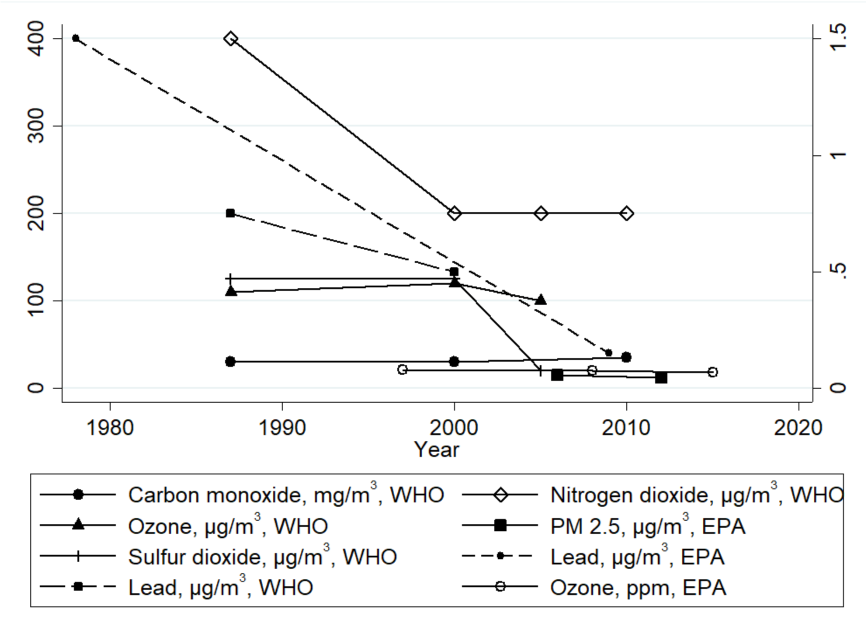
Online Appendix for Hausman and Stolper, "Inequality, Information Failures, and Air Pollution"

In Appendix Section A1, we present the figures and table referenced in the Background section of the paper. In Section A2, we provide an overview of exponential pollution decay, which motivates our theoretical analysis in the main paper. In Section A3, we provide derivations and proofs for the models in the paper. Finally, in Section A4, we present three descriptive empirical exercises that document the likelihood of disproportionate hidden pollution exposure.

A1 Reporting and Standards Have Become Stricter Over Time

Figure A1: Air Pollution Guidelines Have Become Tighter



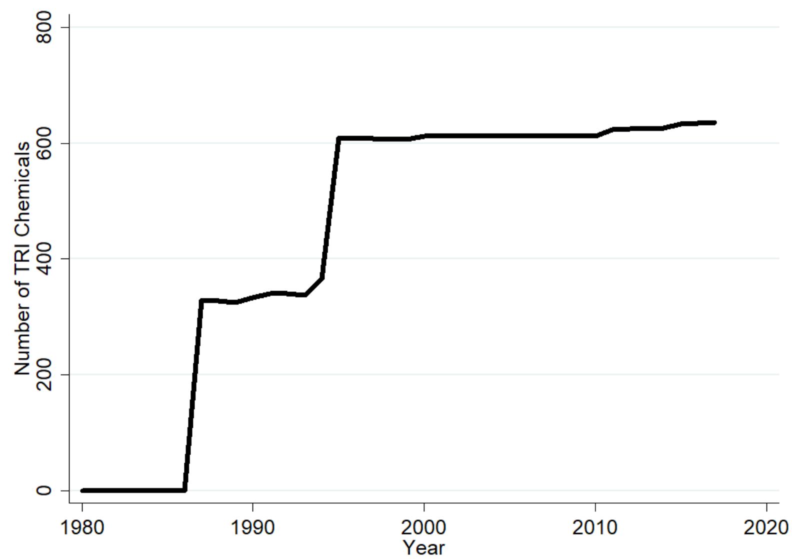
Note: This figure plots the changes in EPA standards and WHO guidelines for selected air pollutants. The left axis is used for all pollutants except lead and the EPA's ozone standard, which use the right axis. Some guidelines use the midpoint of a range; see Appendix Table A1 for the full range. For 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).

