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Inequality, information failures, and air pollution

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ABSTRACT

Research spanning several disciplines has repeatedly documented disproportionate pollution exposure in low-income communities and communities of color. Among the various proposed causes of this pattern, those that have received the most attention are income inequality, discrimination, and firm costs (of inputs and regulatory compliance). We argue that an additional channel – information – is likely to play an important role in generating disparities in pollution exposure. We present multiple reasons for a tendency to underestimate pollution burdens. Using a model of housing choice, we then derive conditions under which "hidden" pollution leads to an inequality — even when all households face the same lack of information. This inequality arises when households sort according to known pollution and other disamenities, which we show are positively correlated with hidden pollution. To help bridge the gap between environmental justice and economics, we discuss the relationship between hidden information and three different distributional measures: exposure to pollution; exposure to hidden pollution; and welfare loss due to hidden pollution.

0. Introduction

Pollution exposure has repeatedly been found to be disproportionately experienced in low-income communities and communities of color. This observation is the foundation of the environmental justice (EJ) movement and a frequent subject of study in several social science and medical fields, including sociology, demography, geography, urban planning, public health, environmental studies, and economics.[1] Research has documented a persistent statistical correlation between race, ethnicity, and/or income on the one hand and the siting of hazardous waste facilities on the other.[2] Beyond just the siting of polluting facilities, ambient air quality itself has been linked to socioeconomic and demographic indicators.[3]

Understanding the causes of disproportionate exposure in any given context is vital to the design of policy to address it; different causes suggest different solutions. A few potential causal mechanisms receive the lion's share of attention in the academic literature. First, income inequality may cause lower-income people to "select" residential areas where environmental quality is lower. This willingness-to-pay based story (commonly referred to as "coming to the nuisance") "continues to receive the most attention from economists interested in environmental justice questions" (Banzhaf, 2011). Second, direct discrimination on the part of firms or government, by race or other demographic factor, could produce inequities in pollution exposure — indeed, some use the term "environmental racism" interchangeably with environmental injustice (Mohai et al., 2009b). Third, firms could choose to locate

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[1] For examples from each of these disciplines, see Bullard (1983), Taylor (2000), Holifield (2001), Pastor et al. (2001), Agyeman et al. (2002), Brulle and Pellow (2018), Mohai and Saha (2006), Mohai et al. (2009b,a), Banzhaf (2012), Mohai and Saha (2015), Banzhaf et al. (2019a) and Banzhaf et al. (2019b).

[2] Seminal papers include United States General Accounting Office (1983), United Church of Christ (1987) and Bullard et al. (2007).

[3] See, e.g., Kriesel et al. (1996), Depro and Timmins (2012) and Tessum et al. (2019).

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in places where their costs (including labor, land, transportation, and regulatory compliance) are lowest (Wolverton, 2009), which may similarly be where the relatively lower income and/or minorities are more likely to live. This mechanism extends to encompass the case in which firms follow a "path of least resistance", targeting communities with less political power on the grounds of cost minimization (Hamilton, 1995).

In this paper, we argue that existing research on disproportionate pollution exposure underweights the importance of another factor: information. There are many obstacles to accurate information about environmental quality and its benefits: companies and governments may have incentives to hide pollution, there are only so many pollution monitors, and our scientific understanding of health impacts continues to evolve. Missing and inaccurate information has the potential to affect housing choices, siting decisions of polluting enterprises, and government policy (like permitting, inspection, and enforcement) alike. We focus here on housing choice: if households sort into homes based on information about environmental amenities – or even just other attributes that are correlated with them – then missing or wrong information should be expected to affect the empirical distribution of pollution exposure.

Though the economics literature has documented widespread cases of limited information regarding environmental quality,[4] there has been far less focus placed on the distributional and justice-related implications of this market failure. We provide exactly that focus: we investigate the relationship between environmental quality and income in a model of residential location choice that nests various forms of limited or missing information. The most closely related research is by Ma (2019), who shows that failing to model limited information biases willingness to pay estimates for pollution clean-up, and that in her application, minority and low-income homeowners place a high value on information about pollution. Also related is work by Bakkensen and Ma (2020), who model heterogeneity in preferences for flood risk in a setting of limited information and argue that improved information provision would be progressive.[5] In contrast to these studies, we investigate how environmental inequities can arise from *uniform* limitations to perfect information – that is, when all individuals are equally wrong or uninformed – and focus on the example of air pollution and housing choice.

We begin by summarizing some of the many potential reasons why information about environmental quality could be limited or missing, as well as reasons to believe that households underestimate, rather than overestimate, air pollution and its damages. For instance, scientists frequently discover new biological pathways for adverse health impacts of pollutants. Companies sometimes hide emissions. Households are aware of some, but not all, known health impacts of pollutants, and they can experience psychological biases when understanding pollution impacts.

We then develop a model of the housing decision near a point source of pollution when air quality is not precisely known. Our aim in working with this model is to provide intuition for how information failures affect both physical pollution exposure and welfare across households, with a particular focus on how the impacts differ across income levels. We assume particular functional forms for utility and the pollution dissipation process, to show an intuitive comparative statics analysis with closed-form expressions. While the model focuses on the relationship between information failures and income-based sorting, we later discuss how the former may interact with racism and other drivers of disproportionate exposure.

Under a typical dispersion process for an air pollutant, and assuming people are under-informed about air pollution, we find that: (1) low-income households are exposed to more pollution; (2) low-income households are exposed to more *hidden* pollution; and (3) low-income households experience greater deadweight loss from a lack of information. While the first relationship is well-known, the latter two results are novel. It is noteworthy that, in our model, even *uniformly* limited information can produce disproportionate pollution exposure and welfare loss for low-income households. This occurs because households sort according to known pollution, which is positively correlated with hidden pollution due to the way pollution dissipates.

We generalize the model by relaxing assumptions on the functional forms of utility and the price of air quality. In equilibrium, households sort into different air quality levels based on their willingness to pay for positively correlated amenities. We replicate the first two results from our more parametric model: low-income households are exposed to greater pollution exposure and also greater *hidden* pollution exposure. Our third result does not always generalize, although both the physical pollution dissipation process and declining marginal utility will work towards the third result holding.

We then discuss the implications and applications of our modeling exercises for empirical research and policymaking. We begin by highlighting conceptual implications, including the importance of accounting for imperfect information in estimation of willingness to pay. We then describe existing empirical work as well as offer descriptive empirical evidence of our own, that both corroborates our model findings and underscores the challenges of estimating the value of information. Next, we discuss policy implications, connecting our work to the current Biden Administration environmental policy agenda and noting the possibility that uniform information provision is distributionally progressive. Lastly, we show how other contexts may also be characterized by a uniform lack of information with disproportionate burdens on low-income communities and people of color.

Our findings build on a long literature in environmental justice (in economics, see, for instance, reviews by Banzhaf 2011, Banzhaf 2012, Hsiang et al. 2019, Banzhaf et al. 2019a, and Banzhaf et al. 2019b). Until recently, household sorting has been the primary mechanism for environmental disparities analyzed in the economics literature (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011; Depro et al., 2015). However, the broader, multi-disciplinary literature highlights several other mechanisms, and empirical research in economics has begun supplying evidence of some of these. Lee (2017) examines the possibility that differential

[4] Among the many examples are Foster and Just (1989), Chivers and Flores (2002), Leggett (2002), McCluskey and Rausser (2003a), Pope (2008a,b), Mastromonaco (2015), Moulton et al. (2018), Von Graevenitz et al. (2018), Bakkensen et al. (2019), Barwick et al. (2019) and Bishop et al. (2020).

[5] Another recent paper is also somewhat related: Bakkensen and Barrage (2018) model heterogeneity in beliefs about flood risk, in order to study the dynamic of the relationship between sea level rise and coastal home prices.

moving costs affect households' ability to "flee the nuisance". Timmins and Vissing (2017) argue that linguistic isolation affects bargaining power in mineral lease negotiations. Shertzer et al. (2016) show historical evidence that non-White neighborhoods in Chicago were more likely to be zoned for industrial uses. Christensen and Timmins (2018) examine discrimination in the real estate market that steers minorities towards more polluted areas. We add to this literature by providing theoretical and empirical evidence that implies unequal pollution and welfare loss from limited information.

