Inequality, Information Failures, and Air Pollution

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Abstract

Research spanning several disciplines has repeatedly documented disproportionate pollution exposure among the poor 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, as well as empirical evidence that this underestimation can disproportionately affect low-income households. 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 because 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.

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Pollution exposure has repeatedly been found to be disproportionately experienced by the poor and people 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 poorer 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, Pellow and Roberts, 2009). Third, firms could choose to locate in places where their costs (including labor, land, transportation, and regulatory compliance) are lowest (Wolverton, 2009), which may similarly be where the relative poor 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 channel: 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. 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 has the potential to affect the empirical distribution of pollution exposure. Though the economics literature has

[1]For examples from each of these disciplines, see Bullard (1983); Taylor (2000); Holifield (2001); Pastor Jr., Sadd and Hipp (2001); Agyeman, Bullard and Evans (2002); Brulle and Pellow (2018); Mohai and Saha (2006); Mohai, Pellow and Roberts (2009); Mohai et al. (2009); Banzhaf (2012); Mohai and Saha (2015); Banzhaf, Ma and Timmins (2019).

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

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

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. Perhaps most closely related is work by Bakkensen and Ma (2019), who models heterogeneity in preferences for flood risk in a setting of limited information and find that improved information provision would be progressive.[5]

We begin by highlighting 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. We document a steady tightening in U.S. air pollution guidelines over time as well, motivated by advances in scientific understanding of health impacts. The steady expansion of toxic release reporting requirements to cover more chemicals also suggests that households have had limited access to information in recent US history. These facts are consistent with the notion that households undervalue the health impacts of air quality when choosing a home because they are not fully informed. In addition, we show evidence from the health literature that households are aware of some, but not all, health impacts of pollutants, and that households experience psychological biases when understanding pollution impacts.

We also document two instances from recent history in which underestimation of pollution burdens disproportionately impacted low-income and non-White neighborhoods. First, we show that neighborhoods with higher airborne lead concentrations had lower percentages of White occupants *just prior to* a tightening of federal lead standards in 2001 based on new epidemiological research on lead's health impacts. Second, we show that neighborhoods near refineries had lower income levels and lower percentages of White occupants in 1999, just before the publication of evidence that the refining industry had widespread unreported emissions. In each case, an observable, "pre-existing" disparity in physical pollution exposure was exacerbated by a lack of full information.

We next show that, in the U.S., air pollution is co-located with other, more salient disamenities – namely, intrusive land uses and noise – and that these disamenities are, in turn, negatively correlated with income.[6] These empirical facts imply that even if households

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

[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.

[6]Here and throughout, we use "salient" to refer to disamenities that are easily discernable, i.e., readily apparent. We contrast these with "hidden" disamenities, like some forms of pollution. In our setting,

are *completely* uninformed about air pollution, they will still tend to sort into houses in such a way that yields relatively higher pollution burdens for low-income households. In fact, controlling for land use and noise significantly weakens the strength of the statistical relationship between income and air quality. This finding is consistent with a setting in which households sort based on salient disamenities and then are unequally impacted by non-salient air pollution.

Motivated by the above discussion and empirical facts, we develop a model of the housing decision near a point source of pollution, when air quality is not precisely known. Our aim with the model is to provide intuition for how information failures impact both physical pollution exposure and welfare across households, with a particular focus on how the impacts differ across income levels. While this model focuses on income inequality; we later turn to extensions applying to racial inequality. We assume particular functional forms for utility and the pollution dissipation process, to show an intuitive comparative statics analysis with closed-form expressions.

Under a typical dispersion process for an air pollutant, and assuming people are underinformed 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 among the poor. 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 allowing the consumer to consider other salient neighborhood amenities (besides air quality) that increase with distance to the point source, and 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.

Our findings build on a long literature in environmental justice (in economics, see, for instance, reviews by Banzhaf 2011, Banzhaf 2012, Hsiang, Oliva and Walker 2019, and Banzhaf, Ma and Timmins 2019). Until recently, household sorting has been the primary

differences in salience across amenities arise out of limited information, not out of behavioral biases.

mechanism for environmental disparities analyzed in the economics literature (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011; Depro, Timmins and O'Neil, 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) proposes and finds evidence that differential moving costs affect households' ability to "flee the nuisance." Timmins and Vissing (2017) find that linguistic isolation affects bargaining power in mineral lease negotiations. Shertzer, Twinam and Walsh (2016) show historical evidence that non-White neighborhoods in Chicago were more likely to be zoned for industrial uses. Christensen and Timmins (2018) identify 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, Lockwood and Taubinsky, 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.

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. (2019).

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

1 Context and Empirical Motivation

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.

In this section, we discuss reasons why households may face limited information, as well as the potential consequences of this information failure for the distribution of pollution burdens. Note that throughout this section, we present empirical facts primarily to *motivate* the theoretical model that follows. Thus the empirical exercises are not intended to in of themselves prove welfare impacts, but rather to motivate the assumptions needed for the theoretical modeling that does allow for analysis of welfare impacts.

1.1 Misestimation of Pollution

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, Rubin and Walker, 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 3,000 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

[8]These numbers come from the EPA monitoring data that we introduce and use in Section 1.3.

[9]Some pollutants are transported across long distance; for instance, concerns about cross-state transport

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 tend to discover new biological pathways for *damages*, rather than finding new health benefits of emissions or ruling out previously-believed pathways for damages. In the United States, industries can typically use new chemicals until damages have been documented by the EPA – suggesting that, *ex post*, the US tends to discover that exposure was worse than thought.

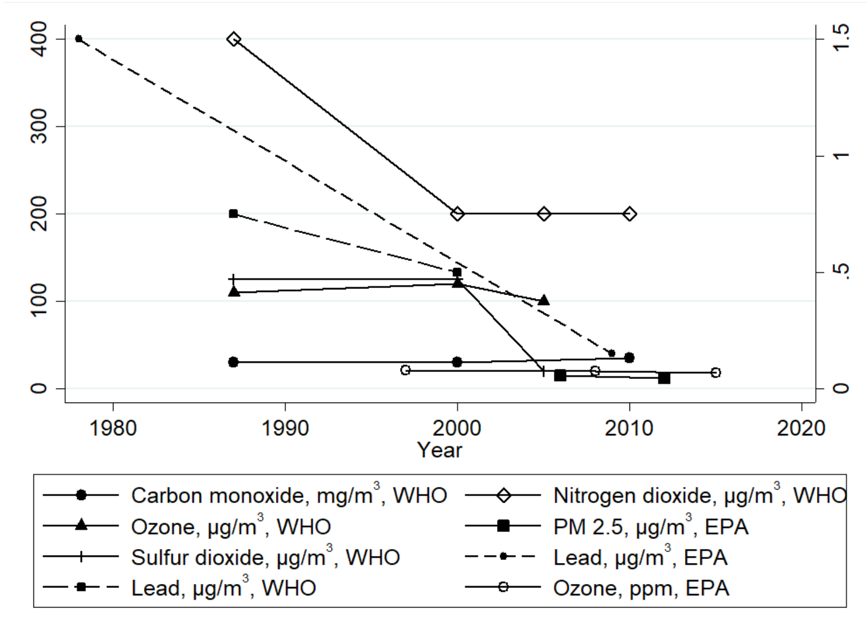
In fact, environmental standards have for the most part become stricter over time, as these new biological pathways for damages are discovered. Figure 1 shows historical changes in EPA standards and World Health Organization (WHO) guidelines for various indoor and outdoor air pollutants (limited to pollutants 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 $\mu g/m^3$, 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, Chi and Zhu, 2017). In addition, consider that some cognitive impacts have only recently been documented by academic researchers (e.g., Bishop, Ketcham and Kuminoff, 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 iden-

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).

Figure 1: Air Pollution Guidelines Have Become Tighter



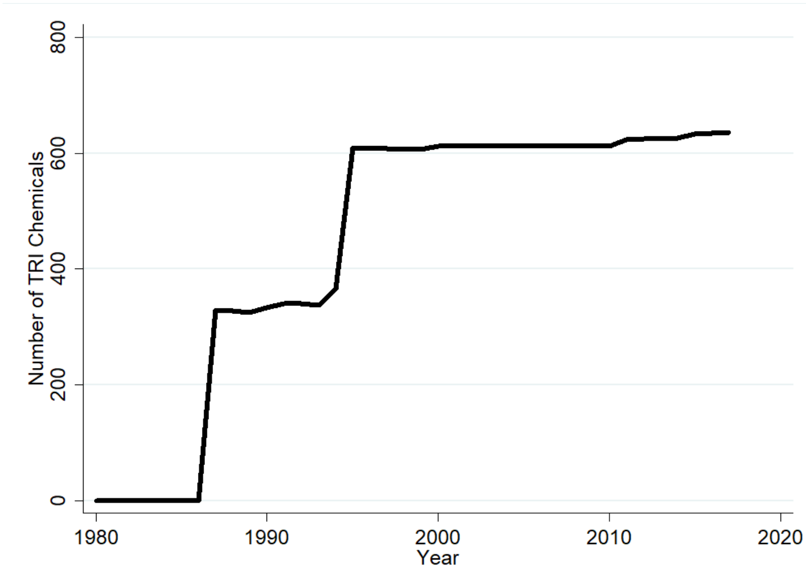
Note: This figure plots the changes in EPA standards and WHO guidelines for selected air pollutants. The left axis is used for all pollutants except lead and the EPA's ozone standard, which use the right axis. Some guidelines use the midpoint of a range; see Appendix Table A1 for the full range. For time frames (e.g., 8-hour standards versus annual average standards), also see Appendix Table A1. This figure plots only those standards and guidelines that have changed over time; for information on standards that have not changed, see original sources: WHO (2000, 2005, 2010, 2017); EPA (2018).

tified 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 optimization 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, Bickerstaff and Davies, 2004; Xu, Chi and Zhu, 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. Figure 2 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]

[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.

Figure 2: Toxic Chemicals Reporting Has Grown Stricter



Note: This figure plots the count of TRI-listed chemicals over time. The TRI program is an EPA-run mandatory reporting program for chemicals with cancer effects, other chronic health effects, significant acute health effects, and significant environmental effects. The source is EPA (2017).

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, Sanders and Wentland (2018) show 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.

Even if a household knows which pollutants are bad, and how bad they are, it will still misestimate pollution damages if true levels of pollution are not readily available. Firms, however, 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, Schreiber and Chang, 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 knowl-

[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).

edge that air pollution in general is damaging, they may still believe that their own neighborhood is not heavily polluted (Bickerstaff and Walker, 2001; Brody, Peck and Highfield, 2004; Xu, Chi and Zhu, 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 overperceives 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, 2003*b*). There are also cases where some members of the public overestimate risk and others underestimate it, such as with lifetime radon exposure (Warner, Mendez and Courant, 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.

1.2 Who Is Impacted by Limited Information?

What might be the effect of underestimation and undervaluation on the distributions of pollution exposure and health effects? To provide some intuition, we present some empirical evidence on the distribution of pollution exposure just prior to the revelation of new information about air quality. First, consider the EPA's 2008 tightening of the federal ambient lead standard. We might infer that prior to 2008, communities experiencing elevated lead concentrations were not fully aware of the emerging information about lead's health impacts. We have no reason to suspect that the public was more aware of lead's impacts than were EPA scientists and regulators. As such, it is worth considering which communities were experiencing the highest ambient lead exposure at the time of the EPA's standard change.[12]

To do so, we assemble EPA monitoring data on annual average concentrations of airborne lead[13] as measured by the speciated $PM_{2.5}$ monitoring network.[14] We locate each monitor in a 5-digit Zip Code Tabulation Area (ZCTA) using latitude and longitude data provided by the EPA and shapefiles from the 2000 Census. To these data, we add demographic characteristics of neighborhoods at the zip code level from the 2000 Census. Descriptive statistics are in Appendix Table A2; we note that the mean level of measured lead is well below the new standard.

[12]Note that our analysis here does not focus on the change in the standard's level per se, but rather is motivated by the existence of new scientific information that caused the standard to change.

[13]Lead exposure can also occur via soil or water contamination, so the air concentrations on which we focus do not represent all forms of lead exposure.

[14]The EPA's Chemical Speciation Network measures the amount of various elements (e.g., arsenic, cadmium, lead, etc.) in collected particulate matter.

We regress each demographic characteristic on the level of airborne lead (logged).[15] We include fixed effects at the level of a core-based statistical area (CBSA), to compare residents of the same metro area with low versus high levels of lead.[16] As we show in Table 1, communities with high lead concentrations tend to have lower incomes, greater unemployment rates, a higher proportion of families below the poverty line, and a higher proportion of people of color. Unsurprisingly, the standard errors are large; only 206 zip codes had a monitor for speciated particulate matter in this year, and we are relying for identification on CBSAs with multiple zip codes containing monitors ($n = 95$). Regressions in the Appendix (Table A3) without CBSA fixed effects yield the same directional impacts, and much greater statistical significance. If we instead use modeled lead concentrations from the 2002 National Air Toxics Assessment, which cover the entire US, we obtain qualitatively similar estimates with more precision (again, see Appendix Table A3).

Overall, the results suggest that low-income communities and people of color have historically been most *physically* impacted by incomplete scientific information about the health impacts of lead. To understand the welfare implications, one could next examine whether households moved following the release of the new scientific information. However, strong assumptions would be needed on (1) the degree to which (and mechanisms by which) the public became aware of the new scientific information; (2) moving costs; and (3) other potential confounders in the housing market over this time period. Rather than conducting such an empirical exercise, we turn below to a theoretical model to understand the nature of the resulting welfare impacts.

A second empirical example illustrates how underreporting of pollution may affect the distributional impacts of emissions. In October 1999, the EPA issued an enforcement alert for the petroleum refining sector. The alert stated that an EPA monitoring program had shown "that the number of leaking valves and components is up to 10 times greater than had been reported by certain refineries," and that as a result, emissions rates of volatile organic compounds (some of them hazardous chemicals) were substantially higher than had been reported by firms (EPA, 1999). We can assess who is likely to have been most impacted by this historical underreporting by investigating the characteristics of people living near refineries prior to the EPA's alert. We thus obtain information on the location of US petroleum refineries from the EPA's National Emissions Inventory (NEI). Specifically, we

[15]We use lead data from 2001, representing an intermediate year between the 2000 Census and the 2008 standard change. Lead monitoring in 1999 and 2000 (i.e., more closely matching the demographic data) is very sparse. Results using data from 2008 (i.e., at the time of the standard change) are very similar to the 2001 results; see Appendix Table A3.

[16]Around 4.5 percent of the population is in a Zip Code Tabulation Area that does not match to a CBSA; we drop these ZCTAs from our regressions.

