An Economic View of Corporate Social Impact

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Abstract

The growing discussions of impact investing and stakeholder capitalism have increased interest in measuring companies' social impact, not just their profits. We conceptualize corporate social impact as the social welfare loss that would be caused by a firm's exit in equilibrium. We then quantify the social impacts of 73 large firms in 12 industries. We field a new survey measuring people's willingness to substitute away from the firms they buy from and work for. We use the survey data to estimate product market and labor market models and simulate counterfactual equilibria after a firm's exit. A key result is that consumer surplus is the most important component of firms' social impact, dwarfing profits (because they overwhelmingly accrue to wealthy people with low social marginal welfare weights), worker surplus, and externalities. Existing impact rating systems have little correlation with our economics-based metric.

JEL Codes: D60, J23, J63, L13, L62, L66, L71, L81, L93, M14, Q54.

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There is growing focus on companies' social impact, in addition to their profitability. Many mutual funds and institutional investors have corporate social responsibility requirements for inclusion in their portfolios. One-third of U.S. assets under management—$17 trillion in total—consider environmental, social, and governance issues, an amount that has doubled since 2015 (SIF Foundation 2020). The Business Roundtable (2019), a group of CEOs, now says that their companies' objectives extend beyond generating shareholder value to include multiple stakeholders and "promoting an economy that serves all Americans." A group of academics and business stakeholders commissioned by the The British Academy (2018) similarly argues that profits "is not the corporate purpose," and that in some cases, "corporate purposes should include public purposes that relate to the firm's wider contribution to public interests and societal goals." Alongside this is an active academic debate about what companies should maximize (e.g. Friedman 1970; Hart and Zingales 2017a, 2017b), why some firms embrace corporate social responsibility,[1] and how impact investors should allocate capital.[2]

A key challenge in this discussion is uncertainty and disagreement about how to actually measure a company's social impact (The Economist 2019). There are third-party rating systems that score companies on dimensions of social impact—product quality, worker treatment, environmental performance, etc.—and then combine these measures to generate a company's overall score. However, most systems do not have a theoretically grounded economic definition of what they want to measure or an objective way to combine across dimensions to calculate the overall score.[3] Perhaps as a result, there is substantial disagreement between different third-party ratings of the same companies (Chatterji et al. 2015).

Our paper begins from the observation that economics offers a set of standard frameworks for conceptualizing and quantifying a company's social impact: consumer and worker surplus, externalities, social welfare, etc. We conceptualize a firm's social impact as the social welfare loss from the firm's exit in equilibrium. Using new survey data and standard approaches from industrial organization, public economics, and labor economics, we then quantify social impact for 73 large companies in the upstream oil industry and 11 differentiated product industries: automobiles,

[1] See, for example, Besley and Ghatak (2005), Heal (2005), Bénabou and Tirole (2010), Hong, Kubik, and Scheinkman (2012), Hong et al. (2019), and Cheng, Hong, and Shue (2020).

[2] See, for example, Brest and Born (2013), Brest, Gilson, and Wolfson (2016), Chowdhry, Davies, and Waters (2019), Landier and Lovo (2020), Green and Roth (2020), Hong, Wang, and Yang (2021), and Roth (2021).

[3] Existing corporate impact rating systems include Just Capital (https://justcapital.com/rankings/), Refinitiv (https://www.refinitiv.com/en/financial-data/indices/esg-index), and MSCI (https://www.msci.com/esg-ratings). As an example, Just Capital polls a representative sample of Americans to quantify the weights that they place on five different issues—workers, customers, communities, environment, and shareholders—and then scores all Russell 1000 companies on these issues using data from SEC filings, media reports, pollution inventories, and other sources. The "product impact-weighted accounts" framework (Serafeim, Trinh, and Zochowski 2020) takes an important step forward by quantifying firms' social impact in dollar units. Key differences between their approach and ours include that (i) we begin from an economic model that delivers a specific notion of social welfare, (ii) they use accounting techniques to estimate consumer surplus and costs, while we use demand estimation, and (iii) they do not quantify contributions to worker surplus.

airlines, six consumer packaged goods (beer, cereal, cigarettes, soda, toothpaste, and yogurt), grocery retail, smartphones, and chain restaurants.

In our model, people with different income-earning ability choose numeraire good consumption, what products to buy in each market, and the firm and local labor market where they work. Some products (e.g., oil) impose consumption externalities, and some products (e.g., cigarettes and soda) also involve "internalities," meaning that consumers have a biased perception of how consumption affects their utility. Firms' profits are redistributed unequally across people. Social welfare is the Pareto-weighted sum of utility across people.

A firm's *individual impact* is the social welfare loss from a firm's exit if all competing firms remain in the market. A firm's *share of industry impact* is the firm's Shapley value for the social welfare loss if all firms in its industry exit the market. These two metrics differ more in markets where aggregate demand is fairly inelastic (so industry impact is large) while consumers substitute easily across firms (so individual impact is small). In our framework, firms will have larger social impact if (i) their consumers and workers are less willing to substitute away, (ii) they serve lower-income consumers or employ workers with low income-earning ability, and (iii) they generate fewer negative externalities and internalities.

We make five key assumptions for empirical implementation: (i) social marginal welfare weights are inversely proportional to income, following a common rule of thumb in the optimal taxation literature (e.g., Saez 2002), (ii) utility is quasilinear in the numeraire and additively separable in labor supply sub-utility, (iii) intermediate goods are produced in perfectly competitive markets with no externalities, (iv) each firm is a small part of the labor market, so its exit does not impact wages offered by other firms, and (v) firms produce one representative product with exogenous characteristics and cost function. Assumptions (ii), (iiii), and (iv) allow us to consider product markets and labor markets in independent partial equilibria, while assumption (v) simplifies our data collection and counterfactual simulations.

We then turn to quantifying social impact for each of our 73 firms. We fielded a new 1,937-person survey that identifies key empirical moments and provides descriptive evidence on Americans' willingness to substitute away from their usual products and current employers. For each of our 11 differentiated product markets, the survey elicited consumption, brand last purchased, customer satisfaction, firm-level price response (whether people would still buy from the same firm if the price increased by 25 percent), and aggregate price response (the extent to which people would reduce consumption if the price of all products in the market doubled). The survey also asked a parallel question about labor supply response (whether people would find a new job if their employer had to cut salaries by 10 percent).

We model differentiated product markets using the standard framework from the industrial organization literature (e.g., Berry, Levinsohn, and Pakes 1995). We use the survey data to estimate a discrete choice demand system for each product market, with firm-specific utility shifters for above-median income consumers, firm-specific random coefficients (which govern each firm's residual demand elasticity), and a random coefficient on all inside goods (which governs the aggregate demand elasticity). We infer marginal costs and simulate counterfactual prices assuming that firms set prices to maximize profits in Nash equilibrium. We treat upstream oil differently: we assume that it is an undifferentiated product and that firms are price takers in the global market. We construct each oil company's global marginal cost curve using field-level data, as in Asker, Collard-Wexler, and De Loecker (2019), and we simulate counterfactual equilibria using estimates of global oil supply and demand elasticities from Caldara, Cavallo, and Iacoviello (2019). For automobiles, airline travel, and oil, we include climate change externalities from carbon dioxide emissions valued at \$51 per ton, the U.S. government's social cost of carbon. For cigarettes and soda, we include health cost externalities and internalities using estimates from the literature.

We model labor markets in the spirit of the differentiated firms framework from the labor economics literature (e.g., Card et al. 2018). Because we have assumed that each firm is so small relative to the labor market that its entry or exit does not affect other firms' wages, we can estimate each firm's contribution to worker surplus by integrating under its residual labor supply function. We assume that worker surplus is distributed uniformly, with dispersion that depends on salary, education, occupation, employer size, and the thickness of the local labor market. We use the survey data to estimate how worker surplus varies with these parameters, then fit those predictions onto the distribution of workers at each firm.

Using these estimates, we quantify corporate social impact for the 73 firms across our 12 industries. A key result is that consumer surplus is the most important component of corporate social impact, dwarfing profits, worker surplus, and externalities. Welfare-weighed profits are relatively small because profits overwhelmingly accrue to high-income people who have low social marginal welfare weights. Worker surplus is relatively small because in our survey, many workers say they would get another job if their employer had to cut salaries. Even for the airline, auto, and oil industries, climate change externalities are relatively small in short-run equilibrium at a \$51 social cost of carbon.

Our estimates of corporate social impact are essentially unrelated to ratings from two prominent environmental, social, and governance rating systems. Part of this is presumably because of limitations in our ability to quantify all components of social impact in dollars, and part may be because existing ratings might be trying to measure slightly different concepts. But this lack of correlation also suggests that the current discussion of corporate social impact might benefit from additional economic foundation, and specifically that existing rating systems may not fully account for the large contribution of consumer surplus to social impact.

Corporate social impact estimates are directly useful for firms that want to measure their impact and for investors, workers, and consumers who want to associate themselves with high-impact firms. However, a firm's social impact is generally not the same the social impact of investing in the firm

(Brest and Born 2013). For example, investing in a high-social impact firm could in equilibrium displace other investors motivated only by profits, who might instead invest in other firms with low social impact (Green and Roth 2020). Corporate social impact estimates are still useful for impact investors because social impact is one key ingredient for optimal impact investing strategies in many models (e.g. Chowdhry, Davies, and Waters 2019; Green and Roth 2020; Roth 2021).

Our analysis has at least three types of limitations. First, one could debate our conceptualization of corporate social impact and the underlying welfarist moral philosophy. For example, our approach may not capture the full importance of diversity and inclusion or the costs and benefits of business practices such as political lobbying and good governance. Second, our static partial equilibrium assumptions are restrictive. For example, we ignore how a firm's exit would affect the pollution and worker surplus at its suppliers. As another example, our framework ignores fixed costs, which privileges firms in capital-intensive industries. Furthermore, we ignore how competitors might adjust product lines and production functions in a response to a firm's exit. If we considered a longer time horizon, a firm's social impact might be very small because competitors could adjust to make the same products and employ the same workers. Third, our empirical implementation uses survey responses instead of market behavior, requires strong functional form assumptions for marginal costs and the surplus provided to inframarginal consumers (Hausman 1996; Petrin 2002), and requires controversial assumptions about the magnitudes of externalities and internalities.

Notwithstanding these limitations, we hope that this paper can be a useful step forward in developing an economic framework to quantify corporate social impact. We think of this paper as a cousin to Hendren and Sprung-Keyser (2020): while they provide a unified welfare analysis of many U.S. government policies, we provide a unified welfare analysis of many large firms.

Sections 1–4 present the theoretical framework, survey data, product market estimates, and labor market estimates, respectively. Section 5 presents our corporate social impact estimates, and Section 6 concludes.

1 Model

1.1 Setup

There are N people indexed by i with income-earning ability θ_i. There are many product markets (automobiles, airline travel, beer, etc.) indexed by m. Within each product market, a set of $\mathcal{J}_m$ products indexed by j are available at prices p_j on each of $\mathcal{T}_m$ of choice occasions indexed by t. The products in each market are made by a set of $\mathcal{F}_m$ firms indexed by f, each of which makes products $\mathcal{J}_{fm}$. There are many local labor markets indexed by l. Within each labor market is a set of firms offering wages $w_{fl}(\theta)$. $\boldsymbol{p}$ and $\boldsymbol{w}(\theta)$ are the vectors of prices and wages across all products and employers.

People choose numeraire good consumption, what product to buy in each market on each choice occasion, and the firm and local labor market where they work. y_{ijt} and y_{ifl} are binary indicators for buying j in t and working at f in labor market l, and n is the quantity of numeraire consumption. $\boldsymbol{y} \coloneqq \{y_{ift}, y_{ifl}\}$ is the vector of all choices. u_{ijt} and u_{ifl} are the utilities from buying j in t and working at fl.

Each person i receives amount π_i of redistributed profits. Person i's income is thus $z_i = \pi_i + \sum_{fl} w_{fl}(\theta_i) y_{ifl}$, so the budget constraint is $n + \sum_m \sum_{t \in \mathcal{T}_m} \sum_{j \in \mathcal{J}_m} p_j y_{ijt} \leq z_i$. Φ is a negative externality, such as climate change or second-hand smoke.

We assume that people have quasilinear utility that is additively separable in consumption, labor disutility, and the externality: $U_i = U_i\left(\sum_m \sum_{t \in \mathcal{T}_m} \sum_{j \in \mathcal{J}_m} u_{ijt} y_{ijt} + n + \sum_{fl} u_{ifl} y_{ifl} - \Phi\right)$, with $U_i' > 0$. Substituting in the budget constraint gives

$$U_i(\boldsymbol{y}; \boldsymbol{p}, \boldsymbol{w}(\theta_i)) = U_i\left(\sum_m \sum_{t \in \mathcal{T}_m} \sum_{j \in \mathcal{J}_m} (u_{ijt} - p_j) y_{ijt} + \pi_i + \sum_{fl} (u_{ifl} + w_{ifl}(\theta_i)) y_{ifl} - \Phi\right), \tag{1}$$

Standard economic models assume that people choose $\boldsymbol{y}$ to maximize equation (1). We relax the utility maximization assumption in two product markets where consumer choice is sometimes argued to be affected by behavioral biases: cigarettes (Gruber and Kőszegi 2001) and soda (Allcott, Lockwood, and Taubinsky 2019a). In those markets, we assume that consumers misperceive u_{ijt} by amount γ_j. They thus maximize "perceived utility" $\tilde{U}_i$, which is the same as equation (1) except with $\tilde{u}_{ijt} \coloneqq u_{ijt} + \gamma_j$ in place of u_{ift}. Following Herrnstein et al. (1993) and the behavioral economics literature, we refer to γ_f as a negative "internality." We set $\gamma_f = 0$ for markets other than cigarettes and soda. Consumer choice is determined by

$$\boldsymbol{y}^* = \arg\max \tilde{U}_i(\boldsymbol{y}; \boldsymbol{p}, \boldsymbol{w}(\theta_i)). \tag{2}$$

Consumers ignore their contribution to profits π_i and externalities Φ when choosing.

Indirect utility is then $V_i(\boldsymbol{p}, \boldsymbol{w}(\theta_i)) = U_i(\boldsymbol{y}^*; \boldsymbol{p}, \boldsymbol{w}(\theta_i))$. Aggregate consumption of product j in market m is $q_j(\boldsymbol{p}) = \sum_{t \in \mathcal{T}_m} \sum_i y^*_{ijt}$.

To close the model, we distribute profits and externalities to people. We define $C_j(q_j)$ as product j's total production cost. Firm f's profits are

$$\Pi_f(\boldsymbol{p}) = \sum_{j \in \mathcal{J}_f} \left[p_j \cdot q_j(\boldsymbol{p}) - C_j(q_j)\right]. \tag{3}$$

Profits may be distributed unequally across people, but the total profits equal the total amount redistributed: $\sum_f \Pi_f(\boldsymbol{p}) = \sum_i \pi_i$.

Consumption of product j imposes negative externality ϕ_j on other people. We assume that externalities are distributed equally across people, so the per-person externality is

$$\Phi = \frac{1}{N} \sum_{m} \sum_{j \in \mathcal{J}_m} q_j(\boldsymbol{p}) \phi_j. \tag{4}$$

Social welfare is the sum of utility, weighted by Pareto weights $\omega_i \geq 0$:

$$W(\boldsymbol{p}, \boldsymbol{w}) = \sum_i \omega_i V_i \left(\boldsymbol{p}, \boldsymbol{w}(\theta_i)\right). \tag{5}$$

1.2 Corporate Social Impact

We define $\boldsymbol{p}^{\mathcal{F}}$ and $\boldsymbol{w}^{\mathcal{F}}(\theta)$ as equilibrium prices and wages with set of firms $\mathcal{F}$ in the market. The welfare loss from firm f's exit conditional on a set of other firms $\mathcal{F}$ in the market is

$$\Delta W_f(\mathcal{F}) \coloneqq W\left(\boldsymbol{p}^{\mathcal{F} \cup f}, \boldsymbol{w}^{\mathcal{F} \cup f}\right) - W\left(\boldsymbol{p}^{\mathcal{F}}, \boldsymbol{w}^{\mathcal{F}}\right). \tag{6}$$

We consider two notions of corporate social impact. Firm f's *individual impact* is the welfare loss from a firm's exit if all other competing firms remain in the market:

$$\Delta W_f^{Individual} = \Delta W_f(\mathcal{F}_m \backslash f). \tag{7}$$

Firm f's *share of industry impact* is the firm's Shapley value for the social welfare loss if all firms in the industry were to exit the market. To calculate this, we define $\mathcal{R}_m$ as the set of all orderings of firms in market m, we define $\mathcal{P}_f^R$ as the set of firms that precede f in order R, and we define F_m as the number of firms in the market. The Shapley value is the average welfare loss from removing f over all permutations of other firms:

$$\Delta W_f^{Shapley} = \frac{1}{F_m!} \sum_R \Delta W_f\left(\mathcal{P}_f^R\right). \tag{8}$$

As an example, consider a simple Bertrand oligopoly. There are two identical firms $f \in \{1, 2\}$ selling fully undifferentiated products with constant marginal cost, and total welfare is unaffected if one firm exits but drops by $\$X$ if both firms exit. Each firm's individual impact is $\Delta W_f^{Individual} = 0$. To calculate the Shapley value, $\mathcal{R}_m = \{(1,2), (2,1)\}$, $\mathcal{P}_1^{(1,2)} = \mathcal{P}_2^{(2,1)} = \{\emptyset\}$, $\mathcal{P}_1^{(2,1)} = \{2\}$, and $\mathcal{P}_2^{(1,2)} = \{1\}$, so $\Delta W_f^{Shapley} = \frac{1}{2}(X + 0) = \frac{1}{2}X$ for each firm: the two identical firms split the \$X total industry impact.