Though our focus in this paper is on air pollution and housing choice, our primary finding emerges generically from the relationship between salient and hidden amenities. As such, we believe hidden disamenities have the potential to create income-based or racial disparities in other contexts where information is likely limited, such as climate change mitigation (Heal and Park, 2016), groundwater source selection (Kremer et al., 2011), and demand for environmental quality in developing countries more generally (Greenstone and Jack, 2015). Our findings also contribute to an active, cross-field literature on the economics of information (Hastings and Weinstein, 2008; Ehrlich, 2014; Kurlat and Stroebel, 2015; Allcott et al., 2019). That a disparity can be produced simply by information that is uniformly limited across individuals stands out in contrast with existing work that focuses on *heterogeneity* in information and its costs.[6]

In light of our findings, we argue that estimation of marginal willingness to pay for environmental quality (MWTP) – a primary concern in environmental and public economics – must account for informational failures. Much of the related literature has used an assumption of full information in analysis of revealed preferences. When limited information is mentioned, it is generally in the context of noting that estimated willingness to pay reflects *beliefs* about environmental quality.[7] We show that our motivating empirical examples can lead to biased estimates of willingness to pay, and that the bias can go in either direction. As such, we argue for the explicit incorporation of information about beliefs, along the lines of what is proposed by Bishop et al. (2020) and Ma (2019).

1. Background

The choice of where to live has substantial consequences for the level of environmental quality a household experiences. At the same time, of course, the housing choice entails decisions about many other characteristics of homes and neighborhoods as well. In making a decision, the potential home buyer must trade off these many characteristics (number of bedrooms, the presence and size of a backyard, quality of the school district, neighborhood air quality, etc.), while considering her household budget and the cost of the house. To the extent that information about environmental quality and its impacts is hidden or missing, households may fail to choose their privately optimal home.

There are good reasons to believe that individuals are not fully informed about local air quality. Pollution is not always visible, nor does it always produce an odor. Moreover, the government's air quality monitoring network is sparse. Economists studying the consequences of this sparseness have primarily focused on the measurement of fine particulate matter ($PM_{2.5}$) (Fowlie et al., 2019; Sullivan and Krupnick, 2018; Zou, 2018), but Environmental Protection Agency (EPA) monitoring is even sparser for other pollutants. In 2016, the EPA reported monitors in around 140 counties for benzene and toluene, 260 for nitrogen dioxide (NO_2), 320 for sulfur dioxide (SO_2), 610 for $PM_{2.5}$, and 790 for ozone — out of a total of more than 3000 counties.[8]

In many places, the public must therefore *infer* air quality based on what might be observable to them: air quality at distant monitors, or a proxy such as the existence of a potentially polluting facility nearby. The use of distance as a proxy has empirical support from research on how people "perceive" pollution (Bickerstaff and Walker, 2001). A household might be aware that concentrations of pollutants tend to be higher close to highways (Currie and Walker, 2011; Herrnstadt et al., 2018), airports (Schlenker and Walker, 2016), industrial facilities (Currie et al., 2015), and power plants (Massetti et al., 2017).[9] In the first part of our theoretical exercise, we will assume that households cannot observe true air quality and instead use distance to a point source as a proxy.

In principle, information limitations could cause a household to underestimate *or* overestimate pollution exposure and its health effects. We suspect that cases of underestimation are widespread in practice, and we offer several pieces of evidence in support of this. First, consider the way science has generally progressed: scientists frequently discover new biological pathways for health damages. In the United States, industries can typically use new chemicals until damages have been documented by the EPA — which suggests that, *ex post*, the US tends to discover that exposure was worse than thought.

In fact, environmental standards have for the most part become stricter over time, as these new biological pathways for damages are discovered. In the Appendix (Figure A1), we show historical changes in EPA standards and World Health Organization (WHO) guidelines for various indoor and outdoor air pollutants (limited to pollutants for which the standards or guidelines have changed). In almost all cases, the EPA and WHO have revised their air quality guidelines downward, reflecting new information about the toxicity of pollutants. As an example, the EPA standard for ambient lead concentrations changed in 2008, from 1.5 $\mu g/m^3$ to 0.15 $\mu g/m^3$,

[6] One could imagine modeling access to information as heterogeneous, as has been done in other contexts. Importantly, though, environmental justice communities have in many cases been adept at sourcing information themselves (O'Rourke and Macey, 2003). We discuss extensions to our treatment of information in Section 5.

[7] One exception is Kask and Maani (1992), who model the hedonic price as a function of information level and uncertainty.

[8] These numbers come from the EPA monitoring data that we introduce and use in Appendix Section A4.

[9] Some pollutants are transported across long distance; for instance, concerns about cross-state transport of air pollution led to regulations on power plants. Even so, power plants are also responsible for nearby deposition of toxics such as chromium, mercury, and nickel (Massetti et al., 2017).

motivated by "important new information coming from epidemiological, toxicological, controlled human exposure, and dosimetric studies" (EPA, 2008, p. 66970).

Given that EPA guidelines and measurements are often the best source of information relevant to the evaluation (and valuation) of environmental quality, it seems likely that households have historically sorted into homes based on the EPA's underestimated health effects of pollution. To the extent that households have their own knowledge of the science on health effects, however, they are still unlikely to know about all biological pathways. For instance, even when households are aware of the negative respiratory impacts of air pollution, they are frequently not aware of negative cardiovascular impacts (Nowka et al., 2011; Xu et al., 2017). In addition, consider that some cognitive impacts have only recently been documented by academic researchers (e.g., Bishop et al., 2018); it thus seems plausible that the public is not yet fully aware of cognitive impacts.

Another reason individuals may underestimate pollution damages is that they may understand the hazards stemming from *some* but not *all* pollutants. For instance, they may associate refineries with sulfates (the foul-smelling air pollutants that are released by refineries) but not with benzene, toluene, and xylenes (chemicals emitted by the refining industry with developmental and/or carcinogenic effects). A 2019 report on California refineries identified 188 chemicals emitted, with varying degrees of toxicity and varying levels of odor (Riveles and Nagai, 2019). It seems likely that individuals are not fully aware of all of these chemicals and their health impacts. Their decisions will incorporate only the impacts of those disamenities of which they are aware. Research suggests that awareness of air pollution depends in large part on whether the pollution is detectable either visually or by smell (Bickerstaff and Walker, 2001; Hunter et al., 2004; Xu et al., 2017), so that invisible and odorless pollution may go unnoticed by the public.

Even for individuals who actively seek out information on chemicals, rather than simply relying on visual or other clues, underestimation of exposure may occur. It is perhaps instructive that the count of chemicals that facilities are required to report has grown substantially over time. Appendix Figure A2 plots over time the number of chemicals listed in the EPA's Toxics Release Inventory (TRI), which requires firms to disclose their use and emissions of listed chemicals; the time trend is dominated by periodic, large expansions to the list.[10] Before a new chemical is added to the list, it is plausible that either (1) households are unaware of the existence of that chemical at a point source, or (2) they believe the chemical is not harmful to human health. Indeed, Moulton et al. (2018) argue that the addition of new industries to the TRI in 2000 changed home prices near the most toxic plants, which the authors attribute to a change in beliefs about pollution levels.

Additionally, firms may have incentives to deceive regulators and underestimate their emissions (Duflo et al., 2013). While some emissions are monitored (e.g., SO_2 emissions from power plants), the EPA relies on self-reporting for other types of emissions (e.g., toxic emissions from industrial facilities). Moreover, companies have occasionally been prosecuted for tampering with monitoring equipment.[11] At the same time, regulators may have incentives to obscure true pollution levels through strategic monitoring (Grainger et al., 2018; Zou, 2018) – for instance, in order to avoid being in non-attainment with federal standards.

Lastly, behavioral bias may well contribute to underestimation of pollution and its damages. According to the literature on pollution perceptions, when individuals *do* report knowledge that air pollution in general is damaging, they may still believe that their own neighborhood is not heavily polluted (Bickerstaff and Walker, 2001; Brody et al., 2004; Xu et al., 2017). This has been termed a "halo effect" or a "halo of optimism".