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.

Figure A2: Toxic Chemicals Reporting Has Grown Stricter

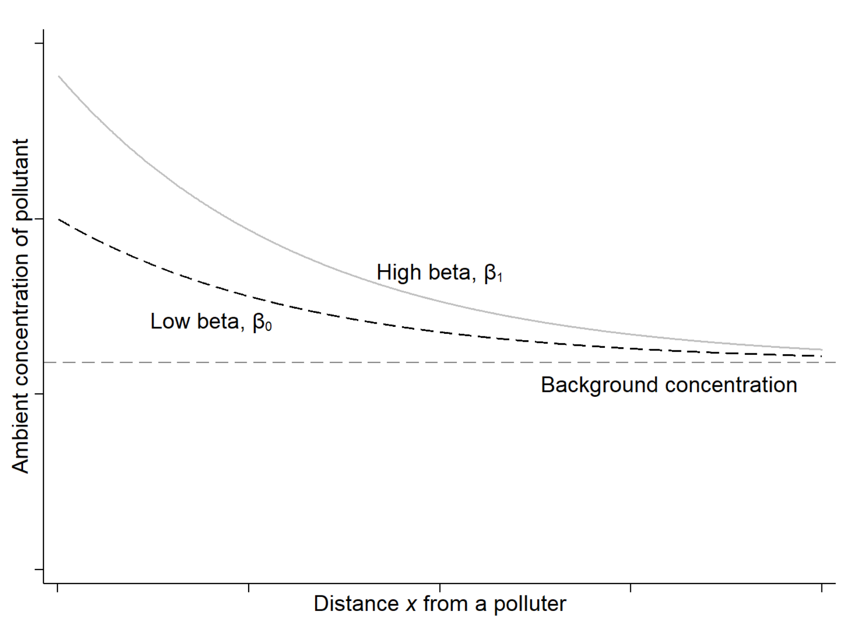


Note: This figure plots the count of Toxics Release Inventory- (TRI-) listed chemicals over time. The TRI program is an EPA-run mandatory reporting program for chemicals with cancer effects, other chronic health effects, significant acute health effects, and significant environmental effects. The source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

A2 Exponential Decay of Pollution with Distance

Our theoretical exercise in the main paper models the air quality – distance relationship using a linearization of exponential pollution decay. Figure A3 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.

Figure A3: 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.

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

($\frac{\partial^2 q}{\partial x \partial \beta} > 0$).

The parameterization of $q(x)$ that we use in the main paper is the result of a Taylor expansion of $q(x) = \tilde{\alpha} - \beta \exp(-x/k)$. The three derivatives of interest described above for exponential decay all retain the same sign after linearization.

A3 Theoretical Derivations

A3.1 Derivation of Demand Functions, Simplified Model

In one of the demand models in the main paper, 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:

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

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.

A3.2 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 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."

A3.3 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 Section A3.1). 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:[1]

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

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

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

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

[1] 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 $\frac{d\Delta U}{dm} < 0$.

A3.4 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 the "Consumer Surplus" figure in the main text. 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:

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

Re-arrange to:

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

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

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

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 $\frac{\partial \Delta \mathrm{CS}}{\partial m}$ expression drops out, and we are left with:

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

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,[2] leaving the entire expression $\gamma(\ln p^\dagger - \ln p^*) + (p^* - p^\dagger)\frac{\gamma}{p^*}$ negative.

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

[2]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.

A3.5 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 A3.4 gives a formal proof. The main text simply gives intuition, and that intuition relies on the height of the consumer surplus triangle in the main text's figure. 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 uninformed 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.

A3.6 Equilibrium under Pure Exchange with Continuous Choice of Distance

Here we maintain the modeling assumptions from 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 Section A3.3, 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 Section A3.1). 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.[3]

To make further progress in signing $\frac{d\Delta U}{dy^0}$, the following partial derivatives are useful:[4]

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

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

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 Section A3.3, 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 Section A3.3, for which p was constant and the expression

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

[4] 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 Section A3.3, 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 Section A3.3, 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.

