152–1156.

BARNES, J. H., E. T. HAYES, T. CHATTERTON AND J. W. LONGHURST, "Policy disconnect: a critical review of UK air quality policy in relation to EU and LAQM

responsibilities over the last 20 years," *Environmental Science & Policy* 85 (2018), 28–39.

BATABYAL, A. A. AND P. NIJKAMP, "Alternate strategies for managing resistance to antibiotics and pesticides," *Environmental Economics and Policy Studies* 7 (2005), 39–51.

BATEMAN, I. J., "Household willingness to pay and farmers' willingness to accept compensation for establishing a recreational woodland," *Journal of Environmental Planning and Management* 39 (1996), 21–44.

BEATTY, T. K. AND J. P. SHIMSHACK, "School buses, diesel emissions, and respiratory health," *Journal of Health Economics* 30 (2011), 987–999.

BEGON, M., J. L. HARPER AND C. R. TOWNSEND, *Ecology. Individuals, populations and communities.* (Blackwell Scientific Publications, 1996).

BELL, M. L. AND D. L. DAVIS, "Reassessment of the lethal London fog of 1952: novel indicators of acute and chronic consequences of acute exposure to air pollution.," *Environmental Health Perspectives* 109 (2001), 389–394.

BHULLAR, K., N. WAGLECHNER, A. PAWLOWSKI, K. KOTEVA, E. D. BANKS, M. D. JOHNSTON, H. A. BARTON AND G. D. WRIGHT, "Antibiotic resistance is prevalent in an isolated cave microbiome," *PLoS One* 7 (2012), e34953.

BISHAI, D. M. AND H. C. LANG, "The willingness to pay for wait reduction: the disutility of queues for cataract surgery in Canada, Denmark, and Spain," *Journal of Health Economics* 19 (2000), 219–230.

BLANQUART, F., "Evolutionary epidemiology models to predict the dynamics of antibiotic resistance," *Evolutionary applications* 12 (2019), 365–383.

BOGGIANO, B., "Long-term effects of the Paraguayan War (1864-1870): from male scarcity to intimate partner violence.," *Working Paper* (2019).

BONDY, M., S. ROTH AND L. SAGER, "Crime is in the air: The contemporaneous relationship between air pollution and crime," (2018).

BONHOEFFER, S., M. LIPSITCH AND B. R. LEVIN, "Evaluating treatment protocols to prevent antibiotic resistance," *Proceedings of the National Academy of Sciences* 94 (1997), 12106–12111.

BONTI-ANKOMAH, S. AND E. K. YIRIDOE, "Organic and conventional food: a literature review of the economics of consumer perceptions and preferences," *Organic Agriculture Centre of Canada* 59 (2006), 1–40.

BROWN, E. M. AND D. NATHWANI, "Antibiotic cycling or rotation: a systematic review of the evidence of efficacy," *Journal of antimicrobial chemotherapy* 55 (2005), 6–9.

BROWN, G. AND D. F. LAYTON, "Resistance economics: social cost and the evolution of antibiotic resistance," *Environment and Development Economics* 1 (1996), 349–355.

BRUNEKREEF, B. AND S. T. HOLGATE, "Air pollution and health," *The Lancet* 360 (2002), 1233–1242.

BUZBY, J. C. AND J. R. SKEES, "Consumers want reduced exposure to pesticides on food," *Food Review/National Food Review* 17 (1994), 19–22.

CAIRNS, J. A. AND M. VAN DER POL, "The estimation of marginal time preference in a UK-wide sample (TEMPUS) project: a review," *Health Technology Assessment* 4 (2000).

CAMERON, T. A., "The impact of grouping coarseness in alternative grouped-data regression models," *Journal of Econometrics* 35 (1987), 37–57.

CAMERON, T. A. AND D. D. HUPPERT, "OLS versus ML estimation of non-market resource values with payment card interval data," *Journal of Environmental Economics and Management* 17 (1989), 230–246.

CAMERON, T. A. AND J. QUIGGIN, "Estimation using contingent valuation data from a "dichotomous choice with follow-up" questionnaire," *Journal of Environmental Economics and Management* 27 (1994), 218–234.

CAUDILL, L. AND B. LAWSON, "A unified inter-host and in-host model of antibiotic resistance and infection spread in a hospital ward," *Journal of theoretical biology* 421 (2017), 112–126.