Estimation of pollution levels and associated health damages could, of course, go in the opposite direction, and psychologists have pointed to instances where the public over-perceives the level of risk relative to academic scientists. For instance, researchers have argued that the public experiences "dread" of the risk of a nuclear power plant accident beyond what is implied by actuarial risk (Abdulla et al., 2019). As another example, cleaned-up hazardous waste sites may continue to be "stigmatized" (McCluskey and Rausser, 2003b). There are also cases where some members of the public overestimate risk and others underestimate it, such as with lifetime radon exposure (Warner et al., 1996). We do not rule out upward bias in perceived pollution, but we nonetheless focus on downward bias in the remainder of our analysis, since we believe that direction of bias to be more widespread.

2. A stylized model of location choice

We begin with a simplified model of housing demand under limited information, drawing on our previous discussion of pollution perception and misinformation. The model is fairly standard in that it depicts a household optimizing over the choice of air quality and a numeraire representing all other goods, given a budget constraint. We alter this setup to capture the information limitation in which we are interested: the household cannot observe air quality directly and instead uses distance to a point source as a proxy.[12] We derive demand for distance, i.e., air quality, under full information, and then we compare it with what happens when the household underestimates the added utility gained by moving further from the pollution source. Finally, we discuss the assumptions embedded in this modeling exercise.

[10] Note that the Toxics Release Inventory was created as part of the 1986 Emergency Planning and Community Right-to-Know Act and, as such, was originally intended to increase the information about pollution available to communities and decision-makers.

[11] Consider, for instance, a 2017 case against Berkshire Power Company and Power Plant Management Services, Inc. (https://cfpub.epa.gov/compliance/criminal_prosecution), or the case against Volkswagen (https://www.epa.gov/vw/learn-about-volkswagen-violations).

[12] Because we model housing demand as demand for distance, our model shares many features with a monocentric city model in an Alonso–Muth–Mills framework. The primary differences are that (1) we are interested in distance to a polluter (such that distance brings positive utility) rather than to a central business district (such that distance brings commuting costs); and (2) we focus on income heterogeneity, whereas the simplest monocentric city models begin with homogeneous income. Income sorting in monocentric city models is discussed in Arnott (2011) and Duranton and Puga (2015) and citations therein.

In this section, we assume a parameterization of the utility function, a parameterization of the physical pollution dissipation process, and a simplified housing price function. After working through this more specific model, we present a more generalized model in the next section that relaxes the functional form assumptions on demand, pollution dissipation, and housing prices.

Suppose a consumer gets utility from two goods:

- q healthiness, a function of air quality. However, q is not directly observable by the consumer (nor by other market participants). Instead, the consumer has a belief about the level of q in a location, based on what is observable: distance x to the source of pollution.[13] Thus, q is a function of x and exogenous parameters like the amount of pollution emitted at the point source.
- y all other goods, both housing (e.g., square footage) and non-housing (e.g., food).[14]

Here we have collapsed the impact of the point source on pollution and the impact of pollution on health into a single function, as the distinction is not important for our purposes. As such, we refer to q throughout as "healthiness" and "air quality" interchangeably.

We initially assume Cobb–Douglas preferences: utility $U(q, y) = q^{\gamma} y^{1-\gamma}$; we consider alternative preferences in Section 3. It is important to note that, even though the consumer infers rather than observes the level of q at the time she makes her decision, the true value of q is what ultimately impacts her utility. For instance, she may immediately experience health impacts such as asthma, without knowing that the asthma was caused by q. Or she may experience a delayed health impact such as cancer. We are not the first to allow for an input into the utility function that is unobservable to the agent (Foster and Just, 1989; Leggett, 2002; Just et al., 2004).[15]

To model the relationship between air quality q and distance x, we use a linear approximation of exponential decay. A large literature spanning environmental sciences (Hu et al., 1994; Rooarda-Knape et al., 1999; Zhu et al., 2002; Karner et al., 2010; Apte et al., 2017) and economics (Currie et al., 2015) suggests that pollution tends to decay exponentially with distance to its source. Numerous airborne pollutants have been evaluated, including criteria pollutants such as PM and NO_2 and toxic pollutants such as benzene. A similar relationship has been found for health outcomes such as low birthweight and premature birth (Currie and Walker, 2011). In our context, linearizing exponential decay eases calculations while retaining the key properties (i.e., first and second derivatives) of an exponential decay model. We describe exponential decay in more detail in Appendix Section A2.

We assume that healthiness from air quality improves with distance according to the following equation:

$$q = \alpha_0 - \alpha_1 \beta + \beta x \tag{1}$$

One can think of β as the amount of pollution emitted by a point source, or as the impact that a given level of pollution has on individual's health. A larger β parameter lowers air quality ($\frac{\partial q}{\partial \beta} < 0$) while increasing the importance of distance for air quality ($\frac{\partial q}{\partial x} > 0$). In addition, the marginal effect of distance on air quality rises in β ($\frac{\partial^2 q}{\partial x \partial \beta} > 0$). α_0 and α_1 are parameters affecting "background" environmental quality and pollution/healthiness at the point source, respectively.[16]

Fig. 1 plots healthiness as a function of distance for two possible values of β. For intuition, we can imagine that $x = 0$ is the location of a point source of pollution; then, air quality increases at a constant rate in distance from the point source. With larger β, pollution at the point source is higher, but so is the marginal effect of distance on air quality (the labeled points in Fig. 1 can be ignored for now).

The consumer's maximization problem is

$$\max_{x,y} \; U(q(x), y) \quad s.t. \quad px + y = m \tag{2}$$

where p is the price of distance, the price of y is normalized to one, and m is income. Here, we assume that the house price is linear in distance to the point source.[17] We also assume that the price schedule does not shift in response to changes in information; this assumption is most appropriate when only a small number of households experience changes in information. In Section 2.3, we relax these assumptions by allowing for endogenous prices in a pure exchange economy.[18]

Because the consumer does not observe q, she does not incorporate it directly in her maximization problem. Instead she maximizes over what she can observe, by making an assumption about the relationship between q and x. Under full information, the consumer knows the true value of the β parameter that relates q and x, which we denote β_1. In contrast, under limited information she believes that the parameter takes some perceived value β_0. We assume that $\beta_0 < \beta_1$ (i.e., distance matters more for true utility than the consumer is aware), but of course one could solve the model under the opposite assumption. So her true utility is determined by the true air quality $q(x, \beta_1)$, but when misinformed, she will choose x to maximize utility assuming $q(x, \beta_0)$.

[13] We consider proxies other than distance in the more generalized model that follows.

[14] Note that here the numeraire embeds all housing characteristics other than pollution exposure — so that we are implicitly assuming that other characteristics are not correlated with distance to the point source. In the more generalized model that follows, we allow for additional characteristics that are correlated with distance and therefore pollution exposure.

[15] For a lengthier discussion of utility and preferences in the context of limited information, see Hausman (2012).

[16] We assume that $x < \alpha_1$, so that $\frac{\partial q}{\partial \beta} = -\alpha_1 + x < 0$.

[17] House prices that increase with distance could arise from a standard hedonic model, as in Greenstone (2017).

[18] For simplicity, we define income as exogenous to the model; research has, however, shown that pollution can affect income (Graff Zivin and Neidell, 2012). This may exacerbate the inequalities we document.