As another example, the cigarette industry as a whole might have very negative industry impact due to the externalities and internalities from its products, but a single cigarette company (even one with large market share) might have positive individual impact $\Delta W_f^{Individual}$ if a firm's exit does not reduce externalities and internalities because aggregate demand is inelastic.

The Shapley value is not the only way to allocate total industry impact to individual firms—for example, we could allocate based on share of sales. However, the Shapley value is the only map from total industry impact to shares of individual impact that satisfies four intuitive properties: linearity, null player, efficiency, and symmetry (Shapley 1953). Linearity means that the results are homogeneous of degree one, and null player means that a firm with $\Delta W_f(\mathcal{F}) = 0, \forall \mathcal{F}$ has zero Shapley value. Efficiency means that the Shapley values sum to the total industry impact. Symmetry means that firms that always contribute the same $\Delta W_f(\mathcal{F})$ have the same Shapley value. Allocating industry impact to firms based on share of sales would violate symmetry if firms that have the same sales generate different consumer surplus, for example because consumers are less willing to substitute away from certain firms.

1.3 Assumptions for Empirical Implementation

Distributional preferences. Following the optimal taxation literature, we define $g_i := \omega_i V_i'$ as the social marginal welfare weight: the social value of increasing person i's consumption by \$1. We define $a(z_i)$ as after-tax income as a function of pre-tax income z_i. We parameterize distributional preferences by ρ:

$$g_i = \kappa a(z_i)^{-\rho}. \tag{9}$$

We set $\kappa = N/\left[\sum_i a(z_i)^{-\rho}\right]$, so that the average welfare weight is $\bar{g}(z) = 1$. We calculate after-tax income $a(z)$ from before tax-income z using the distributional national accounts data from Piketty, Saez, and Zucman (2020).

In our empirical implementation, we consider two cases. First, we consider $\rho = 0$, so all people are weighted equally: $g_i = 1, \forall z$. In this case, W is just total surplus. Second, we consider $\rho = 1$, so $g_i \propto 1/a(z_i)$, which approximately corresponds to log utility. In this case, we refer to W, consumer surplus, and other objects as "weighted." While ρ is a normative parameter with no objectively correct value, Saez (2002), Saez and Piketty (2013), Allcott, Lockwood, and Taubinsky (2019a), and other optimal taxation papers use $\rho = 1$ as a benchmark, and Chetty (2006) shows that this is consistent with observed labor supply behavior in the U.S.

Partial equilibrium assumptions. We impose two additional assumptions that allow us to analyze product and labor markets in partial equilibrium. First, we assume that intermediate goods are produced in perfectly competitive factor markets with no externalities, so we can ignore general equilibrium effects up the supply chain. Second, we assume that each individual firm is a small share of the labor market, so its exit doesn't affect wages at other firms or the outside options of its employees. With these assumptions plus our additively separable quasilinear utility specification in equation (1), we can model product and labor markets separately.

Representative product. We assume that each firm sells one representative product in one market. The representative product has initial price $p_f = 1$ (which will change endogenously in counterfactual scenarios), total cost function $C_f(q_f)$, externality ϕ_f, and internality γ_f. No firm operates in more than one product market in our data.

To estimate corporate social impact, we still need (i) the distribution of utilities u_{ift} and u_{ifl}, (ii) cost functions $C_f(q_f)$, (iii) externalities ϕ_f and internalities γ_f, and (iv) equilibrium assumptions to simulate counterfactual $\boldsymbol{p}$. The next three sections present the data and estimation strategies for those objects.

2 Survey

We estimate firms' corporate social impact in the United States in 2019. We define firms f at the level of the stock ticker (for publicly traded firms) or holding company (for private firms), using 2019 firm ownership.

Our primary data source is a survey that we fielded in July 2021 on Lucid, a standard online survey panel.[4] The survey begins by looping through our 11 differentiated product markets: autos, airline travel, consumer packaged goods (cereal, cigarettes, carbonated soft drinks, beer, yogurt, and toothpaste), grocery retail, chain restaurants, and smartphones.

Using the auto market as an example, the survey questions are as follows.

Consumption: Do you currently own or lease a vehicle?

Yes | No

Brand: What brand is your vehicle?

Acura | Chevrolet | Ford | ...

Customer satisfaction: Overall, how satisfied are you with [Chevrolet]?

0 (not at all satisfied) | ... | 10 (extremely satisfied)

Price response: Imagine that the price of all [Chevrolet] vehicles and all other vehicles made by [General Motors] were **25%** higher. Would you still have chosen a [Chevrolet], or some other vehicle made by [General Motors], even at the higher price?

Yes | No

Aggregate price response: Now imagine that the price of all vehicles doubled. Would you still have a vehicle?

Yes | No

Outside option type: You said you would not have a vehicle if the price of all vehicles doubled. What would you have primarily done instead?

[4] The survey is available from https://mit.co1.qualtrics.com/jfe/form/SV_4OrCsEDx2rnmWMu.

Take fewer trips | Taxis, Uber, Lyft, or other ride hailing services | Public transit | Walk or bike | ...

The questions and response options varied somewhat by industry. In the block of auto market questions, the survey also asked people to report their vehicle's model name (for example, "Honda Civic" or "Ford Excursion") and whether they would still have bought that model if the price were 25 percent higher. For most industries, the *consumption* question was, "How many dollars would you say you spent on [product] in an **average month** before the pandemic?" and the *brand* question was "What kind of [product] did you buy most recently?" The brand list included all major brands in the market. For all industries other than autos and smartphones, *aggregate price response* was phrased more continuously, asking "how much less" people would buy if all prices doubled. The *outside option type* response options varied by market, focusing on separating outside options with different levels of internalities and externalities.

After the product market questions, the survey asked questions about people's "primary employment," including whether they are currently employed more than 20 hours per week, their employer's size and industry, their occupation, and worker satisfaction. The survey then asked an analogue to the *price response* question:

> *Worker price response*: Imagine your primary employer faced major new competition and had to permanently cut everyone's salary by **10%**. Would you keep working there, even at the lower salary?
>
> Yes | No (I'd get a new job or stop working)

To ensure high-quality data, the survey included two attention check questions and re-elicted monthly grocery and cereal spending at the end. We dropped any respondents who (i) failed either attention check, (ii) reported grocery or cereal spending that differed by more than 35 percent, if that difference was more than 10 percent of the average answer, (iii) reported unusually high or low spending in more than two product markets, or (iv) responded with more than 100 characters of text when asked their vehicle's model name. This screening dropped 25 percent of respondents, leaving a total of 1,937 valid respondents. Within these valid responses, we also winsorize spending in each product market at we judged to be reasonable levels.

In all figures and tables, we weight the valid respondents for national representativeness in four household income bins, share male, share white, share age 45 and over, and share with a college degree. To avoid precision loss, we winsorize the weights on $[1/3, 3]$. See Appendix Table A1 for the demographics of the unweighted and weighted samples.

We check and validate the survey responses in three ways. First, we compare firms' market shares and average customer income in the survey data to external sources such as the National

Household Transportation Survey (for autos), the DB1B data (for airlines), and Nielsen (for consumer packaged goods). The firm-level correlations are 0.86 for market shares and 0.94 for income. Second, we show that *price response* is positively correlated with *customer satisfaction*, as expected. See Appendix A for details.

Third, we compare the product demand and labor supply elasticities implied by our survey responses to outside estimates. The automobile model-level price elasticity is -3.68, which is in the range of estimates reported in Berry, Levinsohn, and Pakes (1995), and the aggregate elasticity of auto demand is 0.91, which is close to the value of 1.0 suggested in Berry, Levinsohn, and Pakes (2004). The soda aggregate elasticity (-1.01) lines up well with empirical estimates using market data (Allcott, Lockwood, and Taubinsky 2019b). The cigarette aggregate elasticity (-0.95) is higher than early estimates reported in Chaloupka and Warner (2000) and Gallet and List (2003), but it is consistent with some recent estimates (Cotti et al. 2020; Allcott and Rafkin 2021). The labor supply elasticity (5.7) is higher than estimates in Manning (2011), and Card et al. (2018) say that 4 is a "reasonable near-competitive benchmark." Labor supply may have been unusually elastic given the tight labor market at the time of the survey in summer 2021.

Our survey (and its role in our estimation strategy below) are inspired by the auto market survey in Berry, Levinsohn, and Pakes (2004). Their survey asked people to report the car they would have bought if their current car was not available; the responses are used to identify the distribution of random coefficients. Our approach is comparable, except that our price response question may be more cognitively challenging than their second choice question.

2.1 Other Data

We also collect total 2019 revenues for each firm in the 11 differentiated product markets. Airline revenues are from the U.S. Department of Transportation (2021) DB1B dataset, auto revenues are from data we purchased from Wards, CPG revenues are from NielsenIQ Homescan, restaurant revenues are from Technomic (2021), and smartphone revenues are from Statcounter (2021).

3 Product Markets

In this section, we specify equilibrium assumptions and functional forms for utility in order to estimate counterfactual prices, consumer surplus, profits, and externalities.

3.1 Differentiated Product Markets: Supply and Demand System

Our differentiated product market model and estimation follow the standard approach in the industrial organization literature (e.g. Berry, Levinsohn, and Pakes 1995). We assume that firms in our differentiated product markets set prices to maximize profits Π_f in a static Nash-Bertrand equilibrium with constant marginal costs C'_f.[5] Firm $f's$ first-order condition for the price of its representative product is

$$p_f - C'_f = \frac{q_f}{-\partial q_f(\boldsymbol{p})/\partial p_f}. \tag{10}$$

The demand system is a standard random coefficient logit model. We separate consumers into high and low (approximately above- and below-median) income groups $z \in \{A, B\}$, each with population share μ_z, and we define A_i and B_i as above- and below-median income indicators. To estimate the model, we specialize to the case of additively separable utility:

$$\tilde{u}_{ift} = \left(\underbrace{\xi_f}_{\substack{\text{unobserved}\\\text{characteristic}}} + \underbrace{\gamma_f}_{\text{internality}} + \underbrace{A_i\zeta_f}_{\substack{\text{income-firm}\\\text{effect}}} + \underbrace{\sigma_f\nu_{if}}_{\text{firm RC}} + \underbrace{\sigma_n\nu_{in}}_{\text{inside good RC}} + \underbrace{\epsilon_{ift}}_{\substack{\text{extreme value}\\\text{utility shock}}} \right) / \eta. \tag{11}$$

The income-firm effect ζ_f controls differences in preferences for firm f for above- vs. below-median income consumers. The standard deviation σ_f of firm-specific random coefficients controls elasticity and consumer surplus by firm. The standard deviation σ_n of the inside good random coefficient controls the aggregate price elasticity. We let $\boldsymbol{\nu}_i := \{\nu_{if}, \nu_{in}\}$ denote the vector of random coefficients. We assume that ν_{if} and ν_{in} take independent standard normal distributions. To use the logit model, we assume that the taste shock ϵ_{ift} is distributed type 1 extreme value. η is a scaling factor that maintains ϵ_{ift} at the type 1 extreme value variance ($\pi^2/6$), while maintaining $\tilde{u}_{ift}$ in units of dollars.

As usual in a logit model, we define "representative utility" as the net benefit from a product minus the extreme value utility shock, in units of the extreme value shock, conditional on a realization of random coefficients $\boldsymbol{\nu}_i$. Income group z's representative utility for firm f's product is

$$V_{zf}(p_f, \boldsymbol{\nu}_i) = \eta(-p_f + u_{ift}) - \epsilon_{ift} = -\eta p_f + \xi_f + \gamma_f + A_i\zeta_f + \sigma_f\nu_{if} + \sigma_n\nu_{in}. \tag{12}$$

For the outside good $f = 0$, we set $V_{z0} = 0$.

Income group z's choice probability (over the distribution of $\boldsymbol{\nu}_i$) takes the usual logit form:

$$P_{zf}(\boldsymbol{p}) = \mathbb{E}_{\boldsymbol{\nu}} \left[\frac{e^{V_{zf}(p_f, \boldsymbol{\nu}_i)}}{1 + \sum_{k \in \mathcal{F}_m} e^{V_{zk}(p_k, \boldsymbol{\nu}_i)}} \right], \tag{13}$$

where k also indexes firms. Aggregating across income groups, firm f's choice probability is $P_f(\boldsymbol{p}) = \sum_z \mu_z P_{zf}(\boldsymbol{p})$, and firm f's total quantity sold is $q_f(\boldsymbol{p}) = NT_m P_f(\boldsymbol{p})$.

Using the usual Small and Rosen (1981) log-sum formula, income group z's perceived consumer

[5] This assumes that common ownership does not influence pricing, consistent with the results of Backus, Conlon, and Sinkinson (2021).

surplus in market m is

$$\widetilde{CS}_{zm}(\boldsymbol{p}) := \mathbb{E}_{\boldsymbol{\nu}}\left[\frac{1}{\eta}\ln\left(1+\sum_{f\in\mathcal{F}} e^{V_{zf}(p_f,\boldsymbol{\nu}_i)}\right)\right] + K, \tag{14}$$

where K is a constant. Accounting for internalities using the formula in Allcott (2013), the consumer surplus loss from firm f's exit condition on the set of other firms $\mathcal{F}$ in the market is

$$\Delta CS_f(\mathcal{F}) = N\sum_z \mu_z g(z)\cdot T_m\left[\widetilde{CS}_{zm}(\boldsymbol{p}^{\mathcal{F}\cup f}) - \widetilde{CS}_{zm}(\boldsymbol{p}^{\mathcal{F}}) - \sum_f \gamma_f\left(P_{zf}(\boldsymbol{p}^{\mathcal{F}\cup f}) - P_{zf}(\boldsymbol{p}^{\mathcal{F}})\right)\right]. \tag{15}$$

3.2 Differentiated Product Markets: Estimation Strategy and Counterfactuals

Our estimation strategy for differentiated product markets broadly follows Berry, Levinsohn, and Pakes (2004), except that the price response parameter η is identified using microdata. We use survey data to identify ζ_f, η, σ_f, and σ_n, setting the residuals $\delta_f := \xi_f + \gamma_f$ to match aggregate market shares. We then assume that firms maximize profits in Nash-Bertrand equilibrium and infer each firm's marginal cost from its first-order condition.

The estimation includes all firms in the survey data that had at least 25 respondents as customers. All other firms in the product market are combined into an "other" firm $f = o$, which we assume always has $p_o = C'_o = 1$. We estimate the "other" firm's ζ_{Ao} and δ_o but fix its σ_o to the average σ_f of the non-other firms.

We define s_f as firm f's observed revenue share. In each market, we set the number of choice occasions equal to twice industry revenues, so the outside option share is initially $s_0 = 0.5$.

Define $\boldsymbol{p}^0$ as baseline prices, $\boldsymbol{p}'_f$ as the price vector after firm f increases prices by 25 percent, and $\boldsymbol{p}'$ as the price vector after all prices double. F_{if} is an indicator for whether respondent i bought from firm f. H_{if} is an indicator for whether respondent i bought from firm f and would still buy from f at higher price $\boldsymbol{p}'_f$ (from the *price response* survey question), while $O_i \in [0, 1]$ is the share of inside good consumption that respondent i would maintain if all prices doubled (from the *aggregate price response* question).

