Consumer Choice and Corporate Bankruptcy*

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Abstract: We estimate the indirect costs of corporate bankruptcy associated with lost customers. In incentivized experiments, randomly informing consumers about a firm's Chapter 11 reorganization lowers their willingness to pay for the firm's products by 18-35%. Up to 48% of consumers are aware of major bankruptcies. Using our experiments to estimate a structural model, we show that a Chapter 11 bankruptcy causally reduces a firm's value by 10-31%, depending on the industry, through lost customers. We show that these costs are unlikely to arise before bankruptcy. Our results thus provide novel support for the tradeoff theory, a pillar of corporate finance.

Keywords: bankruptcy, structural estimation

1 Introduction

How costly is a corporate default? This question is central to corporate finance: according to the "tradeoff theory," firms choose a debt structure by trading off the benefits of debt with the costs of a potential default (Kraus and Litzenberger, 1973). A long literature shows

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that firms use low leverage despite large benefits of debt, implying default costs are large (Graham, 2000). Yet large firms often resolve defaults using Chapter 11 bankruptcy, avoiding liquidation and paying puzzlingly small direct legal costs (Weiss, 1990).

The prevailing explanation for this puzzle is that *indirect* bankruptcy costs must be large — firms use little debt because a bankruptcy would scare off customers, destroying value (Altman, 1984). However, these indirect costs are notoriously difficult to quantify because unobserved negative shocks can cause both a bankruptcy and a loss of customers. Existing estimates of indirect costs confound defaults with the shocks that cause them. Are indirect bankruptcy costs really large, or is a core theory of corporate finance wrong?

We combine methods from marketing, experimental economics, and industrial organization to measure the indirect costs of bankruptcy. Specifically, we use three incentivized experiments to estimate the causal effect of corporate bankruptcy on consumer demand for a bankrupt firm's products. We randomly vary the firm's bankruptcy status, holding all other firm and product details fixed. We find that knowledge of a Chapter 11 bankruptcy filing causally reduces a consumer's willingness to pay for the bankrupt firm's products by 18-35%, depending on the industry. We also find that up to 48% of consumers are aware of major corporate bankruptcies, so a bankruptcy impacts a large fraction of the bankrupt firm's consumer base. Estimating a structural discrete-choice model, we show that the indirect costs of bankruptcy can destroy 10% to 31% of producer surplus, depending on the industry. By these estimates, indirect bankruptcy costs alone are large enough for trade-off-theory models to explain observed leverage ratios (Glover, 2016). Our methodology can be used to estimate the customer-attrition costs of other financial or strategic firm actions.

We consider three reasons why consumers might care about a corporate bankruptcy. First, consumers might worry that a bankruptcy could lead to liquidation, preventing valuable future interactions with a firm including the use of warranties, return policies, and reward programs. Similarly, consumers with a preference for brand familiarity and loyalty dislike liquidations and the associated switching costs. Second, consumers might fear that a firm's bankruptcy will cause the firm to reduce the quality of its products or services during bankruptcy. In this "current-quality hypothesis," consumers worry a bankrupt firm will try to conserve cash by firing employees, reducing inventory, failing to maintain its assets, or increasing prices. Third, consumers might be concerned that a bankruptcy is a negative signal of a firm's inherent quality. We show that the first two concerns both significantly contribute to the effect of bankruptcy on consumer demand. In contrast, the third concern about the longer-run quality signal of a bankruptcy filing appears to have little effect.

Measuring the effect of bankruptcy on consumer demand is difficult because of an omitted-variable problem: unobservable adverse economic shocks can cause both a firm's bankruptcy filing and a reduction in consumer demand for the firm's products. To isolate the decline in demand caused by a firm entering bankruptcy, we need an estimate of what demand would have been had the same firm not entered bankruptcy. We form such an estimate with randomized experiments. We incentivize participants to honestly report their willingness to pay for firms' products. In our first two experiments, we focus on firms currently in bankruptcy. In a randomly assigned treatment group, we disclose these bankruptcies to consumers. This across-participant randomized variation in bankruptcy awareness allows us to estimate the causal effect of learning that a firm is bankrupt on preferences for that firm's products.

Even in our control group, a meaningful portion of consumers were already aware of these corporate bankruptcies. We thus provide the first direct evidence that many consumers are aware of major bankruptcies. We account for this in our analysis using an intent-to-treat design. We instrument for bankruptcy awareness with our randomized information-provision treatment. In two-stage-least-squares (2SLS) regressions, we show that knowledge of a bankruptcy causally lowers willingness to pay by 21% to 35% of the control-group mean.

We generalize these results in a third experiment. We ask participants to make hypothetical purchase decisions. Participants receive prizes based on the preferences implied by their hypothetical choices. Each participant reports her willingness to pay for the same products from the same firms. Holding all other details fixed, we vary the bankruptcy status of each firm across participants. Because participants evaluate hypothetical situations, we can vary the bankruptcy statuses of both real and fictional firms without deception. We also vary other details of each bankruptcy, allowing us to understand the mechanisms by which bankruptcy affects consumer decision making. This randomized across-participant variation in firm bankruptcy status allows us to directly estimate how a consumer's knowledge of a bankruptcy impacts her demand for the bankrupt firm's products.

Our third experiment considers three industries: airlines, car manufacturers, and retail stores. We focus on these consumer-facing industries because of the high number of large historical bankruptcies in these industries. Across all of these industries, we find that knowledge of a firm's bankruptcy causally reduces a consumer's willingness to pay for that firm's products; depending on the industry, willingness to pay declines by 18% to 24%. For airlines and retail, the current-quality hypothesis accounts for two-thirds of the decrease in willingness to pay and future interactions account for the remaining third. For car manufacturers, which produce a durable good, this relationship is reversed.

We also show that a substantial fraction of consumers are aware when a large firm files for bankruptcy. We present a list of firms and ask participants to select which, if any, have ever filed for bankruptcy. A large fraction of consumers correctly identify historical bankruptcies: for example, 48% of participants are aware that J.C. Penney filed for bankruptcy. Similarly, when asked to rate firms based on how close they ever came to bankruptcy, participants give high ratings to firms that have filed for bankruptcy. In contrast, among firms that never filed for bankruptcy, this perceived-as-close-to-bankrupt measure has no correlation with empirical distress measures like poor credit ratings. Thus, while participants are aware of bankruptcy filings, they are not aware of pre-bankruptcy financial distress.

The negative consumer response to corporate bankruptcies that we document harms both bankrupt firms, which lose market share, and consumers, who may have previously derived surplus from a bankrupt firm's products. To quantify these losses, we use our third experiment to estimate a structural discrete-choice model. In the model, consumers choose between differentiated goods. Firms compete on prices. We estimate the model using a combination of experiment data and historical data on market shares and prices.

Using the estimated model, we explore counterfactual scenarios in which various historical bankruptcies never occurred. We find that high-profile bankruptcies have dramatic effects on firms and consumers, even after accounting for the fraction of consumers that are not aware of these bankruptcies. For example, relative to the unobserved counterfactual in which American Airlines (AA) did not file for bankruptcy, AA's bankruptcy reduced consumer welfare by 3.4%. AA's bankruptcy reduced AA's producer surplus by 11.5%. Within our sample of large bankruptcies, a bankruptcy filing reduces the bankrupt firm's producer surplus by 10% to 31%. Bankruptcy reduces consumer surplus by 2.4% to 6.8%. Our model also shows that bankrupt firms typically set prices slightly lower than they would in the absence of bankruptcy, while competitors opportunistically increase prices.

Our third experiment also allows us to infer consumer perceptions about the survival probabilities of bankrupt firms. Surprisingly, the average consumer has accurate beliefs about the survival prospects of a bankrupt airline. However, consumers dramatically underestimate the likelihood that a large car manufacturer will survive bankruptcy. Using our structural model, we show that educating consumers can significantly dampen the effects of a car-manufacturer bankruptcy filing on producer and consumer surplus.

Finally, we calibrate a standard dynamic-capital-structure model to quantify the impact of these bankruptcy costs on nonbankrupt firms. We model a firm that chooses its leverage in anticipation of its future default decision and associated bankruptcy costs. In Internet Appendix F, we show that firms optimally choose substantially lower leverage ratios than they would in the absence of our estimated indirect bankruptcy costs. For example, in a counterfactual in which General Motors knew it would face zero indirect bankruptcy costs, it would increase its leverage by 15 percentage points, improving its ex-ante firm value through higher interest tax shields. While it is infeasible to erase indirect bankruptcy costs, this counterfactual nonetheless highlights the importance of indirect bankruptcy costs for nonbankrupt firms.