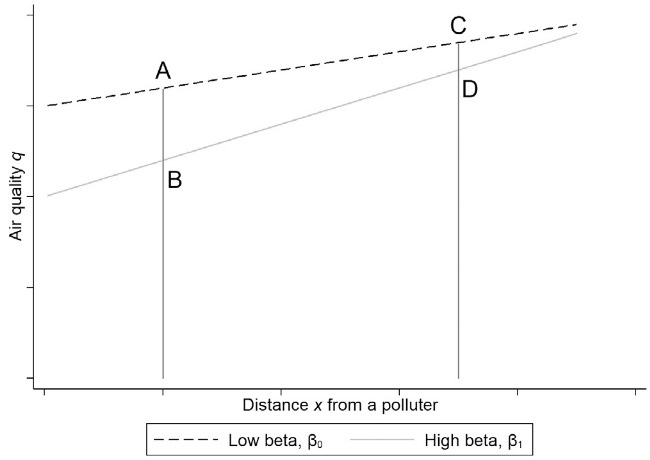

Fig. 1. Incorrect information regarding air quality. This figure plots the function $q = \alpha_0 - \alpha_1 \beta + \beta x$ for *perceived* air quality (the dashed black line with a low β) versus *experienced* air quality (the gray line with a high β). The point A is the perceived air quality for a low-income household, and B the experienced air quality for that same household. C and D give believed and experienced air quality, respectively, for a high-income household.

2.1. Demand for environmental quality

We solve the consumer's utility maximization problem to obtain the demand for distance. Initially, we assume the household correctly perceives the relationship between distance and air quality. As we show in the Appendix (Section A3.1), demand for distance is given by:

$$x^* = \frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta)}{\beta} \tag{3}$$

This is similar to the typical Cobb–Douglas demand equation, but with a linear shifter that depends on preferences and on the relationship between air quality and distance.

From this demand equation, it is straightforward to see that distance from the point source is a normal good: $\frac{\partial x^*}{\partial m} = \frac{\gamma}{p} > 0$. Since $\frac{\partial q^*}{\partial x^*} = \beta$, we have that $\frac{\partial q^*}{\partial m} = \frac{\gamma \beta}{p} > 0$: air quality is also a normal good. This occurs because low-income households choose less distance to the pollution source, due to their budget constraint. This result provides the basis for one potential definition of an environmental injustice or disparity:

Environmental Justice Metric 1. *Low-income households experience lower environmental quality, i.e., environmental quality is increasing in income:* $\frac{\partial q^*}{\partial m} > 0$.

This is the metric referred to in much of the economics literature on disproportionate siting and pollution exposure. Environmental justice researchers have pointed to correlations between air quality and income as evidence of the existence of an injustice.[19] Economists have frequently countered that low-income households have *chosen* to sort into neighborhoods with low air quality, that is, to "move to the nuisance". The condition for EJ Metric 1 is the mathematical foundation of the policy prescription that economists have tended to propose in the past: redistribution of income, rather than other environmental or information interventions.

2.2. Information failures and experienced air quality

Suppose now that the household *misperceives* β, believing it to be lower than it truly is. She thus believes that air quality is higher than it really is, and that distance matters less than it truly does. In this case, households experience worse air quality than they expect regardless of income level. However, the amount of *hidden* pollution experienced varies across households. Returning to Fig. 1, we can visualize the relationship between hidden pollution and income.

A relatively lower-income household selects a distance x that yields perceived air quality at point A. However, because air quality is worse than the household believes, it experiences true air quality B. Because air quality is a normal good, the relatively higher-income household chooses a greater distance, believing it has chosen air quality at point C but in reality experiencing air quality at point D. Crucially, because of the physical pollution dissipation process, the wedge between true and believed air quality is larger for the low-income household than for the high-income household. This provides the basis for our second environmental justice metric:

[19] Note that our model has thus far only incorporated income-based inequality. In Section 4, we discuss extensions that apply to racial inequality.

Environmental Justice Metric 2. *Low-income households experience a greater hidden level of pollution, i.e., the amount of hidden pollution is decreasing in income.*

EJ Metric 2 holds if:

$$\frac{d\left(\left|q(x(\beta_0),\beta_1)-q(x(\beta_0),\beta_0)\right|\right)}{dm}<0. \tag{4}$$

The household experiences air quality $q(x(\beta_0),\beta_1)$, in which x is chosen as a function of β_0 but translates into air quality (which impacts utility) as a function of β_1. In contrast, the household has chosen x assuming β_0 and believing it translates into air quality as a function of β_0. We have written the metric in absolute value terms because, recalling that the amount of hidden air quality is negative (the amount of hidden *pollution* is positive) – see Fig. 1 – we find that all households experience a negative amount of hidden air quality, and that this amount is smaller in absolute value for high-income households.

It is easy to see graphically that this holds in Fig. 1, implying the existence of this kind of environmental disparity. We provide a proof using the expressions for $q(x(\beta_0),\beta_1)$ and $q(x(\beta_0),\beta_0)$ in the Appendix (Section A3.2). This metric incorporates some of the intuition that one sees in advocacy reports, which sometimes argue that low-income households have experienced greater levels of hidden pollution when, for instance, firms do not initially reveal the full extent of their emissions or regulatory oversight is weak (United Church of Christ, 1987). Note that whether the disparity implies an injustice may depend in part on the cause of hidden pollution — such as illegal behavior by firms versus a lack of scientific information.

The second environmental justice metric is illuminating, but it is incomplete in two ways. First, it is in units of physical pollution exposure, rather than in utility terms. Second, a more appropriate counterfactual might be not to compare experienced air quality and perceived air quality, but rather experienced air quality and the *optimal* air quality that the household would have chosen, given full information. That is, whereas EJ Metric 2 compares $q(x(\beta_0),\beta_1)$ to $q(x(\beta_0),\beta_0)$, we might care more about a comparison between utility associated with $q(x(\beta_0),\beta_1)$ and utility associated with $q(x(\beta_1),\beta_1)$. We thus turn to an analysis that allows households to re-optimize all of their consumption decisions in response to full information and then calculates the utility gain associated with that ability to fully optimize.

Recall that the demand for distance is given by $x^*=\frac{\gamma m}{p}-\frac{(1-\gamma)(\alpha_0-\alpha_1\beta)}{\beta}$ (Eq. (3)) for whatever β the household perceives, and that the true relationship between distance and air quality is given by $q=\alpha_0-\alpha_1\beta_1+\beta_1 x$ (Eq. (1)). Substituting the expression for x^* into the expression for q, we can write optimal air quality under full information, which we denote q^*, as

$$q^*=q(\beta_1,x^*(\beta_1))=\alpha_0-\alpha_1\beta_1+\beta_1\left(\frac{\gamma m}{p}-\frac{(1-\gamma)(\alpha_0-\alpha_1\beta_1)}{\beta_1}\right) \tag{5}$$

In contrast, the chosen air quality under limited information, which we denote $q^\dagger$, is given by

$$q^\dagger=q(\beta_1,x^\dagger(\beta_0))=\alpha_0-\alpha_1\beta_1+\beta_1\left(\frac{\gamma m}{p}-\frac{(1-\gamma)(\alpha_0-\alpha_1\beta_0)}{\beta_0}\right) \tag{6}$$

Here $x^\dagger$ denotes the consumer's chosen distance under limited information, i.e., what she *believes* to be the optimal distance given her information set. The difference between the optimal and experienced level of air quality is $q^*-q^\dagger=\frac{\alpha_0(1-\gamma)(\beta_1-\beta_0)}{\beta_0}>0$. Under the simplifying assumptions we have made, we see that all households would have re-optimized to a higher level of air quality q^*, and the amount by which they would have changed their air quality purchase $(q^*-q^\dagger)$ does not depend on income.

Lost air quality leads to deadweight loss, and we next explore whether the level of that utility loss varies with income. The difference in utility under full information and under limited information for any household is given by:

$$\Delta U=(q^*)^\gamma(y^*)^{1-\gamma}-(q^\dagger)^\gamma(y^\dagger)^{1-\gamma} \tag{7}$$

This difference represents the value of information. Moreover, it gives us a third potential definition of an environmental disparity:

Environmental Justice Metric 3. *Low-income households experience a greater deadweight loss from incorrect information regarding pollution:* $\frac{d\Delta U}{dm}<0$.

In the Appendix (Section A3.3), we derive the sign of the derivative of ΔU with respect to income, showing that $\frac{d\Delta U}{dm}<0$. Therefore, under the assumptions we have made (limited information; Cobb–Douglas utility; etc.), an environmental disparity of this type exists. The intuition for this is that the low-income household would have received greater marginal utility from avoiding the hidden pollution than would have the high-income household (because of declining marginal utility). Later, we expand on this intuition to show alternative frameworks where it might not hold. We also give intuition using a consumer surplus framework, below.