We approximate income group z's choice probability $P_{zf}(\boldsymbol{p})$ by simulation over random coefficients. Firm f's overall choice probability is $P_f(\boldsymbol{p}) = \sum_z \mu_z P_{zf}(\boldsymbol{p})$. ω_i is respondent i's nationally representative sample weight. $\chi_{im} \in \{1, 0\}$ is an indicator for whether respondent i consumes an inside good in market m.

We can now specify the moments in our method of simulated moments estimator. The "income-firm moments" primarily identify ζ_f by matching the difference in share of purchases by high- vs.

low-income consumers:

$$g_f^{inc} = \left(\frac{\mu_A P_{Af}(\boldsymbol{p}^0) - \mu_B P_{Bf}(\boldsymbol{p}^0)}{1 - P_0(\boldsymbol{p}^0)} \right) - \left(\frac{\sum_i \omega_i \chi_{im} A_i F_{if} - \sum_i \omega_i \chi_{im} B_i F_{if}}{\sum_i \omega_i \chi_{im}} \right). \tag{16}$$

The "substitution moments" primarily identify the scaling factor η and firm random coefficient standard deviations σ_f by matching the predicted and actual responses to a 25 percent price increase:

$$g_f^{sub} = \frac{P_f(\boldsymbol{p}'_f)}{P_f(\boldsymbol{p}^0)} - \frac{\sum_i \omega_i \chi_{im} H_{if}}{\sum_i \omega_i \chi_{im} F_{if}}. \tag{17}$$

We cannot separately identify η and a σ_f for all firms other than through distributional assumptions. To see this, consider a market with only one firm: both η and σ_f determine that firm's price elasticity. We thus fix $\sigma_f = 0$ for the one firm with the smallest substitution moment in each market.[6]

The "outside moments" primarily identify the inside good standard deviation σ_n by matching predicted and actual substitution to a doubling of all prices:

$$g^{out} = \frac{1 - P_0(\boldsymbol{p}')}{1 - P_0(\boldsymbol{p}^0)} - \frac{\sum_i \omega_i \chi_{im} O_i}{\sum_i \omega_i \chi_{im}}. \tag{18}$$

Our estimation procedure follows Berry, Levinsohn, and Pakes (1995, 2004). These three sets of moments $\{g_{zf}^{inc}, g_f^{sub}, g^{out}\}$ give a system that just identifies the parameters $\{\eta, \zeta_f, \sigma_f, \sigma_n\}$. We use method of simulated moments (MSM) to solve for those parameters. In every iteration of the MSM estimation routine, we use the Berry (1994) contraction mapping to find the values of $\delta_f := \xi_f + \gamma_f$ that match simulated and actual aggregate market shares.

We back out marginal costs C'_f by plugging baseline price vector $\boldsymbol{p}^0 = \boldsymbol{1}$, baseline quantities, and the modeled demand response $\partial q_f \left(\boldsymbol{p}^0\right) / \partial p_f$ into the Nash-Bertrand first-order condition from equation (10).

Once we have the demand system and marginal costs, we can simulate counterfactual Nash-Bertrand equilibrium prices $\boldsymbol{p}^{\mathcal{F}}$ for any configuration of firms $\mathcal{F}$. To find the counterfactual prices, we iterate to a fixed point following Conlon and Gortmaker (2020) and Morrow and Skerlos (2011).

3.3 Differentiated Product Markets: Estimation Results

Appendix Tables A2, A3, and A4 present the full set of moments and parameter estimates for all firms in differentiated product industries in our sample.

[6] In most markets, we estimate $\sigma_f > 0$ for all other firms. In the markets where we estimate $\sigma_f = 0$ for some other firm, we re-run the estimation fixing only that firm's σ_f to zero.

3.4 Oil Market

There are two important differences between oil and our differentiated product markets. First, there is limited product differentiation. Second, in this market it would be especially unrealistic to assume that marginal costs are constant and can be inferred from a static Nash-Bertrand equilibrium.

We thus take a different approach in the oil market. We first simulate the removal of firm f from the global oil market and compute the resulting changes in consumer surplus, profits, and externalities. We then assign 20 percent of those quantities to the U.S.

To model the global oil market, we assume that oil is an undifferentiated product sold at price p, and that all consumers and firms are price takers. Global oil demand is $D(p) = \sum_i \sum_{t \in \mathcal{T}_m} \mathbf{1}\left(u_{it} > p\right)$. Firm f's equilibrium supply $q_f(p)$ is such that $C'_f\left(q_f(p)\right) = p$, and global oil supply with set of firms $\mathcal{F}$ in the market is $S(p; \mathcal{F}) = \sum_{f \in \mathcal{F}} q_f(p)$.

We construct the *inframarginal* portions of the cost functions $C_f(q_f)$ for seven major firms (BP, Chevron, ConocoPhillips, Eni, Exxon, Shell, and Total) using data from Rystad on oil production and operating expenses for all oil fields in the world in 2018, following Asker, Collard-Wexler, and De Loecker (2019).

We define p^0 and q^0 as 2018 price and quantity: \$71 per barrel of Brent crude and 99 million barrels per day. We assume that a competitive fringe of other firms produces the remaining oil. We assume that extramarginal aggregate supply is linear with slope such that the supply elasticity at (p^0, q^0) equals 0.10, the estimate from Caldara, Cavallo, and Iacoviello (2019). We assume that demand $D(p)$ is globally linear with slope such that the elasticity at (p^0, q^0) equals -0.14, the estimate from Caldara, Cavallo, and Iacoviello (2019).

Under those assumptions, we can calculate the market-clearing price $p(\mathcal{F})$ with any set of firms $\mathcal{F}$ in the market:

$$D\left(p(\mathcal{F})\right) = S(p(\mathcal{F}); \mathcal{F}). \tag{19}$$

The consumer surplus loss if firm f exits and leaves remaining firms $\mathcal{F}$ is the trapezoid under the linear demand curve:

$$\Delta CS_f(\mathcal{F}) = \frac{1}{2}\left(D\left(p(\mathcal{F})\right) + D((\mathcal{F} \cup f))\right) \times \left(p(\mathcal{F}) - p(\mathcal{F} \cup f)\right). \tag{20}$$

We calculate each firm's profits by inserting $p(\mathcal{F})$ into equation (3), and we calculate externalities by inserting $q_f(p)$ into equation (4).

The U.S. represents 20 percent of global oil consumption. To make these estimates consistent with the differentiated product industries, which are specific to the U.S., we multiply consumer surplus, profits, and externalities by 0.2. To construct weighted consumer surplus, we allocate consumer surplus to incomes using the distribution of gasoline consumption by income, as implied by vehicle miles traveled and fuel economy in the 2017 National Household Travel Survey. Income is positively associated with gasoline consumption (see Appendix Figure A6), so the welfare weight on consumer surplus is less than one, specifically 0.659.

3.5 Profits

Define $r_i = \{1, 2, ..., 100\}$ as the income percentile of person i, and define z_r as the mean pretax income of taxpayers in percentile r. We assume that profits are distributed such that people at income percentile r receive share $\lambda(r)$ of profits, so

$$\pi_i = \Pi\lambda(r_i). \tag{21}$$

We quantify $\lambda(r)$ using data from Cooper et al. (2016) on the share of total C-corp dividends received by taxpayers at each income percentile.[7] When social marginal welfare weights $g(z)$ are set with curvature $\rho = 1$, the welfare weight applied to corporate profits is then $\sum_{r=1}^{100} g(a(z_r)) \cdot \lambda(r) \approx 0.152$. If $\rho = 0$, meaning that transfers to all income groups receive the same welfare weight, or if corporate profits were distributed equally among all people, this weight would be 1. The weight is much less than 1 because the highest-income people receive most of corporate profits and have low social marginal welfare weights; see Appendix Figure A7.

3.6 Externalities and Internalities

For airlines, autos, and oil, we include climate change externalities valued at a \$51 social cost of carbon, the U.S. government's value for 2021 (Interagency Working Group 2021). For each auto firm, we calculate the lifetime carbon emissions for its average vehicle sold, discounted to the date of sale at three percent per year. For each airline, we calculate the carbon emissions from its average flight.

For cigarettes, we assume the externality is \$0.64 per pack, following DeCicca, Kenkel, and Lovenheim (2021), and the internality is $(1 - \beta) \times H^c = (1 - 0.67) \times \$44.4 = \$14.65$ per pack, where the present focus parameter β is from Chaloupka, Levy, and White (2019) and the health cost of smoking H^c is from Gruber and Koszegi (2001). For soda, we assume that the externality is 0.85 cents per ounce and the internality is 0.93 cents per ounce, following Allcott, Lockwood, and Taubinsky (2019a).

Table 1 presents the resulting average ϕ_f and γ_f by industry per dollar of sales. In most industries, externalities and internalities are relatively small, but the cigarette internality is substantial: \$2.77 per dollar of sales. In all markets, we currently assume that the outside option involves zero internality or externality.

[7] Cooper et al. (2016) only report on the 145 million households that filed 1040 tax forms in 2011, while the Joint Committee on Taxation (2011) estimates that there are 164.4 million tax units including non-filers. We thus shift the data from Cooper et al. (2016) by assuming that non-filing households comprise the bottom $\frac{164.4-145}{164.4} \approx 12\%$ of the income distribution and own no shares.

4 Labor Markets

4.1 Supply and Demand System

In this section, we estimate worker surplus if firm f exits. We leverage a key simplifying assumption introduced in Section 1: each firm is only a small part of the labor market, so its exit doesn't affect other firms' wages. Under that assumption, a firm's contribution to worker surplus is simply the area above its current employees' labor supply function, as illustrated in Figure 1. We estimate that area using the *worker price response* survey question assuming that residual labor supply is globally linear.

Formally, we define w_{i0} and u_{i0} as the wage and utility at worker i's outside option: their next-best employment after current choice fl. To estimate the model, we assume that current workers' surplus from working at fl instead of their outside options (as a percent of current wages) is distributed uniformly with dispersion that depends on observable characteristics $\boldsymbol{x}_{ifl}$:

$$\frac{(u_{ifl} + w_{ifl}) - (u_{i0} + w_{i0})}{w_{ifl}} = \frac{\epsilon_{ifl}}{\boldsymbol{\alpha x}_{ifl}}, \tag{22}$$

with $\epsilon_{ifl} \sim U(0,1)$.

Expected worker surplus (over the distribution of ϵ) is

$$\mathbb{E}_\epsilon \left[WS_{ifl}\right] = \int_0^1 \frac{w_{ifl}\epsilon}{\boldsymbol{\alpha x}_{ifl}} d\epsilon = \frac{w_{ifl}}{2\boldsymbol{\alpha x}_{ifl}}. \tag{23}$$

The change in worker surplus from firm f's exit aggregates equation (23) over all workers in all local labor markets $\mathcal{L}_f$ where firm f has establishments:

$$\Delta WS_f = \sum_{l\in\mathcal{L}_f} \sum_{i\in fl} \frac{w_{ifl}}{2\boldsymbol{\alpha x}_{ifl}}. \tag{24}$$

4.2 Estimation Strategy

We define $L_{ifl}(w)$ as an indicator for whether person i would leave their current employer if salaries were reduced to $w < w_{ift}$:

$$L_{ifl}(w) := \mathbf{1}\left[(u_{ifl} + w) - (u_{i0} + w_{i0}) \le 0\right] \tag{25}$$

$$= \mathbf{1}\left[\epsilon_{ifl} \le (w_{ifl} - w)\,\boldsymbol{\alpha x}_{ifl}/w_{ifl}\right] \tag{26}$$

For the 979 survey respondents who reported being employed and not self-employed, the survey elicited whether they would leave their current employer if the employer had to cut salaries by 10 percent. The response corresponds to $L_{ifl}(0.9 \cdot w_{ifl}) = \mathbf{1}\left[\epsilon_{ifl} \le 0.1\boldsymbol{\alpha x}_{ifl}\right]$. Since $\epsilon_{ifl} \sim U[0,1]$, we can estimate $(0.1\boldsymbol{\alpha})$ in the following linear probability model:

$$\Pr\left[L_{ift}(0.9 \cdot w_{ifl}) = 1\right] = (0.1\boldsymbol{\alpha})\boldsymbol{x}_{ifl}. \tag{27}$$

In our estimates, $\boldsymbol{x}_{ifl}$ includes w_{ifl} (annual earnings from the primary employer), education (a college indicator), occupation (a vector of major occupation indicators), establishment size (the natural log of firm f's total employment in the county), *local market thickness* (the natural log of the number of jobs in i's occupation in local area l), and a constant.

4.3 Estimation Results

Table 2 presents the estimates of $(0.1\boldsymbol{\alpha})$. Column 1 includes only earnings and worker education, column 2 includes a vector of indicators for the major occupation categories defined in the 2010 U.S. census, and column 3 includes establishment size and local labor market thickness. With the full set of covariates in column 3, the coefficients for earnings, service occupations, and establishment size are statistically significantly different from zero. Workers earning \$10,000 more are 3.0 percentage points less likely to leave after a 10 percent wage drop; service workers are 11.6 percentage points more likely to leave than workers in the omitted occupations (management, business, science, or arts); and workers at establishments that are one percent larger are 2.4 percentage points more likely to leave.

To see how we compute worker surplus under our linear labor supply assumption, consider the case where $\boldsymbol{x}_{ifl}$ includes just a constant. About 45 percent of workers would leave their current firm after a 10 percent salary reduction, so if $\boldsymbol{x}_{ifl}$ is a constant, $(0.1\boldsymbol{\alpha}) \approx 0.45$, so $\boldsymbol{\alpha} \approx 4.5$. The average annual earnings in the survey are $\$60,000$, so using equation (23), the expected worker surplus per worker is $\mathbb{E}_{\epsilon}\left[WS_{ifl}\right] \approx \frac{\$60{,}000}{2\times(4.5)\times 1} \approx \$6,667$.

We use these parameter estimates to predict the distribution of worker surplus for all workers at firm f. We use data from InfoUSA to determine the county and employee count for all establishments at each firm in our data. To account for the fact that our product market analyses cover only part of a firm's operations—for example, Apple sells more than just smartphones—we scale down each firm's employee counts by the ratio of its revenue in that product market to its total revenues.[8]

To estimate the distribution of covariates $\boldsymbol{x}_{ifl}$ for workers at an establishment, we assume that the proportion of employees in each occupation category is the same for every firm in a given industry, where these proportions are estimated from the 2010–2019 American Community Surveys

[8]Specifically, we pull each firm's official total U.S. employees and revenues from Compustat, and we denote these as N_f^* and R_f^*, respectively. The firm's U.S. revenue per worker ratio is thus R_f^*/N_f^*. We then denote our product market revenues as R_p and total InfoUSA workers as N_f^{IU}, which may differ from N_f^* due to measurement error. We then re-scale the official total U.S. employees N_f^* to match the revenue per worker ratio R_f^*/N_f^*, so the number of U.S. employees that correspond to the product market we study is assumed to be $N_f^p = N_f^* \cdot \frac{R_f^p}{R_f^*}$. We then implement this adjustment by multiplying all InfoUSA establishment counts by the ratio N_f^p/N_f^{IU}.

(ACS). Using the ACS data, we estimate the local labor market thickness of each occupation in the establishment's county, and we simulate the earnings and education of workers from the national distribution of workers in the occupation. We use equation (23) to compute the worker surplus for the covariates of each simulated worker, and we use equation (24) to aggregate to firm f's total worker surplus. We assume that no person would work for zero pay, so we drop a small share of workers with predicted $\hat{\boldsymbol{\alpha}}\boldsymbol{x}_{ifl} < 1$.

Our covariates predict little heterogeneity across firms in surplus per worker. Thus, a firm's worker surplus in our model is largely determined by its worker count; see Appendix Figure A8.

5 Corporate Social Impact Estimates

5.1 Model-Free Survey Results

Figure 2 presents the aggregate price elasticity of demand for each differentiated product industry in the survey, calculated as (-1)×ln(share who would still buy if the price of all products doubled) / ln(2). Industries toward the left will tend to have larger differences between individual impact and share of industry impact. Toothpaste, groceries, and smartphones have the most inelastic demand, restaurants and especially airlines have the most elastic demand, and all other industries are clustered around an aggregate elasticity of 1.

Figure 3 presents model-free results from the survey that are key to determining each firm's social impact. Each point on the scatterplot is a firm, and each industry has a different marker style. The x-axis has the average income of the firm's consumers. Firms toward the left will generate more welfare-weighted consumer surplus, and thus more weighted corporate social impact, because their consumers have lower income and thus higher social marginal welfare weights. The y-axis has the firm's own-price elasticity, calculated as (-1)×ln(share of consumers who would still buy from the firm after a 25 percent price increase) / ln(1.25). Firms toward the bottom will generate more consumer surplus, and thus more social impact, because consumers can't easily substitute away from their products.