1.1 Contribution to the Literature

This paper's novel contributions to the literature include the following findings: (i) across industries, a Chapter 11 bankruptcy filing causes a dramatic decline in consumer demand for the bankrupt firm's products; (ii) this indirect cost of bankruptcy is large enough to justify observed leverage ratios, consistent with the trade-off theory; (iii) the decline in consumer demand is due to both concerns about a firm's quality during bankruptcy and concerns that a firm may not exist in the future; and (iv) educating consumers about the survival prospects of bankrupt firms can dampen this cost of bankruptcy.

We contribute to several literatures. First, we contribute to the literature estimating the deadweight losses associated with bankruptcy filings: see, for example, Iverson (2018); Iverson, Madsen, Wang, and Xu (2020); Bernstein, Colonnelli, and Iverson (2019); Bernstein, Colonnelli, Giroud, and Iverson (2019); Wang (2022); Hotchkiss (1995); Graham, Kim, Li, and Qiu (forthcoming); Andrade and Kaplan (1998); Glover (2016); Antill (2021, 2022); Matsa (2011); Dou, Taylor, Wang, and Wang (2021); Eraslan (2008); Davydenko, Strebulaev, and Zhao (2012); Jenkins and Smith (2014); Chang and Schoar (2006); Purnanandam (2008); Araujo, Ferreira, Lagaras, Moraes, Ponticelli, and Tsoutsoura (2021); Van Binsbergen, Graham, and Yang (2010); Djankov, Hart, McLiesh, and Shleifer (2008); Duffee (1999); Nadauld and Weisbach (2012). Differing from this literature, we estimate the indirect bankruptcy costs associated with lost customers and show that they are substantial relative to previously studied bankruptcy costs.[1]

Second, we contribute to the literature using experiments to answer finance questions. See, for example, D'Acunto (2015); D'Acunto, Fuster, and Weber (2021); Bernstein, Colonnelli, Iverson, and Hoffman (2022); Colonnelli, Gormsen, and McQuade (2022); Gneezy, Kapteyn, and Potters (2003); Lian, Ma, and Wang (2019); Armantier and Holt (2020); Payzan-LeNestour (2018); Page and Siemroth (2021); Sade, Schnitzlein, and Zender (2006); Drehmann, Oechssler, and Roider (2005); Choi and Robertson (2020); Beshears, Choi, Fuster, Laibson, and Madrian (2013); Beshears, Choi, Laibson, Madrian, and Milkman (2015); Edmans, Gosling, and Jenter (2023); Kuhnen (2015); Mullainathan, Noeth, and Schoar (2012); Kuhnen and Miu (2017). While our methodology is similar to these papers, our paper is the first to use experiments to quantify consumer responses to corporate bankruptcies.

Third, we contribute to the literature studying the product-market consequences of bankruptcy: see, for example, Borenstein and Rose (1995, 2003); Rose (1987); Hortaçsu, Matvos, Shin, Syverson, and Venkataraman (2011); Hortaçsu, Matvos, Syverson, and Venkataraman (2013); Phillips and Sertsios (2013); Malshe and Agarwal (2015); Chevalier (1995); Phillips (1995); Busse (2002); Ciliberto and Schenone (2012). We contribute to this literature by providing the first experimental evidence identifying the causal effect of bankruptcy on consumer demand. Our experiment also provides (i) the first direct evidence that consumers are aware of bankruptcies; (ii) novel direct causal evidence on why consumers care about bankruptcies; and (iii) novel exogenous variation for estimating our structural model of bankruptcies and product-market competition.

Fourth, we contribute to the marketing literature exploring the relationship between firm reputation and consumer demand as well as information provision more broadly. See, for example, Ozturk, Chintagunta, and Venkataraman (2019); Ozturk, Venkataraman, and Chintagunta (2016); Rao and Wang (2017); Fong, Guo, and Rao (2023); Kong and Rao (2021); Burke, Dowling, and Wei (2018); Dodds, Monroe, and Grewal (1991); Malshe and Agarwal (2015); Han, Feit, and Srinivasan (2020); Mainardes, Mota, and Moreira (2020);

[1] By estimating these bankruptcy costs, we also contribute to the theory and structural modeling literature that uses such estimates in models. See, for example, Bhamra, Kuehn, and Strebulaev (2010b,c,a); Kuehn and Schmid (2014); Gomes and Schmid (2010, 2021); Donaldson, Morrison, Piacentino, and Yu (2020); Hackbarth, Mathews, and Robinson (2014).

Noh, So, and Zhu (2022). We contribute to this literature by documenting the fraction of consumers that are aware of a firms' financial status and identifying the specific concerns that consumers have upon learning of financial distress. Further, we contribute to this literature by estimating the causal effect of corporate bankruptcy on consumer demand and showing that consumer behavior can drive firm leverage ratios.

2 Price-List Experiments

We quantify consumer aversion to bankrupt firms using three experiments. In our first experiment, we measure participants' willingness to pay for a firm's gift cards. Randomly informing participants about the firm's bankruptcy, we estimate how bankruptcy impacts demand. In a similar second experiment, we measure how bankruptcy impacts willingness to pay for a product produced by the bankrupt firm. Both of these experimental designs allow us to incentivize honest willingness-to-pay reports with a standard method: the multiple-price-list variation of the Becker, DeGroot, and Marschak (1964) (BDM) method. We now describe these two experiments. We describe our third experiment, which uses hypothetical purchase decisions to generalize our findings, in Section 3.

2.1 The Hertz Experiment

Our first experiment measures the causal effect of Hertz's bankruptcy filing on demand for Hertz's gift cards. We focused on Hertz because it is a large consumer-facing firm that was in Chapter 11 bankruptcy at the time of our survey (November - December 2020). We ran an online Qualtrics survey on a representative sample of U.S. adults, provided by Lucid.

In our experiment, we first exclude participants that fail attention tests. One attention test requires participants to read a lengthy description of corporate missions. The necessary answer to proceed with the survey is buried in the middle. This serves the dual purpose of screening (we drop participants who are not reading carefully) and mitigating experimenter demand (participants may believe the survey is about corporate missions).

We then measure willingness to pay for a $50 gift card at Hertz using a price-list mechanism. Participants make a series of choices between: (i) a $50 Hertz gift card; and (ii) a $Y Enterprise gift card, where $Y increases as participants move down the price list. There are 20 questions, with $Y ranging from $0 to $95 in $5 increments. To incentivize participants to accurately report their preferences, we randomly select 1% of participants to receive one of their preferred gift cards. We randomly select which of their preferred gift cards they receive. This lottery prize is described to the participants. We tell participants that, because of this lottery, it is optimal to honestly report their preferred gift card in each choice. We define the willingness to pay for Hertz as the highest $Y value such that the participant chooses Hertz over Enterprise.

Hertz was in Chapter 11 bankruptcy at the time of this experiment. In a randomly assigned treatment group, we tell participants about Hertz's bankruptcy. Specifically, before completing the price list, we tell control-group participants that "Hertz and Enterprise are rental car companies." Treatment-group participants see the same text, but are also told:

> Hertz filed for Chapter 11 bankruptcy on May 22, 2020. Hertz is still in bankruptcy.

We specify "Chapter 11 bankruptcy" to mimic headlines consumers would likely view.[2] Our goal is to capture a typical consumer's response to this information, including any typical misconceptions about Chapter 11.[3]

After the price list, we measure which participants are aware of Hertz's bankruptcy. We present all participants with a list of firms and ask them to select which, if any, are currently in Chapter 11 bankruptcy. One of the options is "none of the above." We say a participant is aware of Hertz's bankruptcy if they select Hertz from the list. In the control group, this question measures how many consumers are aware of Hertz's bankruptcy. In the treatment group, this measures whether participants remember being told that Hertz is bankrupt.

Finally, we ask questions about each participant's past car-rental experiences and demographics. We use participant answers to these questions as control variables.

2.2 Results of the Hertz Experiment

We define an indicator $Aware_i$ that is equal to one for participants who select that Hertz is currently bankrupt. We find that 26% of our control-group participants are aware that Hertz is bankrupt. Since the control group is randomly selected from a representative sample of U.S. adults, this implies that 26% of U.S. adults were aware of Hertz's bankruptcy during the

[2] See `https://www.axios.com/2020/05/23/hertz-bankruptcy-coronavirus`.