One could also consider a "proportional" version of this metric, in which deadweight loss is divided by income. Such a metric incorporates the idea that low-income households experience greater pollution exposure while simultaneously having fewer economic resources for dealing with the health effects of the hidden pollution, which has been highlighted in some of the related literature (United Church of Christ, 1987; Fleischman and Franklin, 2017). The absolute version defined here is a stricter condition: if it holds, then the proportional version does, too (that is, if $\frac{d\Delta U}{dm}<0$, then $\frac{d\frac{\Delta U}{m}}{dm}<0$); if it does not hold, then the welfare "burden" as a proportion of one's income could still be greater for lower income households.

For some empirical applications, the researcher might not observe the full utility function but may be able to estimate demand and thus consumer surplus. It is easiest to visualize the change in consumer surplus by considering the demand for distance x from

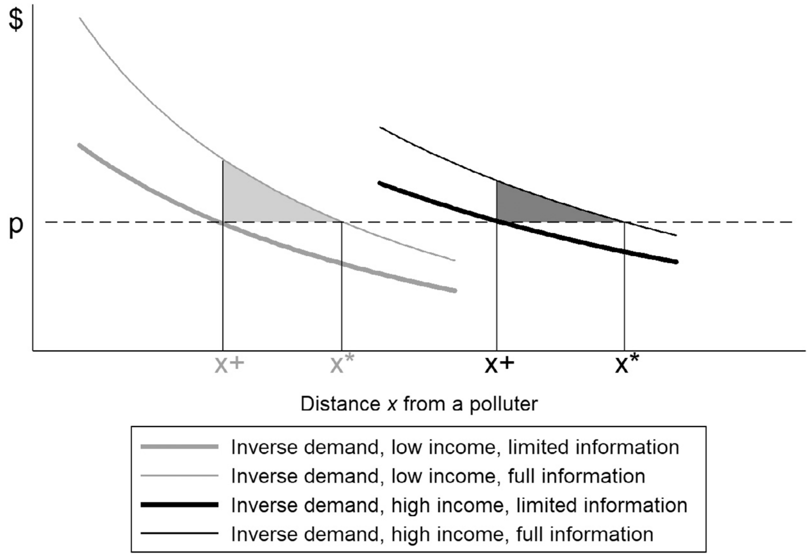

Fig. 2. Consumer surplus. This figure plots demand for distance under full (thin lines) versus biased (thick lines) beliefs about β, for low-income (gray) versus high-income (black) individuals. Shaded areas show deadweight loss from limited information, given by the area under the full-information inverse demand curve over the range $x^{\dagger}$ to x^{*}, minus the change in expenditure.

the point source. Fig. 2 shows how to evaluate this increase in consumer surplus. When believing that air quality relates to distance via a parameter value of β_0, the low-income consumer (gray) demands $x^{\dagger}$, the lowest demand function pictured. If instead informed that air quality relates to distance via β_1, the low-income consumer will demand x^{*}. The consumer surplus gain associated with full information can thus be evaluated as the area under the full-information inverse demand curve over the range $(x^{*}, x^{\dagger})$, minus the change in expenditure. The outer gray demand curve comes from the true underlying utility function and thus is the appropriate demand curve to use for evaluating consumer surplus.

As we show in the Appendix (Section A3.4), $\frac{\partial \Delta CS}{\partial m}$ is negative, so Metric 3 holds under the assumptions we have made when evaluated using consumer surplus rather than the full utility function. For intuition, recall that we have shown that the wedge between $x^{\dagger}$ and x^{*} does not change with income. So in comparing the gray and black areas in Fig. 2, what matters is the height (and the curvature) of demand. We show in the Appendix (Section A3.5) that the height is decreasing with income; that is, $\frac{\partial p^{\dagger}}{\partial m} < 0$, where $p^{\dagger}$ is the price that would have yielded $x^{\dagger}$ in the full information case. So it is intuitive that we show that consumer surplus is also decreasing with income. Below, we discuss to what extent this result generalizes when we relax assumptions about utility, pollution dissipation, and housing prices.

2.3. *Endogenous prices*

Our theoretical analysis thus far has held constant the marginal price of distance. It is natural, however, to wonder what would happen in an equilibrium framework in which prices are allowed to vary with information. We note first that allowing prices to vary endogenously in the model does not affect EJ Metrics 1 and 2. Recall that EJ Metric 1 holds because air quality is a normal good: high-income individuals purchase relatively more air quality, and that holds even when prices vary. EJ Metric 2 says that low-income households are physically more affected by underestimation of pollution damages. This result of the model relies on air quality being a normal good and on the physical pollution dissipation process. Since EJ Metric 2 is about hidden pollution at the uninformed equilibrium, rather than about what happens with re-optimization, it is unaffected by how we model prices.

Turning to EJ Metric 3, we evaluate whether the low-income household experiences greater deadweight loss from limited information than does the high-income household. We explore this setting by modeling pure exchange, in which two individuals have initial endowments of distance to a point source and a numeraire, and the total supply of each good is fixed. The price of distance is therefore endogenous, responding to changes in the perceived utility function.[20] We derive equilibrium outcomes and environmental justice metrics in the Appendix (Section A3.6 and A3.7). Here, we describe the intuition for what happens when prices change.

The key point from this exercise is that the price of distance is higher when pollution is known to be higher (specifically, when β is higher). This happens because the marginal value of distance x is greater at every level of x, so both households have greater

[20] We note that our analysis holds income from housing fixed — the changing price of x only affects the perceived utility function, not initial wealth. Mathematically, we show that the utility benefit of full information decreases in the initial allocation of the numeraire good, i.e., y^0.

demand for distance under full information. That is, under limited information, the price of distance is artificially too low. Since high-income households purchase more distance, an artificially low price helps the high-income household more than it helps the low-income household. Meanwhile, as before, low-income households also experience more hidden air pollution (EJ Metric 2), and in a full-information counterfactual, increasing distance would have meant larger marginal gains in utility for the low-income household (because of declining marginal utility).

Overall, then, we see that the intuition regarding a larger deadweight loss for low-income households is not overturned by allowing prices to vary endogenously in this pure exchange economy with Cobb–Douglas preferences. A formal proof for EJ Metric 3 can be found in the Appendix (Section A3.6). The Appendix also shows similar intuition for a pure exchange model in which there are two houses at fixed distances (Section A3.7).

3. Generalized model

The models in Section 2 yield three key results: lower income households choose relatively less air quality than their richer counterparts; they experience relatively more hidden air pollution; and they experience relatively more utility loss from limited information. Note that the only difference across households is their income level; we do not need to impose any particular heterogeneity in preferences or access to information across households to see inequalities from information failures (although we discuss the potential for such heterogeneity below in Section 4). The same mistake made by all households leads to inequality — not just in pollution exposure, but in welfare itself. Next, we develop a more general model that relaxes some of our assumptions, so that we might better understand which aspects of the model drive the key results.

Consider a household that, as before, derives utility from healthiness q (a function of air quality) that is not directly observable by the consumer but is a function of distance x to a source of pollution. We now posit that this household also gets utility from salient neighborhood amenities s, which are similarly a function of distance x to a pollution source, in addition to all other goods y. We assume that $\frac{\partial q}{\partial x} > 0$ and $\frac{\partial s}{\partial x} > 0$: both amenities increase with distance, so that they are positively correlated.[21] One can interpret s as salient pollution and q as hidden pollution, or s as salient health impacts of air pollution and q as non-salient ones. Alternatively, one can interpret s as salient *non*-pollution amenities (such as lack of noise, or availability of green space) that are correlated with hidden pollution q – we provide empirical context for this interpretation in the following section.[22]

In this version of our model, we do not impose a Cobb–Douglas utility function. We do assume that all goods provide positive utility at a declining rate ($U_q > 0$, $U_{qq} < 0$, and the corresponding conditions for s and y). We also relax our previous assumption of house prices rising linearly in distance to the point source: now, we only require that house prices increase with distance according to some hedonic price schedule, which need not be either strictly concave or strictly convex. We continue to assume that the hedonic price schedule does not shift with changes in information, but we note that the distributional effects of such a shift are ambiguous (Kuminoff and Pope, 2014).