Table 1: Demographic Characteristics Were Correlated with Ambient Lead Exposure in 2001

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Log airborne lead concentration	-4.21	0.44	2.67	-11.72**	5.50	5.27**
	(2.60)	(0.43)	(1.71)	(4.57)	(4.09)	(2.40)
Observations	203	203	203	203	203	203
Within R^2	0.04	0.02	0.04	0.10	0.03	0.07
Mean of dep. var.	37.07	4.80	13.18	74.61	16.37	11.98

Note: This table reports estimates and standard errors from six separate regressions. The dependent variable is listed above each column. Lead concentrations are logged lead in PM2.5 form. The unit of observation is a 5-digit Zip Code Tabulation Area. Income is the median household income in the zip code, in thousands of 1999 dollars. Percent below poverty refers to the percentage of families below the poverty line. Percentage White, Black, and Latino/a refer to the percentage of individuals. Data source: Census for demographics; EPA for ambient lead concentrations. All regressions include CBSA fixed effects. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

analyze all zip codes with a facility in the 1999 NEI that was classified in SIC sector 2911 (Petroleum Refining); 210 zip codes had such a facility in 1999. Using the 2000 Census data described above, we examine differences in demographic characteristics across zip codes with and without a refinery. Note that the 2000 Census asks about income in 1999, i.e., at the time the Enforcement Alert was published.

We regress each demographic variable on the refinery indicator, including CBSA fixed effects, to compare communities in the same metro area.[17] Results, in Table 2, show that zip codes with refineries in them had significantly lower income levels and significantly higher proportions of non-White families and families below the poverty line. (We again show results without CBSA effects in the Appendix, in Table A4.) Thus, it appears that the communities most physically impacted by the historical underreporting were economically disadvantaged and non-White. Again, one could examine whether households moved following this change in information about refineries, but strong assumptions would be needed for identification. Alternatively, one could examine price impacts. However, our goal with this example is not to demonstrate that this particular incident reflected a large-scale environmental injustice – rather, our goal is to provide examples of some of the many instances in which households may have underestimated risk, with differential exposure resulting from this information failure. In Section 2, we turn to a theoretical analysis to understand welfare impacts.

[17] The NEI dataset appears to classify some facilities, such as tank farms, as SIC 2911, in addition to refineries. We perform a fuzzy string match to match EPA NEI facilities to petroleum refineries listed in the US Energy Information Administration's (EIA) Petroleum Supply Annual. Regressions using the subset of facilities that match to the EIA report (located in 137 zip codes, rather than 210) yield similar results; see Appendix Table A4.

Table 2: Demographic Characteristics Were Different Near Refineries in 1999

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Refinery in zip code	-4.01***	0.43**	2.07***	-4.29***	2.10**	5.90***
	(1.03)	(0.21)	(0.53)	(1.17)	(1.00)	(0.68)
Observations	23,952	23,892	23,833	23,912	23,912	23,912
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00
Mean of dep. var.	42.24	3.42	9.00	85.68	8.53	7.15

Note: This table reports estimates and standard errors from six separate regressions. The dependent variable is listed above each column. The unit of observation is a 5-digit Zip Code Tabulation Area. Income is the median household income in the zip code, in thousands of 1999 dollars. Percent below poverty refers to the percentage of families below the poverty line. Percentage White, Black, and Latino/a refer to the percentage of individuals. Data source: Census for demographics; EIA'S Petroleum Supply Annual and EPA's National Emissions Inventory for refinery locations. All regressions include CBSA fixed effects. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

1.3 Co-located Amenities

Above, we have suggested that households may sort on proxies such as distance to point sources, or they may sort based on the most salient pollutants. Next we show that, even in the absence of any information about pollution, households may engage in sorting behavior that, to the econometrician, appears to be pollution-based. This could occur because of co-located amenities. 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. 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.[18] Similarly, suppose a household is unaware that small airports are sources of lead exposure (Zahran et al., 2017) but wishes to avoid airport noise.

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.[19] To shed light on this correlation, we assemble data on air pollution, noise pollution, and land

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

[19]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.

use. From the EPA's monitoring network, we collect ambient concentrations of four criteria pollutants – NO_2, ozone, $PM_{2.5}$, and SO_2 – and two toxic pollutants – benzene and toluene. As described above, these latter two compounds are emitted by the refining industry (as well as other industries) and have negative developmental and/or carcinogenic effects. We focus on benzene and toluene both because (1) refining has been a focus of the environmental justice movement (Fleischman and Franklin, 2017); and (2) the monitoring network of these chemicals is denser than is the monitoring of other hazardous air pollutants.

We observe annual average concentrations by monitor for the year 2001 (which matches the time period of our land use data),[20] and we locate each monitor in a 5-digit ZCTA using latitude and longitude data provided by the EPA. Unfortunately, even for these six criteria and hazardous pollutants (which have the densest coverage in the EPA dataset), monitoring is quite incomplete; we observe the fewest zip codes for toluene (215 total) and the most for ozone (1,116 zip codes) in our analysis.[21]

We collect data on one additional measure of pollution exposure, modeled cancer risk, from the EPA's 2002 National Air Toxics Assessment (NATA). This measure takes emissions data from the National Emissions Inventory – covering both point and nonpoint sources – and imputes cancer risk.[22] An advantage of these data is that the EPA presents estimates for every zip code, so we have broader coverage than for the measured pollution concentration data.[23] Additionally, the variable aggregates the risk associated with many different pollutants. A disadvantage is that the risk is modeled based on NEI emissions, rather than measured in the way that concentrations of our six criteria and toxic pollutants come directly from pollution monitors.[24]

We merge these pollution exposure variables with noise and land use data.[25] Noise data come from the Department of Transportation's National Transportation Map. Like

[20]In Appendix Table A5, we show results using pollution measures from 2016.

[21]We provide coverage maps in Appendix Figure A1.

[22]More specifically, the NATA uses NEI emissions, dispersion and deposition models, and an inhalation exposure model (which includes components such as a human activity pattern database).

[23]The EPA NATA data are at the Census Tract level. We match these to zip codes using a 2010 US Department of Housing and Urban Development crosswalk. Around 0.2 percent of the conterminous US population is in a ZCTA that does not directly merge with the NATA data; we drop these ZCTAs from our cancer risk regression.

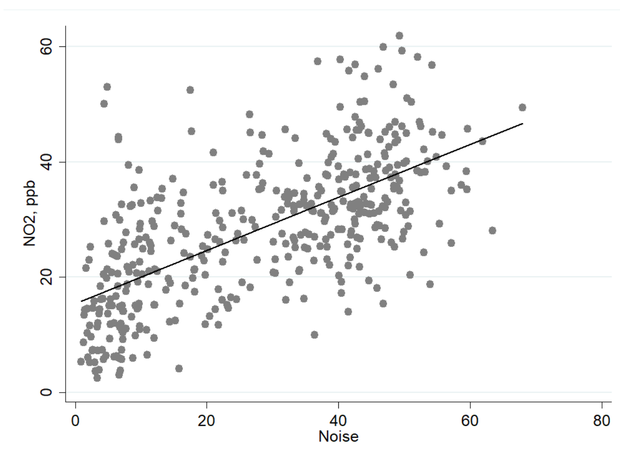
[24]The EPA cautions that NATA should not be used for analyses such as "pinpoint[ing] specific risk values within a census tract," but argues that the results "help to identify geographic patterns and ranges of risks across the country" (Environmental Protection Agency, 2011, p 5) We use the NATA data in ways consistent with the latter, but caveat our results accordingly. Interestingly, one of the reasons EPA provides caution about NATA data is that they have, over time, provided "a better and more complete inventory of emission sources, an overall increase in the number of air toxics evaluated, and updated health data for use in risk characterization" (Environmental Protection Agency, 2011, p 6) – supporting our argument that historically, pollution exposure has been (unintentionally) underreported.

[25]Again, we use 2000 Census shapefiles to match locations to ZCTAs.

our estimates of cancer risk, our estimates of noise are modeled, rather than measured. They are based on information about major roadways as well as airports, and "represent the approximate average noise energy due to transportation noise sources over the 24 hour period."[26] Meanwhile, land use data are published by the US Geological Survey at the Department of the Interior.[27] The key variable is a land use classification – such as "developed - high intensity," "developed - medium intensity," "water," or "wetlands"– derived from satellite imaging. We tabulate descriptive statistics in Appendix Table A2.

We start by examining the correlation between salient disamenities (noise and ugly views) and NO_2. NO_2 causes negative health effects such as asthma and cardiovascular conditions, and mobile sources (trucks and cars) are a major contributor to NO_2. Figure 3 plots NO_2 concentrations against noise levels and reveals a strong positive correlation between these two disamenities. Figure 4 plots NO_2 against a zip code's proportion of land dedicated to high-intensity development; the fitted relationship is similarly positive. From these two figures, then, it is clear that a household wishing to avoid noise or to avoid high-intensity development (perhaps because of visual disamenities) would also likely avoid high concentrations of NO_2.

Figure 3: Noise Is Correlated with Pollution Exposure



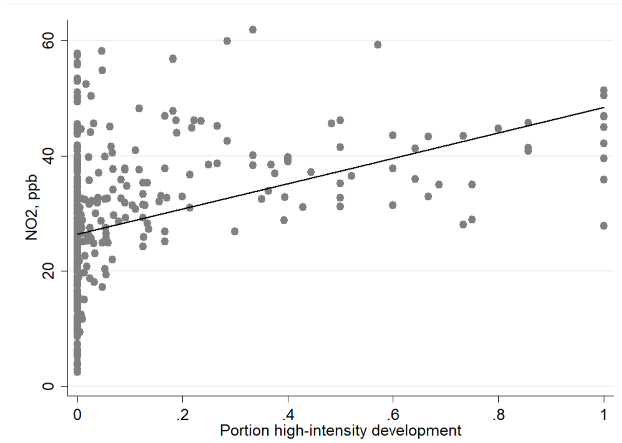
Note: This figure plots the annual average NO_2 level (measured in parts per billion) in a 5-digit Zip Code Tabulation Area in 2001 against the transportation noise in that area (measured in L_{Aeq}, roughly equivalent to decibels). Data sources are the EPA and the DOT; see text for details. The black line shows a linear fit. Roughly 400 zip codes have NO_2 monitors.

We next turn to regression analysis. Table 3 shows regressions of each measure of pollution exposure on the more salient disamenities of noise and land use. The pollution exposure

[26]This description is from http://osav-usdot.opendata.arcgis.com/. We use 2018 noise data; data for 2001 are not available.

[27]Specifically, we use the 2001 Land Cover 100 Meter Resolution - Conterminous United States, Albers Projection data.

Figure 4: Land Use Is Correlated with NO_2 Pollution Exposure



Note: This figure plots the annual average NO_2 level (measured in parts per billion) in a 5-digit Zip Code Tabulation Area in 2001 against the portion of the land in that zip code dedicated to high-intensity development. Data sources are the EPA and the USGS; see text for details. The black line shows a linear fit. Roughly 400 zip codes have NO_2 monitors.

variables are all in logs, as is the noise variable. The land use variables each represent the percentage of the zip code's area that is dedicated to a particular land use. The omitted category of land use is forest. We include fixed effects at the level of a core-based statistical area in all seven regressions. These regressions are not intended to provide causal estimates of amenities on pollution exposure. Rather, they are intended to show cross-sectional correlations between ambient amenities and pollution exposure. The thought experiment that they are designed to replicate is: if an individual were to choose one zip code over another (within a metro area) based on the geographic variation in noise level and land use, what is the typical level of pollution to which she would be exposed? Because individuals make these decisions infrequently, we rely solely on cross-sectional variation.

Column 1 shows that a higher level of the salient disamenity implies a higher measure of pollution exposure. When an individual accepts a doubling of noise, she also accepts a roughly 13 percent higher concentration of NO_2, statistically significant at the one-percent level. Similarly, if she were to move from an entirely forested area to an area that was entirely high-intensity development, she would experience roughly 60 log points more NO_2 (or more than 80 percent), again statistically significant at the one-percent level. As one moves from high-intensity development down to low-intensity development, the pollution exposure drops. Wetlands and barren land have the lowest levels of NO_2, conditional on the CBSA fixed effects and on a level of noise.

Ozone shows the opposite pattern. Ozone forms from the interaction of two separate

Table 3: Pollution Risk is Correlated with Other Disamenities

	NO2	Ozone	PM2.5	SO2	Benzene	Toluene	Cancer risk
Noise	0.13***	-0.01**	0.06***	0.06	0.19	0.19	0.04***
	(0.04)	(0.01)	(0.02)	(0.06)	(0.14)	(0.15)	(0.00)
Land use:							
Developed, high intensity	0.60***	-0.22***	0.28***	0.22	0.55**	0.69**	0.93***
	(0.11)	(0.03)	(0.04)	(0.17)	(0.26)	(0.29)	(0.01)
Developed, medium intensity	0.35***	-0.12***	0.21***	-0.06	0.59**	0.49*	0.55***
	(0.10)	(0.02)	(0.04)	(0.16)	(0.25)	(0.28)	(0.01)
Developed, low intensity	0.33***	-0.05*	0.10**	-0.01	0.29	0.88**	0.53***
	(0.12)	(0.03)	(0.04)	(0.19)	(0.31)	(0.36)	(0.01)
Developed, open space	0.40**	0.02	0.14**	-0.03	0.36	0.14	0.51***
	(0.19)	(0.04)	(0.06)	(0.27)	(0.44)	(0.47)	(0.01)
Water	0.32	0.01	0.04	0.25	0.54	0.33	0.27***
	(0.22)	(0.06)	(0.10)	(0.43)	(0.47)	(0.51)	(0.02)
Wetlands	-0.75***	-0.10**	0.14	-0.00	0.39	0.47	0.16***
	(0.22)	(0.05)	(0.08)	(0.34)	(0.42)	(0.46)	(0.02)
Farmland	0.07	-0.02	0.17***	-0.12	-0.17	-0.38	0.00
	(0.10)	(0.02)	(0.04)	(0.18)	(0.28)	(0.31)	(0.01)
Barren land	-0.61	0.12	-0.96***	0.26	0.28	-0.30	0.02
	(0.41)	(0.10)	(0.23)	(1.07)	(2.36)	(2.55)	(0.06)
Observations	408	1,049	980	465	216	208	23,328
Within R^2	0.49	0.21	0.32	0.04	0.28	0.34	0.48

Note: This table reports estimates and standard errors from seven separate regressions. The dependent variable in the first six columns is log ambient concentrations; in the last column it is log total cancer risk. The unit of observation is a 5-digit Zip Code Tabulation Area. The noise variable is also logged. Land use variables are the portion of the zip code dedicated to that land use; the omitted category of land use is forest. All regressions include CBSA fixed effects. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

types of chemicals: nitrogen oxides (NO_x) and volatile organic compounds (VOCs). While human activity emits both of these pollutant types, vegetation is major source of VOCs (Auffhammer and Kellogg, 2011). As a result, rural and suburban areas can have high levels of ozone concentration.