[3] Interestingly, when asked at the end of our second survey about what happens in Chapter 11, 70% of control participants agree with the statement "some firms exit bankruptcy and continue operating."

bankruptcy. Therefore, our "treatment" (learning Hertz is bankrupt) is imperfectly assigned. We thus use an intent-to-treat design, instrumenting for awareness of Hertz's bankruptcy with the randomly assigned treatment.

Let $Treat_i$ be an indicator for i being randomly selected to learn Hertz is bankrupt. Let WTP_i denote individual i's willingness to pay for the Hertz gift card (Section 2.1). Finally, let X_i denote a vector of control variables including: (i) an indicator equal to one if participant i has previously rented from Hertz; (ii) an indicator equal to one if participant i has previously rented from Enterprise; (iii) an indicator variable that is equal to one if the participant is male; (iv) the participant's age, proxied by a series of indicator variables that are equal to one if the age is in a particular interval (e.g., 35-44 years old); (v) the participant's income, proxied by a series of indicator variables that are equal to one if the income is in a particular interval (e.g., \$50,000 to \$74,999); and (vi) a series of indicator variables for different education levels (e.g., high-school graduate).

We first regress $Aware_i$ on $Treat_i$. Column (1) of Table 1 shows that treatment increases awareness of Hertz's bankruptcy by 65 percentage points. Using robust standard errors, the F-statistic is 650. Next, letting $\hat{Aware}_i$ denote the fitted value from this regression, we regress WTP_i on $\hat{Aware}_i$. Column (2) of Table 1 shows our two-stage-least-squares (2SLS) estimate: learning that Hertz is bankrupt lowers willingness to pay by 35% of the control-group mean.

This first experiment demonstrates two key facts. First, 26% of U.S. adults were aware that Hertz was bankrupt during its bankruptcy. Second, learning that Hertz is bankrupt lowers willingness to pay for Hertz by 35%. Internet Appendix A provides further details.

2.2.1 Discussion

"Experimenter demand" concerns — participants might respond in the way they believe the experimenter wants — are less likely if participants are incentivized to truthfully report their preferences. Encouragingly, in Table A.8, we show that adding incentives to our price-list experiment increases the magnitude of our main result. This is inconsistent with the concern that experimenter-demand effects inflate our treatment-effect estimates.

2.3 The Instant Pot Experiment

We replicate the results of our first experiment in a similar second experiment. Relative to the Hertz experiment, our second experiment has three key differences. First, we study a different company: Instant Brands, the manufacturer of the popular Instant Pot pressure cooker. Second, we measure willingness to pay for a physical good — an Instant Pot — rather than a gift card. This alleviates concerns that our findings are driven by concerns about whether gift cards will be honored in bankruptcy. Third, we make bankruptcy less salient in our treatment. Participants read a long news article about Instant Brands and the treatment-group article briefly mentions the bankruptcy in the middle of the article.

Specifically, we ran a second online Qualtrics survey on a different representative sample of U.S. adults, provided by Lucid. We ran the experiment in September 2023, shortly after Instant Brands filed for Chapter 11 bankruptcy.[4] As in our Hertz experiment, we begin by excluding participants that fail attention checks. We then ask participants to read an article about Instant Brands. The article is roughly 450 words and is designed to match the length and content of a standard news article. In a randomly assigned control group, participants read an article describing the history of Instant Brands and various features of its products. In a randomly assigned treatment group, participants read an article that is identical to the control-group article with one difference: halfway through the article, we mention that Instant Brands filed for Chapter 11 bankruptcy and is still operating as a bankrupt company. Our treatment is thus the same as in the first experiment in the sense that we randomly inform participants about a firm's bankruptcy. However, we inform participants in a subtler manner that more closely matches the experience of reading a news article.

We then measure willingness to pay for an Instant Pot using a price-list mechanism. Participants make a series of choices between: (i) physically receiving a 3 Quart Instant Pot Duo 7-in-1 Electric Pressure Cooker; and (ii) a cash-equivalent Visa gift card for \$Y, where \$Y increases as participants move down the price list. There are 21 questions, with \$Y ranging from \$0 to \$100 in \$5 increments. As before, we incentivize participants to report their actual willingness to pay with a lottery. We explain that 1% of participants will receive one of their choices, implying that it is optimal to honestly report their preference in each choice. We define the willingness to pay for the Instant Pot as the highest \$Y value such

[4] Instant Brands filed for Chapter 11 on June 12, 2023 and was still in bankruptcy in September. See https://www.instantbrandsrestructuring.com/.

that the participant chooses the Instant Pot over the $Y cash equivalent.

After the price list, we use the same approach from our first experiment to determine which participants are aware of Instant Brands' bankruptcy. We conclude by asking questions about each participant's demographics and past purchases. Internet Appendix B provides further details on our second experiment.

2.4 Results of the Instant Pot Experiment

Our analysis of the Instant Pot experiment mirrors our analysis of the Hertz experiment in Section 2.2. We construct variables $Aware_i$, $Treat_i$, and WTP_i with the same interpretations as before. We define a vector X_i containing the following control variables: (i) the number of times the participant has purchased Pyrex products (a brand owned by Instant Brands), proxied by a series of indicator variables that are equal to one if the number of purchases is in a particular interval; (ii) the participant's ethnicity, captured by a series of indicator variables for different ethnicities; (iii) an indicator variable that is equal to one if the participant is male; (iv) the participant's age, proxied by a series of indicator variables that are equal to one if the age is in a particular interval (e.g., 35-44 years old); (v) the participant's income, proxied by a series of indicator variables that are equal to one if the income is in a particular interval (e.g., $50,000 to $74,999); and (vi) a series of indicator variables for different education levels (e.g., high-school graduate); (vii) the country in which the participant was born, captured by indicator variables for different countries. As described in our AEA preregistration, we exclude participants that currently own a pressure cooker or have spent money to buy an Instant Pot.

We first regress $Aware_i$ on $Treat_i$. Column (3) of Table 1 shows that treatment increases awareness of Instant Brands' bankruptcy by 89 percentage points. Using robust standard errors, the F-statistic is 432. Next, we regress WTP_i on $\hat{Aware}_i$, the value of $Aware_i$ instrumented by the treatment. Column (4) of Table 1 shows our 2SLS estimate: learning that Instant Brands is bankrupt lowers willingness to pay by 21% of the control-group mean.

Our second experiment confirms that bankruptcy substantially lowers demand for the bankrupt firm's products. While our 2SLS estimate is smaller in our second experiment than in our first experiment, it is still sizeable. The difference in size could be due to noise: using robust standard errors, the 95% confidence interval for our 2SLS estimate in the second experiment includes estimates up to 40% of the control-group mean. Alternatively, the difference in size could be due to the distinction between a physical product and a gift card, or due to the bankruptcy being less salient in the second experiment.

In our second experiment, only 2% of the control group is aware of Instant Brands' bankruptcy. This is far lower than the 26% of control-group participants that are aware of Hertz's bankruptcy. This difference is not surprising. While the Instant Pot is a well-known product, the parent company Instant Brands is an obscure private company. It listed less than $1 billion in liabilities on its bankruptcy filing petition.[5] In contrast, Hertz is a well-known public company. It listed over $24 billion in liabilities on its filing petition.[6] This nonetheless implies that the indirect costs of bankruptcy are likely small for less well-known companies. For this reason, we are careful to account for the level of bankruptcy awareness in our structural estimation (Section 5).

3 Generalizing and Determining Mechanisms with a Third Experiment

The approach used in our first two experiments can only measure the effect of current bankruptcies on consumer demand. If a firm is not currently bankrupt, it would be deceptive to tell participants the firm is bankrupt. This is limiting. To generalize our results to a wider set of firms and industries without deception, our third experiment considers hypothetical purchase decisions. Since participants consider hypothetical situations, we can tell treated participants to imagine that any firm is bankrupt to estimate that bankruptcy's impact. We now describe the experimental design.

3.1 Incentivizing Participants

The experiment begins with attention tests. We exclude participants that fail these tests. We then incentivize participants to honestly report their willingness to pay for goods in hypothetical purchase decisions. In the spirit of Kessler, Low, and Sullivan (2019), we tell participants that their responses will be used to determine potential lottery prizes. This makes it incentive compatible for participants to take the hypothetical decisions seriously without deceiving participants. We provide details in Internet Appendix C.

[5] See https://document.epiq11.com/document/getdocumentbycode?docId=4191210&projectCode=INB&source=DM.

[6] See https://restructuring.ra.kroll.com/hertz/.