Suppose the consumer is completely uninformed about air pollution. Then she optimizes according to the following:

$$\max_{x,y} \; U(s(x), y) \quad s.t. \quad p(x) + y = m \tag{8}$$

She fails to incorporate $q(x)$ into her decision-making, since she is unaware of how it impacts her utility. She does, however, incorporate distance to the point source into her decision, since distance yields other, salient amenities (visible pollution, a lack of noise, or a nice view). Note that this setup nests the narrower model of the last section, in which the salient disamenity – known pollution – is captured in $q(x)$ and the non-salient disamenity – hidden pollution – is positively correlated with the choice $q^{\dagger}$.

We derive first-order and second-order conditions for this problem in the Appendix (Section A3.8). Using comparative statics, we show that $\frac{\partial x^{\dagger}}{\partial m} > 0$ (i.e., distance is a normal good) if $\frac{\partial p}{\partial x^{\dagger}} U_{y^{\dagger}y^{\dagger}} > U_{s^{\dagger}y^{\dagger}} \frac{\partial s^{\dagger}}{\partial x^{\dagger}}$.[23] This is similar to the standard condition for a normal good, except that it incorporates the potential for the hedonic price schedule to be non-linear as well as the impact of distance x on salient amenities s at the misinformed optimum.

Because $\frac{\partial s}{\partial x} > 0$ (the salient amenity is increasing in distance), we know that if distance is a normal good, then the salient amenity is a normal good as well. Thus, the condition for the first environmental justice metric holds: low-income households experience higher levels of pollution. In general, salient environmental quality will be a normal good unless U_{sy} is negative and large. Similarly, because $\frac{\partial q}{\partial x} > 0$ ("hidden" environmental quality is increasing in distance), we know that if distance is a normal good, hidden environmental quality is as well. Thus, under very few assumptions, the condition for EJ Metric 2 holds too, and lower income households are exposed to greater levels of hidden pollution.

Turning to the third environmental justice metric, we ask whether the welfare impact of incorrect information is larger for low-income or high-income households. As before, we can evaluate the difference in utility at the optimal bundle under full information

[21] In this generalized model, it would be straightforward to incorporate an interpretation of x other than distance, since all we are assuming is that both salient and non-salient amenities are correlated with some signal variable x.

[22] We highlight lack of noise and availability of green space because they are directly tied to the same industrial sources that produce pollution. In this model, other non-pollution amenities, such as school quality and crime, are assumed to be part of the y good; however, one could extend the model to allow them to be correlated, whether positively or negatively, with distance x.

[23] Other housing papers simply assume normality of the good in question; for a discussion of this assumption and how it leads to a single-crossing property in sorting models, see Epple and Romer (1991).

(q^*, s^*, y^*) versus the selected bundle under limited information $(q^\dagger, s^\dagger, y^\dagger)$. The bundle (q^*, s^*, y^*) is determined by optimization under full information:

$$\max_{x,y} \; U(q(x), s(x), y) \quad s.t. \quad p(x) + y = m \tag{9}$$

We evaluate the difference in the utility given by the two bundles:

$$\Delta U = U(q^*, s^*, y^*) - U(q^\dagger, s^\dagger, y^\dagger) \tag{10}$$

Thus,

$$\frac{d\Delta U}{dm} = U_{q^*}\frac{\partial q^*}{\partial m} + U_{s^*}\frac{\partial s^*}{\partial m} + U_{y^*}\frac{\partial y^*}{\partial m} - U_{q^\dagger}\frac{\partial q^\dagger}{\partial m} - U_{s^\dagger}\frac{\partial s^\dagger}{\partial m} - U_{y^\dagger}\frac{\partial y^\dagger}{\partial m} \tag{11}$$

While this is unambiguously negative in the simplified model presented in Section 2, it cannot in general be signed as is; it depends on additional assumptions about utility.

Consider instead how utility changes for a small perturbation of the value of x around the uninformed equilibrium $(q^\dagger, s^\dagger, y^\dagger)$. This utility change is given by $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}\mathrm{d}x$.[24] We show above that $q^\dagger$ is smaller for low-income consumers than for high-income consumers (s is a normal good, so x is a normal good, so q is a normal good). As a result, $U_{q^\dagger}$ is larger for low-income consumers (recall that $U_{qq} < 0$). Also, because of how pollution dissipates, it will typically be the case that $\frac{\partial q^\dagger}{\partial x^\dagger}$ is weakly larger for low-income consumers.[25] Put together, $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}$ is larger for low-income consumers, which works in favor of Metric 3 holding. However, we do not know whether $\mathrm{d}x$ is larger for low-income or high-income consumers. In the simplified Cobb–Douglas model we present in the previous section, $\mathrm{d}x$ is invariant to income, but that need not be the case in general. In the Appendix (Section A3.9) we show that similar intuition applies for Stone–Geary utility, which in our simplified model yields $\mathrm{d}x$ that is invariant to income. However, we also show in the Appendix (Section A3.10) that $\mathrm{d}x$ is increasing in income for a utility function with Constant Elasticity of Substitution (CES). In keeping with this, we can show parameterizations of CES utility for which Metric 3 does hold, as well as parameterizations for which it does not.

In general, if $\mathrm{d}x$ is much larger for high-income consumers, outweighing the $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}$ effect, then Metric 3 will not hold.[26] Overall, in cases where pollution dissipates with distance, air quality is a normal good, and consumers underestimate the true level of pollution, low-income households will be more exposed to hidden pollution. Whether deadweight loss is larger for these households is an empirical question. We turn to the broader subject of empirical considerations in the next section.

4. Applications

The exercises in Sections 2 and 3 are theoretical, and they are specifically focused on air pollution and housing choice when households sort into homes based on income. In this section, we connect our analysis and findings to the broader context of real-world environmental and energy policy. We begin by discussing the implications of our modeling exercises for empirical work. Next, we review existing empirical work that corroborates our model findings and underscores the challenges of estimating the value of information going forward. Third, we describe an empirical exercise of our own (laid out in full in Appendix Section A4.2) that illustrates how co-located disamenities could produce disproportionate hidden pollution exposure. Fourth, we highlight the policy implications of our findings. Fifth, and finally, we illustrate the potential relevance of our modeling exercise in other settings.

4.1. Implications of our modeling work for empirics

There is a long-standing economics literature, spanning multiple settings, on the adverse impacts of limited information. Our model departs from this literature in its treatment of the distribution of missing information. Whereas other papers are motivated by or focus exclusively on the implications of *heterogeneity* in information or in the willingness to pay for information, we assume that every individual is wrong about air quality in the same way. In our simplified model, all individuals have the same mistaken belief about a key parameter in the estimation of air quality or its health impacts (which we model through β). In our more general model, all individuals might even know nothing about air quality and choose locations based on other salient home attributes and goods. We stress that cross-sectional differences in knowledge of air quality, in access to healthcare, or in underlying co-morbidities would also affect the distribution of pollution exposure, and they could either exacerbate or alleviate inequality.

Our model does abstract from several theoretically- and empirically-established facts about preferences, prices, and pollution. We model imperfect information on only dimension (air quality); future empirical work could explore the efficiency and equity

[24] To see this, write the change in utility as a change in the marginal utilities from s and q and y, when the consumer buys slightly more x and slightly less y: $\mathrm{d}U = U_{s^\dagger}\frac{\partial s^\dagger}{\partial x^\dagger}\mathrm{d}x + U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}\mathrm{d}x + U_{y^\dagger}\mathrm{d}y$. Then recall that the change in expenditure on x must be equal to the negative of the change in expenditure on y, from the budget constraint, and that $U_{s^\dagger}\frac{\partial s^\dagger}{\partial x^\dagger}$ must be equal to $\frac{\partial p}{\partial x}U_{y^\dagger}$, from the first-order conditions. This leaves only the expression $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}\mathrm{d}x$.