The firms with the highest customer income at the right of the figure include Alaska Airlines and JetBlue, Amazon groceries (Whole Foods and Amazon Fresh), and Chobani yogurt. The firms with the lowest customer income at the left of the figure are LG smartphones, Kia cars, Lorillard cigarettes, Walmart groceries, and Yoplait yogurt. The firms with most elastic demand are Hyundai, Mazda, and Spirit Airlines. There are no major outliers with especially inelastic demand.

The figure also labels all auto companies. Customers of BMW and Volkswagen have the highest average incomes, while customers of Kia have the lowest incomes. BMW and Volkswagen also have the most price-inelastic demand, while Hyundai, Mazda, and Nissan have the most elastic demand. The largest auto firms in the U.S. (GM, Ford, Honda, Toyota, and Fiat Chrysler) are clustered at average customer incomes around $75,000 and own-price elasticities around 3.

5.2 Corporate Social Impact Estimates

Appendix Table A5 presents the components of corporate social impact for all firms in our sample. As an illustration, Figure 4 presents results for all automobile and cigarette companies. This figure considers individual impact, not share of industry impact. Within each firm, the left bar presents estimates with equal social marginal welfare weights at all incomes ($\rho = 0$), while the right bar presents weighted estimates with curvature $\rho = 1$.

Focusing on the auto industry results in Panel (a), there are four results to highlight. First, the largest firms (Fiat Chrysler, Ford, GM, Honda, and Toyota) have the most social impact. For example, our estimates imply that if GM were to exit, total surplus would decrease by about $33 billion per year. Second, firms impose significant pecuniary externalities on their competitors. For example, our Nash-Bertrand pricing assumptions and demand system estimates imply that GM earns $25 billion per year in variable profits, but its exit would increase competitors' profits by $18 billion per year.

Third, in the unweighted estimates, the firms with the most inelastic demand from Figure 3, BMW and Volkswagen, also naturally have the highest ratios of consumer surplus to profits. Fourth, the firms that sell to the highest-income consumers, again BMW and Volkswagen, naturally have their consumer surplus decrease the most in the weighted estimates. By contrast, the firms that sell to lower-income consumers, especially Kia, have their consumer surplus increase with the weighting.

The cigarette results in Panel (b) are different for one key reason: the $2.77 internality per dollar of revenue, as described in Section 3.6. While cigarettes deliver positive perceived consumer surplus, the actual internality-adjusted consumer surplus is negative in our model, and cigarette companies have negative social impact.

Figure 5 plots welfare-weighted individual impact against revenue for all firms in our sample excluding cigarette companies, using a log scale to accommodate the diversity of firm sizes. The R^2 of this relationship is 0.88. This strong correlation implies a simple takeaway: the firms that generate more social impact are simply those that sell more products and employ more workers. Some of this high correlation may be due to limitations in our ability to quantify all channels of social impact, but it's natural to think that some strong correlation would remain even with a more extensive quantification.

For the remaining results, we focus on the *ratio* of corporate social impact to revenues. Figure 6 presents the ratio of weighted individual impact against the own-price elasticity from the survey data, for all differentiated product firms excluding cigarette companies. There are two results to highlight. First, there is meaningful variation in impact / revenue even after excluding cigarettes, ranging from about 0.1 to 1.0. Second, much of this variation in weighted individual impact is explained by the own-price elasticity computed directly from the survey data. (The remaining variation is largely explained by the share of consumers who are below-median income.)

Figure 7 presents the components of social impact for the average firm in each industry in our sample. Within each industry, the first and second bars present unweighted and weighted individual impacts, while the third bar presents the share of unweighted industry impact calculated using Shapley values, using equation (8). There are several results to highlight.

First, consumer surplus is by far the most important component of corporate social impact. Profits shrink markedly in the weighted estimates, as they are multiplied by a welfare weight of 0.152 calculated in Section 3.5. Worker surplus is small because the survey responses imply especially elastic labor supply; firms' labor supply would have to be much more inelastic for worker surplus to be a large share of social impact. Externalities are only a small share of impact at the standard parameter values described in Section 3.6, even in the Shapley value results.

Second, even though we assume that oil is an undifferentiated product, oil companies generate large consumer surplus in our model by keeping prices low. Because supply and demand are so inelastic, when any oil company exits, the price rises substantially, generating a large transfer from consumers to the remaining firms as well as a moderate reduction in externalities. Third, the industries with larger ratios of unweighted individual firm impacts to unweighted Shapley values are those with higher ratios of aggregate demand elasticity to average own-price elasticity, including autos, airlines, and expecially groceries, smartphones, and toothpaste.

Figure 8 compares our weighted individual impact metric per dollar of revenues to two major rating systems: CSRHub and Just Capital. The figure shows that these existing ratings have little relationship to our economically grounded measure of corporate social impact. Part of this is presumably because of limitations in our ability to quantify all channels of social impact and because existing ratings may intend to measure slightly different concepts. However, this lack of correlation also suggests that our approach may offer additional conceptual contributions. In particular, since much of the variation in our ratings is driven by our survey estimates of consumers' willingness to substitute to other firms, this suggests that existing rating systems may not fully account for the large contribution of consumer surplus to social impact.

The cigarette companies at the left of this figure are particularly striking examples. While the internality assumptions described in Section 3.6 are very uncertain, in our model these assumptions imply that cigarette companies reduce social welfare by billions of dollars each year. Rating systems that deprioritize consumer surplus could easily generate very different scores for cigarette companies.

6 Conclusion

The growing discussions of impact investing and stakeholder capitalism have generated interest in measuring companies' social impact, not just their profits. In this paper, we have laid out an economically grounded definition of corporate social impact and have quantified the social impact of 73 large companies in 12 industries across the U.S. economy. As we have described throughout the paper, there are many caveats and limitations related to the welfarist moral philosophy, our static partial equilibrium assumptions, and our empirical implementation. These limitations mean that there may be important factors of social impact that we have not measured and incorporated. Despite the many limitations, we hope that our work can be a useful step forward in developing an economic framework to measure corporate social impact.

Perhaps the key result from our analysis is that consumer surplus is the primary driver of corporate social impact. This highlights the importance of accurately measuring consumer surplus when trying to quantify a firm's social impact. This result also connects to the long discussion, dating at least to Friedman (1970), of what firms should try to maximize. Our estimates suggest that the key to social impact is to do what many firms are already trying to do as they maximize profits: make more differentiated products that more consumers want to buy.

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Table 1: **Average Externality and Internality per Dollar of Sales by Product Market**

Industry	(1) Externality (/$ sales)	(2) Internality (/$ sales)
Airline	$0.06	–
Auto	$0.03	–
Cigarette	$0.12	$2.77
Oil	$0.34	–
Soda	$0.19	$0.21

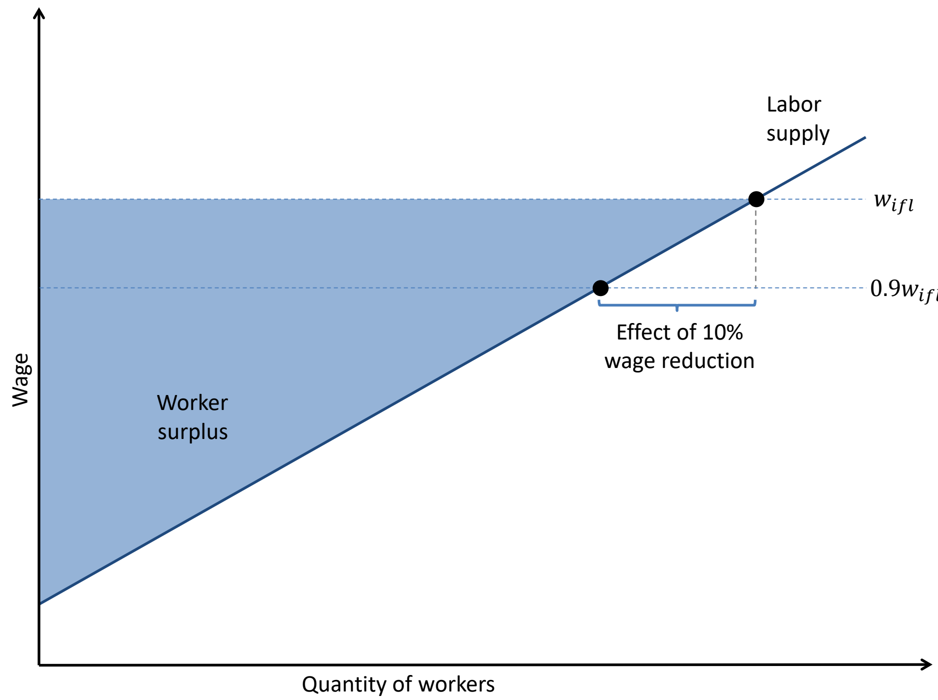
Notes: This table presents the averages across firms of externalities and internalities per dollar of sales, by industry. We assume that all other product markets have zero externalities and internalities.

Table 2: **Predictors of Worker Response to a 10 Percent Salary Reduction**

	(1)	(2)	(3)
Earnings ($10,000)	-0.030^{***}	-0.028^{***}	-0.030^{***}
	(0.004)	(0.004)	(0.004)
Bachelor's degree	−0.028	−0.037	−0.044
	(0.034)	(0.035)	(0.035)
Occupation: service		0.113^{**}	0.116^{**}
		(0.055)	(0.055)
Occupation: sales and office		0.042	0.051
		(0.038)	(0.038)
Occupation: natural resources, construction, maintenance		-0.121^{*}	−0.088
		(0.062)	(0.064)
Occupation: production, transportation, material moving		−0.001	0.005
		(0.059)	(0.061)
ln(employees)			0.024^{***}
			(0.007)
ln(local labor demand)			0.007
			(0.008)
Observations	979	979	979
R^2	0.080	0.090	0.101

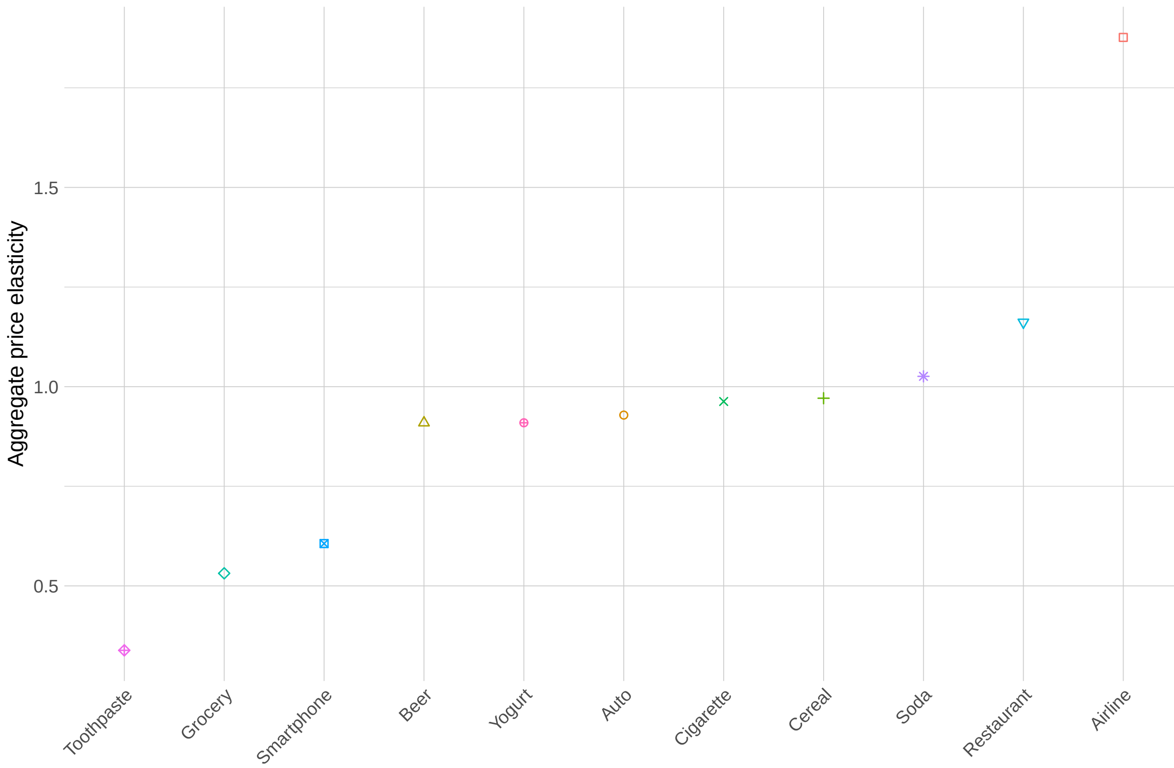
Notes: This table provides estimates of equation (27), a regression of *worker price response* (whether respondents would leave their job if their primary employer had to permanently cut salaries by 10 percent) on individual, employer, and labor market covariates. The omitted occupation category is management, business, science, and arts. *Employees* is the employer's number of employees in the county. *Local labor demand* is the number of workers in the 2010–2019 American Community Surveys (ACS) who worked in the same county and occupation. Standard errors are in parentheses. *, **, ***: statistically significant with 10%, 5%, and 1% confidence, respectively.

Figure 1: **Illustration of Worker Surplus Calculation**



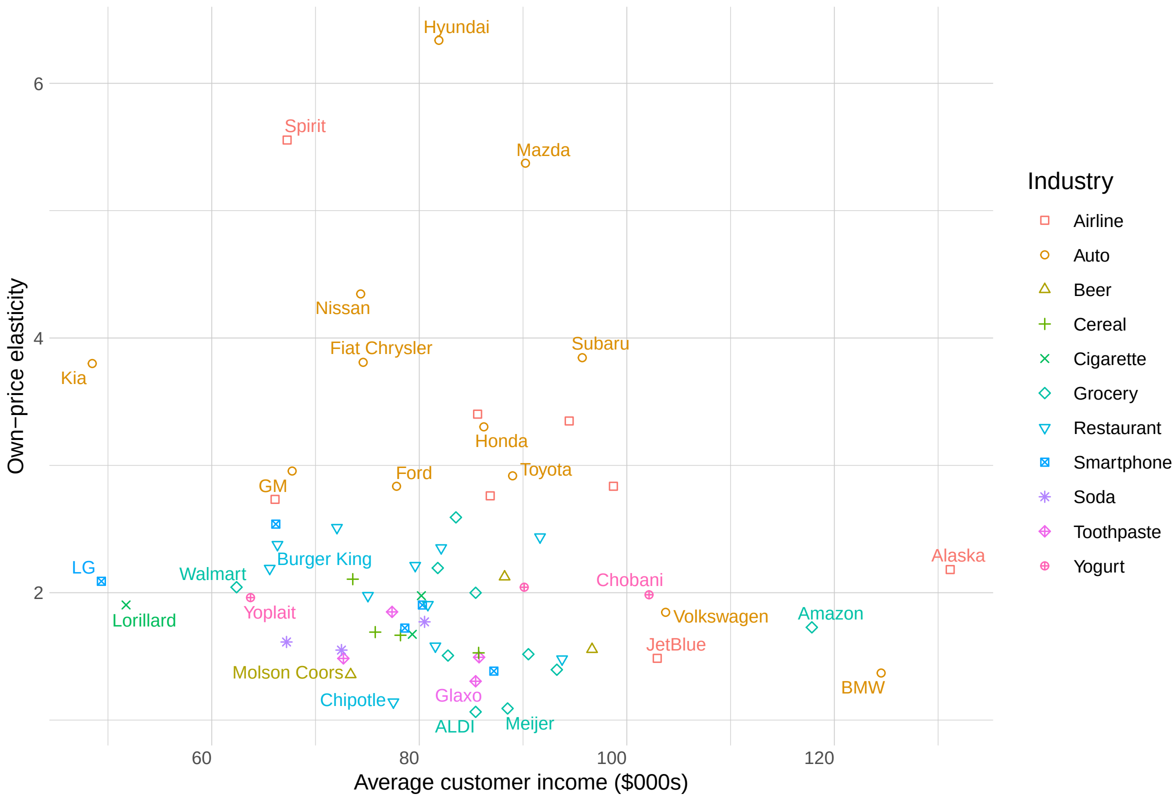
Notes: This figure illustrates our strategy for estimating a firm's contribution to worker surplus. Since we assume that each firm is a "small" share of the labor market, a firm's worker surplus is the area above its current employees' labor supply function. We estimate that area using the *worker price response* survey question assuming that residual labor supply is linear.