A3.7 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:

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

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:

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

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.

A3.8 Optimization in the General Model

In one of the demand models in the main paper, 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.

A3.9 Stone-Geary Preferences

Suppose we assume that the consumer has Stone-Geary utility $U(q, y) = (q - \eta_1)^{\gamma}(y - \eta_2)^{(1-\gamma)}$. As before, 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:

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

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

$$\begin{aligned} m - px - y &= 0 \\ \gamma (q - \eta_1)^{\gamma-1}\left(\frac{\partial q}{\partial x}\right)(y - \eta_2)^{1-\gamma} - \lambda p &= 0 \\ (1-\gamma)(q - \eta_1)^{\gamma}(y - \eta_2)^{-\gamma} - \lambda &= 0 \end{aligned}$$

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

$$\frac{q^* - \eta_1}{y^* - \eta_2} = \frac{1}{p} \cdot \frac{\gamma}{1-\gamma} \cdot \frac{\partial q^*}{\partial x^*}$$

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:

$$x^* = \frac{\gamma m}{p} - \frac{(1-\gamma)(\alpha_0 - \alpha_1\beta - \eta_1)}{\beta} - \frac{\gamma\eta_2}{p}$$

When a household learns the true β, she will move farther away:

$$\frac{\partial x^*}{\partial \beta} = \frac{(1-\gamma)(\alpha_0 - \eta_1)}{\beta^2}$$

However, the extent to which she does so does not depend on her income. This result is true in our Cobb-Douglas model as well. Equivalently, $\frac{\partial x^*}{\partial m} = \frac{\gamma}{p}$, which does not depend on β.

A3.10 Constant Elasticity of Substitution (CES) Preferences

Suppose we assume that the consumer has CES utility $U(q, y) = (q^\gamma + y^\gamma)^{1/\gamma}$. As before, 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:

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

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

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

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

$$\frac{q^*}{y^*} = \left(\frac{p}{\frac{\partial q^*}{\partial x^*}}\right)^{\frac{1}{\gamma-1}}$$

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:

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

We can explore this in two ways. First, recall the intuition we provide in Section 3. We can evaluate 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 $U_{q^\dagger} \frac{\partial q^\dagger}{\partial x^\dagger} \mathrm{d}x$. As we discuss in the main text, $U_{q^\dagger}$ is larger for low-income consumers and $\frac{\partial q^\dagger}{\partial x^\dagger}$ is weakly larger for low-income consumers. That leaves the question of whether $\mathrm{d}x$ is larger for low-income or high-income consumers.

In our Cobb-Douglas model, $\frac{dx^*}{dm}$ does not depend on β. When a household learns pollution is worse, she moves farther away from the point source – but the extent to which she does so does not depend on her income. In contrast, for CES utility, we have:

$$\frac{dx^*}{dm} = \frac{1}{\beta^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p} > 0$$

Distance is a normal good, as expected. How does the distance-income relationship vary with β?

$$\frac{d^2 x^*}{dm d\beta} = \frac{\left(\frac{\gamma}{1-\gamma}\right) p^{\frac{1}{1-\gamma}} \beta^{\frac{1}{\gamma-1}}}{\left(\beta^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p\right)^2} > 0$$

High-income households move even further away than do low-income households if they learn pollution is bad. In the intuition we use in our generalized model, this means that DWL could be larger or smaller for high-income households; it is unclear. Low-income households have a larger marginal utility from gains in x, and a weakly larger translation into improvements in q (here, equivalent translation, as the dissipation function is linear), but a smaller change in x when they learn the true β.

As we next show, whether DWL is larger or smaller for high-income households depends on the dissipation function parameters, the utility parameters, income, and prices. That is, it is straightforward to show parameterizations for which DWL is either increasing or decreasing in income m. We show two examples, for which preferences are identical, but prices are different, that lead to these two different distributional effects.