This incentive approach is less standard than the price-list mechanism used in our first two experiments.[7] Nonetheless, we believe our participants honestly report their preferences because (i) we give an incentive to do so, (ii) there is no incentive to misreport, (iii) we find similar results with traditional BDM incentives (Section 2), and (iv) the use of incentives often has little or no effect on participant responses in experiments (Haaland, Roth, and Wohlfart, 2023).[8]

3.2 Randomizing Information and Measuring Willingness to Pay

In the second stage of the experiment, we randomly assign each participant into one of seven information conditions. We measure how each information set affects participants' willingness to pay for goods. Specifically, each participant provides their willingness to pay for the same ten goods and services. However, each participant sees different information, depending on the assigned condition, about the firms that provide the goods. Once assigned to an information condition, a participant sees the same information in all ten questions. For example, in the "bankruptcy" information group, the product-providing firm is bankrupt in all ten questions. We now provide details.

3.2.1 Willingness-to-Pay Questions

We ask participants to make ten hypothetical purchase decisions from firms in three industries: car manufacturers, airlines, and retailers. We focus on these consumer-facing industries because of the high number of large historical bankruptcies. Also, these industries are broadly representative of durable goods, services, and nondurable goods. Participants answer all the willingness-to-pay questions for a given industry before moving on to the next industry. We randomize the order in which participants see each industry.

In each purchase decision, the participant is asked to report their hypothetical willingness to pay for a good or service: a car, an airline ticket, or a shirt. The participant is told the price that one firm, "Firm A," charges for this product. The participant is then asked to report how much they would hypothetically be willing to pay for the same product from

[7] We cannot use the price list here because the goods come from hypothetical firms with hypothetical bankruptcy statuses.

[8] We ran an unincentivized version of our Hertz price-list experiment and find results that are similar to the results of Section 2, see Internet Appendix A.

another firm, "Firm B." In each industry, we include one generic example (literally Firm A versus Firm B). In other questions, Firm A and Firm B are specific firms: Ford versus Tesla, JetBlue versus Southwest, and American Eagle versus Express.[9] Table 2 describes the ten willingness-to-pay questions, listing Firm B, Firm A, and the Firm-A reference price for each question. Internet Appendix C.2 provides details.

3.2.2 Randomizing Information

Each participant is randomly assigned to one of seven information groups. For "control" group participants, each question simply (i) describes a good or service, (ii) states Firm A's price, and (iii) asks for the willingness to pay for the same product at Firm B. In the other six information groups, participants see an additional fact about Firm B. We now summarize the information presented to each group about Firm B. We display exact quotes in Table 3.

For the "bankruptcy" group, each question also includes the following text:

"Please imagine that [Firm B] filed for Chapter 11 bankruptcy and is still in bankruptcy."

The identity of Firm B varies across questions (see Table 2). Each other information group sees a modified version of the above quote in all ten questions. The "survival 50" group is told that Firm B is currently in bankruptcy, but experts anticipate the firm has a 50% chance of emerging, allowing the firm to continue operating. The "survival 100" group is told that Firm B is currently in bankruptcy, but experts anticipate the firm has a 100% chance of emerging, allowing the firm to continue operating. The "quality" group is told that Firm B is currently in bankruptcy, but an independent agency assessed that Firm B's quality has not changed since bankruptcy. These information conditions are designed to test the current-quality hypothesis and the importance of survival concerns. Additionally, the "pre-bankruptcy" group is told that financial experts estimate that Firm B has a 50% chance of filing for Chapter 11 bankruptcy in the next six months. The "post-bankruptcy" group is told that Firm B filed for Chapter 11 bankruptcy, emerged, and is now operating as a nonbankrupt company. These conditions are designed to measure when indirect distress costs occur.

[9] We chose these particular firms because they have never been in bankruptcy. There is thus little risk of control-group participants associating any firm with a bankruptcy.

3.3 Follow-Up Questions

Finally, we ask each participant to rate the extent to which various concerns affected their willingness-to-pay decisions. We also assess each participant's knowledge of actual historical bankruptcies: participants select which firms in a given list have ever been bankrupt, if any. Each participant answers these questions for one industry, which corresponds to the industry in their final willingness-to-pay question. Importantly, this is the first time that the control group has seen the word "bankruptcy." We conclude by asking for demographic information.

3.4 Discussion

By design, our experiment measures the effect of a firm's bankruptcy on consumers that are aware of the bankruptcy. It also measures the fraction of consumers that are aware of major historical bankruptcies. In Section 5, we combine these estimates with a structural model to estimate the overall causal effect of bankruptcy on producer and consumer surplus.

We measure the impact of a bankruptcy on how consumers perceive the firm. The relevant counterfactual is thus the perception of the firm that consumers would have had before learning the firm is bankrupt.

3.5 Final Experiment-Participant Sample

We ran our experiment online from January - February 2022 using a survey marketplace called Lucid.[10] Lucid provides a representative sample of U.S. adults.[11] Following our preregistered sample-selection criteria, our final sample consists of 1,749 participants and 17,490 willingness-to-pay-question responses.

4 Reduced-Form Results from the Third Experiment

4.1 The Causal Effect of Bankruptcy on Consumer Demand

For each participant i in each of $q = 1, 2, ..., 10$ questions (Table 2), we measure the participant's willingness to pay WTP_{iq} for some Firm B's product or service. In each question, we tell the participant how much an equivalent product costs at another Firm A. We define the

[10]We preregistered our experiment and sample. See Internet Appendix C.3.

[11]Table D.2 compares the demographic composition of our sample to that of the U.S.

normalized willingness to pay WTP_{iq}^{norm} as the ratio of the willingness to pay for Firm B's product to the price of Firm A's product in question q:[12]

$$WTP_{iq}^{norm} \equiv \Big(\text{WTP at Firm B} \Big) \, / \, \Big(\text{Given Price at Firm A} \Big) . \tag{1}$$

We define mutually exclusive binary indicator variables for information groups. For example, $Bankruptcy_i = 1$ implies i is told that Firm B is bankrupt in all questions, etc. Importantly, a given participant i remains in the same information group for all ten questions $q = 1, ..., 10$. Our identification thus comes from comparisons across participants. We estimate the following participant-question-level equation, estimating a separate regression for each industry:

$$\begin{aligned} WTP_{iq}^{norm} &= \alpha + \kappa \textit{Pre-Bankruptcy}_i + \beta \textit{Bankruptcy}_i + \eta \textit{Post-Bankruptcy}_i \\ &\quad + \delta \textit{Quality}_i + \gamma \textit{Survival 50}_i + \rho \textit{Survival 100}_i + \epsilon_{iq}. \end{aligned} \tag{2}$$

We omit the indicator for control-group participants. The coefficient α on the constant term may thus be interpreted as the average normalized willingness to pay for control-group participants. Similarly, the coefficients on the treatment-group indicators may be interpreted as differences in average normalized willingness to pay, relative to the control group. We cluster standard errors at the participant level.

Each column of Table 4 shows our estimates of equation (2) for one industry. We first consider the coefficients on $Bankruptcy_i$. Knowledge of a bankruptcy filing substantially reduces willingness to pay, relative to the control-group average. The average normalized willingness to pay among participants who are told that an airline is bankrupt is dramatically lower than the corresponding average among control-group participants — the difference in means is 21.8% of the reference airline price. Put differently, comparing participants who believe an airline is bankrupt to those that believe it is not, an airline's bankruptcy reduces willingness to pay by 24% of the control-group average willingness to pay (.218/.898). We observe similar patterns across industries. A retail bankruptcy reduces average willingness to pay

[12] Following our preregistration, we truncate this value at three, replacing values of the normalized willingness to pay that exceed three with the value three instead. A value of three means that the participant is willing to pay three times as much for a good or service from Firm B compared to Firm A. Additionally, we require participants to report $WTP_{iq} \geq 0$.

by 18.6% of the control-group mean (.179/.962). Likewise, a car-manufacturer bankruptcy reduces willingness to pay by 22% of the control-group mean (.193/.879).

We next consider the coefficients on *Post-Bankruptcy*$_i$. Interestingly, most of the impact of a bankruptcy filing disappears once a firm exits bankruptcy. Comparing participants who believe an airline was previously bankrupt to those that believe it is solvent, an airline's prior bankruptcy reduces willingness to pay by only 8.5% of the control-group mean (.076/.898). For car manufacturers, a prior bankruptcy only reduces willingness to pay by 5.5% of the control-group average (.048/.879). This implies that while participants do have some concerns with a firm that was ever in bankruptcy, their concerns about inherent quality issues are not as strong as concerns about current quality during bankruptcy or future interactions.