[25] If pollution dissipation is linear, then $\frac{\partial q^\dagger}{\partial x^\dagger}$ is invariant to income. More realistically, if the dissipation follows exponential decay, then $\frac{\partial q^\dagger}{\partial x^\dagger}$ is larger for low-income consumers.

[26] Similarly, in evaluating consumer surplus over distance, rather than the full utility function, whether deadweight loss increases or decreases with income will depend on whether the change in distance is increasing or decreasing, as well as whether the height of the inverse demand curve is increasing or decreasing. Both of these could be evaluated in particular empirical contexts, for instance via stated preference analysis.

implications of imperfect information about a vector of attributes such as school quality, crime, and intergenerational mobility (Chetty and Hendren, 2018a,b). Also, we model households as differing only in their incomes (Ellickson, 1971),[27] but real-world preference heterogeneity can lead to different equilibrium sorting of households into locations (Epple and Platt, 1998). We also employ a static model that allows (in our more general version) the price of distance to adjust but no other general equilibrium effects; see, for instance, Kuminoff et al. (2013) for an in-depth review of such effects, and Bayer et al. (2016) for a dynamic model of housing demand. Thirdly, we have not modeled other sources of inequality. For instance, inequality in access to health care could interact with the inequalities we document (Mullins and White, 2020); additionally, there is empirical evidence that pollution affects labor productivity and therefore income (Graff Zivin and Neidell, 2012). We have chosen to focus on a relatively simpler model in order to highlight the basic logic of our argument, but the added complexity of real-world markets and behavior means that the effect of limited information on inequality likely varies from setting to setting.

Despite the restrictions of our theoretical exercise, the results that it produces have important implications for the revealed preference models that are frequently used in environmental economics. Such models assume that agents have full information, or at least that the economist is able to observe agents' beliefs about the goods over which they are choosing. We argue in Section 1 that many individuals are not fully informed about their pollution exposure. The empirical researcher, then, must take a stand on what individuals' beliefs are regarding their exposure. As Hausman (2012) argues, when we observe Romeo choosing poison over eloping with Juliet, we must remember that Romeo believes that Juliet has died: "he does not prefer death to life with Juliet. His choice does not reveal his preference, because he is mistaken about what the alternatives are among which he is choosing" (p 28). Similarly, when we observe households sorting across neighborhoods, we must acknowledge that they are frequently mistaken about the level of health risks across neighborhoods, and temper our conclusions regarding their preferences accordingly.

In fact, our results point to the possibility of *either* overestimation of marginal willingness to pay *or* underestimation of marginal willingness to pay in empirical revealed preference studies of, for instance, air quality and the housing market. Suppose a researcher observes that a household is willing to pay $100 more for house A than for house B, where the two houses are identical except for one unit less of ambient pollution at house A. From this, the researcher concludes that the household has a marginal willingness to pay to avoid pollution of $100 per unit. If it turns out that house A also has 1 unit less of a salient disamenity (such as noise), about which the home-buyer is aware but the econometrician is not, then of course the empirical estimate is biased, and the homeowner actually has a marginal willingness to pay of less than $100 per unit of air quality (some of the $100 was spent to avoid the other disamenity). In this case, the researcher has overestimated the willingness to pay.

However, suppose that households are not fully informed, and they believe that house A has only 0.5 units less of ambient pollution (because of imperfect monitoring, fraud on the part of the polluting firm, etc.). In that case, the home-buyer that is willing to pay $100 more actually has a marginal willingness to pay of $200 per unit of air quality. This point is illustrated in an empirical application in Ma (2019), where willingness to pay estimates are significantly larger after accounting for incomplete information in a Bayesian updating framework. As such, we argue that hedonic methods should account for limited information regarding amenities more explicitly than has generally been done in the literature. Bishop et al. (2020) also argue for incorporating information and subjective beliefs, pointing to the possibility of using survey data.

4.2. Evidence from existing empirical work

In this section we discuss how existing empirical work corroborates our primary theoretical findings. In the Appendix (Section A4), we also provide descriptive empirical evidence of our own that is consistent with our first and second environmental justice metrics.[28] We do not attempt to empirically estimate causal effects of information failures on welfare, but we discuss opportunities for future empirical work.

We highlight three empirical studies that, through their findings, illustrate the potential for uniformly imperfect information to cause disproportionate pollution exposure and welfare loss among low income households. The first is by Currie and Walker (2011), who investigate the impacts of the introduction of EZ-Pass toll lanes on health, demographics, and property values. Their estimates imply a large negative effect of traffic congestion on infant health relative to the previous literature, which suggests that households may not have historically been fully aware of the true health impacts of traffic before making their housing choices. They also find incomes to be relatively lower near busy roads. Thus, despite a lack of complete information about pollution and its health impacts, households still sorted into homes such that those with lower income experience more air pollution. Finally, they fail to find short-run changes in demographics and housing prices in the aftermath of EZ-Pass toll openings. This fact could be driven by lack of information, though other explanations (like stickiness driven by moving costs) are possible.

Currie et al. (2015), meanwhile, examine the various impacts of polluting plant openings and closings. Notably for our context, they show that the *existence* of a plant – a relatively salient disamenity – changes home values, but the *relative toxicity* of a plant (which is perhaps less salient) does not. They suggest that "a possible explanation for the absence of such a pattern is that households have imperfect information. Given the lack of scientific evidence about the health effects of exposure, such ignorance would not be surprising" (p 697). The authors also find that house price declines in response to plant openings are largest in disadvantaged

[27] In particular, our modeling exercise is consistent with early theory on equilibrium sorting that uses the "single-crossing property" of Ellickson (1971).

[28] In particular, we assess who is likely to have experienced the most hidden pollution exposure in two specific empirical settings of information failure: one in which the failure is an underestimate of the health effects of lead pollution, and another in which the failure is underreporting of emissions by refineries.

communities; this suggests that willingness to pay for environmental quality is not lower among disadvantaged communities when pollution is salient.

Finally, Ma (2019) estimates marginal willingness to pay (MWTP) for brownfield remediation, using a structural model of information shocks. She finds that ignoring households' lack of information leads to underestimation of MWTP, and that minority and low-income groups place a higher value on information in this context. This suggests that information provision would help these groups the most, consistent with our model. Furthermore, the benefit of information is large relative to the value of cleanup itself: Ma notes that "Comparing the estimates under learning to that from assuming full information, the MWTP [for a decrease in contamination] with learning is 50% higher than the willingness to pay estimate without learning, rising from \$326.15 per unit of contamination to \$499.01" (p 1376).

These papers support the notion that imperfect information accounts for a meaningful fraction of disproportionate pollution exposure among low income households and people of color, but more empirical work on the subject is needed. Distinguishing the effects of information failures from those of other factors is quite challenging, however, for several reasons. First, it is difficult to accurately measure "informedness". In Ma's case, for example, brownfield assessment reports are used as a proxy for households' information; as Ma notes, though, this requires an assumption that households actually observe the information contained in these reports (and moreover that such information is accurate). Second, the researcher must be able to distinguish informedness from forward-looking behavior (Ma, 2019). In the housing context, individuals may choose to live somewhere based on the *expectation* of future improvements in environmental quality, and this may be confused with a lack of information if not explicitly modeled. Third, frictions like the cost of moving and the cost of obtaining information may explain behavior and similarly must be disentangled from the effects of information or a lack thereof. For instance, a household that does not move after an apparent negative shock to local amenities may not know about the shock, or it may know but not be able to move.

For these and other reasons, researchers have often only been able to *infer* a lack of information indirectly from empirical findings that appear inconsistent with full information (e.g., Currie et al., 2015; Lang and Cavanagh, 2018). More direct evidence of the impact of imperfect information on experienced environmental quality and welfare will require panel data on information levels, demographics, income, and property values, in addition to consideration of the aforementioned frictions and dynamics. Armed with such data, researchers may be able to elucidate information's effect on equity in the air quality context as well as others, like energy efficiency and water quality.