CHANG, Y., S. CHUSRI, R. SANGTHONG, E. MCNEIL, J. HU, W. DU, D. LI, X. FAN, H. ZHOU, V. CHONGSUVIVATWONG ET AL., "Clinical pattern of antibiotic overuse and misuse in primary healthcare hospitals in the southwest of China," *PLoS One* 14 (2019), e0214779.

CHAY, K. Y. AND M. GREENSTONE, "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession," *The Quarterly Journal of Economics* 118 (2003), 1121–1167.

COAST, J., R. D. SMITH AND M. R. MILLAR, "An economic perspective on policy to reduce antimicrobial resistance," *Social science & medicine* 46 (1998), 29–38.

COLOMBO, S., N. HANLEY AND J. LOUVIERE, "Modeling preference heterogeneity in stated choice data: an analysis for public goods generated by agriculture," *Agricultural Economics* 40 (2009), 307–322.

CONEUS, K. AND C. K. SPIESS, "Pollution exposure and child health: Evidence for infants and toddlers in Germany," *Journal of Health Economics* 31 (2012), 180–196.

CURRIE, J. AND M. NEIDELL, "Air pollution and infant health: what can we learn from California's recent experience?," *The Quarterly Journal of Economics* 120 (2005), 1003–1030.

CURRIE, J. AND R. WALKER, "Traffic congestion and infant health: Evidence from E-ZPass," *American Economic Journal: Applied Economics* 3 (2011), 65–90.

CZERNECKI, B., M. PÓŁROLNICZAK, L. KOLENDOWICZ, M. MAROSZ, S. KENDZIERSKI AND N. PILGUJ, "Influence of the atmospheric conditions on PM 10 concentrations in Poznań, Poland," *Journal of Atmospheric Chemistry* 74 (2017), 115–139.

D'AGATA, E. M., M. DUPONT-ROUZEYROL, P. MAGAL, D. OLIVIER AND S. RUAN, "The impact of different antibiotic regimens on the emergence of antimicrobial-resistant bacteria," *PLoS One* 3 (2008), e4036.

D'AGATA, E. M., P. MAGAL, D. OLIVIER, S. RUAN AND G. F. WEBB, "Modeling antibiotic resistance in hospitals: the impact of minimizing treatment duration," *Journal of Theoretical Biology* 249 (2007), 487–499.

DARBY, K., M. T. BATTE, S. ERNST AND B. ROE, "Decomposing local: A conjoint analysis of locally produced foods," *American Journal of Agricultural Economics* 90 (2008), 476–486.

DAVIDSON, R., J. G. MACKINNON ET AL., "Estimation and inference in econometrics," *OUP Catalogue* (1993).

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DAVIES, J. AND D. DAVIES, "Origins and evolution of antibiotic resistance," *Microbiology and Molecular Biology Reviews* 74 (2010), 417–433.

D'COSTA, V. M., C. E. KING, L. KALAN, M. MORAR, W. W. SUNG, C. SCHWARZ, D. FROESE, G. ZAZULA, F. CALMELS, R. DEBRUYNE ET AL., "Antibiotic resistance is ancient," *Nature* 477 (2011), 457.

DERYUGINA, T., G. HEUTEL, N. H. MILLER, D. MOLITOR AND J. REIF, "The mortality and medical costs of air pollution: Evidence from changes in wind direction," *American Economic Review* 109 (2019), 4178–4219.

DÍAZ, F. J. M., F. M.-C. PLEITE, J. M. M. PAZ AND P. G. GARCÍA, "Consumer knowledge, consumption, and willingness to pay for organic tomatoes," *British Food Journal* (2012).

DOBRUSHKIN, V., *Applied Differential Equations with Boundary Value Problems* (CRC Press, 2017).

DUPONT, D. P., "Do children matter? An examination of gender differences in environmental valuation," *Ecological Economics* 49 (2004), 273–286.

ECDC, E. AND EMA, "ECDC/EFSA/EMA second joint report on the integrated analysis of the consumption of antimicrobial agents and occurrence of antimicrobial resistance in bacteria from humans and food-producing animals: Joint Interagency Antimicrobial Consumption and Resistance Analysis (JIACRA) Report," *EFSA Journal* 15 (2017), e04872.

ELBASHA, E. H., "Deadweight loss of bacterial resistance due to overtreatment," *Health Economics* 12 (2003), 125–138.

GOLDMAN, B. J. AND K. L. CLANCY, "A survey of organic produce purchases and related attitudes of food cooperative shoppers," *American Journal of Alternative Agriculture* (1991), 89–96.