Table 4 shows that the pre-bankruptcy treatment effect is almost as large as the bankruptcy treatment effect. A consumer who is aware that a firm is approaching bankruptcy will thus avoid that firm almost as much as she would avoid a bankrupt firm. Importantly, we show in Section 4.6 that consumers are not aware which firms are close to bankruptcy. In contrast, Section 4.5 shows that many consumers are aware when a firm files for bankruptcy.

4.2 Causal Evidence on Mechanisms

Next, we examine the mechanisms by which bankruptcies affect consumer demand. We begin with the quality-treatment group. Participants in this group report their willingness to pay for bankrupt firms. However, participants are told that, according to an independent agency, each firm's bankruptcy has not affected the firm's quality. Table 4 shows that this reassurance mitigates most of the impact of a bankruptcy. For example, participants who receive this reassurance reduce their willingness to pay for airline tickets by 8.1% of the reference price, relative to control-group participants. The quality reassurance thus eliminates 63% of the baseline effect of an airline bankruptcy filing (21.8% of the reference price). Comparing the equivalent coefficients in column (2), we see that quality reassurance eliminates 61.5% of the impact of a retail-company bankruptcy. Quality reassurance reduces the effect of a car-manufacturer bankruptcy by 58.5%.

We now turn to the importance of future consumer-firm interactions. Consumers may respond to bankruptcy filings because they fear a liquidation will prevent future interactions with the firm. If these survival concerns are important, then consumers should be reassured by learning that a firm is likely to survive bankruptcy. In the survival-100 group, participants report their willingness to pay for bankrupt firms. However, we tell participants that financial experts estimate that these bankrupt firms will almost certainly survive bankruptcy. Table 4 shows that eliminating survival concerns reduces the impact of a bankruptcy. For example, survival-100-group participants reduce their willingness to pay for airline tickets by 14.6% of the reference price, relative to control-group participants. The survival reassurance thus eliminates 33% of the baseline effect of an airline bankruptcy filing. Interestingly, this suggests that current quality concerns and survival concerns entirely explain the impact of an airline bankruptcy: removing survival concerns eliminates 33% of the impact and quality reassurance eliminates 63% of the impact. Further, this suggests that concerns about quality during an airline's bankruptcy are twice as important as concerns that the airline will liquidate.[13] Examining column (2), we see a similar pattern for retail: removing survival concerns eliminates 36% of the impact of bankruptcy, while quality reassurance eliminates 61.5% of the impact. In contrast, survival concerns are more important for car manufacturers. Removing the possibility of a liquidation eliminates 62% of the baseline effect of a car-manufacturer bankruptcy filing. This is intuitive, since cars are durable goods for which warranties and future part purchases are likely to be important for consumers.

4.3 Survey Evidence on Mechanisms

We complement the causal evidence of Table 4 with additional survey evidence. Specifically, after participants finish their willingness-to-pay questions, they are asked to rate the extent to which various specific concerns affected their decisions. For example, we consider the concern "I worry that a bankrupt airline is unsafe," which relates to the quality of an airline during bankruptcy. In each of these follow-up questions, we give a specific concern and ask participants to respond on a scale from one (not at all concerned) to seven (very concerned), with four being a neutral answer.

Tables D.8, D.9, and D.10 in Internet Appendix D display the average rating, by industry, that participants report for a series of concerns. We include only those participants in the bankruptcy-treatment group. For the airline industry, the strongest concerns relate to delays and cancellations, as well as a concern that the airline might cease to operate before an already-purchased flight. Consistent with cars being a durable good, the strongest concerns

[13]Supporting this view, we show in Table D.1 that the causal effect of bankruptcy is similar for flights purchased three months or one month before departure.

for car purchases relate to losing a warranty and not being able to find replacement parts. For retail bankruptcies, the strongest concerns relate to difficulty in returning items and a lack of inventory. In all industries, participants are not concerned that bankruptcy is a negative signal of pre-bankruptcy fraud, overpricing, or poor quality.

4.4 Implied Survival Probabilities and Consumer Education

As described in Section 4.2, equation (2) reveals the importance of survival concerns. By comparing the coefficients β, γ, and ρ in equation (2), we can infer the average perceived likelihood of bankruptcy survival in each industry. For example, in column (1) of Table 4, moving from a 50% chance of survival to 100% increases WTP_{iq}^{norm} by 0.164. Assuming a linear effect of survival probability, this implies a 100% increase in survival probability increases WTP_{iq}^{norm} by 0.328. Comparing the baseline effect of bankruptcy ($-.218$) to the effect of a bankruptcy with a 50% survival probability ($-.310$), this implies the average belief is that $50\% + (.310 - .218)/0.328 = 78\%$ of airlines survive bankruptcy. Likewise, the average belief is that 56% of car manufacturers survive bankruptcy. We compare these to historical bankruptcy survival rates by industry. We obtain survival outcomes for historical bankruptcies involving at least \$1 billion in assets from Bankruptcydata.com.[14]

We find that consumers act as if they believe 78% of airlines survive bankruptcy. This is surprisingly accurate: Historically, 76% of large airlines survive bankruptcy. There is thus little scope for educating consumers about the survival prospects of bankrupt airlines. However, participants are less informed for car-manufacturer bankruptcies. Participants act as if 56% of car manufacturers survive bankruptcy. Historically, 100% of large car manufacturers survive bankruptcy. Table 4 shows that increasing survival beliefs by 44 percentage points increases willingness to pay by .193-.074 = .119. That is, educating consumers about car-manufacturer survival prospects would eliminate .119 / .193 = 62% of the effect of a car-manufacturer bankruptcy on willingness to pay.[15] We explore this further using our structural model.

[14]For each acquisition, we manually verify whether the firm continued to operate as an independent entity.

[15]Applying this methodology to retail firms leads to a negative number, suggesting that participants act as if the survival rate for retail firms is zero. The historical survival rate is 64%.

4.5 What Fraction of Consumers are Aware of Bankruptcies?

Our experiment quantifies the fraction of consumers that are aware of various historical bankruptcies. For each industry, we show participants a list of firms and ask them to select which firms, if any, have ever filed for bankruptcy.[16] We include many firms that have filed for bankruptcy and many that have not. We provide a "none of the above" option. We say a participant is aware of a historical bankruptcy if she selects the corresponding firm from the list. For each firm on the list that ever filed for bankruptcy, we calculate the fraction of participants aware of the bankruptcy.

Table 5 displays the results. For a typical large airline bankruptcy, about 15-20% of participants are aware of the bankruptcy. Between 37% and 44% of participants are aware of the major car-manufacturer bankruptcies. Roughly 48% of participants are aware of J.C. Penney's bankruptcy, but a smaller fraction are aware of other historical retail bankruptcies. These awareness numbers are likely a lower bound: all of these bankruptcies happened in the past - some over ten years ago. In a complementary experiment described in Section 2, we find that 26% of consumers were aware of Hertz's bankruptcy at the time of the bankruptcy.

These results are not driven by consumers mistakenly believing that all firms have been bankrupt at some point. For each firm in our survey, we define *Bankruptcy Awareness* as the fraction of participants reporting the firm is bankrupt. We define an indicator variable *Actual Bankruptcy* that is equal to one for firms that ever filed for Chapter 11 bankruptcy. We estimate a firm-level regression of *Bankruptcy Awareness* on *Actual Bankruptcy*. Table 6 shows a significant positive relationship with an adjusted R^2 of 0.276. Consumers are 12 percentage points more likely to report a firm was bankrupt at some point if it ever filed for bankruptcy. On average, only 6.5% of participants mistakenly think a firm was once bankrupt if in reality it never was.

4.6 Ignorance of Pre-Bankruptcy Financial Distress

Participants in the pre-bankruptcy-treatment group are told that a firm has a 50% chance of filing for bankruptcy in the next six months. Table 4 shows that knowledge of this pre-bankruptcy distress causally reduces demand for the distressed firm.

This raises the question of whether consumers know which firms are close to bankruptcy.

[16] Note that this is the first time that the control group has seen the word "bankruptcy."

To measure this, we ask the pre-bankruptcy-group participants to rate firms, on a scale from one to five, based on how close each firm came to bankruptcy over the period from 2010-2019. For each firm, we define *Near-Bankruptcy Awareness* as the average participant rating. We examine the extent to which this variable correlates with realized financial distress.

To begin, we test whether *Near-Bankruptcy Awareness* is driven by actual bankruptcy filings: consumers might perceive a firm as close to bankruptcy because at some point it was bankrupt. We estimate a firm-level regression of *Near-Bankruptcy Awareness* on *Actual Bankruptcy*. Table 6 shows a significant positive relationship with an adjusted R^2 of 0.225.