As shown above, the consumer selects distance x as follows:

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

From this, we can calculate the informed q^* and uninformed $q^\dagger$:

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

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

Similarly, we can also calculate the informed y^* and uninformed $y^\dagger$:

$$y^* = m - p \cdot \left(\left(\frac{m}{\beta_1^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p} \right) - \left(\frac{(\alpha_0 - \alpha_1 \beta_1)\, \beta_1^{\frac{1}{\gamma-1}} p^{\frac{1}{1-\gamma}}}{\beta_1^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p} \right) \right)$$

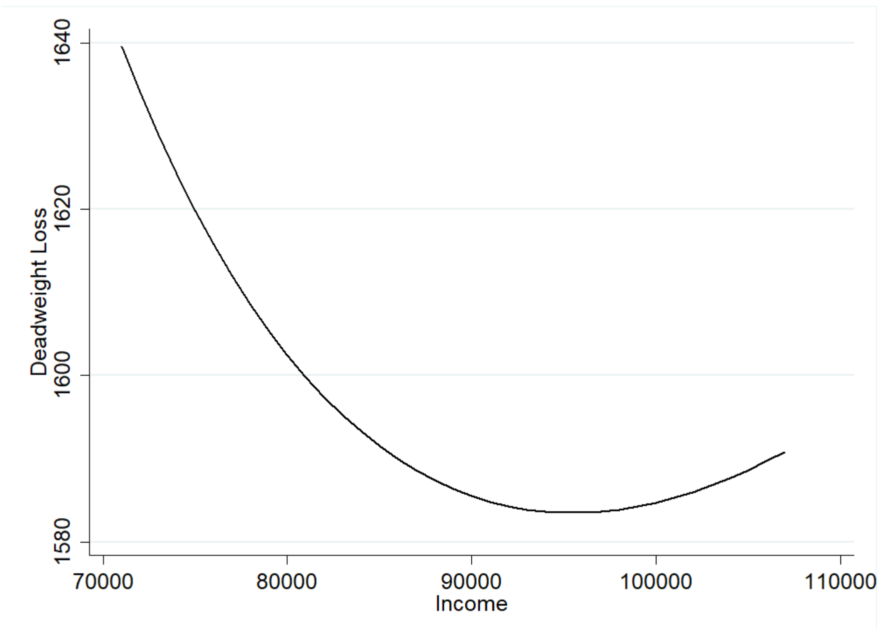
$$y^\dagger = m - p \cdot \left(\left(\frac{m}{\beta_0^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p} \right) - \left(\frac{(\alpha_0 - \alpha_1 \beta_0)\, \beta_0^{\frac{1}{\gamma-1}} p^{\frac{1}{1-\gamma}}}{\beta_0^{\frac{\gamma}{\gamma-1}} p^{\frac{1}{1-\gamma}} + p} \right) \right)$$

From these, we can calculate DWL:, $U(q^*, y^*) - U(q^\dagger, y^\dagger)$. We show one example parameterization for which DWL is decreasing in m for some regions of m and increasing in others. The parameter values are as follows:

- $\alpha_0 = 9000$
- $\alpha_1 = 17000$
- $\beta_0 = 0.4$
- $\beta_1 = 0.5$
- $\gamma = 0.7$
- $p = 1$
- $71000 < m < 107000$

As Figure A4 shows, DWL is decreasing in m up until approximately $m = 95000$; it is increasing in m thereafter. Note these parameter values are not chosen to be empirically realistic; rather to show a simple case for which DWL could be either increasing or decreasing in m. Overall, with CES utility, it becomes an empirical question whether high-income or low-income households are made better off by improved information.

Figure A4: Deadweight Loss at Various Income Levels, CES Utility



Note: This figure plots deadweight loss across different income levels, for the parameterization described in the text.

A4 Empirical Exercises

A4.1 Who Is Impacted by Limited Information?