GOOSSENS, H., M. FERECH, R. VANDER STICHELE, M. ELSEVIERS, E. P. GROUP ET AL., "Outpatient antibiotic use in Europe and association with resistance: a cross-national database study," *The Lancet* 365 (2005), 579–587.

GREEN, C. P., J. S. HEYWOOD AND M. NAVARRO, "Traffic accidents and the London congestion charge," *Journal of public economics* 133 (2016), 11–22.

GREEN, C. P., J. S. HEYWOOD AND M. N. PANIAGUA, "Did the London congestion charge reduce pollution?," *Regional Science and Urban Economics* 84 (2020), 103573.

GRUNDSTROM, M., L. TANG, M. HALLQUIST, H. NGUYEN, D. CHEN AND H. PLEIJEL, "Influence of atmospheric circulation patterns on urban air quality during the winter," *Atmospheric Pollution Research* 6 (2015), 278–285.

HAGHIRI, M., J. E. HOBBS AND M. L. MCNAMARA, "Assessing consumer preferences for organically grown fresh fruit and vegetables in Eastern New Brunswick," *International Food and Agribusiness Management Review* 12 (2009), 1–20.

HANEMANN, M., J. LOOMIS AND B. KANNINEN, "Statistical efficiency of double-bounded dichotomous choice contingent valuation," *American Journal of Agricultural Economics* 73 (1991), 1255–1263.

HOLGATE, S., J. GRIGG, R. AGIUS, J. R. ASHTON, P. CULLINAN, K. EXLEY, D. FISHWICK, G. FULLER, N. GOKANI, C. GRIFFITHS ET AL., "Every breath we take: The lifelong impact of air pollution, Report of a working party.," (Royal College of Physicians, 2016).

HOLUB, F., L. HOSPIDO AND U. J. WAGNER, "Air pollution and labor supply: Evidence from social security data," (2016).

HUANG, D., H. ANDERSSON AND S. ZHANG, "Willingness to pay to reduce health risks related to air quality: Evidence from a choice experiment survey in Beijing," *Journal of Environmental Planning and Management* 61 (2018), 2207–2229.

HUTCHINSON, W. G., R. SCARPA, S. M. CHILTON AND T. MCCALLION, "Parametric and Non-Parametric Estimates of Willingness to Pay for Forest Recreation in Northern Ireland: A Discrete Choice Contingent Valuation Study with Follow-Ups," *Journal of Agricultural Economics* 52 (2001), 104–122.

JANKE, K., "Air pollution, avoidance behaviour and children's respiratory health: Evidence from England," *Journal of Health Economics* 38 (2014), 23–42.

JIN, J., Z. WANG AND S. RAN, "Comparison of contingent valuation and choice experiment in solid waste management programs in Macao," *Ecological Economics* 57 (2006), 430–441.

Johnston, S. L., P. K. Pattemore, G. Sanderson, S. Smith, M. J. Campbell, L. K. Josephs, A. Cunningham, B. S. Robinson, S. H. Myint, M. E. Ward et al., "The relationship between upper respiratory infections and hospital admissions for asthma: a time-trend analysis.," *American Journal of Respiratory and Critical Care Medicine* 154 (1996), 654–660.

Kaier, K., "Economic modeling of the persistence of antimicrobial resistance," *Natural Resource Modeling* 25 (2012), 388–402.

Karakonstantis, S. and D. Kalemaki, "Antimicrobial overuse and misuse in the community in Greece and link to antimicrobial resistance using methicillin-resistant S. aureus as an example," *Journal of Infection and Public Health* 12 (2019), 460–464.

Kardos, N., "Overuse of Antibiotics and Antibiotic Resistance in Medical Applications Featuring Carbapenemase Resistant Enterobacteriaceae (CRE.," *SOJ Microbiology & Infectious Diseases, 5 (5), 1–21* (2017).

Knittel, C. R., D. L. Miller and N. J. Sanders, "Caution, drivers! Children present: Traffic, pollution, and infant health," *Review of Economics and Statistics* 98 (2016), 350–366.

Laxminarayan, R., G. M. Brown et al., "Economics of antibiotic resistance: a theory of optimal use," *Journal of Environmental Economics and Management* 42 (2001), 183–206.

Laxminarayan, R. and M. L. Weitzman, "On the implications of endogenous resistance to medications," *Journal of Health Economics* 21 (2002), 709–718.