Next, we test whether consumers know which nonbankrupt firms came close to bankruptcy. We compare *Near-Bankruptcy Awareness* to credit ratings, a measure of financial distress. We obtain credit-rating data from FISD. For each firm referenced in the survey, we define *Worst Credit Rating* as the worst credit rating that the firm was given (across Fitch, Moodys, and S&P) over the period from 2010-2019, coded on a numerical scale.

We estimate a firm-level regression of *Near-Bankruptcy Awareness* on *Actual Bankruptcy* and *Worst Credit Rating*. Table 6 shows that conditional on whether a firm filed for bankruptcy, there is no relationship between *Near-Bankruptcy Awareness* and *Worst Credit Rating*. The coefficient on *Worst Credit Rating* is economically and statistically insignificant. To confirm this, we exclude firms that filed for bankruptcy and regress *Near-Bankruptcy Awareness* on *Worst Credit Rating*. The adjusted R^2 is negative.

To summarize, when consumers believe a firm is near bankruptcy, their willingness to pay for that firm declines. However, our results show that consumers are only aware of a firm's distress once it files for bankruptcy.

4.7 External Validity

It is impossible to directly test the extent to which our results can be extrapolated beyond our experiment. Outside of an experiment, any correlation between consumer demand and corporate bankruptcy is confounded by the unobserved factors that led to the bankruptcy.

However, it is plausible that our experiment results correspond to consumer behavior in other settings for four reasons. First, our experiment participants have a real incentive to truthfully report their preferences (Kessler, Low, and Sullivan, 2019). Second, Table D.2 confirms that our experiment participants comprise a demographically representative sample of U.S. adults. Third, Table D.3 shows that our experiment participants regularly make the types of purchases that we ask about in our experiment. Fourth, Table D.4 shows that our results are robust to focusing on those participants who most frequently make these purchases. Tables D.5, D.6 and D.7 show that our results are robust to focusing on participants who have previously purchased from the name brands.

5 Structural Model Estimation

Next, we estimate a structural model to infer how historical bankruptcies impacted market shares, consumer welfare, pricing, and producer surplus. In our model, consumers choose which product to purchase. Firms compete for customers through endogenous pricing decisions. The model setup is standard (Berry, Levinsohn, and Pakes, 1995), with one new feature: a consumer's utility derived from a product might change if the producer is bankrupt.

We use our third experiment to estimate parameters that are otherwise difficult to estimate: (i) consumer price sensitivity, (ii) consumer awareness of corporate bankruptcies, and (iii) the extent to which consumers care about bankruptcies. We combine these estimates with observational data to examine the impacts of historical bankruptcies. For this structural estimation, we focus on airlines and car manufacturers due to data limitations.[17]

5.1 Discrete-Choice Model

In our model, consumer i gets indirect utility u_{ijtd} from purchasing good j from firm f_j in market t. We let d index industries: car manufacturers or airlines. For car manufacturers, a good is a car or light truck. A market is a vehicle class (e.g., "large SUV") in a given year. For airlines, a good is a flight. A market is a flight route in a given quarter. We provide details in Internet Appendix E.

There are J_t goods available in market t. In every historical market, we assume there is also an outside option ($j = 0$). This outside option represents not flying or not purchasing a new vehicle. For $j \neq 0$, we assume that indirect utility is given by the following equation:

$$u_{ijtd} = \delta_{jt} + \alpha_{id} p_{jt} + \beta_{id} A_{ijt} B_{jt} + \epsilon_{ijtd}. \tag{3}$$

[17] Specifically, we obtain datasets containing historical prices and market shares for motor vehicles and flights. Measuring prices and market shares, or even defining markets, is extremely difficult for retail goods. We leave this exercise for future work.

In this equation, δ_{jt} is a parameter capturing the average taste for good j in market t. The average price of good j in market t is given by p_{jt}. The binary variable B_{jt} indicates whether the firm f_j providing good j is bankrupt in the time period associated with market t. The binary random variable A_{ijt} takes a value of one if and only if consumer i is aware of firm f_j's bankruptcy. For each bankrupt firm f_j, we calibrate $\mathbb{P}(A_{ijt} = 1)$ to match our survey evidence (Table 5). The random coefficients α_{id} and β_{id} capture consumer i's idiosyncratic sensitivity to prices and bankruptcies, respectively, in industry d. Finally, the error ϵ_{ijtd} captures the idiosyncratic tastes of consumer i. We normalize the outside-option indirect utility to equal $u_{i0td} = \epsilon_{i0td}$ for all i, t, d.

We make standard distributional assumptions. For each d, we assume that α_{id}, β_{id} are normally distributed across consumers:

$$\alpha_{id} \sim N(\bar{\alpha}^d, \sigma_\alpha^d), \qquad \beta_{id} \sim N(\bar{\beta}^d, \sigma_\beta^d), \tag{4}$$

where we estimate the parameters $\{\bar{\alpha}^d, \sigma_\alpha^d, \bar{\beta}^d, \sigma_\beta^d\}$. Finally, we assume that the error ϵ_{ijtd} has a Type I extreme value distribution.

Consumer i chooses $j \in \{0, 1, ..., J_t\}$ to maximize her indirect utility u_{ijtd}. We refer to this expected optimized utility $\mathbb{E}[\max_j u_{ijtd}]$ as consumer welfare.

We augment this model of consumer choice with a standard model of firm pricing decisions. Let p_t denote a $J_t \times 1$ vector of prices with components p_{jt}. Let $S_{jt}^{model}(p_t)$ denote good j's market share in market t given the vector of prices $p_t = \{p_{1t}, ..., p_{jt}, ...\}$. By equation (3), these model-implied market shares are given by the well-known logit formula:

$$S_{jt}^{model}(p_t) = \mathbb{E}_{\alpha_{id}, \beta_{id}, A_{ijt}} \left[\frac{\exp\left(\delta_{jt} + \alpha_{id} p_{jt} + \beta_{id} A_{ijt} B_{jt} \right)}{1 + \sum_{k=1}^{J_t} \exp\left(\delta_{kt} + \alpha_{id} p_{kt} + \beta_{id} A_{ikt} B_{kt} \right)} \right]. \tag{5}$$

The 1 in the denominator captures the outside option. Following the literature, we assume good j's provider in market t has a constant marginal cost c_{jt}. The per-unit profit associated with good j is thus $p_{jt} - c_{jt}$. Let G_{ft} denote the set of goods j in market t provided by firm f. We assume that each firm in market t simultaneously chooses prices to maximize profits. A pricing equilibrium is thus given by a vector of prices p_t^* such that, for any f, the prices

$\{p^*_{jt}\}_{j\in G_{ft}}$ solve firm f's optimization problem:

$$\sup_{\{p_{jt}\}_{j\in G_{ft}}} \sum_{j\in G_{ft}} S^{model}_{jt}\left((\{p_{jt}\}_{j\in G_{ft}}, \{p^*_{kt}\}_{k\notin G_{ft}}) \right) \times \left(p_{jt} - c_{jt} \right). \tag{6}$$

In words, firm f chooses prices for all the goods G_{ft} it provides. Firm f accounts for how its market share depends on these prices and the prices of all goods $k \notin G_{ft}$ not provided by firm f. Each firm solves this problem, taking competitors' prices as given. We refer to the optimized objective in equation (6) as firm f's producer surplus.

5.2 Estimation

While our model assumptions are standard in the literature, we depart from the standard estimation procedure. We do this in order to take full advantage of the randomized variation in our experiment. We now briefly summarize our estimation procedure, providing details in Internet Appendix E.

Our estimation procedure has two steps. In the first step, we use data from our third experiment to estimate the consumer-taste parameters $\{\bar{\alpha}^d, \sigma^d_\alpha, \bar{\beta}^d, \sigma^d_\beta\}$ for cars and flights. Recall that control-group participants report their willingness to pay for a firm's goods in a hypothetical market with two firms: Firm A or Firm B. For any price p_B that Firm B might charge, we can thus calculate its experiment-implied market share: the fraction of participants willing to pay p_B for Firm B's good. Our experiment thus reveals how any change in prices would impact a firm's market share, holding everything else fixed. This is ideal variation to identify the model parameters $\{\bar{\alpha}^d, \sigma^d_\alpha\}$ governing price sensitivity. Comparing treated-participant responses to control-participant responses similarly reveals how a bankruptcy would impact market share, holding everything else fixed. This is ideal variation to identify the model parameters $\{\bar{\beta}^d, \sigma^d_\beta\}$ governing bankruptcy sensitivity. Formalizing this intuition, we estimate the consumer-taste parameters by the Generalized Method of Moments (GMM). Table 7 shows our estimates along with asymptotic participant-clustered standard errors. Internet Appendix E.1 provides details on this step of the estimation.