There are a great many instances in which individuals, communities, and societies have realized that pollution was worse or more detrimental than previously thought. In this subsection, we briefly introduce two such instances and present descriptive empirical facts that clarify who is likely to have borne the historical health burden of collective information failure. These empirical exercises are not intended to in of themselves prove welfare impacts, but rather to provide intuition for the results of our theoretical modeling.

Consider first new information about the health impacts of lead that emerged from research in the mid-2000s. This information was so compelling that the EPA dropped the federal ambient lead standard by an order of magnitude in 2008. Prior to this information becoming public, we might infer that communities had incorrect beliefs about the health damages of high lead concentrations. This could be modeled in our theoretical framework as an incorrect belief about β if higher levels of lead had proportionately higher damages to health. As such, it is worth considering which communities were experiencing the highest ambient lead exposure at the time of the EPA's standard change. Note that the analysis that follows 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.

We assemble EPA monitoring data on annual average concentrations of airborne lead[5] as measured by the speciated $PM_{2.5}$ monitoring network.[6] 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.

We regress each demographic characteristic on the level of airborne lead (logged).[7] 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.[8] As we show in Panel A of

[5]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.

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

[7]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 A4.

[8]Around 4.5 percent of the population is in a Zip Code Tabulation Area that does not match to a CBSA;

Table A3, 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 without CBSA fixed effects, in Appendix Table A4, 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 A4).

The simplest interpretation of these results (particularly the first three columns, relating to income, unemployment, and poverty) might be that lack of lead pollution is a normal good – i.e., our first environmental justice metric. However, this would miss the key point that communities were not fully aware of lead's impacts. Indeed, the results also point to our second environmental justice metric – that low-income communities (and people of color) were historically the most physically impacted by incomplete scientific information about the health impacts of lead. To measure the welfare implications (our third metric), one could next examine whether households moved following the release of the new scientific information. However, additional data or 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.

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). Again, this can be modeled as implying an incorrect belief about the β parameter in our model – given the way pollution dissipates, being closer to a refinery would imply proportionately higher concentrations of air pollution.

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 analyze all zip codes with a facility in the 1999 NEI that was classified in SIC sector 2911 (Petroleum Refining); 210 zip codes had

we drop these ZCTAs from our regressions.

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.[9] Results, in Panel B of Table A3, 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 show results without CBSA effects in Appendix Table A5). Thus, it appears that the communities most physically impacted by the historical underreporting were economically disadvantaged and non-White. These results again are consistent with both our first and second environmental justice metrics; additional modeling assumptions and empirical evidence would be needed to analyze the full welfare impacts.

A4.2 Co-located Amenities

In this Appendix section, we study the empirical relationships between disamenities of different levels of salience, as motivated by our general model and summary discussion of correlated disamenities in the main text. To do so, we assemble data on air pollution, noise pollution, and land 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),[10] 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

[9]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 A5.

[10]In Appendix Table A7, we show results using pollution measures from 2016.

ozone (1,116 zip codes) in our analysis.[11]

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.[12] 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.[13] 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.[14]

We merge these pollution exposure variables with noise and land use data.[15] Noise data come from the Department of Transportation's National Transportation Map. Like 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."[16] Meanwhile, land use data are published by the US Geological Survey at the Department of the Interior.[17] 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. The left-hand panel

[11] We provide coverage maps in Appendix Figure A6.

[12] 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).

[13] 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.

[14] 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.

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

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

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

of Figure A5 plots NO_2 concentrations against noise levels and reveals a strong positive correlation between these two disamenities. The right-hand panel similarly 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.

We next turn to regression analysis. Table A6 shows regressions of each measure of pollution exposure on the more salient disamenities of noise and land use. The pollution exposure 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 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 $PM_{2.5}$.[18]