Leicester Hospitals Annual Reports, *www.leicestershospitals.nhs.uk/aboutus/performance/pu* *and-reports/annual-reports/* (2007-2012), NHS.

Long, J. S., "Regression models for categorical and limited dependent variables, Sage Publications," *Thousand Oaks, CA.[Google Scholar]* (1997).

Lusk, J. L., T. Nilsson and K. Foster, "Public preferences and private choices: effect of altruism and free riding on demand for environmentally certified pork," *Environmental and Resource Economics* 36 (2007), 499–521.

Lusk, J. L., F. B. Norwood and J. R. Pruitt, "Consumer demand for a ban on antibiotic drug use in pork production," *American Journal of Agricultural Economics* 88 (2006), 1015–1033.

MAGNUSSON, E. AND J. CRANFIELD, "Consumer demand for pesticide free food products in Canada: a probit analysis," *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 53 (2005), 67–81.

MARGARYAN, S., "Low emission zones and population health," Technical Report, HCHE Research Paper, 2019.

MASSAD, E., S. LUNDBERG AND H. M. YANG, "Modeling and simulating the evolution of resistance against antibiotics," *International journal of bio-medical computing* 33 (1993), 65–81.

MASTERTON, R. G., "Antibiotic heterogeneity," *International Journal of Antimicrobial Agents* 36 (2010), S15–S18.

MEACOCK, R., L. ANSELMI, S. R. KRISTENSEN, T. DORAN AND M. SUTTON, "Higher mortality rates amongst emergency patients admitted to hospital at weekends reflect a lower probability of admission," *Journal of health services research & policy* 22 (2017), 12–19.

MORETTI, E. AND M. NEIDELL, "Pollution, health, and avoidance behavior evidence from the ports of Los Angeles," *Journal of human Resources* 46 (2011), 154–175.

NEIDELL, M., "Public information and avoidance behavior: Do people respond to smog alerts?," *Center for Integrating Statistical and Environmental Science Technical Report* 24 (2006).

———, "Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations," *Journal of Human resources* 44 (2009), 450–478.

NEIDELL, M. J., "Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma," *Journal of Health Economics* 23 (2004), 1209–1236.

NIKOLAOU, M. AND V. H. TAM, "A new modeling approach to the effect of antimicrobial agents on heterogeneous microbial populations," *Journal of Mathematical Biology* 52 (2006), 154–182.

O'NEILL, J. ET AL., "Antimicrobials in agriculture and the environment: reducing unnecessary use and waste," *The Review on Antimicrobial Resistance* (2015), 1–44.

———, *Tackling drug-resistant infections globally: final report and recommendations* (2016).

Owusu, V. and M. Owusu Anifori, "Consumer willingness to pay a premium for organic fruit and vegetable in Ghana," *International Food and Agribusiness Management Review* 16 (2013), 67–86.

Phelps, C. E., "Bug/drug resistance: sometimes less is more," *Medical Care* (1989), 194–203.

Pintarić, S., I. Zeljković, T. Bodrožić-Džakić, M. Vrsalović, D. Zekanović and H. Pintarić, "Correlation between atmospheric air pollution by nitrogen dioxide meteorological parameters and the number of patients admitted to the Emergency Department," *Medica Jadertina* 42 (2012), 97–98.

Rodriguez, E. M., M. V. Lacaze and B. Lupín, "Contingent valuation of consumers' willingness-to-pay for organic food in Argentina," Technical Report, 2008.

Rosello, A., K. Pouwels, M. D. De Cellès, E. Van Kleef, A. Hayward, S. Hopkins, J. Robotham, T. Smieszek, L. Opatowski and S. Deeny, "Seasonality of urinary tract infections in the United Kingdom in different age groups: longitudinal analysis of The Health Improvement Network (THIN)," *Epidemiology & Infection* 146 (2018), 37–45.

Rowthorn, R. and G. M. Brown, "Using antibiotics when resistance is renewable," *Battling Resistance to Antibiotics and Pesticides: An Economic Approach* (2003), 17–41.

Samoli, E., E. Aga, G. Touloumi, K. Nisiotis, B. Forsberg, A. Lefranc, J. Pekkanen, B. Wojtyniak, C. Schindler, E. Niciu et al., "Short-term effects of nitrogen dioxide on mortality: an analysis within the APHEA project," *European Respiratory Journal* 27 (2006), 1129–1138.

Scarpa, R. and I. Bateman, "Efficiency gains afforded by improved bid design versus follow-up valuation questions in discrete-choice CV studies," *Land Economics* (2000), 299–311.