In the second step, we turn to observational data on historical markets. We obtain average prices and market shares for all airlines on all U.S. flight routes from the Department of Transportation's Airline Origin and Destination Survey (DB1B). We obtain manufacturer suggested retail prices and sale volumes for all U.S.-new-vehicle sales from Wards Intelligence. For each good j in each market t in each dataset, we estimate the good-taste parameter δ_{jt}. We do this by matching observed market shares with model-implied market shares. Formally, given (i) observed prices, (ii) observed market shares, and (iii) our consumer-taste-parameter estimates, there is a unique set of good-taste parameters $\{\delta_{jt}\}$ such that the model-implied market shares (5) match the observed market shares. We apply this well-known result using the standard contraction-mapping algorithm (Nevo, 2000) to estimate $\{\delta_{jt}\}$ for all the goods and markets in our datasets. Finally, we estimate marginal costs c_{jt} such that model-implied optimal prices match observed prices. Internet Appendix E.3 provides details on this step of the estimation.

5.3 Counterfactual: Estimating Costs of Historical Bankruptcies

We now consider our key counterfactual: what if various historical bankruptcies had never occurred? For this exercise, we first use our estimates to simulate producer surplus and consumer-welfare values in each market t for which some good provider f_j was bankrupt ($B_{jt} = 1$). We then assume counterfactually that $B_{jt} = 0$ and solve numerically for a new pricing equilibrium $p_t^{counter}$ satisfying (6).[18] Finally, we simulate to calculate counterfactual market shares, producer surplus, and consumer welfare.

Table 8 displays the results. To begin, consider American Airlines (AA), which filed for bankruptcy on 11/29/2011 and emerged on 12/9/2013. Taking a passenger-volume-weighted average across routes during this period, we find that AA lowered its price by only 0.4% relative to the unobserved counterfactual in which AA were not bankrupt. Competitors slightly increased prices relative to the prices they would have chosen in the absence of AA's bankruptcy. However, AA's bankruptcy had a substantial causal effect on market shares, lowering AA's passenger-weighted average market share by 10.2%. As a result, AA's bankruptcy causally reduced AA's producer surplus (the objective in (6)) by 11.5%. While many consumers shifted away from AA because of the bankruptcy, those who remained with AA lost a meaningful fraction of the surplus they previously enjoyed. Specifically, taking a passenger-weighted average across all consumers on all airlines and all routes, AA's bankruptcy causally reduced consumer welfare by 3.4%.

[18] That is, we solve numerically for a pricing equilibrium given the market shares defined by (5) with $B_{jt} = 0$ for the relevant goods.

The bankruptcies of Delta Airlines and United Airlines had similar effects (Table 8). United lost 13.5% of its producer surplus during its bankruptcy, relative to the unobserved counterfactual in which United never went bankrupt. The bankruptcies of General Motors and Chrysler had even larger effects, lowering their producer surpluses by 27% and 31%, respectively. These were larger because more consumers are aware of car-manufacturer bankruptcies than airline bankruptcies (Table 5).

Next, we show that the impact of a bankruptcy in a given market depends on the bankrupt firm's market share. For each bankruptcy and each affected market, we calculate the model-implied causal effect of the bankruptcy on the bankrupt firm's market share. We calculate the bankrupt firm's median market share across all its markets during its bankruptcy. We average these causal effects across all markets in which the bankrupt firm's observed market share was below that firm's median market share. We likewise calculate an average across markets with above-median market share (Table 8). The impact on market share is largest, in percentage terms, in markets where a firm has relatively little market share. Intuitively, a bankruptcy causes a firm f_j to lose customers who would have slightly preferred good j to some competitor k in the absence of bankruptcy. These borderline customers represent a smaller fraction of customers for firms with a large market share, which explains the pattern in causal effects on market shares in Table 8. Since price responses are small, the causal effects of bankruptcy on producer surpluses display a similar pattern with similar magnitudes. In contrast, the effect of a bankruptcy on consumer welfare displays the opposite pattern. Intuitively, consumers are only affected by a bankruptcy if they would have chosen the firm's good in the absence of a bankruptcy.

Interestingly, we find evidence suggesting that airlines attempt to improve quality during bankruptcy. Specifically, in each quarter, we calculate each airline's median δ_{jt} estimate across routes. Figure D.1 shows that the median tastes for Delta and AA trended upward after their bankruptcy filings. This implies that without the strong negative consumer responses to these bankruptcy filings, these firms actually would have gained market share.

5.3.1 Can Consumer Education Help?

Finally, we use the estimated model to explore the effects of educating consumers about corporate bankruptcy. Section 4.4 shows that, on average, consumers (i) have correct beliefs about bankrupt-airline-survival prospects, and (ii) incorrectly believe an underestimate of the likelihood that a car manufacturer will survive bankruptcy.[19] What if consumers were educated about car-manufacturer bankruptcy survival prospects?

To answer this question, we hold each bankruptcy status B_{jt} fixed and consider a counterfactual in which consumers hold the rational belief (Section 4.4) that large car manufacturers survive bankruptcy. We adjust the distribution of bankruptcy sensitivities β_{id} to reflect this belief: we multiply each β_{id} by (.074 / .193) to match the reduced-form causal effect of removing survival concerns (Table 4). For each car manufacturer bankruptcy, we resimulate consumer choices and producer and consumer surplus with these counterfactual $\{\beta_{id}\}$. We then compare these values to the corresponding values in the no-bankruptcy counterfactual. This reveals how each bankruptcy would impact consumers who are educated on true survival probabilities, relative to the counterfactual of no bankruptcy filing. Internet Appendix E.5 provides details.

The bankruptcy of General Motors reduced consumer welfare by 6.8%, but it only would have reduced consumer welfare by 3.3% if consumers were educated about bankruptcy survival rates (Table 8). This comparison reveals that reducing bankruptcy sensitivities has a nonlinear effect on utility-maximizing consumers: Reducing bankruptcy sensitivities by 62% only reduces the impact on consumer welfare by roughly 52%. Nonetheless, Table 8 shows that this counterfactual consumer education would dramatically reduce the negative effects of bankruptcy on producer and consumer welfare.

6 Conclusion

In this paper, we show that a corporate bankruptcy filing causally reduces consumer demand for the bankrupt firm's products. We quantify this indirect cost of bankruptcy across industries. Many consumers are aware of corporate bankruptcies and these consumers react strongly, lowering their willingness to pay for a bankrupt firm by 18% to 35%. This decline in demand is caused by consumers' concerns about both current quality issues with bankrupt firms and the possible loss of future interactions with these firms.

Andrade and Kaplan (1998) estimate that severe financial distress is associated with a 10% to 20% decline in firm value. Based on a larger sample, Glover (2016) estimates that the average default costs a firm 25% of its value. While the direct costs of bankruptcy are sub-

[19]We focus on car manufacturers in this counterfactual for this reason.

stantial for small firms (Antill, 2021), direct costs are relatively minor for large firms (Weiss, 1990). Academics have reconciled these facts by conjecturing that indirect bankruptcy costs must be large. Our structural estimation confirms this: indirect costs associated with lost customers can destroy 10% to 30% of firm value.[20]

Additionally, we show that educating consumers about bankruptcy survival prospects can improve producer and consumer surplus. It is thus important to help consumers make decisions with accurate information about bankruptcy and the survival prospects of bankrupt firms.[21]

[20]It is still possible that higher deadweight losses in bankruptcy can improve ex-ante welfare by motivating efficient pre-bankruptcy behavior or mitigating externalities (Antill and Grenadier, 2019; Antill and Clayton, 2021; Donaldson, Gromb, and Piacentino, 2020).

[21]This is especially important given the reluctance of consumers to acquire information relevant for their decisions when that information is negative (Fong and Hunter, 2022).

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Table 1: Price List Experiments

This table shows the results of our first and second experiments (Section 2). Let $Aware_i$ denote an indicator equal to one for participants i who are aware of the firm's bankruptcy (Hertz in experiment one, Instant Brands in experiment two). Let $Treat_i$ be an indicator for i being randomly selected to learn that the firm is bankrupt. Let WTP_i denote the willingness to pay for the good (a $50 Hertz gift card in experiment one, an Instant Pot in experiment two). Columns (1) and (3) show the results of ordinary-least-squares (OLS) regressions of $Aware_i$ on $Treat_i$ in the first and second experiment samples, respectively. Columns (2) and (4) show the results of 2SLS regressions of WTP_i on $Aware_i$, where we instrument for awareness using $Treat_i$. All regressions include the control variables described in Section 2. We report robust standard errors in parentheses. In our third experiment, we use participant-clustered standard errors because we include multiple observations for each participant; since the analysis for this table includes one observation for each participant, we opt for robust standard errors only in this table.