4.3. Evidence on the role of co-located disamenities

The general model in Section 3 shows that, in theory, disproportionate pollution exposure can emerge even when households know nothing about local pollution; this happens because households sort on observable (dis)amenities that are co-located with hidden pollution. In the absence of information about air quality, a household will choose the best (i.e., highest-utility) residential location based on other, more salient attributes (though the choice may *appear* to be pollution-based to the econometrician). For instance, suppose a household is unaware of the work by Currie and Walker (2011) documenting the health impact of roadway congestion, and as a result, it does not take into consideration differential exposure according to distance to highways or other busy routes. At the same time, the household does know that highways are noisy and ugly. All else equal, it would not like to live too close to the highway, wishing to avoid noise and wanting a nicer view.[29] Similarly, suppose a household is unaware that small airports are sources of lead exposure (Zahran et al., 2017) but wishes to avoid airport noise. Finally, a household may be aware of some but not all pollutants, and pollutants are frequently highly correlated with one another (Currie and Neidell, 2005).

This thought exercise suggests that the correlation between these salient amenities (i.e., lack of noise and lack of an ugly view) and the hidden amenity (lack of health-damaging air pollutants) is an important determinant of experienced environmental quality.[30] To shed light on this correlation, we assemble fine-grained data on air pollution, noise pollution, and land use from the EPA, the US Department of Transportation, and US Department of the Interior.

In the Appendix (Section A4.2), we use both visual evidence and regression analyses to show that salient amenities are highly correlated with pollution. As a result, if an individual were to choose one neighborhood over another based on differences in noise levels and land use amenities, her exposure to air pollution would be impacted even if she were not intentionally making a decision based on pollution levels. In this context, the model in Section 3 shows how environmental inequities can arise, if a lack of noise and access to land use amenities are normal goods. We also provide suggestive evidence in the Appendix that these co-located amenities are indeed normal goods. While the existing literature has focused on the empirical difficulties with observing various co-located amenities, we show that in addition the researcher must observe whether each amenity is known to the households — otherwise, estimated willingness to pay could be biased in that it reflects different levels of information or salience across correlated amenities.

4.4. Policy implications

Our work underscores the importance of considering information-based policies in pursuit of distributional equity. Access to accurate information about the location of pollution and polluters has long been a focus of environmental justice communities

[29] Von Graevenitz (2018) shows empirical evidence on the value of reduced road noise.

[30] Here and throughout, we refer to "experienced" environmental quality as the true level to which a household is exposed, as opposed to "perceived" environmental quality, the level which the household believes it is getting.

and scholars. Recent Biden Administration policy follows suit: Executive Order (EO) 14008 (“Tackling the Climate Crisis at Home and Abroad”), signed just one week into the Biden Presidency, contains multiple references to the creation of new data tools and communication strategies for the purposes of addressing environmental injustices. It directs the Council on Environmental Quality to “create a geospatial Climate and Economic Justice Screening Tool” and to “annually publish interactive maps highlighting disadvantaged communities”. It also directs the EPA to “create a community notification program to monitor and provide real-time data to the public on current environmental pollution, including emissions, criteria pollutants, and toxins, in frontline and fenceline communities — places with the most significant exposure to such pollution”.

Our main conceptual finding – that a lack of or mistaken information may exacerbate disproportionate pollution exposure (and resulting welfare loss) among low income households and people of color – underscores the importance of considering the aforementioned types of actions named in EO 14008. In particular, our work implies that information provision has the potential to be not just efficiency-improving, but also distributionally progressive. This potential is augmented by the fact that information-based policies may be significantly lower cost and less politically challenging to implement than other proposed solutions (though they are not *sufficient* for full equity). Thus, further research into the effects of pollution on well-being, more expansive environmental monitoring, and better communication of facts about the location, magnitude, and impacts of pollution are all promising avenues for addressing persistent environmental injustice.

4.5. Extensions to other contexts

We have shown that a lack of a full information can theoretically do more than just cause overall efficiency (i.e., deadweight) loss; it can also exacerbate the disparities that emerge from environmental quality being a normal good. In the context of the causes of disproportionate exposure, then, we can say that our model shows how missing information works through the “moving to the nuisance” channel. However, it could also act through other channels less directly dependent on income, such as racism or targeting based on political power. For instance, if racism in the housing market leads communities of color to be more exposed to salient pollution, missing information may cause such communities to be more exposed to hidden pollution as well. In general, systematic underestimation of pollution and its impacts has the potential to make existing inequality worse than previously thought. In this regard, our findings are relevant to the discussion of climate justice across countries: there is evidence that the damages of climate change are experienced disproportionately by low-income countries (Dell et al., 2012; Heal and Park, 2016), and as-yet undiscovered impacts of climate change may amplify the disparity.

In both our simplified model and our generalized model, two conditions drive our results: (1) a salient normal good; and (2) a positively correlated non-salient good. In contexts where these conditions are satisfied, limited information may contribute to inequality. We thus believe that information failures have the potential to create disparities in other environmental and energy contexts. Consider, first, the application of water quality. Willingness to pay for it has been shown to rise with both income and information provision (Jalan and Somanathan, 2008; Graff Zivin et al., 2011). It is plausible that in some contexts – for example, rural groundwater quality (Kremer et al., 2011) – less salient water quality may be positively correlated with more salient attributes of a water source, such as the source’s visual appearance. This example also illustrates that our model and findings may be relevant for all kinds of pollution avoidance behavior, whether it is the housing choice, the decision to purchase an air filter or mask, or the selection of a water source.

A second application of potential relevance is household energy efficiency. Evidence suggests that households are not fully informed about the value of energy efficiency (Graff Zivin and Novan, 2016; Cassidy, 2018) and that wealthier households are more energy efficient (Bednar et al., 2017). If the salient attributes of energy-using durables (for instance, the newness of a refrigerator or other home appliance) are positively correlated with the harder-to-measure energy efficiency, then income differences and information failures may interact to produce efficiency loss and inequality in energy-related outcomes. In fact, such inequality is one the main premises behind the field of “energy justice” (Hernandez, 2015).

5. Conclusion

There are several reasons to believe that individuals are lacking accurate information on local air pollution and its health impacts. In this paper, we demonstrate how this information failure can theoretically lead not just to economic inefficiency but also to inequality in pollution exposure and in well-being. We do this by deriving equilibrium comparative statics in two different models of residential location choice under limited information, which we motivate by pairing existing research with descriptive statistics on air quality and air quality standards. Our results suggest the potential for disparities under modest assumptions: relative to their higher-income counterparts, lower-income individuals experience greater pollution exposure, greater *hidden* pollution exposure, and – in some situations – greater welfare loss (as compared to full-information outcomes).

We close by highlighting three conceptual points that emerge from our work. First, the economics literature on the distribution of pollution exposure and the associated disutility focuses primarily on the roles of income, firm costs, and discrimination in a full-information world. To this literature, we add evidence that information limitations play an integral role as well, thus complicating the standard “moving to the nuisance” story. Second, there is a gap between economists and non-economists in the definition and understanding of what constitutes an environmental “injustice”. We help bridge this gap by jointly investigating the effects of income and information, and by considering not just pollution exposure but also *hidden* pollution exposure and welfare loss. Third, the estimation of willingness to pay for environmental quality has conventionally relied on revealed preference methods under an assumption of full information. We argue that the tendency of individuals to misestimate or underestimate air quality presents challenges to the interpretation of revealed-preference estimates.

There are several areas in which future research could advance our understanding of information, environmental quality, and welfare. Future empirical work could focus on estimating the effects of information provision, the value of information, and how the welfare impacts of information vary across groups. Where real-world quasi-experimental information shocks are not available, contingent valuation methods with randomly-varying levels of information could perhaps be used to calculate the value of information. Both quasi-experimental work and survey work could also help uncover the contexts in which pollution is most valuable, depending, for instance, on whether pollution is relatively salient or relatively hidden absent a policy intervention.

Future modeling work, meanwhile, could incorporate some of the phenomena that are not in the models presented here — such as the evolution of beliefs about pollution over time, the cost of obtaining information, and uncertainty. We have left our model deliberately simple, to show the potential for environmental disparities under very few assumptions, but future models could incorporate these additional considerations. Lastly, we have focused specifically on the role of information in the housing choice, but information also likely has played and continues to play important roles in both industrial siting and government policy decisions as well; we believe that future research on these roles would be very valuable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102552.

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