Figure 2: **Aggregate Price Elasticity by Industry**



Notes: This figure presents the aggregate price elasticity for each of the differentiated product industries in our sample. Aggregate price elasticity is calculated from responses to the *aggregate price response* survey question: (-1)×ln(share who would still buy if the price of all products doubled) / ln(2).

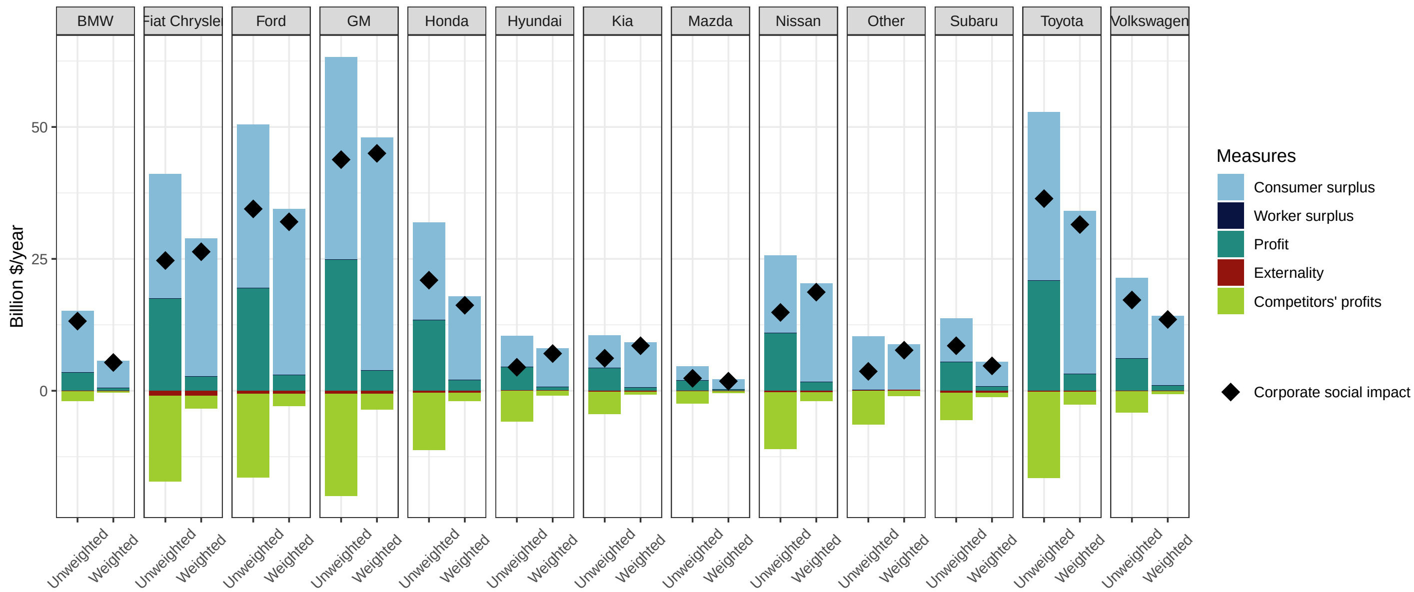
Figure 3: **Average Customer Income and Price Response by Firm**



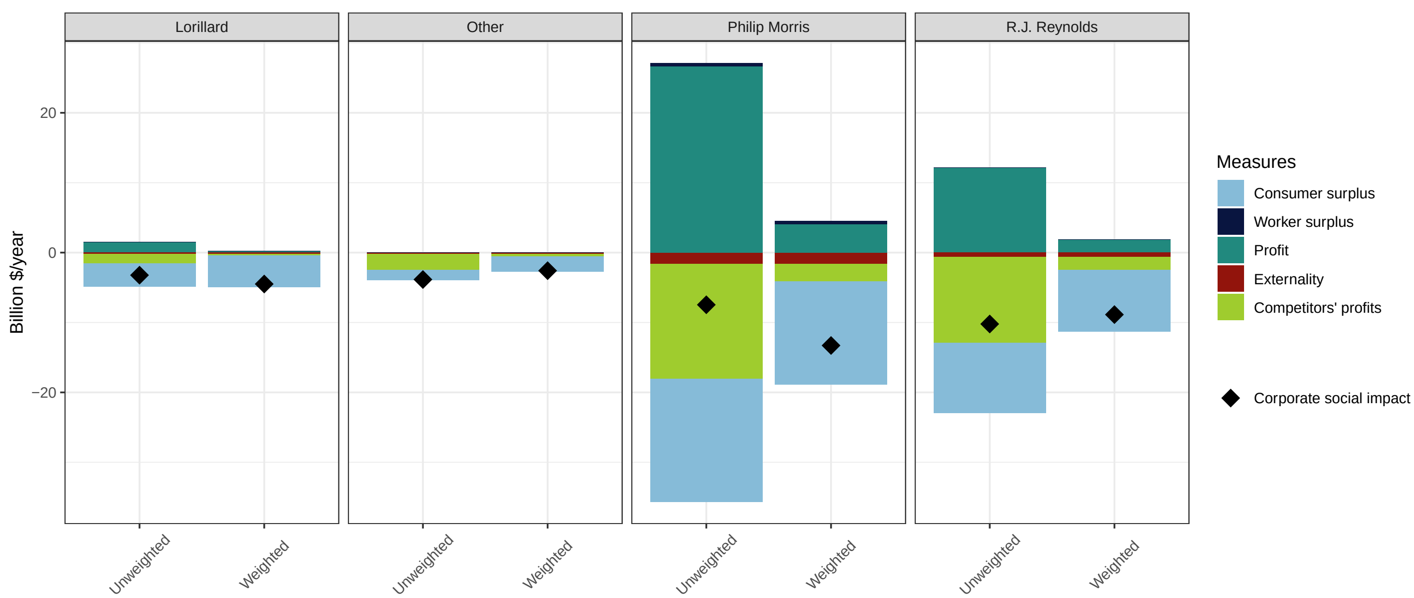
Notes: This figure presents average customer income against own-price elasticity for each firm in the differentiated product industries in our sample. Own-price elasticity is calculated from responses to the *price response* survey question: (-1)×ln(share who would still buy from the firm after a 25 percent price increase) / ln(1.25).

Figure 4: **Components of Social Impact by Firm**

(a) **Automobile Industry**

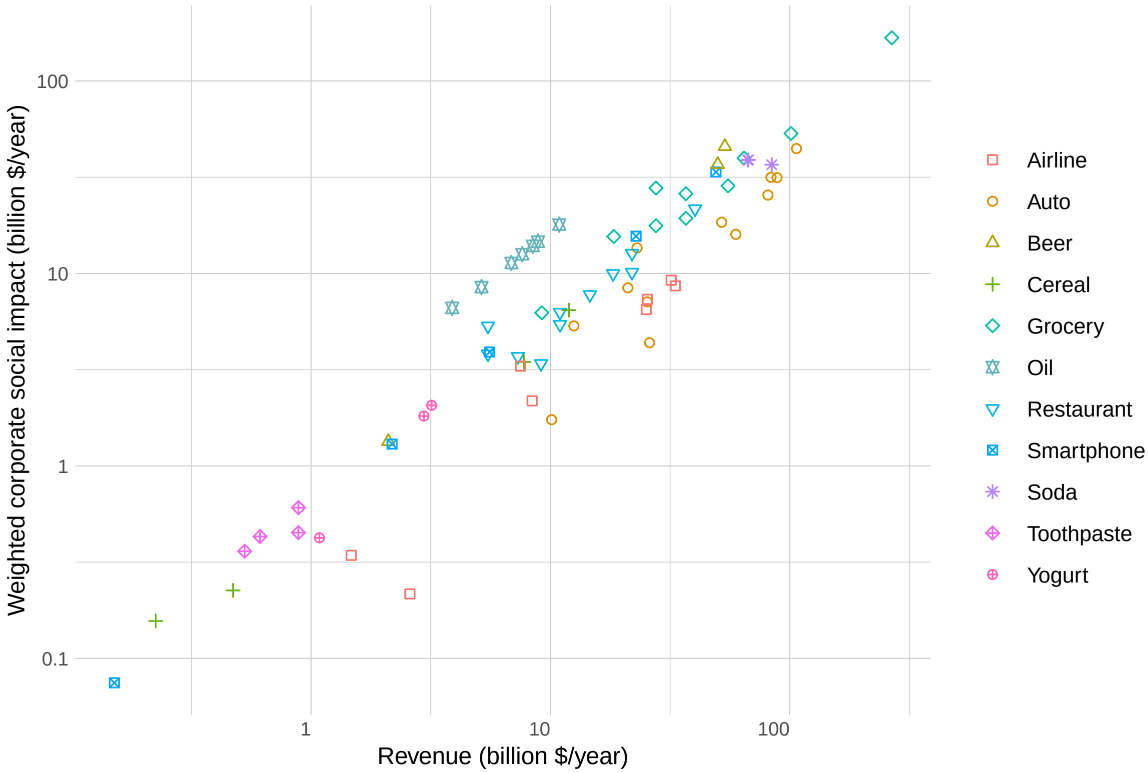


(b) **Cigarette Industry**



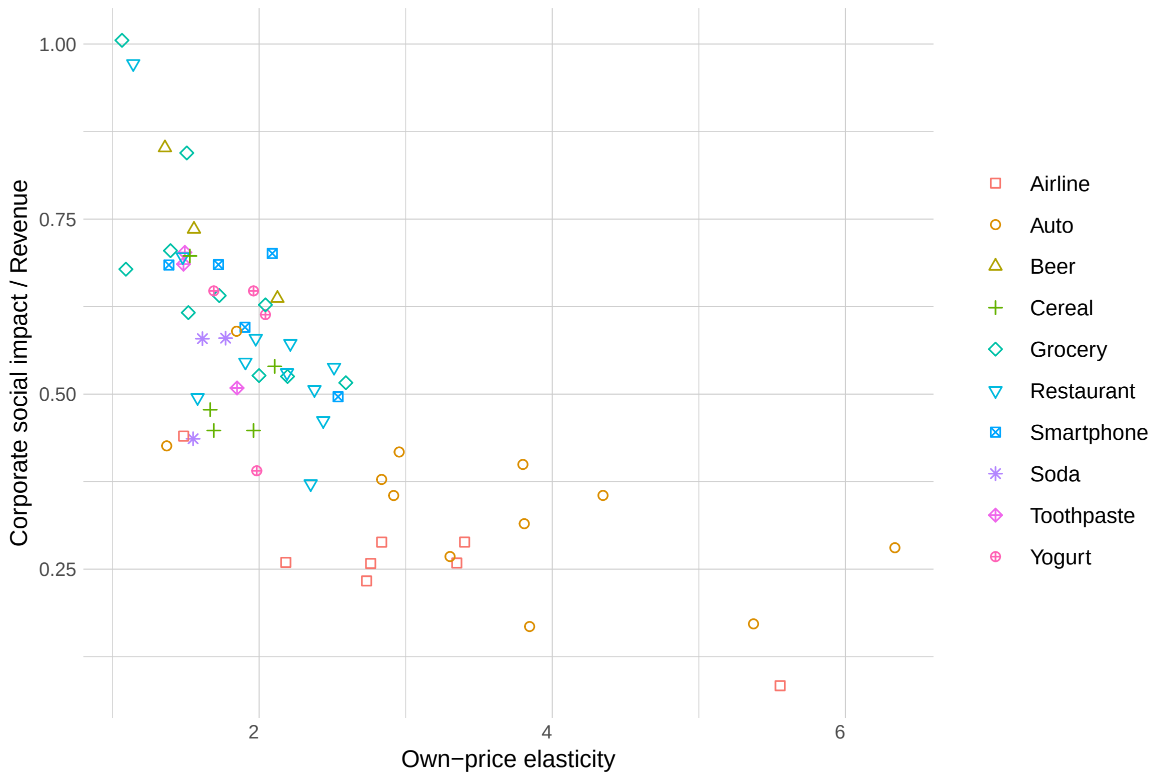
Notes: Panels (a) and (b) present the components of individual impact by firm in the automobile and cigarette industries. The first bar in each pair presents the firm's individual impact with equal social marginal welfare weights across income groups ($\rho = 0$). The second bar presents the firm's individual impact with a curvature of $\rho = 1$ on social marginal welfare weights, which approximately corresponds to log utility.

Figure 5: **Weighted Corporate Social Impact versus Revenue**



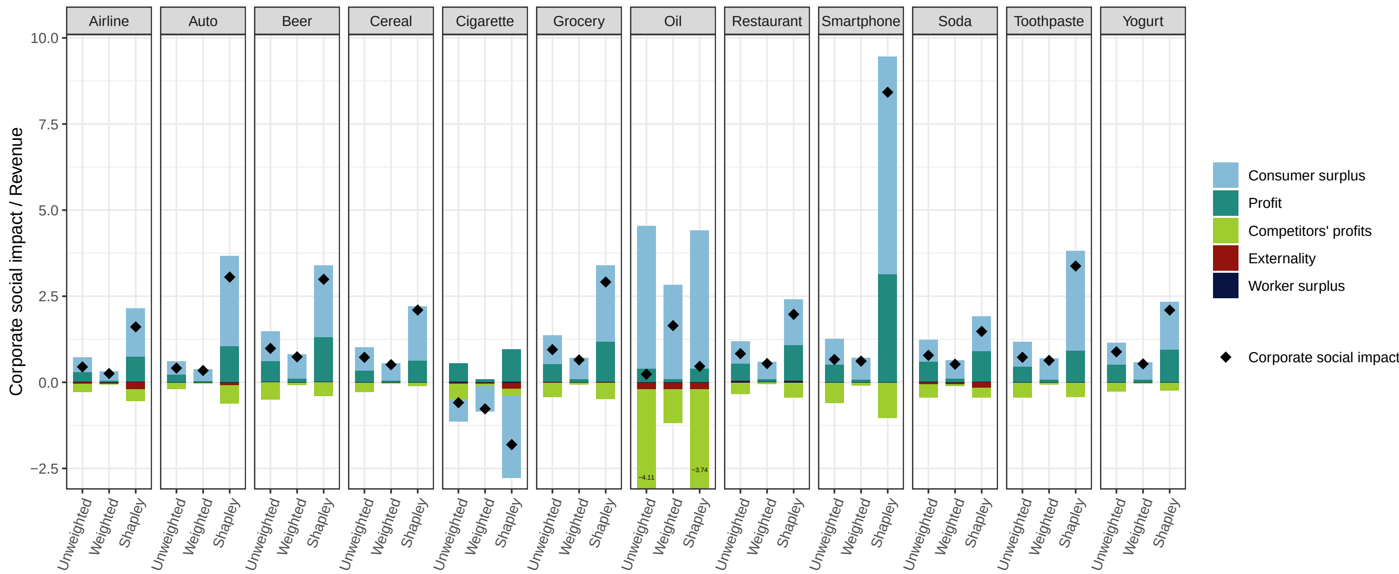
Notes: This figure presents weighted individual impact against revenue for each firm in our sample. This figure excludes cigarette companies, which are estimated to have negative social impact.