$PM_{2.5}$, however, follows a pattern similar to that of NO_2, with the highest concentrations in zip codes that are noisy and more intensely developed. As with NO_2, the concentrations decline as one moves from high-intensity development to medium- and then low-intensity development. SO_2 does not follow this clear pattern, perhaps because it is travels fairly far (Burtraw et al., 2005). However, "the largest threat of SO_2 to public health is its role as a precursor to the formation of secondary particulates, a constituent of particulate matter" (Burtraw et al. 2005, p. 257), so the $PM_{2.5}$ results are arguably more relevant for the thought exercise we are carrying out. Benzene, toluene, and cancer risk all follow a pattern similar to that of NO_2 and $PM_{2.5}$.[28]

[28] In the cancer risk regression, there is a positive and statistically significant coefficient on both the water and wetlands variables. Part of the explanation may be that ports and other industrial facilities are located

Overall, across the seven regressions, we see that five major types of pollutants are closely and positively correlated with noise and land use. The two exceptions are ozone (which displays the opposite relationship) and SO_2 (for which no statistically significant relationship appears in the regression results). We take this as evidence that non-salient environmental disamenities are co-located with more salient ones, and we study the effects of this co-location in the generalized form of our theoretical model.

1.4 Co-located Amenities Explain Variation in Socio-Economic Variables

Before developing the theoretical model, it is worth briefly examining whether these co-located disamenities are correlated with household sorting decisions. Using the income data from the 2000 Census that we described above, we regress median household income at the zip code level on four types of disamenities. As before, we include CBSA fixed effects to compare households within a metro area.

First, we regress income on $PM_{2.5}$, the criteria pollutant we described above that has substantial health impacts. Column 1 of Table 4 shows that zip codes with high levels of $PM_{2.5}$ have significantly lower incomes. A ten percent increase in $PM_{2.5}$ concentrations is associated with a seven percent decrease in income. Similarly, zip codes with higher cancer risk have significantly lower incomes. A ten percent increase in cancer risk is associated with a five percent decrease in income (Column 2).[29]

Overall, it is clear that two important measures of health risk from pollution exposure are correlated with income levels in economically and statistically significant ways. Low-income communities are exposed to more damaging pollution. Is this because ambient environmental quality is a normal good, in line with the "moving to the nuisance" story?

To answer this question, we next run a "horse race" by including noise levels and land use variables in the regression. Specifically, we regress zip code level log income on logged $PM_{2.5}$, logged noise levels, and variables representing the portion of land dedicated to different types of development as opposed to, e.g., forest. As can be seen in Column 3 of Table 4, the magnitudes of the coefficients on $PM_{2.5}$ and cancer risk are much smaller than in Columns 1 and 2, and they lose statistical significance. In contrast, high-intensity development is associated with a significantly lower income level. This suggests that co-located disamenities

near water. Coverage maps in Appendix Figure A2 show where water and wetlands appear.

[29] To ease comparisons across columns, in Table 4 we have limited the sample in all columns to zip codes with information on $PM_{2.5}$, cancer risk, noise, and land use. This drops the many zip codes without a $PM_{2.5}$ monitor. To avoid limiting the sample further, we focus just on these two pollutants, which have important health effects. Regressions for additional pollutants are provided in Appendix Tables A6 and A7.

Table 4: Income is Correlated with Disamenities

	(1)	(2)	(3)
PM 2.5 (log)	-0.65***		-0.15
	(0.09)		(0.09)
Cancer risk, per million (log)		-0.45***	-0.12**
		(0.04)	(0.05)
Log noise			0.06*
			(0.03)
Land use:			
Developed, high intensity			-0.87***
			(0.10)
Developed, medium intensity			-0.61***
			(0.09)
Developed, low intensity			-0.19**
			(0.09)
Developed, open space			0.07
			(0.12)
Water			-0.85***
			(0.22)
Wetlands			-0.18
			(0.18)
Farmland			-0.00
			(0.09)
Barren land			-1.42***
			(0.49)
Observations	980	980	980
Within R^2	0.09	0.17	0.39

Note: This table reports estimates and standard errors from three separate regressions. The dependent variable in all columns is logged median household income in 1999. The unit of observation is a 5-digit Zip Code Tabulation Area. The noise, PM 2.5, and cancer risk variables are also logged. Land use variables are the portion of the zip code dedicated to that land use; the omitted category of land use is forest. All regressions include CBSA fixed effects. All three columns restrict the sample to zip codes with PM 2.5, cancer risk, noise, and land use data. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

may be playing an important role in the decision of households of where to live.

In the Appendix (Table A8), we show that similar results hold if one instead considers sorting by race: in regressions of the portion of a zip code that is White on either $PM_{2.5}$ or on cancer risk, we estimate negative and statistically significance effects. However, in the horse race regression, these coefficients' magnitudes again drop, while the coefficients on land use are large and statistically significant. We also see similar results when the dependent variable is home values and when the dependent variable is monthly renter costs. Overall, much of the correlation between socio-economic variables and pollution is explained by land use. Importantly, we note that households may still have a positive willingness to pay for ambient environmental quality, because the small coefficients on $PM_{2.5}$ and cancer risk in the horse race regressions could reflect a lack of information rather than a lack of willingness to pay.

In summary, we have documented evidence, both from the existing literature and our own empirical analysis, on the limited nature of information about local air quality and its consequences. We highlight three stylized facts from this body of evidence. First, information about pollution is generally incomplete, in stark contrast to the assumptions made in many housing demand papers. Second, households likely underestimate the true level of pollution exposure they face, or the health impacts of such pollution exposure. Moreoever, we show two cases where this underestimation physically impacts low-income communities disproportionately. Third, air pollution is generally co-located with more salient disamenities like noise and intrusive land use. We use all of these stylized facts in the next two sections, where we introduce and analyze our model. Our empirical exercises do not, on their own, allow us to evaluate the welfare impacts of limited information and co-located amenities. A comprehensive empirical exercise analyzing welfare changes would require strong assumptions on the exact level of information before and after a policy change and would need to disentangle the change in information from other changes in the housing market. It would also need to account for stickiness arising from moving costs. Instead, we turn to theoretical models to understand the nature of the welfare impacts.

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.[30] 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. As we noted in the previous section, this could occur, for example, through underreporting by the point source or a lack of knowledge about the health impacts

[30]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 homogenous income. Income sorting in monocentric city models is discussed in Arnott (2011) and Duranton and Puga (2015) and citations therein.

of pollution.

In this section, we will 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 does not assume particular functional forms for demand, pollution dissipation, and housing prices. This generalized model also incorporates the context in which there are salient amenities that are co-located with environmental quality.

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.[31] 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., cheeseburgers).[32]

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.

In this section, we assume Cobb-Douglas preferences: $U(q, y) = q^{\gamma} y^{1-\gamma}$. 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, Hueth and Schmitz, 2004).[33]

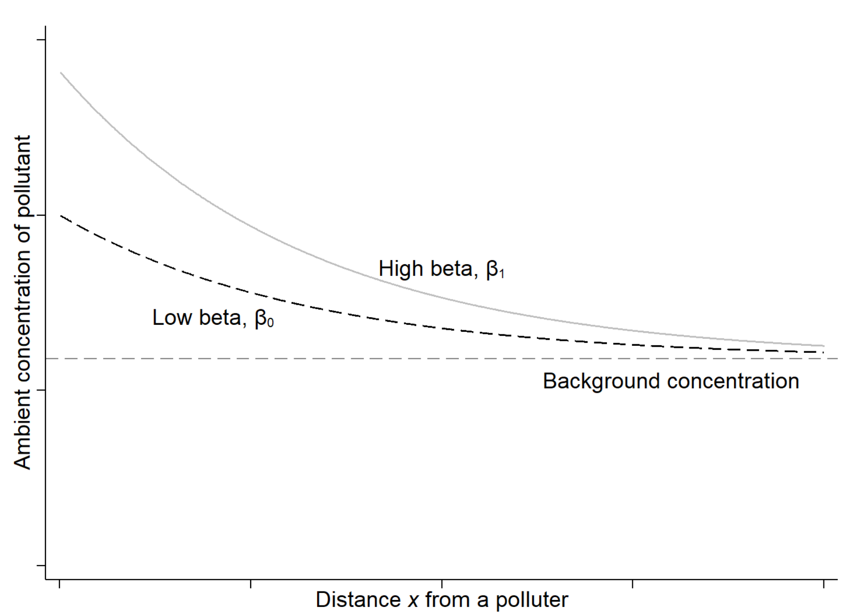
The next component of the model is pollution decay: the relationship between emissions and ambient air quality at different distances. A large literature has found that pollution tends to decay exponentially with distance to its source. Much of this literature comes from the environmental sciences (Hu et al., 1994; Rooarda-Knape et al., 1999; Zhu et al., 2002;

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

[32] 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.

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

Figure 5: Exponential Decay of Pollution



Note: This figure plots the function $C(x) = \alpha + \beta \exp(-x/k)$ for two levels of β: low β_0 and high β_1. Pollution is higher in β, and especially higher at small distances; put differently, air quality is lower in β, and especially lower at small distances.

Karner, Eisinger and Niemeier, 2010; Apte et al., 2017), but Currie et al. (2015) also document such a relationship using econometric methods. Numerous airborne pollutants have been evaluated, including criteria pollutants such as PM and NO_2 and toxic pollutants such as benzene. Additionally, while we focus here on pollution as the variable of interest, a similar relationship has been found for health outcomes such as low birthweight and premature birth (Currie and Walker, 2011).

Figure 5 shows a typical pollution decay function, in which ambient pollution concentration C is a function of distance x: $C(x) = \alpha + \beta \exp(-x/k)$, where "the urban background parameter α represents concentrations far-from-highway..., the near-road parameter β represents the concentration increment resulting from proximity to the highway, and the decay parameter k governs the spatial scale over which concentrations relax to α" (Apte et al., 2017, p 7004). This particular quote is from research on roadways, but note that similar decay has been found for other sources.

We can re-write air quality q, i.e., the absence of pollution, as $q(x) = \tilde{\alpha} - \beta \exp(-x/k)$. With this type of pollution dissipation, the effect of the near-source parameter β declines with distance x. Formally, note that $\frac{\partial q}{\partial \beta} < 0$ and $\frac{\partial q}{\partial x} > 0$; air quality decreases with the near-source parameter and increases with distance, respectively. Furthermore, $\frac{\partial^2 q}{\partial x \partial \beta} > 0$; the marginal effect of distance on air quality rises in β. An alternative interpretation is that the negative impact of β gets closer to zero as distance increases.

For intuition regarding the partial derivatives, consider the case where firms are hiding their emissions, i.e., are misleading the public about the magnitude of the parameter β. Then, air quality everywhere is worse than the public believes (since $\frac{\partial q}{\partial \beta} < 0$) and air quality is especially worse close to the firm ($\frac{\partial^2 q}{\partial x \partial \beta} > 0$).

To ease calculations in the model, we simplify this exponential decay process by taking a linear approximation. Specifically, we assume that healthiness from air quality improves with distance according to the following equation:[34]

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

A larger β parameter lowers air quality, while also increasing the importance of distance for air quality. For instance, β could represent the amount of pollution actually emitted by a point source. Alternatively, β could represent the impact that a given level of pollution has on an individual's health. Note that, as in the exponential version, $\frac{\partial q}{\partial \beta} < 0$; $\frac{\partial q}{\partial x} > 0$; and $\frac{\partial^2 q}{\partial x \partial \beta} > 0$.

Figure 6 plots healthiness as a function of distance for two possible values of β. We highlight two points about this function. First, air quality is linear in distance. In reality, pollution dissipation is non-linear, as is the pollution-health dose response function. We think of our linear parameterization as a starting point that provides a useful approximation for small changes in distance. Second, the two lines depicted in Figure 6 cross at some distance threshold, past which a larger β *increases* air quality. In the model that follows, we assume that a household is living close enough to the point source that this case does not occur.[35]

The consumer's maximization problem is

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

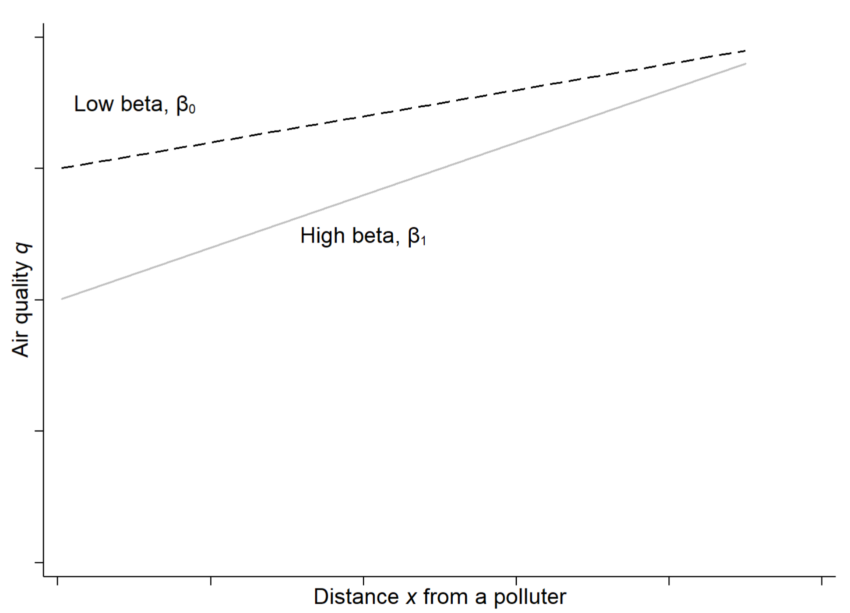
where p is the price of distance, the price of y is normalized to one, and m is income. Here, we assume that house price is linear in distance to the point source.[36] We also assume that the price schedule does not shift in response to changes in information; this assumption is most appropriate when 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.

[34]This equation follows from a Taylor expansion of $q(x) = \tilde{\alpha} - \beta \exp(-x/k)$.

[35]That is, we assume that $x < \alpha_1$, so that $\frac{\partial q}{\partial \beta} = -\alpha_1 + x < 0$.

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

Figure 6: Environmental Quality Increases with Distance



Note: This figure plots the function $q = \alpha_0 - \alpha_1\beta + \beta x$ for two levels of β: low β_0 and high β_1. α_0 and α_1 values are identical for the two functions. Air quality is lower in β within this range, and especially lower at small distances.