Schlenker, W. and W. R. Walker, "Airports, air pollution, and contemporaneous health," *The Review of Economic Studies* 83 (2016), 768–809.

Scott, A., A. Maynard and R. Elliott, *Advances in health economics* (Wiley Online Library, 2003).

Scott, A. M., E. Beller, P. Glasziou, J. Clark, R. W. Ranakusuma, O. Byambasuren, M. Bakhit, S. W. Page, D. Trott and C. Del Mar, "Is antimicrobial administration to food animals a direct threat to human health? A rapid systematic review," *International Journal of Antimicrobial Agents* 52 (2018), 316–323.

Simeonova, E., J. Currie, P. Nilsson and R. Walker, "Congestion pricing, air pollution and children's health," Technical Report, National Bureau of Economic Research, 2018.

Smith, E. A. L., "Air Pollution: Meeting Nitrogen Dioxide Targets," Technical Report, UK Parliament, The Honorary House of Commons, 2017.

Spicknall, I. H., B. Foxman, C. F. Marrs and J. N. Eisenberg, "A modeling framework for the evolution and spread of antibiotic resistance: literature review and model categorization," *American Journal of Epidemiology* 178 (2013), 508–520.

Stuart, B., "The antibiotic paradox: How miracle drugs are destroying the miracle," (1992).

Sulis, G., B. Daniels, A. Kwan, S. Gandra, A. Daftary, J. Das and M. Pai, "Antibiotic overuse in the primary health care setting: a secondary data analysis of standardised patient studies from India, China and Kenya," *BMJ Global Health* 5 (2020), e003393.

Tang, K. L., N. P. Caffrey, D. B. Nóbrega, S. C. Cork, P. E. Ronksley, H. W. Barkema, A. J. Polachek, H. Ganshorn, N. Sharma, J. D. Kellner et al., "Restricting the use of antibiotics in food-producing animals and its associations with antibiotic resistance in food-producing animals and human beings: a systematic review and meta-analysis," *The Lancet Planetary Health* 1 (2017), e316–e327.

Tetteh, J. N., F. Matthäus and E. A. Hernandez-Vargas, "A survey of within-host and between-hosts modelling for antibiotic resistance," *Biosystems* 196 (2020), 104182.

TOLTZIS, P., M. J. DUL, C. HOYEN, A. SALVATOR, M. WALSH, L. ZETTS AND H. TOLTZIS, "The effect of antibiotic rotation on colonization with antibiotic-resistant bacilli in a neonatal intensive care unit," *Pediatrics* 110 (2002), 707–711.

UREÑA, F., R. BERNABÉU AND M. OLMEDA, "Women, men and organic food: differences in their attitudes and willingness to pay. A Spanish case study," *International Journal of Consumer Studies* 32 (2008), 18–26.

VAN DUIJN, P. J., W. VERBRUGGHE, P. G. JORENS, F. SPÖHR, D. SCHEDLER, M. DEJA, A. ROTHBART, D. ANNANE, C. LAWRENCE, J.-C. N. VAN ET AL., "The effects of antibiotic cycling and mixing on antibiotic resistance in intensive care units: a cluster-randomised crossover trial," *The Lancet Infectious Diseases* 18 (2018), 401–409.

WALSH, C. ET AL., *Antibiotics: actions, origins, resistance.* (American Society for Microbiology (ASM), 2003).

WANDEL, M. AND A. BUGGE, "Environmental concern in consumer evaluation of food quality," *Food Quality and Preference* 8 (1997), 19–26.

WEBB, G. F., E. M. D'AGATA, P. MAGAL AND S. RUAN, "A model of antibiotic-resistant bacterial epidemics in hospitals," *Proceedings of the National Academy of Sciences* 102 (2005), 13343–13348.

WHO, *Antimicrobial resistance: global report on surveillance* (World Health Organization, 2014).

WHO ET AL., "Antibiotic resistance: Multi-country public awareness survey," (2015).

WILEN, J. E. AND S. MSANGI, "Dynamics of Antibiotic Use," *Battling Resistance to Antibiotics and Pesticides: An Economic Approach* (2003), 17.

WILLIAMS, P. R. AND J. K. HAMMITT, "Perceived risks of conventional and organic produce: pesticides, pathogens, and natural toxins," *Risk Analysis* 21 (2001), 319–330.

WOOLDRIDGE, J. M., *Econometric analysis of cross section and panel data* (MIT press, 2010).