Figure 6: **Weighted Corporate Social Impact per Dollar of Revenue versus Own-Price Elasticity**



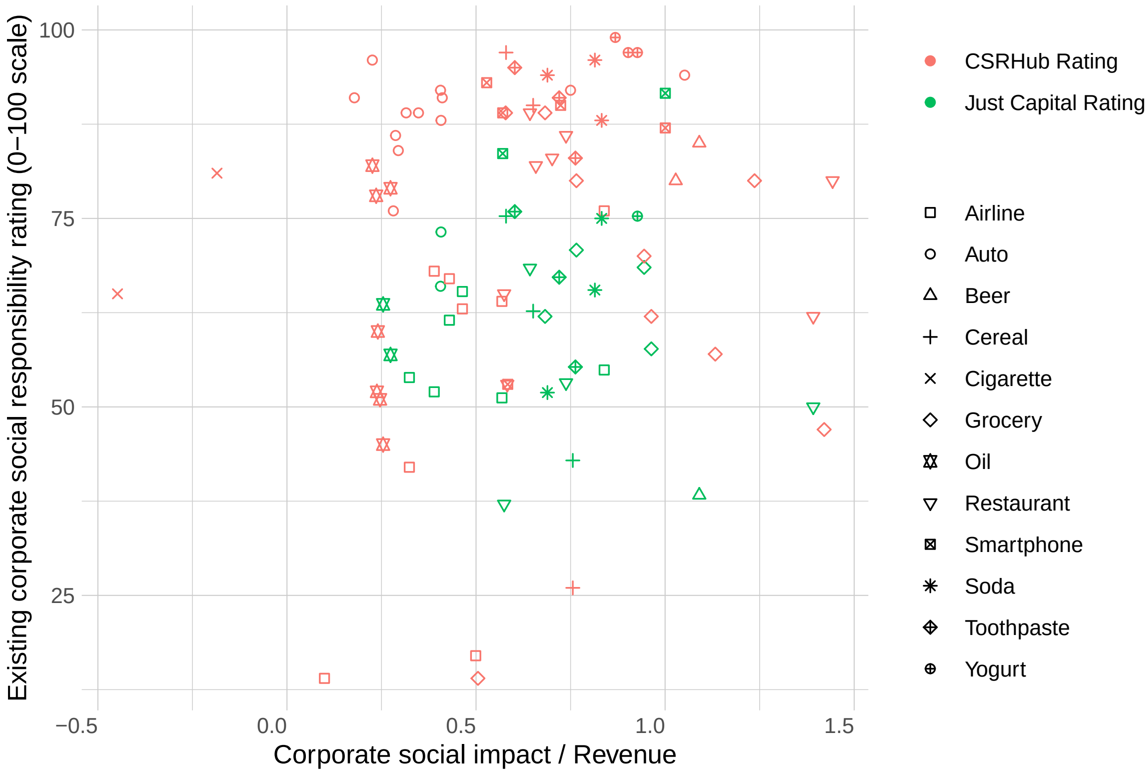
Notes: This figure presents weighted individual impact per dollar of revenue against own-price elasticity for each firm in the differentiated product industries in our sample. Own-price elasticity is calculated from responses to the *price response* survey question: (-1)×ln(share who would still buy from the firm after a 25 percent price increase) / ln(1.25). This figure excludes cigarette companies, which are estimated to have negative social impact.

Figure 7: **Average Corporate Social Impact per Dollar of Revenue by Industry**



Notes: This figure presents the components of corporate social impact for the (unweighted) average firm in each industry. The first bar in each group presents the average firm's individual impact with equal social marginal welfare weights across income groups ($\rho = 0$). The second bar presents the average firm's individual impact with a curvature of $\rho = 1$ on social marginal welfare weights, which approximately corresponds to log utility. The third bar presents the average firm's share of industry impact (the Shapley value for the social welfare loss if all firms in the industry exited the market), with equal social marginal welfare weights ($\rho = 0$).

Figure 8: **Corporate Social Impact versus Prior Metrics**



Notes: This figure presents our estimate of individual impact per dollar of revenues against existing ratings from CSRHub (https://www.csrhub.com/csrhub/) and Just Capital (https://justcapital.com/rankings/), for all firms in our sample for which data are available.

Online Appendix

An Economic View of Corporate Social Impact

Hunt Allcott, Giovanni Montanari, and Brandon Tan

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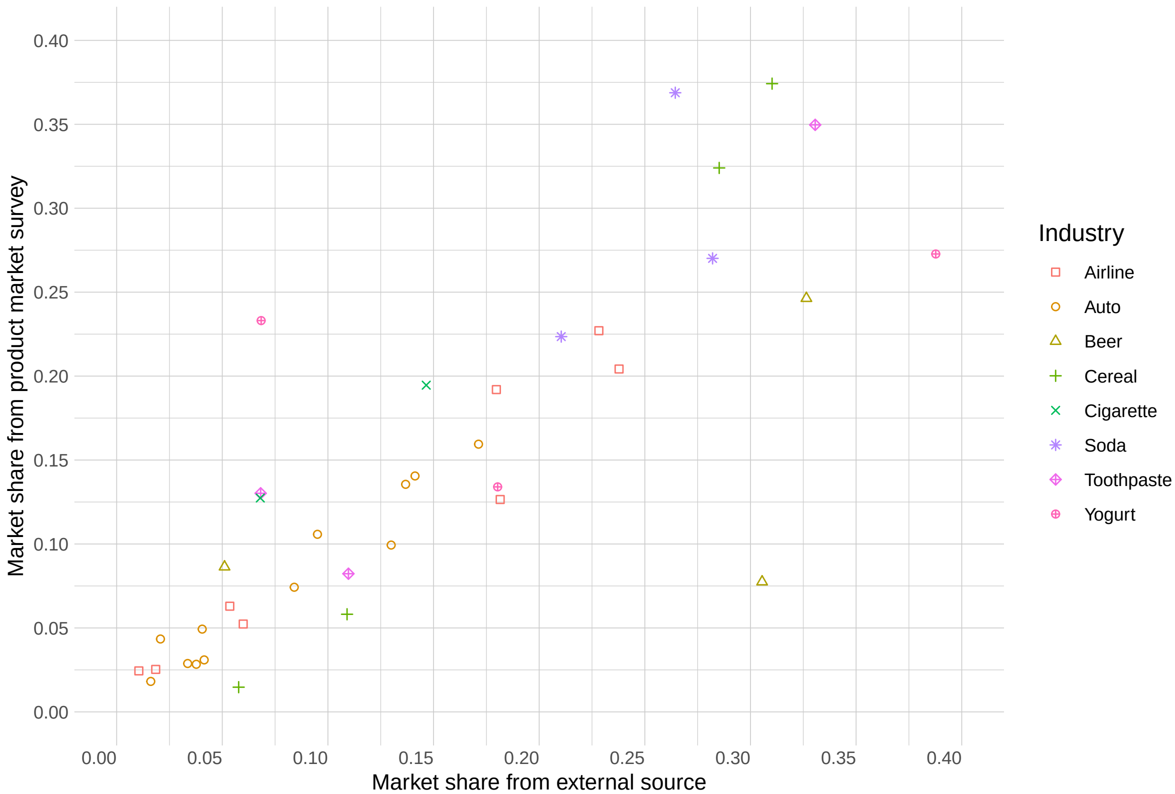
A Survey Appendix

Table A1: **Demographics in Weighted Sample**

	(1) Unweighted sample	(2) Weighted sample	(3) U.S. adults
Male	0.47	0.49	0.49
White	0.79	0.73	0.72
College	0.51	0.43	0.42
Age over 45	0.58	0.54	0.54
Income 0 to $39,999	0.44	0.31	0.31
Income $40,000 to $59,999	0.16	0.16	0.15
Income $60,000 to $99,999	0.25	0.23	0.23
Income $100,000 or more	0.15	0.30	0.31

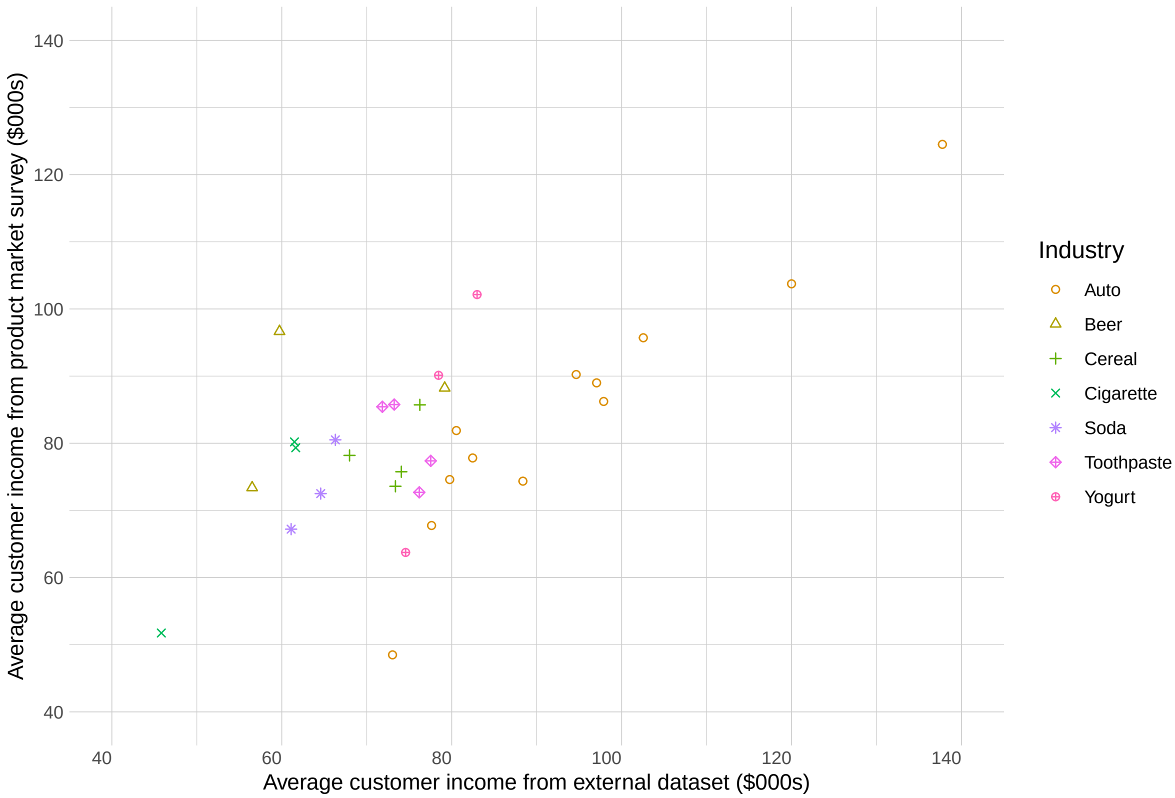
Notes: Column 1 presents mean demographics from our survey respondents, column 2 presents the weighted mean demographics from our survey respondents, and column 3 presents average demographics of American adults using data from the 2019 American Community Survey. The sample weights are initially calculated to weight the survey respondents to be nationally representative and then winsorized at $[1/3, 3]$ to reduce precision loss.

Figure A1: **Survey vs. External Market Shares**



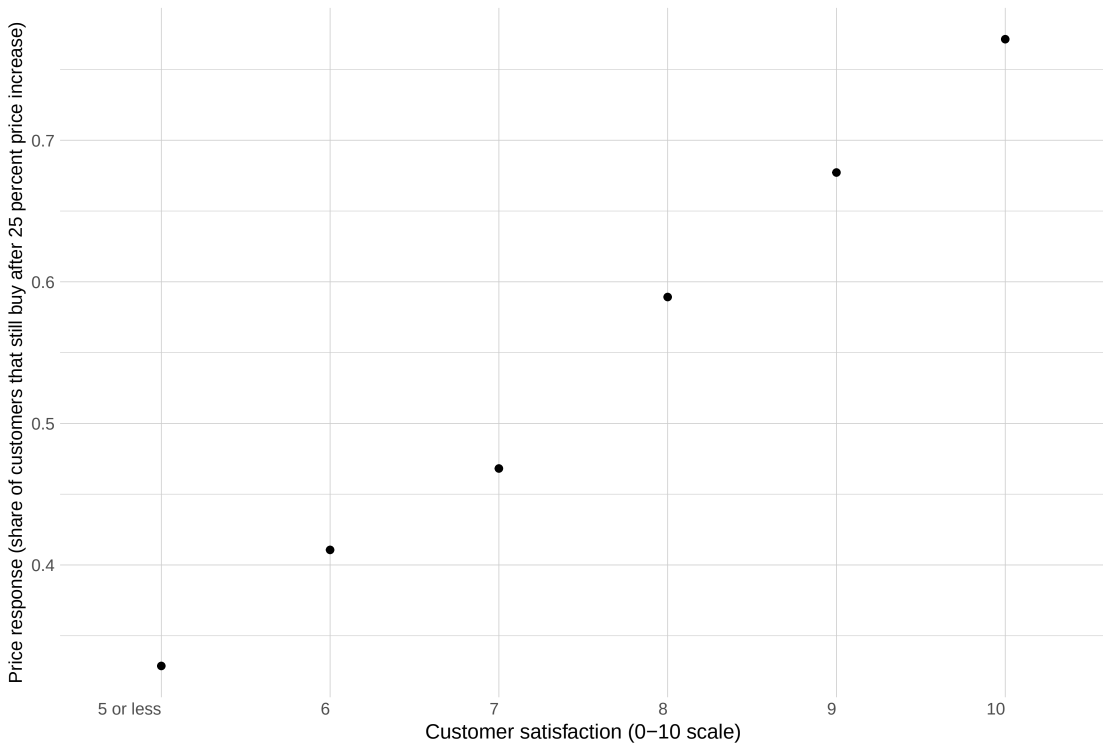
Notes: This figure presents market share from our survey against market share from an external source for firms in eight differentiated product industries in our sample. The external sources are the DB1B dataset (for airlines), Wards (for autos), and NielsenIQ (for beer, cereal, cigarettes, soda, toothpaste, and yogurt).

Figure A2: **Survey vs. External Customer Income**



Notes: This figure presents average customer income from our survey against average income from an external source for firms in eight differentiated product industries in our sample. The external sources are the DB1B dataset (for airlines), Wards (for autos), and NielsenIQ (for beer, cereal, cigarettes, soda, toothpaste, and yogurt).

Figure A3: **Customer Satisfaction and Price Response**



Notes: This figure presents the average *price response* (the share of customers that still buy from the same firm after a 25 percent price increase) for each value of *customer satisfaction*, using all responses in our survey.

B Product Market Appendix

B.1 Parameter Estimates and Counterfactual Prices

Table A2: **Product Market Moments by Firm**

Industry	Firm	(1) Market share	(2) Share of purchases by below-median income consumers	(3) Share of purchases retained after 25% price increase	(4) Own-price elasticity
Airline	Alaska	0.03	0.09	0.61	2.18
	Allegiant	0.01	0.42	0.54	2.73
	American	0.12	0.22	0.47	3.35
	Delta	0.12	0.22	0.53	2.84
	JetBlue	0.03	0.19	0.72	1.48
	Southwest	0.09	0.29	0.54	2.76
	Spirit	0.01	0.43	0.29	5.55
	United	0.09	0.34	0.47	3.4
Auto	BMW	0.01	0.15	0.74	1.37
	Fiat Chrysler	0.07	0.37	0.43	3.81
	Ford	0.07	0.38	0.53	2.84
	GM	0.09	0.45	0.52	2.96
	Honda	0.05	0.33	0.48	3.3
	Hyundai	0.02	0.35	0.24	6.34
	Kia	0.02	0.49	0.43	3.8
	Mazda	0.01	0.24	0.3	5.37
	Nissan	0.04	0.36	0.38	4.35
	Subaru	0.02	0.29	0.42	3.85
	Toyota	0.07	0.3	0.52	2.92
	Volkswagen	0.02	0.19	0.66	1.85
	Other	0.02	0.39		
Beer	Anheuser-Busch	0.22	0.3	0.71	1.56
	Molson Coors	0.23	0.4	0.74	1.36
	Sazerac	0.01	0.24	0.62	2.12
	Other	0.04	0.28		
Cereal	General Mills	0.18	0.39	0.69	1.69
	Kellogg	0.28	0.42	0.62	2.11
	Post	0.01	0.36	0.69	1.67
	Quaker	0.01	0.33	0.71	1.53
	Other	0.02	0.38		
Cigarette	Lorillard	0.02	0.58	0.65	1.9
	Philip Morris	0.3	0.42	0.64	1.98
	R.J. Reynolds	0.15	0.44	0.69	1.67
	Other	0.03	0.71		
Grocery	ALDI	0.02	0.37	0.79	1.06
	Ahold	0.02	0.34	0.61	2.19
	Albertsons	0.03	0.32	0.56	2.59
	Amazon	0.02	0.2	0.68	1.73
	Costco	0.04	0.24	0.71	1.52
	Kroger	0.06	0.32	0.64	2
	Meijer	0.01	0.24	0.78	1.09
	Publix	0.02	0.36	0.73	1.4
	Wakefern	0.01	0.34	0.71	1.51
	Walmart	0.17	0.49	0.63	2.04
	Other	0.09	0.41		
Smartphone	Apple	0.31	0.28	0.73	1.38
	Google	0.01	0.46	0.65	1.9
	LG	0.03	0.63	0.63	2.09
	Lenovo	0	0.47	0.57	2.54
	Samsung	0.14	0.38	0.68	1.72
	Other	0	0.67		
Restaurant	Burger King	0.04	0.48	0.61	2.19
	Chick-fil-A	0.03	0.34	0.7	1.58
	Chipotle	0.02	0.28	0.78	1.14
	Domino's	0.02	0.49	0.59	2.38
	Inspire Brands	0.05	0.4	0.65	1.91
	JAB	0.02	0.21	0.72	1.48
	McDonald's	0.12	0.45	0.57	2.51
	Starbucks	0.06	0.26	0.58	2.44
	Subway	0.03	0.4	0.61	2.21
	Wendy's	0.03	0.29	0.59	2.35
	Yum! Brands	0.06	0.42	0.64	1.98
	Other	0.01	0.33		
Soda	Coca-Cola	0.14	0.39	0.67	1.77
	Dr Pepper 7 Up	0.18	0.38	0.71	1.55
	Pepsi	0.15	0.45	0.7	1.61
	Other	0.03	0.49		
Toothpaste	Church & Dwight	0.1	0.35	0.72	1.49
	Colgate	0.15	0.41	0.72	1.48
	Glaxo	0.09	0.34	0.75	1.3
	Procter & Gamble	0.15	0.37	0.66	1.85
	Other	0.01	0.42		
Yogurt	Chobani	0.05	0.22	0.64	1.98
	Danone	0.14	0.32	0.63	2.04
	General Mills	0.15	0.45	0.65	1.96
	Other	0.16	0.4		

Notes: This table presents the key moments used for demand estimation for each firm in the differentiated product industries in our sample. Own-price elasticity is calculated from responses to the *price response* survey question: (-1)×ln(share who would still buy from the firm after a 25 percent price increase) / ln(1.25).