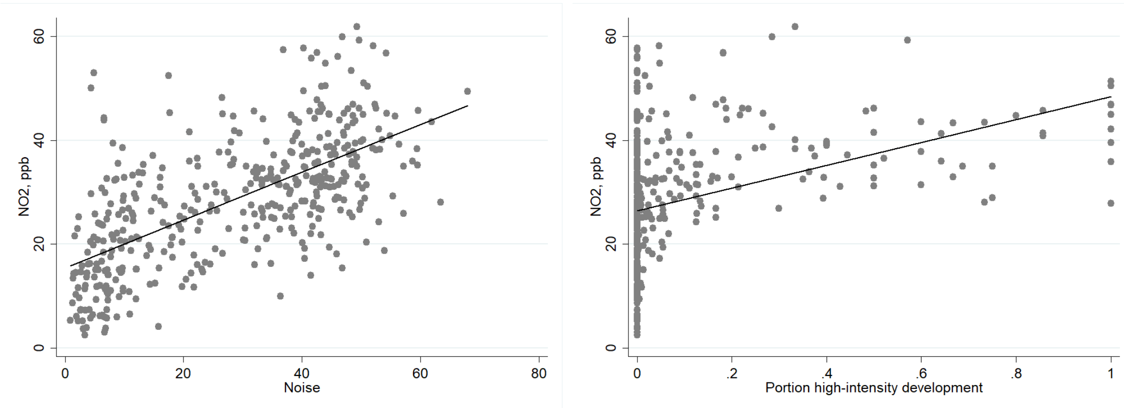
Overall, across the seven regressions, we see that five major types of pollutants are closely and positively correlated with noise and land use. The two exceptions are ozone (which displays the opposite relationship) and SO_2 (for which no statistically significant relationship appears in the regression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

Finally, in Appendix Tables A8 through A10, we briefly examine 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 various types of disamenities.[19] We show first that zip codes with high levels of $PM_{2.5}$ and zip codes with higher cancer risk have significantly lower incomes. We then run a "horse race" regression by including noise levels and land use variables. We show that the magnitudes of the coefficients on $PM_{2.5}$ and cancer risk drop substantially and lose statistical significance. In contrast, high-intensity development is associated with a significantly lower income level. This suggests that co-located disamenities may be playing an important role in the decision of households of where to live. 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.

[18] 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 near water. Coverage maps in Appendix Figure A7 show where water and wetlands appear.

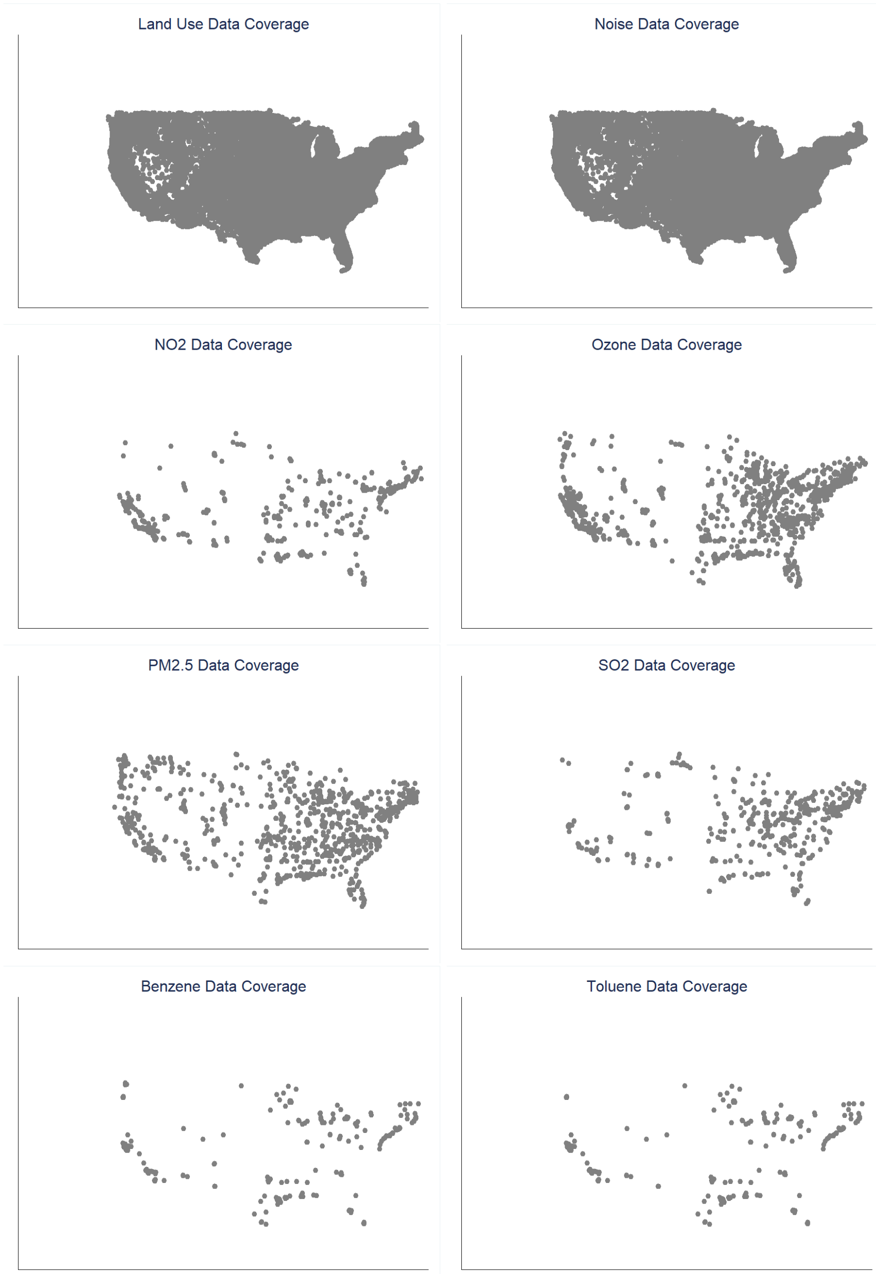
[19] As before, we include CBSA fixed effects to compare households within a metro area.