Because the consumer doesn't observe q, she doesn't 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 $q(x, \beta_0)$.

2.1 Demand for Environmental Quality

We solve the consumer's utility maximization problem to obtain the demand for distance. We begin by assuming the household correctly perceives the relationship between distance and air quality. As we show in the Appendix (Section A2.1), 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.[37] 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 tend to propose: redistribution of income, rather than direct intervention in the housing market. Here and throughout, our metrics do not imply a particular policy prescription on our part. Rather, we wish to formalize existing concepts used in the literature, which we believe will allow for more fruitful dialogue across disciplines going forward.

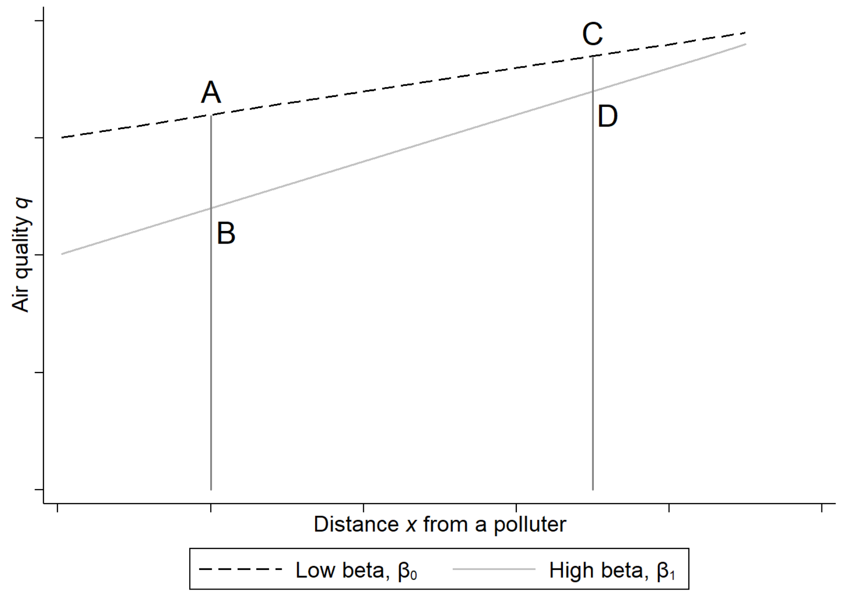
This policy debate in part reflects underlying questions about whether the *disparity* is also an *injustice*. In this paper, we generally refer to disparities and inequalities when outcomes across individuals are different. We use the term "environmental injustice" in keeping with a long-standing literature and social movement. We leave to the reader's judgment whether the disparities we document fit the definition of an injustice, noting that the answer may vary across contexts. The cause of income inequality may matter, such as whether it is in part the result of racism or other discrimination. See, for example, Deaton (2013) for a related debate on health inequalities and injustices.

2.2 Misinformation 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

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

Figure 7: Misinformation Regarding Air Quality



Note: 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 grey 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.

households. We show this in Figure 7, which depicts perceived and experienced air quality as a function of distance.

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:

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:

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

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 Figure 7 – 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 Figure 7, 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 A2.2). 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 illegal behavior by firms versus a function of 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 (Equation 3)

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

for whatever β the household perceives, and that the true relationship between distance and air quality is given by (Equation 1)

$$q = \alpha_0 - \alpha_1 \beta_1 + \beta_1 x$$

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 $q^* - q^\dagger = \frac{(1-\gamma)(\alpha_0-\alpha_1\beta_1)(\beta_1-\beta_0)}{\beta_0} > 0$. 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 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:* $\frac{d\Delta U}{dm} < 0$.

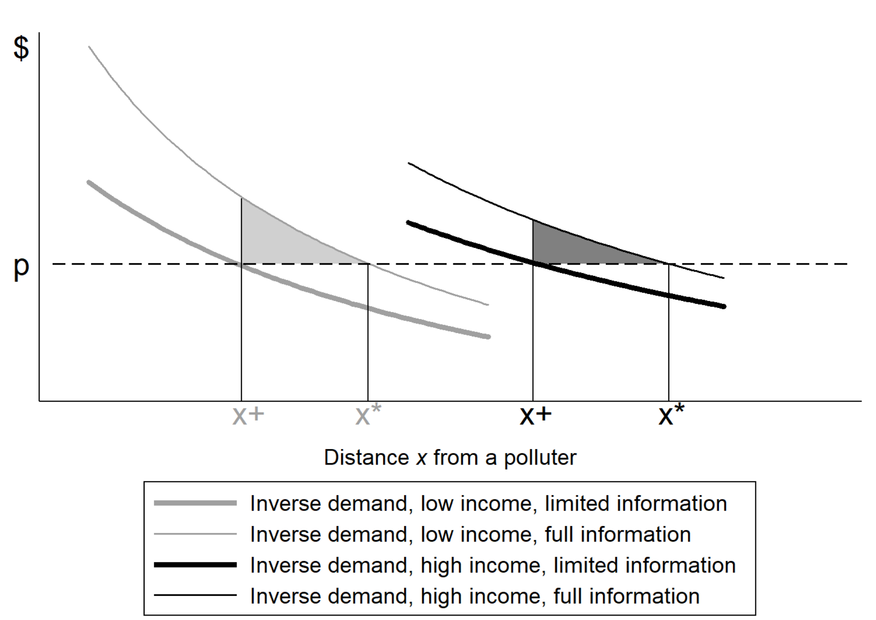
In the Appendix (Section A2.3), we derive the sign of the derivative of ΔU with respect to income, showing that $\frac{d\Delta U}{dm} < 0$. Therefore, under the assumptions we have made (limited information; Cobb-Douglas utility; etc.), an environmental disparity of this type exists. The intuition for 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 poorer households.

Frequently the researcher does not observe the full utility function but is 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 the point source. Figure 8 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 (grey) 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 grey demand curve comes from the true underlying utility function and thus is the appropriate demand curve to use for evaluating consumer surplus.

Figure 8: Consumer Surplus



Note: This figure plots demand for information under full (thin lines) versus biased (thick lines) beliefs about β, for low-income (grey) 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.

As we show in the Appendix (Section A2.4), $\frac{\partial \Delta \text{CS}}{\partial m}$ 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 grey and black areas in Figure 8, what matters is the height (and the curvature) of demand. We show in the Appendix (Section A2.5) 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 a general 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 does not incorporate 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 households. 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.[38] We derive equilibrium outcomes and environmental justice metrics in the Appendix (Sections A2.6 and A2.7). 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 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.

[38]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.

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 A2.6). The Appendix also shows similar intuition for a pure exchange model in which there are two houses at fixed distances (Section A2.7).

3 Generalized Model

To summarize Section 2, we show three results under what we believe are fairly innocuous assumptions: poorer 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 make assumptions about heterogeneity in preferences or access to information across households. The same mistake made by all households leads to inequality – not just in pollution exposure, but in welfare itself. In Section 3, we examine the same relationships in a more general model that nests both underestimation of air pollution and co-located disamenities.

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.[39] This is consistent with the empirical evidence documented in Section 1 using air quality, noise, and land use data.

In this version of our model, we do not assume any particular functional form. Neither do we restrict the utility function, other than to 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). Finally, we 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

[39]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.

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 (a lack of noise, or a nice view). An alternative interpretation of this setup is that $s(x)$ represents the health impacts of air pollution that the consumer knows about, whereas $q(x)$ represents the health impacts about which she is unaware. This interpretation 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 A2.8). Using comparative statics, we show that $\frac{\partial x^\dagger}{\partial m} > 0$ (i.e., distance is a normal good) if $\frac{\partial p}{\partial x^\dagger} U_{y^\dagger y^\dagger} > U_{s^\dagger y^\dagger} \frac{\partial s^\dagger}{\partial x^\dagger}$. 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 misinformation 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 (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 $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}\mathrm{d}x$.[40] 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.[41] 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 don't 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. 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.[42]

Overall, this more general model suggests that environmental justice metrics of the first two types are likely to be widespread in practice: both visible and hidden pollution are likely to be disproportionately experienced by low-income communities. Whether this translates into larger welfare losses depends on additional modeling assumptions, but our initial model with particular functional forms shows one set of circumstances under which the welfare loss caused by limited information is largest for low-income households.

[40] 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 $U_{q^\dagger}\frac{\partial q^\dagger}{\partial x^\dagger}\mathrm{d}x$.

[41] 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.

[42] 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.

4 Discussion

We have shown that, under modest assumptions, a lack of a full information does more than just cause overall efficiency (i.e., deadweight) loss; it also exacerbates 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, Jones and Olken, 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 generic conditions drive our results: (1) a salient normal good; and (2) a positively correlated non-salient good. Anywhere these conditions are satisfied, limited information may contribute to inequality. We believe that information failures have the potential to create disparities in other environmental and energy contexts. Consider water quality: willingness to pay for it has been shown to rise with both income and information provision (Jalan and Somanathan, 2008; Graff Zivin, Neidell and Schlenker, 2011). Moreover, 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.

Analogously, our model may fit the setting of 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, Reames and Keoleian, 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).

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 and health would also affect the distribution of pollution exposure, and they could either exacerbate or alleviate inequality.

Our results 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 here 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 and 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. 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. (2019) also argue for incorporating information and subjective beliefs, pointing to the possibility of using survey data.

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 misinformation 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). Depending on the source of income inequality and the cause of information failures, some of these disparities may be considered injustices.

We believe that our results inform several important pursuits. First, the economics literature on the distribution of pollution exposure and the associated disutility focuses primarily on the role 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. All of this has policy implications: the Environmental Protection Agency is legally required to consider environmental justice concerns, and distributional outcomes continue to be of widespread political and social interest.

We note several areas in which future research could advance our understanding of information, environmental quality, and welfare. In our modeling exercise, we set aside a number of phenomena that may affect choices and utility under limited information, such as the evolution of beliefs about pollution over time or other dynamic effects. In addition, we abstract from the notions of costly information and uncertainty. One could consider modeling information as sufficiently costly that no individual obtains it on their own, but as cheap to disseminate – this would appear to match the community-based “bucket brigades” that have emerged in some areas (O’Rourke and Macey, 2003). 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.

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Online Appendix

This Appendix provides additional summary statistics pertaining to the data we use in Section 1.3. It also provides derivations and proofs for the models in Sections 2 and 3.

A1 Data Appendix

To match data sources to zip codes, we start with EPA's air quality data, which provide latitude and longitude coordinates for each monitor. We then use GIS to match these to ZCTA locations (shapefiles) from the U.S. Census Bureau. We drop non-conterminous US observations (Alaska, Hawaii, Puerto Rico, and the U.S. Virgin Islands).

We conduct similar exercises for the noise and land use data. Land use data are provided as dummy values at a 100 meter resolution. For computational purposes, we decrease the resolution level of the land use data by a factor of 10 (taking the modal land use value) before overlaying zip code shapefiles. Within a zip code, we take the mean of each land use dummy value to approximate the portion of the zip code dedicated to each land use.

Demographic characteristics are provided by ZCTA directly from the Census Bureau. ZCTA-to-CBSA matches are also provided by the Census Bureau.

A1.1 Descriptive Statistics and Robustness Checks

Table A1: Air Pollution Guidelines and Standards

Year	Pollutant	Standard	Value
1987	Carbon monoxide	1 hour, mg/m^3, WHO	30
2000	Carbon monoxide	1 hour, mg/m^3, WHO	30
2010	Carbon monoxide	1 hour, mg/m^3, WHO*	35
1987	Lead	1 year, $\mu g/m^3$, WHO	0.5-1.0
2000	Lead	1 year, $\mu g/m^3$, WHO*	0.5
1978	Lead	3 month, $\mu g/m^3$, EPA	1.5
2009	Lead	3 month, $\mu g/m^3$, EPA*	0.15
1987	Nitrogen dioxide	1 hour, $\mu g/m^3$, WHO	400
2000	Nitrogen dioxide	1 hour, $\mu g/m^3$, WHO*	200
2005	Nitrogen dioxide	1 hour, $\mu g/m^3$, WHO	200
2010	Nitrogen dioxide	1 hour, $\mu g/m^3$, WHO	200
1987	Ozone	8 hours, $\mu g/m^3$, WHO	100-120
2000	Ozone	8 hours, $\mu g/m^3$, WHO*	120
2005	Ozone	8 hours, $\mu g/m^3$, WHO*	100
1997	Ozone	8 hours, ppm, EPA	0.08
2008	Ozone	8 hours, ppm, EPA*	0.075
2015	Ozone	8 hours, ppm, EPA*	0.07
2006	PM2.5	annual, $\mu g/m^3$, EPA	15
2012	PM2.5	annual, $\mu g/m^3$, EPA*	12
1987	Sulfur dioxide	24 hours, $\mu g/m^3$, WHO	125
2000	Sulfur dioxide	24 hours, $\mu g/m^3$, WHO	125
2005	Sulfur dioxide	24 hours, $\mu g/m^3$, WHO*	20