Table A3: **Product Market Parameter Estimates by Firm**

Industry	Firm	(1) δ ($:= \xi + \gamma$)	(2) ζ	(3) σ
Airline	Alaska	10.26	5.07	-10.05
	Allegiant	10.45	5.61	-14.91
	American	6.88	1.31	-0.73
	Delta	7.16	2.11	-1.37
	JetBlue	10.78	7.91	-15.86
	Southwest	7.13	2.4	-2.07
	Spirit	6.24	0	-2.47
	United	5.79	0	0.09
Auto	BMW	25.72	15.51	-48.77
	Fiat Chrysler	-0.29	2.44	2.26
	Ford	0.41	3.58	0.59
	GM	-0.34	3.47	1.54
	Honda	1.3	3.47	-0.61
	Hyundai	-0.97	0	2.02
	Kia	-3.14	3.28	-0.82
	Mazda	1.74	2.45	-2.55
	Nissan	-0.73	2.34	1.14
	Subaru	3.75	2.99	-3.42
	Toyota	0.75	3.79	0.68
	Volkswagen	6.12	9.33	-15.82
	Other	0.82	4.39	-2.63
Beer	Anheuser-Busch	32.71	0.31	0.1
	Molson Coors	46.92	0	0.36
	Sazerac	2.13	0.05	-47.4
	Other	1.68	0.88	-31.67
Cereal	General Mills	5.6	3.15	-0.45
	Kellogg	4.72	0	1.61
	Post	10.22	8.31	-19.7
	Quaker	3.12	12.6	-24.91
	Other	29.07	6.01	-31.76
Cigarette	Lorillard	-1.43	2.45	-2.68
	Philip Morris	0.55	0	1.44
	R.J. Reynolds	0.56	0	0.78
	Other	-30.87	0.82	-0.18
Grocery	ALDI	3.99	0	-13.64
	Ahold	3.89	3.47	-4.34
	Albertsons	4.59	1.78	-2.01
	Amazon	3.59	0.05	-7.89
	Costco	5.12	6.67	-5.35
	Kroger	22.7	4.88	-2.75
	Meijer	4.56	2.01	-29.89
	Publix	4.81	4.15	-12.51
	Wakefern	5.31	3.36	-12.24
	Walmart	5	5.9	-0.21
	Other	6.94	5.86	-3.18
Smartphone	Apple	3.56	0	-0.01
	Google	3.09	2.23	-4.65
	LG	2.06	1.58	-2.22
	Lenovo	31.15	0	-32.96
	Samsung	3.31	1.28	-0.97
	Other	2.43	1.02	-5.81
Restaurant	Burger King	3.22	2.84	-1.79
	Chick-fil-A	3.33	6.78	-5.07
	Chipotle	1.63	1.41	-14.07
	Domino's	2.3	0.01	-1.67
	Inspire Brands	1.54	0	-2.83
	JAB	1.79	0	-11.71
	McDonald's	2.94	0	-0.09
	Starbucks	2.23	2.25	-0.99
	Subway	6.57	2	-2.22
	Wendy's	4.34	5.55	-2.32
	Yum! Brands	2.01	1.48	-1.49
	Other	1.61	1.64	-8.16
Soda	Coca-Cola	1.8	0	-0.11
	Dr Pepper 7 Up	1.57	0.89	0.08
	Pepsi	1.72	1.07	-0.34
	Other	1.3	0.65	-1.66
Toothpaste	Church & Dwight	6.08	3.14	-3.47
	Colgate	6.8	2.41	-2.37
	Glaxo	6.96	3.91	-4.68
	Procter & Gamble	7.24	0	-2.15
	Other	9.94	2.37	-9.18
Yogurt	Chobani	2.38	0	-34.17
	Danone	2.21	0	-0.13
	General Mills	2.56	0.32	0.04
	Other	35.55	0.96	-0.15

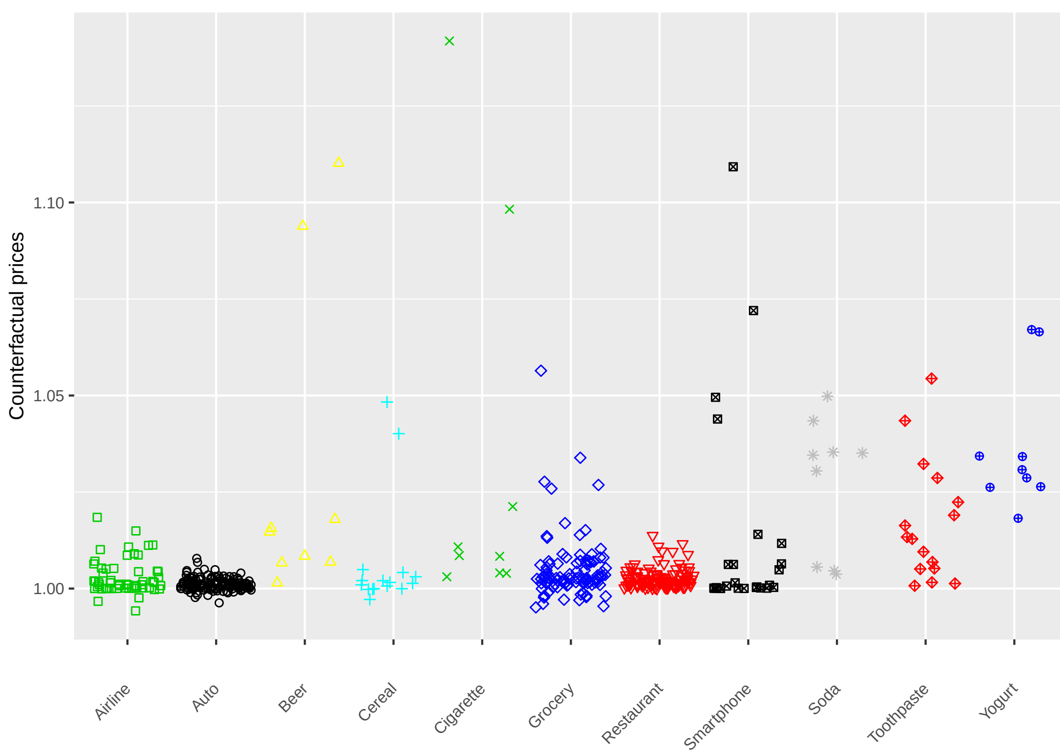
Notes: This table presents the demand parameter estimates for each firm in the differentiated product industries in our sample.

Table A4: **Product Market Parameter Estimates by Industry**

Industry	(1) η	(2) σ_n
Airline	4.52	4.13
Auto	6.15	9.42
Beer	1.96	2.53
Cereal	4.86	6.66
Cigarette	2.26	3.15
Grocery	2.58	5.65
Restaurant	2.33	2.19
Smartphone	2.29	4.15
Soda	2.03	2.29
Toothpaste	3.11	11.55
Yogurt	2.2	2.91

Notes: This table presents the industry-level parameter estimates for each differentiated product industry in our sample.

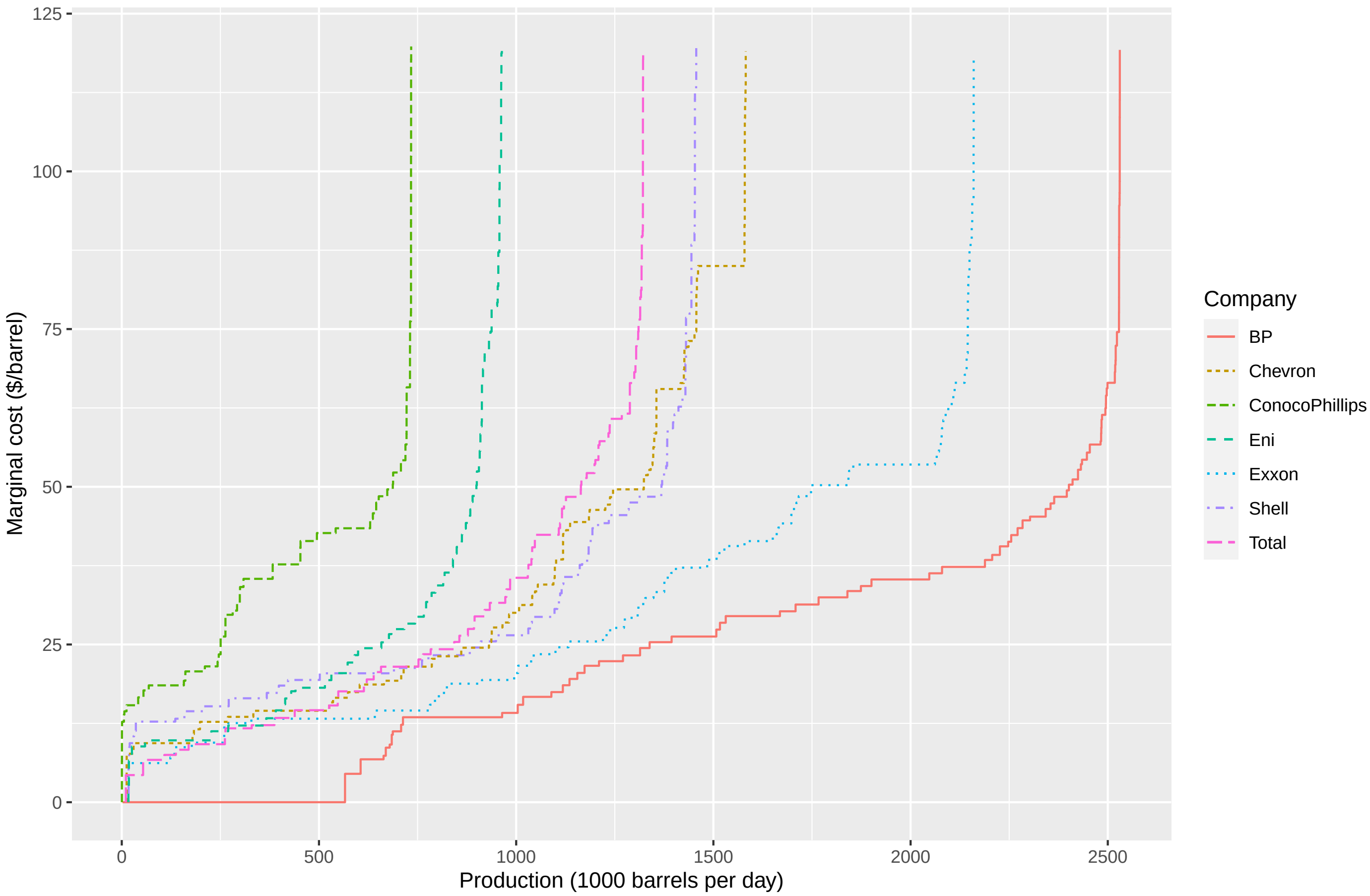
Figure A4: **Counterfactual Equilibrium Prices in Response to Individual Firm Exit**



Notes: This figure presents all counterfactual equilibrium prices in response to the exit of each individual firm in each differentiated product industry in our sample. Each firm is assumed to sell a representative good with baseline price of $1.

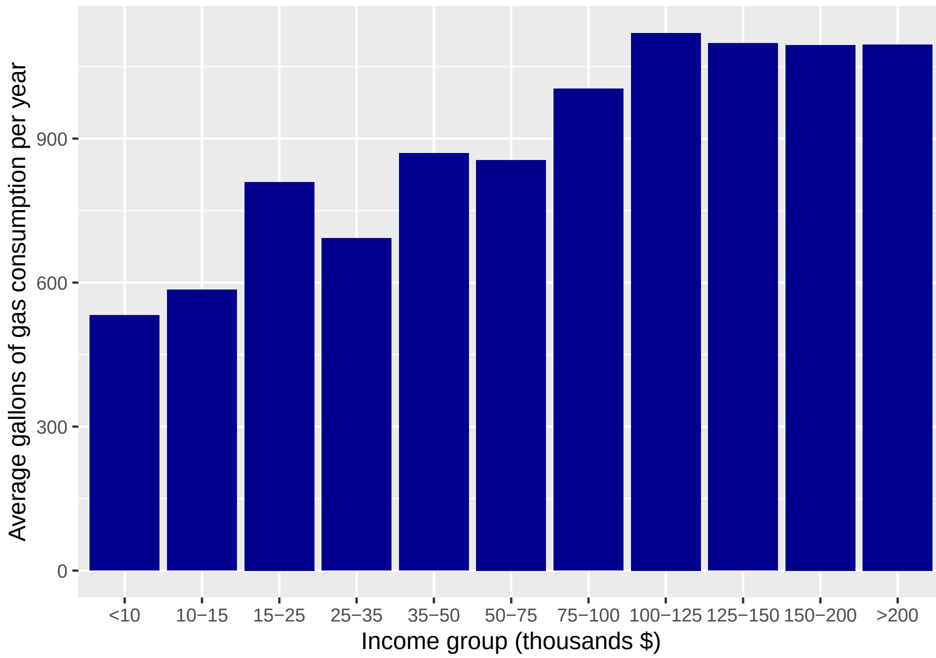
B.2 Oil Market Appendix

Figure A5: **Marginal Cost Curves by Firm**



Notes: This figure presents the marginal cost curves for each oil company in our sample. These are calculated by aggregating over field-level marginal costs using data from Rystad.

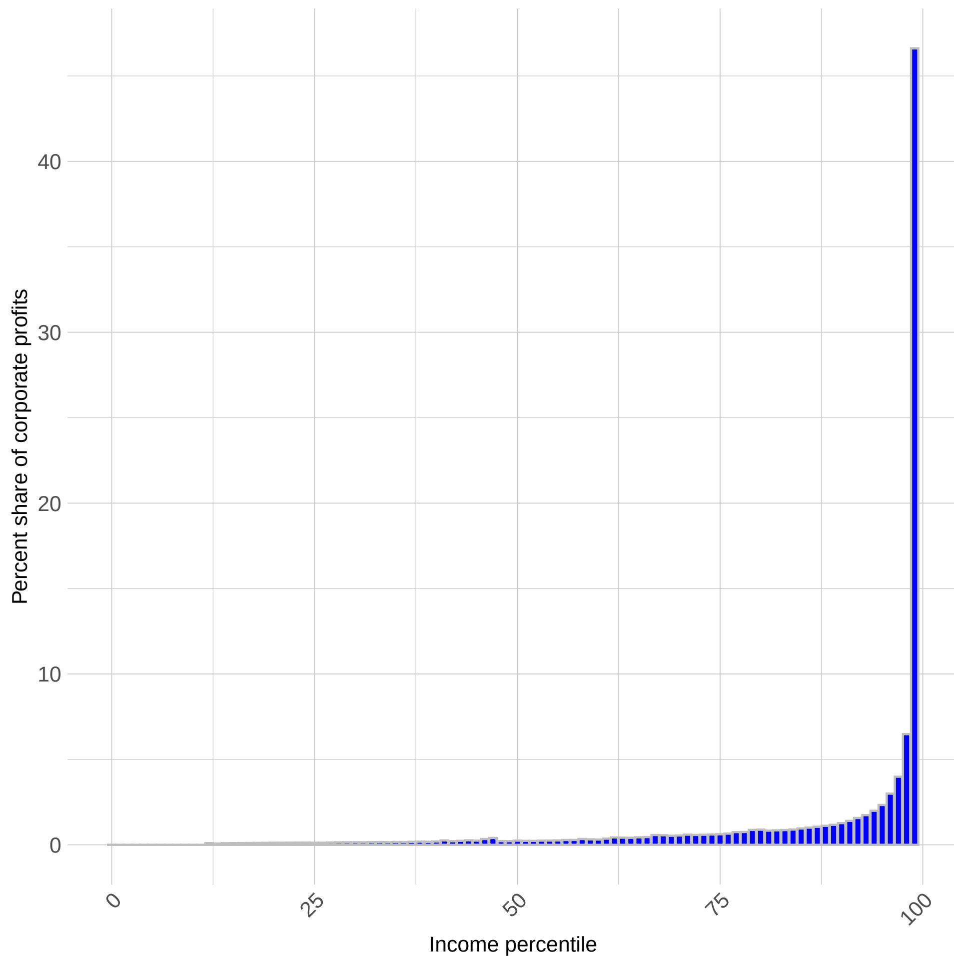
Figure A6: **Gasoline Consumption by Income**



Notes: This figure presents average gasoline consumption by income group, using microdata on vehicle miles traveled and fuel economy from the National Household Travel Survey.