Figure A5: Noise and Land Use Are Correlated with Pollution Exposure



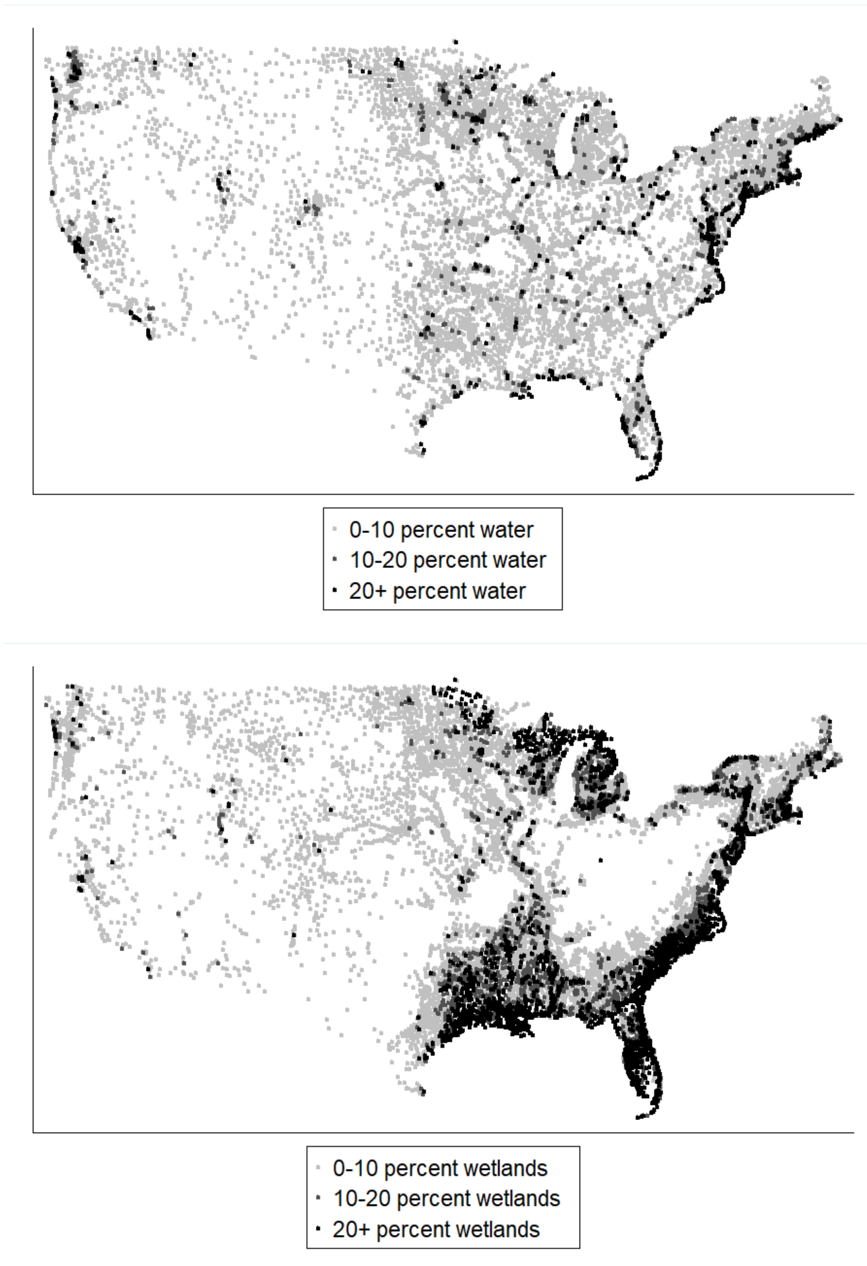
Note: The left-hand figure plots the annual average NO_2 level (measured in parts per billion) in a 5-digit Zip Code Tabulation Area in 2001 against the transportation noise in that area (measured in L_{Aeq}, roughly equivalent to decibels). The right-hand figure similarly plots the annual average NO_2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