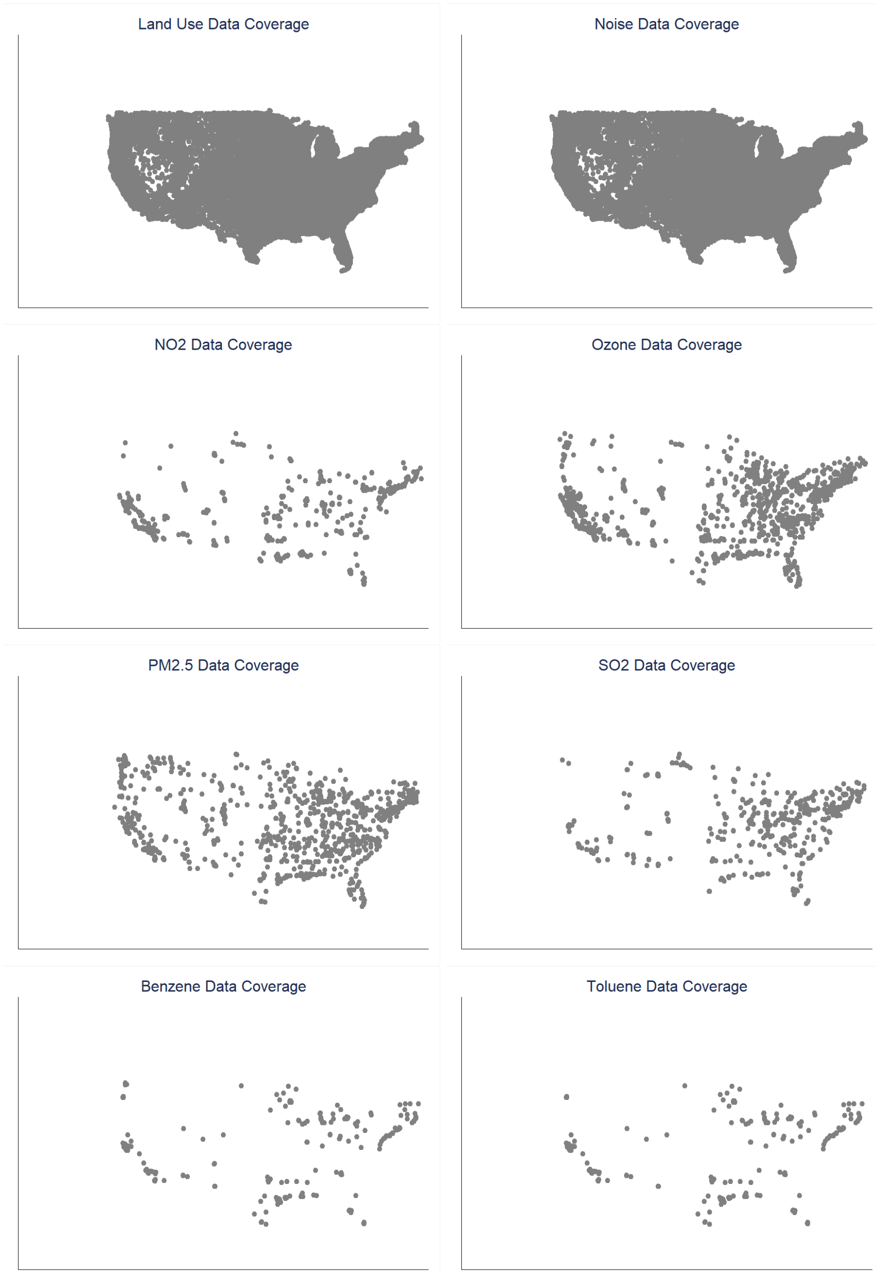
Notes: This table shows changes in EPA standards and WHO guidelines for selected air pollutants. We show all EPA standards that changed. We show WHO guidelines only for those pollutants for which the EPA has a standard and for which the WHO guideline changed. Sources are the WHO (2000, 2005, 2005, 2010, 2017); EPA (2018). Guidelines for less commonly monitored pollutants (e.g. cadmium, dichloromethane) are in the WHO reports.

Table A2: Summary Statistics

	Mean	Std. Dev.	N
Pollution levels:			
Lead in PM2.5, $\mu g/m^3$	0.004	0.007	246
NO2, ppb	28.490	12.354	425
Ozone, ppm	0.046	0.007	1,116
PM 2.5, $\mu g/m^3$	12.571	3.631	1,053
SO2, ppb	14.134	10.025	503
Benzene, ppbc	3.344	2.999	224
Toluene, ppbc	8.475	6.559	215
Cancer risk, per billion	0.024	0.015	31,126
Refinery in zip code, NEI definition	0.006	0.080	32,718
Refinery in zip code, EIA match	0.004	0.065	32,718
Noise, LAeq	14.237	14.068	30,999
Land use:			
Developed, high intensity	0.018	0.099	30,905
Developed, medium intensity	0.047	0.157	30,905
Developed, low intensity	0.067	0.169	30,905
Developed, open space	0.041	0.116	30,905
Barren land	0.003	0.024	30,905
Forest, shrubland, or grassland	0.446	0.371	30,905
Farmland	0.316	0.352	30,905
Wetlands	0.043	0.114	30,905
Water	0.018	0.069	30,905
Demographics:			
Median household income, '000s	38.330	17.452	32,718
Percent unemployed	3.450	3.199	31,712
Percent of families below the poverty line	9.891	9.152	31,590
Percent White	86.746	19.564	31,789
Percent Black	7.806	16.300	31,789
Percent Latino/a	6.375	13.500	31,789

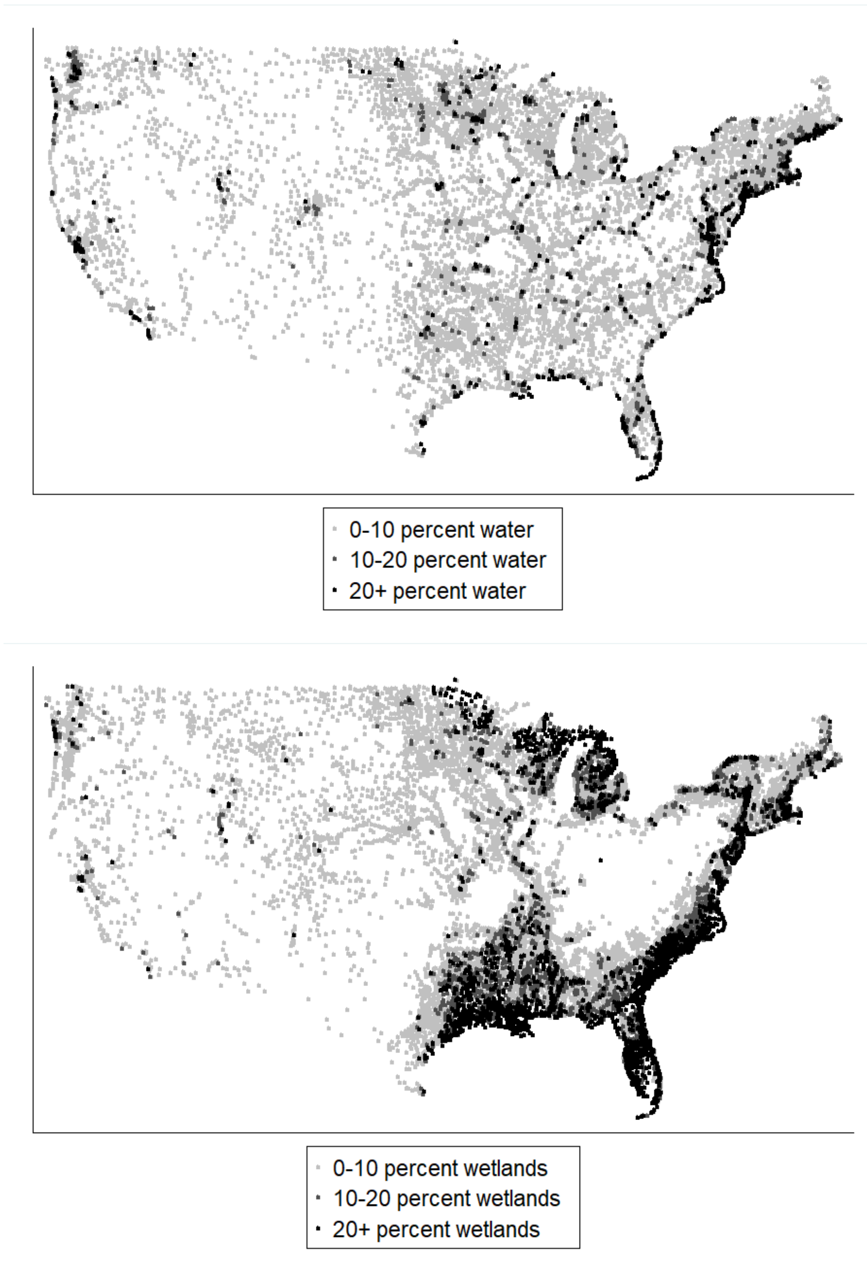
Notes: A unit of observation is a Zip Code Tabulation Area. Air pollution data are annual averages for the year 2001. Each air pollutant is measured using whatever averaging time is used for the primary standard (e.g. 1-hour vs 8-hour vs 24-hour) that was in effect in 2018. Noise data are in a 24-hr equivalent sound level (LEQ, denoted by LAeq) noise metric. Data are from the Environmental Protection Agency, the Energy Information Administration, the US Geological Survey, the Department of Transportation, and the Census. See text for details.

Figure A1: Data Coverage



Note: These figures plot a dot in each Zip Code Tabulation Area with both land use data and the additional data (either noise or air quality).

Figure A2: Water and Wetlands Locations



Note: These figures plot a dot in each Zip Code Tabulation Area with a non-zero portion of the ZCTA devoted to water or wetlands.

Table A3: Robustness: Demographic Characteristics Were Correlated with Ambient Lead Exposure

Panel A. Using 2008 Ambient Lead Data

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Log airborne lead concentration	-6.25**	1.26	2.83	-10.93**	2.97	5.28*
	(2.85)	(0.80)	(2.53)	(4.67)	(3.88)	(2.89)
Observations	290	290	288	290	290	290
Within R^2	0.05	0.03	0.01	0.06	0.01	0.04
Mean of dep. var.	36.72	4.98	13.17	74.82	15.65	11.82

Panel B. Using 2001 Ambient Lead Data, No CBSA Fixed Effects

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Log airborne lead concentration	-1.67**	0.49**	2.89***	-11.39***	10.88***	0.88
	(0.85)	(0.23)	(0.64)	(1.46)	(1.34)	(1.15)
Observations	245	245	244	245	245	245
R^2	0.02	0.02	0.08	0.20	0.21	0.00
Mean of dep. var.	36.20	4.71	13.04	77.52	13.93	11.39

Panel C. Using Modeled Ambient Lead Concentration Data from the 2002 NATA

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Log lead concentration	-1.10***	0.59***	1.55***	-9.33***	6.24***	3.62***
	(0.17)	(0.03)	(0.09)	(0.19)	(0.16)	(0.11)
Observations	23,867	23,808	23,753	23,827	23,827	23,827
Within R^2	0.00	0.01	0.01	0.10	0.06	0.04
Mean of dep. var.	42.28	3.41	8.98	85.69	8.53	7.15

Note: This table is identical to Table 1 in the main text, but with the changes noted in the panel titles. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A4: Robustness: Demographic Characteristics Were Correlated with Proximity to Refineries

Panel A. Using only refineries listed in the EIA's Petroleum Supply Annual

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Refinery in zip code	-3.75***	0.48*	2.29***	-4.07***	1.48	5.96***
	(1.26)	(0.25)	(0.65)	(1.42)	(1.21)	(0.83)
Observations	23,952	23,892	23,833	23,912	23,912	23,912
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00
Mean of dep. var.	42.24	3.42	9.00	85.68	8.53	7.15

Panel B. Using all NEI-listed facilities, No CBSA Fixed Effects

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Refinery in zip code	-0.17	0.83***	3.15***	-12.69***	5.46***	10.57***
	(1.21)	(0.22)	(0.63)	(1.35)	(1.13)	(0.93)
Observations	32,718	31,712	31,590	31,789	31,789	31,789
R^2	0.00	0.00	0.00	0.00	0.00	0.00
Mean of dep. var.	38.33	3.45	9.89	86.75	7.81	6.37

Note: This table is identical to Table 2 in the main text, but with the changes noted in the panel titles. *** Statistically significant at the 1% level; ** 5% level; * 10% level..

Table A5: Robustness: 2016 Air Quality Data

	NO2	Ozone	PM2.5	SO2	Benzene	Toluene	Cancer risk
Noise	0.23***	0.00	0.09***	-0.27**	-0.03	0.06	0.04***
	(0.06)	(0.00)	(0.02)	(0.13)	(0.09)	(0.14)	(0.00)
Land use:							
Developed, high intensity	0.77***	-0.16***	0.19***	0.51	0.49***	0.79***	0.93***
	(0.17)	(0.02)	(0.06)	(0.32)	(0.17)	(0.27)	(0.01)
Developed, medium intensity	0.42***	-0.08***	0.19***	0.52*	0.57***	0.96***	0.55***
	(0.15)	(0.02)	(0.05)	(0.28)	(0.17)	(0.27)	(0.01)
Developed, low intensity	0.54***	-0.03	0.06	0.06	0.30	0.66*	0.53***
	(0.19)	(0.02)	(0.06)	(0.35)	(0.21)	(0.33)	(0.01)
Developed, open space	0.36	0.01	0.14*	0.02	0.30	-0.12	0.51***
	(0.25)	(0.02)	(0.08)	(0.52)	(0.31)	(0.49)	(0.01)
Water	0.88**	-0.02	0.12	-0.17	1.08**	3.01***	0.27***
	(0.36)	(0.05)	(0.13)	(0.89)	(0.43)	(0.66)	(0.02)
Wetlands	-0.50	-0.05	0.14	-0.81	-0.67	0.86	0.16***
	(0.32)	(0.04)	(0.14)	(0.61)	(0.44)	(0.68)	(0.02)
Farmland	0.25	-0.06***	0.16***	0.07	0.18	0.03	0.00
	(0.17)	(0.01)	(0.05)	(0.34)	(0.23)	(0.37)	(0.01)
Barren land	-0.08	0.02	0.09	1.55	0.50	-1.78	0.02
	(0.69)	(0.09)	(0.43)	(1.83)	(1.68)	(2.60)	(0.06)
Observations	402	1,103	829	390	192	188	23,328
Within R^2	0.43	0.12	0.22	0.06	0.28	0.43	0.48

Note: Regressions are identical to Table 3 in the main text, but with 2016 air quality data. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A6: Robustness: Income is Correlated with Disamenities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NO2 (log)	-0.46***	-0.30***						
	(0.06)	(0.08)						
Ozone (log)			0.94***	0.29***				
			(0.11)	(0.11)				
PM 2.5 (log)					-0.65***	-0.19**		
					(0.09)	(0.09)		
SO2 (log)							-0.13**	-0.07
							(0.05)	(0.04)
Log noise		0.16***		0.05***		0.05		0.05
		(0.05)		(0.02)		(0.03)		(0.05)
Land use:								
Developed, high intensity		-0.89***		-0.93***		-0.94***		-0.85***
		(0.14)		(0.09)		(0.09)		(0.12)
Developed, medium intensity		-0.57***		-0.55***		-0.65***		-0.63***
		(0.12)		(0.06)		(0.08)		(0.11)
Developed, low intensity		-0.32**		-0.28***		-0.22**		-0.17
		(0.15)		(0.07)		(0.09)		(0.13)
Developed, open space		0.07		0.15		0.05		0.27
		(0.23)		(0.11)		(0.12)		(0.19)
Water		-0.22		-0.16		-0.94***		-0.33
		(0.27)		(0.18)		(0.22)		(0.30)
Wetlands		-0.27		-0.33**		-0.18		0.05
		(0.27)		(0.13)		(0.18)		(0.24)
Farmland		-0.08		-0.02		0.01		0.10
		(0.13)		(0.06)		(0.09)		(0.13)
Barren land		-1.06**		-0.16		-1.36***		-0.58
		(0.49)		(0.29)		(0.49)		(0.76)
Observations	408	408	1,049	1,049	980	980	465	465
Within R^2	0.18	0.38	0.09	0.31	0.09	0.38	0.02	0.35