B.3 Profit Calculation

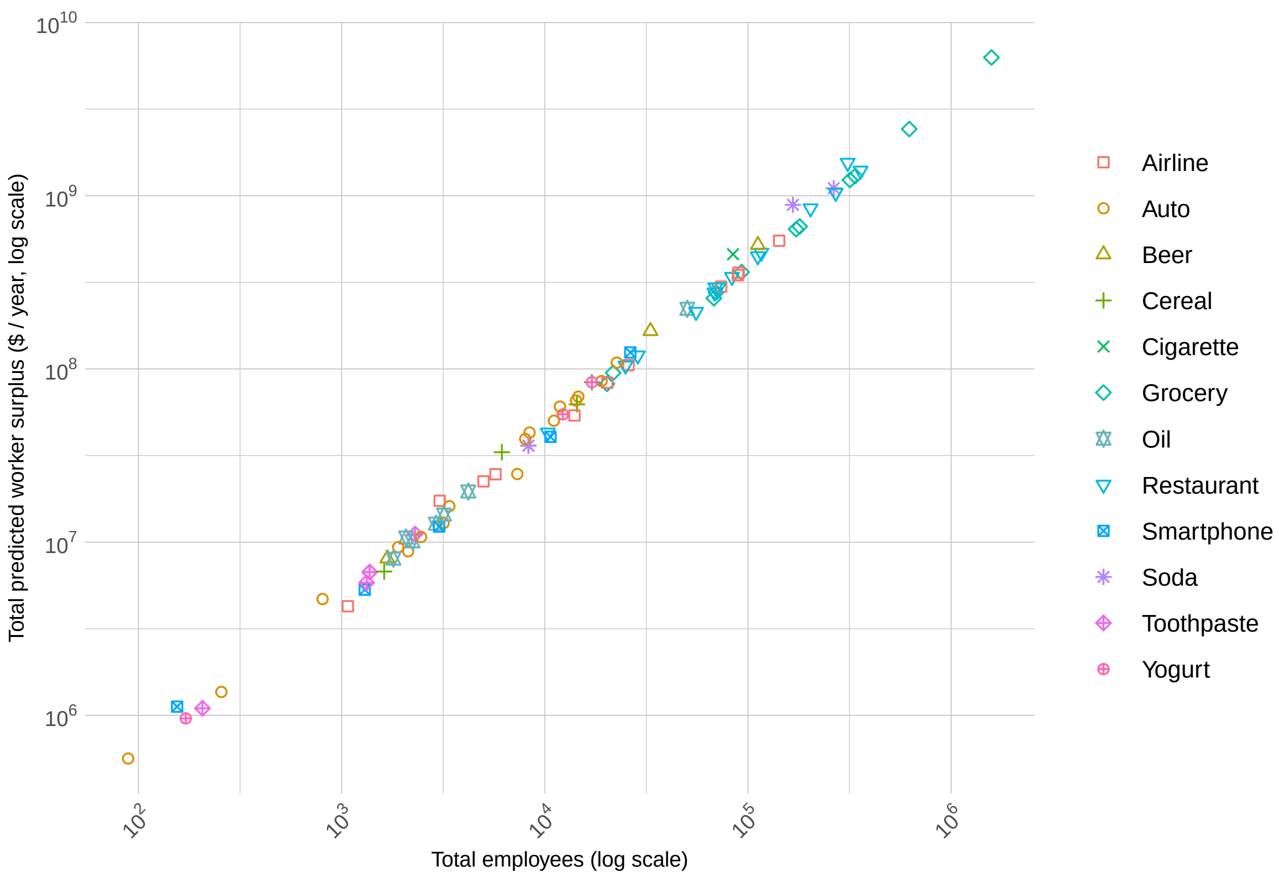
Figure A7: **Share of Dividends Received by Income Percentile**



Notes: This figure presents the share of C-corp dividends received by people in each income percentile, using data from Cooper et al. (2016). To adjust for the fact that Cooper et al. (2016) only considers households who file 1040 tax forms, we assume that the bottom 12 percent of the income distribution do not file taxes and earn zero dividends.

C Labor Market Appendix

Figure A8: **Total Estimated Worker Surplus by Firm**



Notes: This figure presents worker surplus against total employees for each firm in our sample.

D Corporate Social Impact Results Appendix

Table A5: **Components of Individual Impact by Firm**

Industry	Firm	(1) Consumer surplus	(2) Profit	(3) Competitor profit	(4) Externality	(5) Worker surplus	(6) Corporate social impact	(7) Product market revenues	(8) Consumer surplus (weighted)	(9) Profit (weighted)	(10) Competitor profit (weighted)	(11) Worker surplus (weighted)	(12) Corporate social impact (weighted)
Airline	Alaska	4.31	2.68	-2.08	-0.25	0.11	4.77	-8.39	2.23	0.41	-0.32	0.11	2.18
	Allegiant	0.65	0.44	-0.37	-0.01	0.02	0.73	-1.47	0.32	0.07	-0.06	0.02	0.34
	American	11.77	9.33	-8.62	-0.06	0.55	12.96	-33.29	8.02	1.42	-1.31	0.55	8.62
	Delta	12.87	9.48	-7.94	0.06	0.36	14.82	-31.96	8.57	1.44	-1.21	0.36	9.22
	JetBlue	5.54	2.61	-1.65	-0.29	0.08	6.29	-7.50	3.36	0.40	-0.25	0.08	3.30
	Southwest	10.10	7.39	-6.37	-0.62	0.30	10.81	-25.16	6.66	1.13	-0.97	0.30	6.49
	Spirit	0.72	0.58	-0.72	-0.34	0.02	0.26	-2.59	0.56	0.09	-0.11	0.02	0.22
	United	7.98	6.54	-6.58	-0.07	0.35	8.23	-25.42	7.07	1.00	-1.00	0.35	7.34
Auto	BMW	11.62	3.50	-1.92	-0.03	0.01	13.18	-12.53	5.12	0.53	-0.29	0.01	5.34
	Fiat Chrysler	23.53	17.49	-16.33	-0.88	0.06	23.87	-81.09	26.17	2.67	-2.49	0.06	25.53
	Ford	30.90	19.49	-15.92	-0.51	0.05	34.01	-83.50	31.49	2.97	-2.43	0.05	31.57
	GM	38.33	24.87	-19.39	-0.56	0.07	43.32	-106.67	44.17	3.79	-2.95	0.07	44.51
	Honda	18.53	13.38	-10.95	-0.29	0.04	20.71	-59.55	15.84	2.04	-1.67	0.04	15.96
	Hyundai	5.78	4.50	-5.82	0.05	0.01	4.52	-25.38	7.26	0.69	-0.89	0.01	7.12
	Kia	6.07	4.36	-4.27	-0.13	0.01	6.05	-21.07	8.52	0.67	-0.65	0.01	8.42
	Mazda	2.71	1.95	-2.30	-0.08	0.00	2.29	-10.12	1.87	0.30	-0.35	0.00	1.74
	Nissan	14.74	10.89	-10.78	-0.28	0.04	14.61	-51.93	18.68	1.66	-1.64	0.04	18.45
	Subaru	8.24	5.42	-5.12	-0.36	0.01	8.18	-25.96	4.67	0.83	-0.78	0.01	4.36
	Toyota	31.96	20.84	-16.38	-0.14	0.07	36.34	-88.49	30.83	3.18	-2.50	0.07	31.43
	Volkswagen	15.26	6.08	-4.14	0.03	0.02	17.26	-23.02	13.22	0.93	-0.63	0.02	13.58
Beer	Anheuser-Busch	39.09	31.08	-19.25	0.00	0.52	51.44	-50.03	34.48	4.74	-2.93	0.52	36.80
	Molson Coors	44.80	34.53	-21.07	0.00	0.17	58.43	-53.59	43.43	5.26	-3.21	0.17	45.65
	Sazerac	2.13	1.09	-1.51	0.00	-0.00	1.71	-2.10	1.40	0.17	-0.23	-0.00	1.34
Cereal	General Mills	4.41	2.40	-2.41	0.00	0.08	4.49	-7.75	3.39	0.37	-0.37	0.08	3.47
	Kellogg	6.63	3.81	-2.73	0.00	0.06	7.77	-11.94	6.22	0.58	-0.42	0.06	6.44
	Post	0.31	0.15	-0.13	0.00	0.03	0.36	-0.47	0.19	0.02	-0.02	0.03	0.23
	Quaker	0.22	0.08	-0.07	0.00	0.01	0.23	-0.22	0.15	0.01	-0.01	0.01	0.16
Cigarette	Lorillard	-3.36	1.49	-1.36	-0.18	-0.00	-3.41	-2.90	-4.51	0.23	-0.21	-0.00	-4.67
	Philip Morris	-17.67	26.67	-16.46	-1.55	0.46	-8.56	-46.23	-14.85	4.06	-2.51	0.46	-14.38
	R.J. Reynolds	-10.06	12.14	-12.29	-0.58	-0.00	-10.80	-24.09	-8.85	1.85	-1.87	-0.00	-9.45
Grocery	Ahold	21.68	16.18	-17.21	0.00	0.64	21.29	-36.82	18.85	2.47	-2.62	0.64	19.34
	Albertsons	31.58	22.43	-27.34	0.00	1.23	27.90	-55.23	28.03	3.42	-4.17	1.23	28.51
	ALDI	32.84	16.09	-9.79	0.00	0.10	39.24	-27.62	26.71	2.45	-1.49	0.10	27.76
	Amazon	23.05	14.83	-12.06	0.00	0.28	26.09	-27.62	17.00	2.26	-1.84	0.28	17.69
	Costco	52.12	33.78	-25.11	0.00	1.30	62.09	-64.44	37.10	5.15	-3.83	1.30	39.72
	Kroger	61.10	47.65	-42.06	0.00	2.43	69.12	-101.26	50.03	7.26	-6.41	2.43	53.31
	Meijer	10.98	4.89	-4.85	0.00	0.36	11.38	-9.21	5.88	0.75	-0.74	0.36	6.25
	Publix	34.43	20.83	-14.22	0.00	0.66	41.71	-36.82	24.28	3.18	-2.17	0.66	25.96
	Wakefern	22.52	10.68	-7.89	0.00	0.26	25.57	-18.41	14.87	1.63	-1.20	0.26	15.55
	Walmart	157.49	132.47	-91.89	0.00	6.28	204.35	-266.97	155.05	20.19	-14.00	6.28	167.52
Oil	BP	36.72	3.52	-36.32	-1.75	0.01	2.18	-8.87	24.20	0.84	-8.69	0.01	14.62
	Chevron	34.96	3.31	-34.59	-1.66	0.01	2.03	-8.44	23.04	0.79	-8.27	0.01	13.90
	Conoco	16.15	1.53	-16.07	-0.77	0.22	1.06	-3.89	10.64	0.37	-3.84	0.22	6.62
	Eni	21.39	2.03	-21.25	-1.02	0.01	1.16	-5.15	14.09	0.49	-5.08	0.01	8.49
	Exxon	45.01	4.29	-44.40	-2.15	0.01	2.77	-10.89	29.66	1.03	-10.62	0.01	17.94
	Shell	31.63	3.01	-31.33	-1.50	0.01	1.82	-7.63	20.85	0.72	-7.49	0.01	12.58
	Total	28.48	2.71	-28.24	-1.35	0.02	1.62	-6.87	18.77	0.65	-6.75	0.02	11.33
Restaurant	Burger King	7.62	6.94	-4.97	0.00	0.04	9.63	-14.62	7.42	1.06	-0.76	0.04	7.76
	Chick-fil-A	7.57	5.90	-3.76	0.00	0.47	10.17	-10.97	4.64	0.90	-0.57	0.47	5.43
	Chipotle	5.66	3.41	-1.71	0.00	0.28	7.63	-5.48	4.79	0.52	-0.26	0.28	5.33
	Domino's	3.54	3.20	-2.65	0.00	0.10	4.20	-7.31	3.51	0.49	-0.40	0.10	3.70
	Inspire Brands	10.94	9.50	-5.94	0.00	-0.00	14.49	-18.28	9.43	1.45	-0.91	-0.00	9.97
	JAB	6.15	3.43	-2.01	0.00	0.34	7.91	-5.48	3.26	0.52	-0.31	0.34	3.82
	McDonald's	20.87	19.29	-13.36	0.00	1.40	28.20	-40.22	19.34	2.94	-2.04	1.40	21.64
	Starbucks	11.06	10.02	-8.03	0.00	1.04	14.10	-21.94	8.79	1.53	-1.22	1.04	10.14
	Subway	5.75	5.19	-3.99	0.00	0.85	7.80	-10.97	5.25	0.79	-0.61	0.85	6.28
	Wendy's	4.49	4.04	-3.50	0.00	0.30	5.32	-9.14	3.02	0.62	-0.53	0.30	3.40
	Yum! Brands	12.18	10.92	-7.37	0.00	0.45	16.19	-21.94	11.72	1.66	-1.12	0.45	12.71
Smartphone	Apple	41.32	30.27	-22.53	0.00	0.12	49.18	-49.15	32.34	4.61	-3.43	0.12	33.64
	Google	1.48	1.08	-1.32	0.00	0.01	1.24	-2.18	1.33	0.16	-0.20	0.01	1.30
	Lenovo	0.12	0.07	-0.12	0.00	0.01	0.08	-0.15	0.07	0.01	-0.02	0.01	0.07
	LG	3.71	2.73	-3.19	0.00	-0.00	3.25	-5.57	3.98	0.42	-0.49	-0.00	3.91
	Samsung	18.19	12.33	-14.07	0.00	0.04	16.50	-22.79	15.84	1.88	-2.14	0.04	15.61
Soda	Coca-Cola	43.53	37.57	-27.39	-0.18	0.89	54.41	-66.82	36.50	5.73	-4.17	0.89	38.75
	Dr Pepper 7 Up	48.49	50.20	-31.59	-9.19	0.04	57.95	-84.13	43.02	7.65	-4.81	0.04	36.70
	Pepsi	44.18	39.70	-26.83	-2.19	1.10	55.96	-67.24	38.06	6.05	-4.09	1.10	38.94
Toothpaste	Block Drug	0.42	0.25	-0.23	0.00	0.01	0.45	-0.53	0.35	0.04	-0.04	0.01	0.36
	Church & Dwight	0.45	0.28	-0.27	0.00	0.00	0.47	-0.61	0.43	0.04	-0.04	0.00	0.43
	Colgate	0.62	0.41	-0.40	0.00	0.01	0.64	-0.89	0.59	0.06	-0.06	0.01	0.61
	Procter & Gamble	0.55	0.39	-0.41	0.00	0.01	0.53	-0.88	0.45	0.06	-0.06	0.01	0.45
Yogurt	Chobani	0.73	0.55	-0.35	0.00	0.00	0.94	-1.08	0.39	0.08	-0.05	0.00	0.42
	Danone	1.82	1.51	-0.71	0.00	0.05	2.67	-2.96	1.64	0.23	-0.11	0.05	1.82
	General Mills	1.95	1.64	-0.72	0.00	0.08	2.96	-3.19	1.84	0.25	-0.11	0.08	2.06

Notes: This table presents the components of individual impact for all firms in our sample. The "weighted" estimates impose a curvature of $\rho = 1$ on social marginal welfare weights, which approximately corresponds to log utility. All other estimates use equal social marginal welfare weights across income groups ($\rho = 0$).