Figure A6: 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 A7: 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 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	39.630	16.230	31,645
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.

Table A3: Demographic Characteristics Were Correlated with Pollution Exposure *Prior* to Full Information Provision

	Income, '000s	% Unempl.	% Below Poverty	% White	% Black	% Latino/a
Panel A. Ambient Lead Exposure in 2001						
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
Panel B. Refinery Locations in 1999						
Refinery in zip code	-4.30***	0.43**	2.07***	-4.29***	2.10**	5.90***
	(1.01)	(0.21)	(0.53)	(1.17)	(1.00)	(0.68)
Observations	23,854	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.	42.42	3.42	9.00	85.68	8.53	7.15

Note: This table reports estimates and standard errors from twelve separate regressions. The dependent variable is listed above each column. In Panel A, the independent variable is ambient lead concentrations: logged lead in PM2.5 form. In Panel B, the independent variable is a dummy for whether a refinery is located in the zip code. 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; 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. " "

Table A4: 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	289	290	288	290	290	290
Within R^2	0.05	0.03	0.01	0.06	0.01	0.04
Mean of dep. var.	36.85	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	-0.63***	0.59***	1.55***	-9.33***	6.24***	3.62***
	(0.17)	(0.03)	(0.09)	(0.19)	(0.16)	(0.11)
Observations	23,774	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.	42.45	3.41	8.98	85.69	8.53	7.15

Note: This table is identical to Panel A of Table A3 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: 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	-4.02***	0.48*	2.29***	-4.07***	1.48	5.96***
	(1.23)	(0.25)	(0.65)	(1.42)	(1.21)	(0.83)
Observations	23,854	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.	42.42	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	-1.48	0.83***	3.15***	-12.69***	5.46***	10.57***
	(1.12)	(0.22)	(0.63)	(1.35)	(1.13)	(0.93)
Observations	31,645	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.	39.63	3.45	9.89	86.75	7.81	6.37

Note: This table is identical to Panel B of Table A3 in the main text, but with the changes noted in the panel titles. *** Statistically significant at the 1% level; ** 5% level; * 10% level..

Table A6: 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.

Table A7: 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 A6 in the main text, but with 2016 air quality data. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A8: 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.

Table A9: 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 A8, 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 A10: 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 A8, 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.

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