Note: This table is identical to Table 4 in the main text, but for additional pollutants. The dependent variable is the log of median household income in a Zip Code Tabulation Area in 1999. The pollutants cannot all be combined into one regression because there are insufficient zip codes with monitors for all pollutants. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A7: Robustness: Income is Correlated with Disamenities

	(1)	(2)	(3)	(4)	(5)	(6)
Benzene (log)	-0.34***	-0.14**				
	(0.06)	(0.06)				
Toluene (log)			-0.25***	-0.06		
			(0.06)	(0.06)		
Cancer risk, per million (log)					-0.08***	0.19***
					(0.01)	(0.01)
Log noise		-0.04		-0.07		0.02***
		(0.09)		(0.10)		(0.00)
Land use:						
Developed, high intensity		-0.92***		-0.95***		-1.06***
		(0.18)		(0.19)		(0.02)
Developed, medium intensity		-0.47***		-0.52***		-0.61***
		(0.17)		(0.18)		(0.01)
Developed, low intensity		-0.16		-0.13		-0.21***
		(0.21)		(0.23)		(0.01)
Developed, open space		-0.10		-0.14		0.14***
		(0.29)		(0.30)		(0.02)
Water		0.19		0.16		-0.07***
		(0.31)		(0.33)		(0.03)
Wetlands		-0.29		-0.32		-0.09***
		(0.28)		(0.30)		(0.02)
Farmland		-0.01		-0.01		0.01
		(0.18)		(0.20)		(0.01)
Barren land		-0.58		-0.65		-0.18**
		(1.56)		(1.62)		(0.08)
Observations	216	216	208	208	23,293	23,293
Within R^2	0.19	0.49	0.13	0.47	0.01	0.22

Note: This table is identical to Table 4 in the main text, but for additional pollutants. The dependent variable is the log of median household income in a Zip Code Tabulation Area in 1999. The pollutants cannot all be combined into one regression because there are insufficient zip codes with monitors for all pollutants. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A8: Race and Prices are Correlated with Disamenities

	% White			Home value			Rent		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PM 2.5 (log)	-32.47***		-4.12	-0.30***		-0.10	-0.16***		-0.07
	(5.60)		(6.27)	(0.10)		(0.12)	(0.05)		(0.06)
Cancer risk, per million (log)		-26.72***	-16.06***		-0.22***	-0.07		-0.11***	-0.07*
		(2.67)	(3.55)		(0.05)	(0.07)		(0.03)	(0.03)
Log noise			4.91**			0.10**			0.08***
			(2.24)			(0.04)			(0.02)
Land use:									
Developed, high intensity			-28.75***			-0.46***			-0.32***
			(6.73)			(0.13)			(0.06)
Developed, medium intensity			-33.19***			-0.61***			-0.21***
			(5.89)			(0.11)			(0.06)
Developed, low intensity			-15.36**			-0.28**			-0.04
			(6.34)			(0.12)			(0.06)
Developed, open space			-7.40			0.26*			0.20**
			(8.15)			(0.15)			(0.08)
Water			-3.04			-0.35			-0.41***
			(15.10)			(0.28)			(0.14)
Wetlands			6.31			-0.16			-0.17
			(12.06)			(0.22)			(0.12)
Farmland			-4.08			-0.05			-0.03
			(6.06)			(0.11)			(0.06)
Barren land			-56.89*			-2.29***			-0.60*
			(33.75)			(0.62)			(0.32)
Observations	980	980	980	974	974	974	978	978	978
Within R^2	0.06	0.15	0.23	0.02	0.03	0.16	0.02	0.03	0.19

Note: This table matches Table 4 in the main text, but with alternative dependent variables: the percentage of ZCTA residents who are White; median home values for owner-occupied homes; and median rent for renter-occupied homes. Data for all dependent variables are from the 2000 Census. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

A2 Theoretical Derivations

A2.1 Derivation of Demand Functions, Simplified Model

In the demand model in Section 2, we assume that utility is Cobb-Douglas in two goods, q and y: $U(q, y) = q^{\gamma} y^{1-\gamma}$. The first good, q, is unobserved healthiness. It is a function of observable distance x to a point source: $q = \alpha_0 - \alpha_1\beta + \beta x$. When households are fully informed, they know the true α_0, α_1, and β parameters. Under limited information, they misperceive the β parameter. The second good, y, is the other (i.e., numeraire) good, unrelated to distance x to the point source.

The individual has the following maximization problem, as stated in Section 2:

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

The first-order conditions that define the optimal bundle (λ^*, x^*, y^*) are as follows:

$$\begin{aligned} m - px - y &= 0 \\ \gamma q^{\gamma-1} y^{1-\gamma} \frac{\partial q^*}{\partial x^*} - \lambda p &= 0 \\ (1-\gamma) q^{\gamma} y^{-\gamma} - \lambda &= 0 \end{aligned}$$

Taking the second and third conditions above, we rearrange them so that the terms containing λ are on the right-hand side. We then divide the second condition by the third and rearrange terms to obtain

$$\frac{q^*}{y^*} = \frac{1}{p} \cdot \frac{\gamma}{1-\gamma} \cdot \frac{\partial q^*}{\partial x^*}$$

Note that we can express q^* as a function of x^*, and that $\frac{\partial q^*}{\partial x^*} = \beta$. Substituting for y^* using the first first-order condition, we find the optimal, full-information choice of distance:

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

Subbing this back into $q(x)$ yields

$$q^* = \alpha_0 - \alpha_1\beta + \beta\frac{\gamma m}{p} + \frac{\beta(\gamma-1)(\alpha_0 - \alpha_1\beta)}{\beta}$$

Substituting x^* into the budget constraint, we can also solve for y^*:

$$y^* = (1-\gamma)m + \frac{p(1-\gamma)(\alpha_0 - \alpha_1\beta)}{\beta}$$

To determine the sign of $\frac{\partial q^*}{\partial m}$, we can differentiate the equation for x^* with respect to m and the equation for q^* with respect to x^* (alternatively, we could differentiate q^* directly with respect to m):

$$\frac{\partial q^*}{\partial m} = \frac{\partial q^*}{\partial x^*}\frac{\partial x^*}{\partial m} = \frac{\gamma}{p}\beta > 0$$

To check that we are at an interior solution, we calculate the bordered Hessian:

$$D^2\mathcal{L}(\lambda, x, y) = \begin{pmatrix} 0 & -p & -1 \\ -p & \gamma(\gamma-1)q^{\gamma-2}y^{1-\gamma}\beta^2 & \gamma(1-\gamma)q^{\gamma-1}y^{-\gamma}\beta \\ -1 & (1-\gamma)\gamma q^{\gamma-1}y^{-\gamma}\beta & (1-\gamma)(-\gamma)q^{\gamma}y^{-\gamma-1} \end{pmatrix}$$

The determinant of this is:

$$\det\bigl(D^2\mathcal{L}(\lambda, x, y)\bigr) = p^2(1-\gamma)\gamma q^{\gamma}y^{-\gamma-1} + 2p\gamma(1-\gamma)q^{\gamma-1}y^{-\gamma}\beta + \gamma(1-\gamma)q^{\gamma-2}y^{1-\gamma}\beta^2$$

Each is these three terms is positive, so the second order conditions are satisfied, and we are at an interior solution.

A2.2 Proof: Low-Income Households Experience A Greater Amount of Hidden Pollution, Simplified Model

The household chooses $x(\beta_0)$ believing that air quality is a function of distance x and the exogenous parameter β_0. However, true air quality is a function of the exogenous parameter β_1. As such, we have the following expression for the level of pollution the household believes it experiences:

$$q(x(\beta_0), \beta_0) = \alpha_0 - \alpha_1\beta_0 + \beta_0(x(\beta_0))$$

In contrast, the level of pollution the household actually experiences is

$$q(x(\beta_0), \beta_1) = \alpha_0 - \alpha_1\beta_1 + \beta_1(x(\beta_0))$$

The difference between these is

$$q(x(\beta_0), \beta_1) - q(x(\beta_0), \beta_0) = -\alpha_1(\beta_1 - \beta_0) + (x(\beta_0))(\beta_1 - \beta_0) = (x(\beta_0) - \alpha_1)(\beta_1 - \beta_0)$$

The first term, $(x(\beta_0) - \alpha_1)$, is negative (see footnote 35 in the main text). The second term, $(\beta_1 - \beta_0)$, is positive. The full difference is therefore negative: the household experiences worse air quality than it believes.

The derivative of this difference with respect to income is:

$$\frac{d(q(x(\beta_0), \beta_1) - q(x(\beta_0), \beta_0))}{dm} = (\beta_1 - \beta_0)\frac{\gamma}{p} > 0$$

Thus, every household experiences worse air quality than it believes, but the magnitude of this experienced air quality deficit drops in income. In other words, low-income households experience more "hidden pollution."

A2.3 Proof: Low-Income Households Experience A Greater Utility Loss, Simplified Model

We wish to compare utility at the optimum – that is, when the household is fully informed and therefore selects the bundle (q^*, y^*) – with the utility experienced when the household misperceives pollution exposure and selects the bundle ($q^\dagger$, $y^\dagger$):

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

First, we re-write this as:

$$\Delta U = \left(\frac{q^*}{y^*}\right)^\gamma y^* - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma y^\dagger$$

We then take the total derivative with respect to income:

$$\frac{d\Delta U}{dm} = \gamma \left(\frac{q^*}{y^*}\right)^{\gamma-1} \frac{\partial\left(\frac{q^*}{y^*}\right)}{\partial m} y^* + \left(\frac{q^*}{y^*}\right)^\gamma \frac{\partial y^*}{\partial m} - \gamma \left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial m} y^\dagger - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma \frac{\partial y^\dagger}{\partial m}$$

The first term in the $\frac{d\Delta U}{dm}$ expression drops out, because $\frac{q^*}{y^*}$ does not depend on income m (see its expression in Appendix A2.1). Note, however, that the third term remains; the equation for $\frac{q^*}{y^*}$ does not apply to $\frac{q^\dagger}{y^\dagger}$ because the bundle $(q^\dagger, y^\dagger)$ is away from the optimum.

To make further progress in signing $\frac{d\Delta U}{dm}$, the following partial derivatives are useful:[43]

$$\frac{\partial y^*}{\partial m} = \frac{\partial y^\dagger}{\partial m} = 1 - \gamma$$

$$\frac{\partial q^\dagger}{\partial m} = \frac{\beta_1 \gamma}{p}$$

We differentiate $(\frac{q^\dagger}{y^\dagger})$ with respect to m and find:

$$\begin{aligned}
\frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial m} &= -q^\dagger (y^\dagger)^{-2} \frac{\partial y^\dagger}{\partial m} + (y^\dagger)^{-1} \frac{\partial q^\dagger}{\partial m} \\
&= -\frac{q^\dagger}{y^\dagger} \cdot \frac{1}{y^\dagger} \cdot (1-\gamma) + \frac{1}{y^\dagger} \cdot \frac{\beta_1 \gamma}{p} \\
&= \frac{1}{y^\dagger} \left(-\left(\frac{q^\dagger}{y^\dagger}\right)(1-\gamma) + \frac{\beta_1 \gamma}{p}\right)
\end{aligned}$$

[43] The derivative $\frac{\partial q^\dagger}{\partial m}$ depends on β_1 because $q^\dagger$ refers to experienced air quality, $q(x^\dagger(\beta_0), \beta_1) = \alpha_0 - \alpha_1\beta_1 + \beta_1 \left(\frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0}\right)$.

Substituting these in and re-arranging, we have:

$$\begin{aligned}
\frac{d\Delta U}{dm} &= \left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma\right)(1-\gamma) - \gamma\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}\frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial m}y^\dagger \\
&= \left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma\right)(1-\gamma) - \gamma\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}\frac{1}{y^\dagger}\left(-\left(\frac{q^\dagger}{y^\dagger}\right)(1-\gamma) + \frac{\beta_1\gamma}{p}\right)y^\dagger \\
&= (1-\gamma)\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma + \gamma(1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \frac{\gamma^2\beta_1}{p}\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \\
&= (1-\gamma)\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)^2\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \frac{\gamma^2\beta_1}{p}\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}
\end{aligned}$$

From the FOCs, we have that $\beta_1\frac{\gamma}{1-\gamma}\frac{1}{p} = \frac{q^*}{y^*}$, so:

$$\begin{aligned}
\frac{d\Delta U}{dm} &= (1-\gamma)\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)^2\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \gamma(1-\gamma)\left(\frac{q^*}{y^*}\right)\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \\
&= (1-\gamma)\left(\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \gamma\left(\frac{q^*}{y^*}\right)\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}\right) \\
&= (1-\gamma)\left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^*}{y^*}\right)^\gamma\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right)\right)
\end{aligned}$$

where $R = \frac{(q^\dagger/y^\dagger)}{(q^*/y^*)} < 1$, since $q^\dagger < q^*$ and $y^\dagger > y^*$.

Our remaining task is to evaluate whether $\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right)$ is greater than or less than 1. To do so, first consider the situation in which $R = 1$. Then

$$\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right) = 1 - \gamma + \gamma = 1$$

In our setting, $0 < R < 1$. To find whether $\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right)$ is greater than or less than 1, we calculate its derivate with respect to R:

$$\begin{aligned}
\frac{d\left[(1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right]}{dR} &= \gamma(1-\gamma)R^{\gamma-1} + \gamma(\gamma-1)R^{\gamma-2} \\
&= \gamma(1-\gamma)R^{\gamma-1} - \gamma(1-\gamma)R^{\gamma-2} \\
&= \gamma(1-\gamma)\left(R^{\gamma-1} - R^{\gamma-2}\right)
\end{aligned}$$

This derivative is negative: both γ and $1-\gamma$ are positive, but the third term is negative. Thus, $\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right) > 1$ when $R < 1$. In turn, $\left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^*}{y^*}\right)^\gamma\left((1-\gamma)R^\gamma + \gamma R^{\gamma-1}\right)\right) < 0$, which ensures that $\frac{d\Delta U}{dm} < 0$.

A2.4 Proof: Low-Income Households Experience A Greater Change in Consumer Surplus, Simplified Model

We argue in the main text that one could evaluate whether the change in consumer surplus from having full information is increasing or decreasing in income. Frequently the researcher does not observe the full utility function, but is able to estimate demand and thus consumer surplus. It is easiest to evaluate consumer surplus in our simplified Cobb-Douglas model by considering the demand for distance x from the point source. The consumer surplus gain associated with full information can be evaluated as the area under the full-information inverse demand curve over the range $(x^*(p), x^\dagger(p))$, minus the change in expenditure, as in Figure 8. The outer grey demand curve comes from the true underlying utility function and thus is the appropriate demand curve to use for evaluating consumer surplus.

To derive an analytic expression for this change in consumer surplus using the model we present in the main text, we take the integral under the inverse demand expression and subtract off the change in expenditure, as follows:

$$\Delta\text{CS} = \left(\int_{p^*(x^*)}^{p^*(x^\dagger)} \frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1} \, \mathrm{d}p \right) - \big(p^*(x^\dagger) - p^*(x^*)\big) \cdot x^\dagger,$$

where $p^*(x^*)$ denotes the actual market price of distance x and $p^*(x^\dagger)$ denotes the implicit price that would have yielded $x^\dagger$ in the full information case. This is equal to:

$$\begin{aligned}
\Delta\text{CS} =& \gamma m \ln\left(p^*(x^\dagger)\right) - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1} \cdot \left(p^*(x^\dagger)\right) \\
& - \gamma m \ln\left(p^*(x^*)\right) + \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1} \cdot \left(p^*(x^*)\right) \\
& - \big(p^*(x^\dagger) - p^*(x^*)\big) \cdot x^\dagger
\end{aligned}$$

We are interested in how the change in consumer surplus that would result from full information varies with income, so we take the derivative of ΔCS with respect to income:

$$\begin{aligned}
\frac{\partial \Delta\text{CS}}{\partial m} =& \frac{\gamma m}{p^\dagger}\frac{\partial p^\dagger}{\partial m} + \gamma \ln p^\dagger - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}\frac{\partial p^\dagger}{\partial m} \\
& - \frac{\gamma m}{p^*}\frac{\partial p^*}{\partial m} - \gamma \ln p^* + \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}\frac{\partial p^*}{\partial m} \\
& - \frac{\partial x^\dagger}{\partial m}(p^\dagger - p^*) - x^\dagger \left(\frac{\partial p^\dagger}{\partial m} - \frac{\partial p^*}{\partial m} \right)
\end{aligned}$$

Noting that the true price p does not change with income, this simplifies to:

$$\frac{\partial \Delta \text{CS}}{\partial m} = \frac{\gamma m}{p^\dagger}\frac{\partial p^\dagger}{\partial m} + \gamma \ln p^\dagger - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}\frac{\partial p^\dagger}{\partial m}$$
$$- \gamma \ln p^* - \frac{\partial x^\dagger}{\partial m}(p^\dagger - p^*) - x^\dagger\left(\frac{\partial p^\dagger}{\partial m}\right)$$

Re-arrange to:

$$\frac{\partial \Delta \text{CS}}{\partial m} = \gamma(\ln p^\dagger - \ln p^*) + (p^* - p^\dagger)\frac{\partial x^\dagger}{\partial m}$$
$$+ \left(\frac{\gamma m}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1} - x^\dagger\right)\frac{\partial p^\dagger}{\partial m}$$

Recall that $\frac{\partial x^\dagger}{\partial m} = \frac{\gamma}{p}$, so:

$$\frac{\partial \Delta \text{CS}}{\partial m} = \gamma(\ln p^\dagger - \ln p^*) + (p^* - p^\dagger)\frac{\gamma}{p^*}$$
$$+ \left(\frac{\gamma m}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1} - x^\dagger\right)\frac{\partial p^\dagger}{\partial m}$$

Next, note that $p^\dagger$ is the price that yields $x^\dagger$ along the true demand curve, i.e., $x^\dagger = (\frac{\gamma m}{p^\dagger} - \frac{(1-\gamma)(\alpha_0-\alpha_1\beta_1)}{\beta_1})$. Therefore the last term in the $\frac{\partial \Delta \text{CS}}{\partial m}$ expression drops out, and we are left with:

$$\frac{\partial \Delta \text{CS}}{\partial m} = \gamma(\ln p^\dagger - \ln p^*) + (p^* - p^\dagger)\frac{\gamma}{p^*}$$

Recall that $p^\dagger > p^*$, so $(\ln p^\dagger - \ln p^*)$ is positive whereas $\frac{p^*-p^\dagger}{p^*}$ is negative. However, $(\ln p^\dagger - \ln p^*)$ is smaller in absolute value,[44] leaving the entire expression $\gamma(\ln p^\dagger - \ln p^*) + (p^* - p^\dagger)\frac{\gamma}{p^*}$ negative.

Then $\frac{\partial \Delta \text{CS}}{\partial m}$ is negative, so EJ Metric 3 holds for Cobb-Douglas preferences with linear dissipation and linear pricing.

[44] Denote $r = \frac{p^\dagger}{p^*}$. Then we are evaluating simply $r-1$ compared to $\ln r$. Since $r - 1 > \ln r$, we have that $\frac{(p^\dagger - p^*)}{p^*} > \ln p^\dagger - \ln p^*$. Note it is easy to see graphically that $r - 1 > \ln r$. More formally, note that $\ln r = r - 1$ for $r = 1$. Then note that $\frac{d(\ln r)}{dr} < \frac{d(r-1)}{dr}$ for all $r > 1$, implying that $\ln r < r - 1$ for all $r > 1$. Also, $\frac{d(\ln r)}{dr} > \frac{d(r-1)}{dr}$ for all $r < 1$, implying that $\ln r < r - 1$ for all $r < 1$. Therefore $\ln r \leq r - 1$ for all r. In the case we are considering, $p^\dagger \neq p^*$, so the inequality is strict.

A2.5 Proof: Implicit Counterfactual Price is Decreasing in Income

In the main text, we discuss how low-income households experience a greater change in consumer surplus in the simplified model (Cobb-Douglas preferences, linear dissipation, fixed prices). Appendix Section A2.4 gives a formal proof. The main text simply gives intuition, and that intuition relies on the height of the consumer surplus triangle in Figure 8. Specifically, we rely on the fact that $p^\dagger$ (the price that would have yielded the uninformed quantity $x^\dagger$ in the full information case) decreases with income m. In this Appendix, we prove mathematically that $\frac{\partial p^\dagger}{\partial m} < 0$.

First, define $p^\dagger$ to be the price that would yield $x^\dagger$ along the full information demand curve:

$$x^\dagger = \frac{\gamma m}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_1)}{\beta_1}$$

And recall that the uniformed demand curve for $x^\dagger$ as a function of the true price p is given by:

$$x^\dagger = \frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_0)}{\beta_0}$$

Therefore by substitution:

$$\frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_0)}{\beta_0} = \frac{\gamma m}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_1)}{\beta_1}$$

Rearranging:

$$\frac{1}{p^\dagger} = \frac{1}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_0)}{\beta_0 \gamma m} + \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_1)}{\beta_1 \gamma m}$$

Simplifying:

$$\frac{1}{p^\dagger} = \frac{1}{p} + \frac{(1-\gamma)\alpha_0(\beta_0 - \beta_1)}{\beta_0 \beta_1 \gamma} \frac{1}{m}$$

Re-write this as:

$$\frac{1}{p^\dagger} = A + \frac{B}{m} = \frac{Am + B}{m} \implies p^\dagger = \frac{m}{Am + B}$$

where $A = \frac{1}{p} > 0$ and $B = \frac{(1-\gamma)\alpha_0(\beta_0 - \beta_1)}{\beta_0 \beta_1 \gamma}$. Recall that $\beta_0 < \beta_1$, so $B = \frac{(1-\gamma)\alpha_0(\beta_0 - \beta_1)}{\beta_0 \beta_1 \gamma} < 0$.

Taking the partial derivative:

$$\frac{\partial p^\dagger}{\partial m} = \frac{B}{(Am + B)^2} < 0$$

The derivative of $p^\dagger$ with respect to income is negative.

A2.6 Equilibrium under Pure Exchange with Continuous Choice of Distance

Here we maintain the modeling assumptions from Section 2 in the main text but allow the price of distance to vary endogenously. Specifically, we now consider a pure exchange economy with two individuals. We assume a fixed total supply of distance X to be divided up between the two individuals in a continuous manner. While this clearly does not map directly into a real-world housing scenario, it can help ground intuition about how prices might behave in general equilibrium and what that might imply for the Cobb-Douglas scenario given above.

The numeraire good also has fixed total supply (Y). We continue to assume that the two individuals have identical preferences and access to information and differ only in their initial endowments. We also continue to assume that pollution decay can be approximated with a linear functional form. Finally, we maintain our assumption that preferences are Cobb-Douglas.

Recall that this implies that individual i's demand for distance is given by:

$$x_i = \frac{\gamma m_i}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta)}{\beta}$$

where m is income (i.e., the value of the initial allocation), p is the price of good x, the numeraire good y has a price of 1, γ is the Cobb-Douglas parameter, and the exogenous parameters $(\alpha_0, \alpha_1, \beta)$ relate distance x to air quality q.

As such, EJ Metric 1 again holds: distance is increasing in m, and since air quality increases with distance, whoever has the greater value of the initial allocation obtains better air quality in equilibrium. Thus EJ Metric 1 holds simply because air quality is a normal good. Furthermore, since the wedge between true and perceived air quality is decreasing in distance (because of the pollution dissipation process), EJ Metric 2 again holds.

To check whether EJ Metric 3 holds, we must evaluate utility for each individual in the limited-information equilibrium versus in the full-information equilibrium. Suppose that individual 1 begins with initial allocation (x_1^0, y_1^0) and individual 2 begins with initial allocation (x_2^0, y_2^0). Denote the equilibrium bundles under limited information $(x_1^\dagger, y_1^\dagger)$ and $(x_2^\dagger, y_2^\dagger)$. Under limited information, the β parameter is believed by all agents to be at level β_0 (in reality, it is at level $\beta_1 > \beta_0$). In equilibrium, $p^\dagger$ is such that total demand across the two consumers is equal to total supply:

$$x_1^\dagger + x_2^\dagger = x_1^0 + x_2^0$$

$$y_1^\dagger + y_2^\dagger = y_1^0 + y_2^0$$

Substituting in the expressions for x_i and m_i, we have:

$$\frac{\gamma(x_1^0 p^\dagger + y_1^0)}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0} + \frac{\gamma(x_2^0 p^\dagger + y_2^0)}{p^\dagger} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0} = x_1^0 + x_2^0$$

Re-arranging to solve for the equilibrium price $p^\dagger$ under limited information:

$$p^\dagger = \frac{\gamma(y_1^0 + y_2^0)}{(1-\gamma)(x_1^0 + x_2^0) + 2\left(\frac{(1-\gamma)(\alpha_0-\alpha_1\beta_0)}{\beta_0}\right)}$$

Denote equilibrium price in the full information scenario as p^*, given by:

$$p^* = \frac{\gamma(y_1^0 + y_2^0)}{(1-\gamma)(x_1^0 + x_2^0) + 2\left(\frac{(1-\gamma)(\alpha_0-\alpha_1\beta_1)}{\beta_1}\right)}$$

We wish to compare utility at the optimum – that is, when the household is fully informed and therefore selects the bundle $(q^*,\ y^*)$ – with the utility experienced when household misperceives pollution exposure and selects the bundle $(q^\dagger,\ y^\dagger)$:

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

This expression is identical to the one in Appendix A2.3, but note that now the two bundles (q^*, y^*) and $(q^\dagger, y^\dagger)$ are at different equilibrium prices p^* and $p^\dagger$. We re-write this as:

$$\Delta U = \left(\frac{q^*}{y^*}\right)^\gamma y^* - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma y^\dagger$$

We want to evaluate whether this is change in utility is larger for low-income or high-income individuals. To do so, we take the derivative with respect to the initial endowment of the numeraire good y, holding constant the total supply of that good, $Y = y_1^0 + y_2^0$. We define "low-income" and "high-income" this way so as to separate out effects of the initial endowment as opposed to the impact of information on total wealth (which would include the price effects of the initial endowment). Taking the total derivative with respect to y^0:

$$\frac{d\Delta U}{dy^0} = \gamma\left(\frac{q^*}{y^*}\right)^{\gamma-1} \frac{\partial\left(\frac{q^*}{y^*}\right)}{\partial y^0} y^* + \left(\frac{q^*}{y^*}\right)^\gamma \frac{\partial y^*}{\partial y^0} - \gamma\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial y^0} y^\dagger - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma \frac{\partial y^\dagger}{\partial y^0}$$

The first term in the $\frac{d\Delta U}{dy^0}$ expression drops out, because $\frac{q^*}{y^*}$ does not depend on the individual's initial endowment y^0 (see its expression in Appendix A2.1). Note, however, that the third term remains; the equation for $\frac{q^*}{y^*}$ does not apply to $\frac{q^\dagger}{y^\dagger}$ because the bundle $(q^\dagger, y^\dagger)$ is away from the optimum.[45]

To make further progress in signing $\frac{d\Delta U}{dy^0}$, the following partial derivatives are useful:[46]

$$\frac{\partial y^*}{\partial y^0} = \frac{\partial y^\dagger}{\partial y^0} = 1 - \gamma$$

$$\frac{\partial q^\dagger}{\partial y^0} = \frac{\beta_1 \gamma}{p^\dagger}$$

We differentiate $(\frac{q^\dagger}{y^\dagger})$ with respect to y^0 and find:

$$\begin{aligned}
\frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial y^0} &= -q^\dagger (y^\dagger)^{-2} \frac{\partial y^\dagger}{\partial y^0} + (y^\dagger)^{-1} \frac{\partial q^\dagger}{\partial y^0} \\
&= -\frac{q^\dagger}{y^\dagger} \cdot \frac{1}{y^\dagger} \cdot (1-\gamma) + \frac{1}{y^\dagger} \cdot \frac{\beta_1 \gamma}{p^\dagger} \\
&= \frac{1}{y^\dagger} \left(-\left(\frac{q^\dagger}{y^\dagger}\right)(1-\gamma) + \frac{\beta_1 \gamma}{p^\dagger} \right)
\end{aligned}$$

This expression is identical to the one in Appendix A2.3, but where the equilibrium price is equal to $p^\dagger$. Substituting these in and re-arranging, we have:

$$\begin{aligned}
\frac{d\Delta U}{dy^0} &= \left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma \right)(1-\gamma) - \gamma \left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \frac{\partial\left(\frac{q^\dagger}{y^\dagger}\right)}{\partial y_i^0} y^\dagger \\
&= \left(\left(\frac{q^*}{y^*}\right)^\gamma - \left(\frac{q^\dagger}{y^\dagger}\right)^\gamma \right)(1-\gamma) - \gamma \left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \frac{1}{y^\dagger} \left(-\left(\frac{q^\dagger}{y^\dagger}\right)(1-\gamma) + \frac{\beta_1 \gamma}{p^\dagger} \right) y^\dagger \\
&= (1-\gamma)\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma + \gamma(1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \frac{\gamma^2 \beta_1}{p^\dagger}\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \\
&= (1-\gamma)\left(\frac{q^*}{y^*}\right)^\gamma - (1-\gamma)^2\left(\frac{q^\dagger}{y^\dagger}\right)^\gamma - \frac{\gamma^2 \beta_1}{p^\dagger}\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}
\end{aligned}$$

From the FOCs, we have that $\frac{q^*}{y^*} = \beta_1 \frac{\gamma}{1-\gamma} \frac{1}{p^*}$. Rearranging, $\gamma(1-\gamma)\frac{p^*}{p^\dagger}\frac{q^*}{y^*} = \beta_1 \gamma^2 \frac{1}{p^\dagger}$ (this is different from the expression in Appendix A2.3, for which p was constant and the expression

[45] Recall that here $q^\dagger$ refers to experienced rather than perceived q.

[46] The derivative $\frac{\partial q^\dagger}{\partial y^0}$ depends on β_1 because $q^\dagger$ refers to experienced air quality, $q(x^\dagger(\beta_0), \beta_1) = \alpha_0 - \alpha_1 \beta_1 + \beta_1 \left(\frac{\gamma y^0}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1 \beta_0)}{\beta_0} \right)$.

simplified). Substituting it in, we have:

$$\begin{aligned}
\frac{d\Delta U}{dy^0} &= (1-\gamma)\left(\frac{q^*}{y^*}\right)^{\gamma} - (1-\gamma)^2\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma} - \gamma(1-\gamma)\left(\frac{p^*}{p^\dagger}\right)\left(\frac{q^*}{y^*}\right)\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1} \\
&= (1-\gamma)\left(\left(\frac{q^*}{y^*}\right)^{\gamma} - (1-\gamma)\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma} - \gamma\left(\frac{p^*}{p^\dagger}\right)\left(\frac{q^*}{y^*}\right)\left(\frac{q^\dagger}{y^\dagger}\right)^{\gamma-1}\right) \\
&= (1-\gamma)\left(\left(\frac{q^*}{y^*}\right)^{\gamma} - \left(\frac{q^*}{y^*}\right)^{\gamma}\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right)\right)
\end{aligned}$$

where $R = \frac{(q^\dagger/y^\dagger)}{(q^*/y^*)}$. This is similar to the expression in Appendix A2.3, but with the new term $\left(\frac{p^*}{p^\dagger}\right)$.

Our task is to evaluate whether the expression $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right)$ is greater than or less than one, because this will tell us the sign of $\frac{d\Delta U}{dy^0}$. The proof that follows is similar to the one in Appendix A2.3, but with a few extra details that were not necessary in the simplified case where the price is exogenous.

Consider the case where $R = \frac{p^*}{p^\dagger}$. Then the expression $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right)$ simplifies to R^{γ}. Note that $\frac{p^*}{p^\dagger} > 1$. Mathematically,

$$\frac{p^*}{p^\dagger} = \left(\frac{\gamma(y_1^0 + y_2^0)}{(1-\gamma)(x_1^0 + x_2^0) + 2\left(\frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}\right)}\right)\left(\frac{(1-\gamma)(x_1^0 + x_2^0) + 2\left(\frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0}\right)}{\gamma(y_1^0 + y_2^0)}\right)$$

Simplifying,

$$\frac{p^*}{p^\dagger} = \frac{(1-\gamma)(x_1^0 + x_2^0) + 2\frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0}}{(1-\gamma)(x_1^0 + x_2^0) + 2\frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}}$$

Since $\beta_0 < \beta_1$, $\frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_0)}{\beta_0} > \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta_1)}{\beta_1}$. Therefore $\frac{p^*}{p^\dagger} > 1$. Therefore $R^{\gamma} = \left(\frac{p^*}{p^\dagger}\right)^{\gamma} > 1$. Therefore $\frac{d\Delta U}{dy^0} < 0$, so EJ Metric 3 holds: low-income households experience greater deadweight loss from limited information.

Next consider the case where $R > \frac{p^*}{p^\dagger}$. Take the derivative with respect to R of the entire expression $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right)$. This derivative is equal to: $\gamma(1-\gamma)\left(R^{\gamma-1} - \left(\frac{p^*}{p^\dagger}\right)R^{\gamma-2}\right)$. Since $\frac{p^*}{p^\dagger} > 1$ and $R > \frac{p^*}{p^\dagger}$, the derivative is positive. Thus $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right) > 1$. Therefore, $\frac{d\Delta U}{dy^0} < 0$ and EJ Metric 3 holds.

Next consider the case where $R < \frac{p^*}{p^\dagger}$. Take the derivative with respect to R of the entire expression $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right)$. This derivative is equal to: $\gamma(1-\gamma)\left(R^{\gamma-1} - \left(\frac{p^*}{p^\dagger}\right)R^{\gamma-2}\right)$. Since $\frac{p^*}{p^\dagger} > 1$ and $R < \frac{p^*}{p^\dagger}$, the derivative is negative. Thus the expression $\left((1-\gamma)R^{\gamma} + \gamma\left(\frac{p^*}{p^\dagger}\right)R^{\gamma-1}\right) >$

1. Therefore, $\frac{d\Delta U}{dy^0} < 0$ and EJ Metric 3 holds.

A2.7 Equilibrium under Pure Exchange with Houses at Fixed Distance

Rather than modeling the choice of two houses at fixed distances from a point source of pollution, we can instead consider a setting with two houses at fixed locations: one house H_H with high air quality, and one house H_L with low air quality. As before, we assume there are no other differences between the two houses. There are also two consumers, individual 1 and individual 2. As before, we assume the two individuals are identical in their preferences and their access to information. All non-housing goods are aggregated into a numeraire good y with price 1 and with total supply Y. Trade can occur via a transfer of size p from one individual to another.

Whether or not a mutually beneficial trade exists depends, in part, on the initial allocation. We first assume that the same individual holds the higher quality house H_H and a larger quantity of good y. In that case, this "high-income" individual will only accept a trade if:

$$U(H_L, y_H + p) > U(H_H, y_H)$$

Subtract $U(H_L, y_H)$ from both sides:

$$U(H_L, y_H + p) - U(H_L, y_H) > U(H_H, y_H) - U(H_L, y_H) \tag{A1}$$

The "low-income" individual will only accept a trade if:

$$U(H_H, y_L - p) > U(H_L, y_L)$$

Subtract $U(H_L, y_L - p)$ from both sides:

$$U(H_H, y_L - p) - U(H_L, y_L - p) > U(H_L, y_L) - U(H_L, y_L - p) \tag{A2}$$

Both Equation A1 and Equation A2 must hold in order for a trade to occur.

If U_{Hy} (the cross partial) is non-negative – such as with Cobb-Douglas or additively separable utility – then the right-hand side of Equation A1 is larger than the left-hand side of Equation A2:

$$U(H_H, y_H) - U(H_L, y_H) > U(H_H, y_L - p) - U(H_L, y_L - p)$$

However, the right-hand side of Equation A2 is larger than the left-hand side of Equation A1 because of declining marginal utility (conditional on H_L, p is worth more if you only have

y_L than when you have y_H):

$$U(H_L, y_L) - U(H_L, y_L - p) > U(H_L, y_H + p) - U(H_L, y_H)$$

Therefore, under these conditions, there is no value of p for which Equations A1 and A2 both hold. In general, we expect this to be true if air quality is a normal good.

Given no trade, suppose that it is revealed that a polluter has been hiding emissions. The typical pollution dissipation process described above implies that air quality is worse everywhere than had been believed, and especially worse for the house with lower air quality H_L. Thus, trade will still not occur, by the same logic as before. Furthermore, both households experience lower utility, and the individual owning home H_L experiences an even bigger difference in utility. This is both because the wedge between true and believed air quality is higher for that individual (because of the way pollution dissipates), and because the marginal utility of air quality is higher for that individual (assuming, as is typical, that marginal utility is declining). There is no feasible re-optimization that improves total welfare. But it is the case that the low-income individual experiences greater hidden pollution (i.e., Metric 2 holds), and that the welfare impact of that hidden pollution is larger for the low-income individual (related to Metric 3, albeit without deadweight loss per se, since in equilibrium the allocations do not change).

Now suppose that in the initial allocation, the individual with the larger initial allocation of good y has the lower quality house H_L. We will assume that housing is a small part of the total budget for each individual and accordingly refer to the individual with a higher initial allocation of y as the "high-income" individual. In this case, trade is possible, and we consider the transfer required to induce such a trade. Utility for each individual, with and without trade, is as follows:

- Low-income individual, no trade: $U(H_H, y_L)$
- High-income individual, no trade: $U(H_L, y_H)$
- Low-income individual, with trade: $U(H_L, y_L + p)$
- High-income individual, with trade: $U(H_H, y_H - p)$

Trade will occur if there is a transfer p such that both parties can be made weakly better off: $U(H_L, y_L + p) \geq U(H_H, y_L)$ and $U(H_H, y_H - p) \geq U(H_L, y_H)$. Suppose again that it is revealed that a polluter has been hiding emissions. To simplify the logic, consider the case of additively separable utility. In this case, the transfer p needed to induce trade is larger: the low-income individual requires a greater payment to accept the drop in utility from moving from H_H to H_L. Furthermore, the high-income individual is willing to make a larger payment to obtain the increase in utility from moving from H_L to H_H. By not knowing about the true level of emissions, the low-income individual has missed out on the full value of the transfer payment p that she would actually require to be weakly better off with trade.

To evaluate welfare, we can consider both the change in utility coming from the housing stock and the change in utility coming from the numeraire good. Both households experience lower utility from housing, and the individual owning home H_L in equilibrium (in this case, the low-income individual) experiences an even bigger difference in utility. This is both because the wedge between true and believed air quality is higher for that individual (due to pollution dissipation), and because the marginal utility of air quality is higher for that individual (due to declining marginal utility). Moreover, the low-income individual is *additionally* worse off from a too-small transfer payment, while the high-income individual is conversely better off for the same reason. Overall then, in this scenario, Metrics 2 and 3 both hold: the low-income individual experiences greater hidden pollution, and a greater utility loss as a result of the information failure.

A2.8 Optimization in the General Model

In the demand model in Section 3, we assume that households gain utility from three goods: salient amenities $s(x)$ that increase with distance to a point source, hidden amenities $q(x)$, and other goods y. Distance to the point source is priced according to some positive hedonic pricing function $p(x)$. The household's optimization problem when unaware of $q(x)$ is:

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

We assume that $\frac{\partial q}{\partial x} > 0$ and $\frac{\partial s}{\partial x} > 0$ (both amenities increase with distance) and $\frac{\partial p}{\partial x} > 0$ (house prices increase with distance). We also assume that all goods provide positive utility at a declining rate: $U_q > 0$, $U_{qq} < 0$, etc.

The first-order conditions that define the chosen bundle $(\lambda^\dagger, x^\dagger, y^\dagger)$ under limited information are as follows:

$$\begin{aligned} m - p(x) - y &= 0 \\ U_s \frac{\partial s}{\partial x} - \lambda \frac{\partial p}{\partial x} &= 0 \\ U_y - \lambda &= 0 \end{aligned}$$

To check that we are at an interior solution, we calculate the bordered Hessian:

$$D^2\mathcal{L}(\lambda, x, y) = \begin{pmatrix} 0 & -\frac{\partial p}{\partial x} & -1 \\ -\frac{\partial p}{\partial x} & U_{ss}\left(\frac{\partial s}{\partial x}\right)^2 + U_s \frac{\partial^2 s}{\partial x^2} - \lambda \frac{\partial^2 p}{\partial x^2} & U_{sy}\frac{\partial s}{\partial x} \\ -1 & U_{sy}\frac{\partial s}{\partial x} & U_{yy} \end{pmatrix}$$

The determinant of this is:

$$-\left(\frac{\partial p}{\partial x}\right)^2 U_{yy} + 2\frac{\partial p}{\partial x} U_{sy} \frac{\partial s}{\partial x} - \left(\frac{\partial s}{\partial x}\right)^2 U_{ss} - U_s \frac{\partial^2 s}{\partial x^2} + \lambda \frac{\partial^2 p}{\partial x^2}$$

For this to be positive, it must be the case that the two positive terms $-\left(\frac{\partial p}{\partial x}\right)^2 U_{yy}$ and $-\left(\frac{\partial s}{\partial x}\right)^2 U_{ss}$ are not swamped by any negative terms in the rest of the expression (the remaining three terms have ambiguous signs, depending on the signs of U_{sy}, $\frac{\partial^2 s}{\partial x^2}$, and $\frac{\partial^2 p}{\partial x^2}$).

Assuming we are not at a corner solution, we can use comparative statics to find the sign of the derivative of distance with respect to income, at the optimum:

$$\begin{pmatrix} \frac{\partial \lambda^\dagger}{\partial m} \\ \frac{\partial x^\dagger}{\partial m} \\ \frac{\partial y^\dagger}{\partial m} \end{pmatrix} = \begin{pmatrix} 0 & -\frac{\partial p}{\partial x} & -1 \\ -\frac{\partial p}{\partial x} & U_{ss}\left(\frac{\partial s}{\partial x}\right)^2 + U_s \frac{\partial^2 s}{\partial x^2} - \lambda \frac{\partial^2 p}{\partial x^2} & U_{sy}\frac{\partial s}{\partial x} \\ -1 & U_{sy}\frac{\partial s}{\partial x} & U_{yy} \end{pmatrix}^{-1} \cdot \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix}$$

By Cramer's Rule, we have:

$$\frac{\partial x^\dagger}{\partial m} = \frac{\begin{vmatrix} 0 & -1 & -1 \\ -\frac{\partial p}{\partial x} & 0 & U_{sy}\frac{\partial s}{\partial x} \\ -1 & 0 & U_{yy} \end{vmatrix}}{\begin{vmatrix} 0 & -\frac{\partial p}{\partial x} & -1 \\ -\frac{\partial p}{\partial x} & U_{ss}\left(\frac{\partial s}{\partial x}\right)^2 + U_s \frac{\partial^2 s}{\partial x^2} - \lambda \frac{\partial^2 p}{\partial x^2} & U_{sy}\frac{\partial s}{\partial x} \\ -1 & U_{sy}\frac{\partial s}{\partial x} & U_{yy} \end{vmatrix}}$$

The numerator will be positive provided that $U_{sy}\frac{\partial s}{\partial x} > U_{yy}\frac{\partial p}{\partial x}$. This is similar to the standard condition under which a good is normal, with additional accounting for the shape of the hedonic price function and the impact that distance x has on the good of interest s. Thus we expect $\frac{\partial x^\dagger}{\partial m} > 0$, i.e., x will be a normal good.