	Aware	WTP	Aware	WTP
	(1)	(2)	(3)	(4)
Treat	0.653***		0.894***	
	(0.026)		(0.043)	
Aware		-17.680***		-11.362**
		(2.432)		(5.389)
Experiment	Hertz	Hertz	Instant	Instant
Estimator	OLS	2SLS	OLS	2SLS
Control Variables	Y	Y	Y	Y
Observations	822	822	161	161
F-Statistic	649.8		432.1	
Control-Group Mean	0.260	49.81	0.0200	53.48

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2: Third Experiment Setup: Willingness-to-Pay Questions

Each participant sees the same ten willingness-to-pay questions. Each willingness-to-pay question has the following format: "Please imagine that you need to purchase a (flight/shirt/car). You are deciding between two (airlines/retailers/car manufacturers): Firm A or Firm B. (Fact about Firm B corresponding to information group). Your desired (flight/shirt/car) costs (Firm A Price) at Firm A. What is the most that you would be willing to pay for an equivalent (flight/shirt/car) at Firm B? Please enter a whole number." This table lists Firm A Price, Firm B, and Firm A for each of the ten questions. There are four questions for airlines: three in which the flight is one month from purchase; one in which the flight is three months from purchase. This leads to a larger sample for airline questions.

Firm A	Firm A Price	Firm B
Retailer A	$35	Retailer B
Express	$35	American Eagle
American Eagle	$15	Express
Airline A	$300	Airline B
JetBlue	$300	Southwest
Southwest	$600	JetBlue
Airline A (3 months)	$300	Airline B
Car Manufacturer A	$47K	Car Manufacturer B
Tesla	$47K	Ford
Ford	$28K	Tesla

Table 3: Third Experiment Setup: Information Groups

Each participant is randomized into one of seven information groups. Once a participant is assigned to an information group, they see the following text describing "Firm B" in all ten willingness-to-pay questions. See Table 2 for the identity of Firm B in each question. The exact text in the quality treatment varies across industries.

Group	Example Text
Control	
Bankruptcy	Please imagine that [Firm B] filed for Chapter 11 bankruptcy and is still in bankruptcy.
Quality	Please imagine that [Firm B] filed for Chapter 11 bankruptcy and is still in bankruptcy. During the bankruptcy, the Better Business Bureau assessed that [Firm B's] quality was not affected by the bankruptcy.
Survival 50	Please imagine that [Firm B] filed for Chapter 11 bankruptcy and is still in bankruptcy. Financial experts estimate that there is a 50% chance that [Firm B] will emerge from bankruptcy and continue operating.
Survival 100	Please imagine that [Firm B] filed for Chapter 11 bankruptcy and is still in bankruptcy. Financial experts estimate that [Firm B] will almost certainly emerge from bankruptcy and continue operating.
Pre-Bankruptcy	Please imagine that financial experts estimate that [Firm B] has a 50% chance of filing for Chapter 11 bankruptcy in the next six months.
Post-Bankruptcy	Please imagine that [Firm B] filed for Chapter 11 bankruptcy, emerged, and is now operating as a non-bankrupt company.

Table 4: How, When, and Why does Bankruptcy Change Consumers' Willingness to Pay?

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups. For each participant in each of 10 questions, we measure the participant's willingness to pay for some Firm B's product or service. In each question, we tell the participant how much an equivalent product costs at another Firm A. We define the normalized willingness to pay as the ratio of the willingness to pay for Firm B's product to the price of Firm A's product. The displayed independent variables are indicators for treatment groups defined in Table 3. We regress normalized willingness to pay on indicator variables for the six treatment groups, omitting the indicator for the control group. We estimate a separate regression for each industry. We estimate a participant-question level regression. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Bankruptcy	-0.218***	-0.179***	-0.193***
	(0.021)	(0.021)	(0.022)
Pre-Bankruptcy	-0.196***	-0.101***	-0.173***
	(0.024)	(0.026)	(0.025)
Post-Bankruptcy	-0.076***	-0.070***	-0.048**
	(0.019)	(0.023)	(0.024)
Quality	-0.081***	-0.069***	-0.080***
	(0.021)	(0.024)	(0.025)
Survival 50	-0.310***	-0.123***	-0.208***
	(0.026)	(0.027)	(0.025)
Survival 100	-0.146***	-0.114***	-0.074***
	(0.022)	(0.023)	(0.027)
Constant	0.898***	0.962***	0.879***
	(0.011)	(0.015)	(0.015)
Industry	Airline	Retail	Car
Observations	6996	5247	5247

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 5: What Fraction of Consumers are Aware of Bankruptcies?

For each industry, we show participants a list of firms and ask them to select which firms, if any, have ever filed for bankruptcy. We include many firms that have filed for bankruptcy and many that have not. We provide a "none of the above" option. We say a participant is aware of a historical bankruptcy if she selects the corresponding firm from the list. For each firm on the list that ever filed for bankruptcy, this table displays the fraction of participants that are aware of the bankruptcy.

	Fraction Aware
Delta Airlines	0.15
United Airlines	0.19
American Airlines	0.17
Continental Airlines	0.22
Frontier Airlines	0.10
Allegiant Airlines	0.08
Hawaiian Airlines	0.02
General Motors	0.44
Chrysler	0.37
J.C. Penney	0.48
Neiman Marcus	0.09
Macy's	0.16
J. Crew	0.06
Brooks Brothers	0.09
Lord + Taylor	0.15
Forever 21	0.17
Hertz	0.26

Table 6: Consumer Ignorance of Pre-Bankruptcy Distress

We present participants with 37 firms and ask them to identify which have filed for bankruptcy in the past. For each firm, we calculate the fraction of participants who believe the firm filed for bankruptcy. We regress this measure on *Actual Bankruptcy*, an indicator equal to one if the firm has ever filed for bankruptcy, and report the result in column (1). Separately, we ask participants to rate 25 firms based on how close the firms came to bankruptcy over the period from 2010-2019. Participants report this measure, *Near-Bankruptcy Awareness*, on a scale from one (never close) to five (very close). We regress *Near-Bankruptcy Awareness* on *Actual Bankruptcy* and report the result in column (2). Next, we calculate *Worst Credit Rating*, the worst credit rating that each firm received between 2010 and 2019, coded on a numerical scale from one (AAA) to 22 (D). We regress *Near-Bankruptcy Awareness* on both *Actual Bankruptcy* and *Worst Credit Rating*, reporting the results in column (3). Finally, we exclude firms that ever filed for bankruptcy and regress *Near-Bankruptcy Awareness* on *Worst Credit Rating*, reporting the result in column (4).

	Bankruptcy Awareness	Near-Bankruptcy Awareness		
	(1)	(2)	(3)	(4)
Actual Bankruptcy	0.118***	0.404***	0.330*	
	(0.031)	(0.143)	(0.172)	
Worst Credit Rating			0.010	0.010
			(0.013)	(0.012)
Constant	0.065***	2.372***	2.275***	2.272***
	(0.021)	(0.076)	(0.144)	(0.138)
Observations	36	25	25	18
Adj. R^2	0.276	0.225	0.213	-0.0176

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Model-Parameter Estimates

We estimate the consumer price-sensitivity and bankruptcy-sensitivity parameters from the model of Section 5 using our experimental data, according to the procedure described in Section 5.2. We estimate the parameters separately for car purchases and flight purchases. For each industry, this table shows Generalized-Method-of-Moments estimates of the model parameters and asymptotic participant-clustered standard errors. For ease of reading, all of the parameter values and standard errors displayed in this table are true estimates multiplied by 1000.

Parameter	Definition	Estimate	Std Error
Airline Estimates			
$\bar{\alpha}$	Mean Price Disutility	-24.87	0.25
σ_α	SD Price Disutility	0.04	1.3
$\bar{\beta}$	Mean Bankruptcy Disutility	-1500.36	11.3
σ_β	SD Bankruptcy Disutility	10.49	181.93
Car Manufacturer Estimates			
$\bar{\alpha}$	Mean Price Disutility	-0.18	0.02
σ_α	SD Price Disutility	0.07	0.05
$\bar{\beta}$	Mean Bankruptcy Disutility	-2103.68	10.77
σ_β	SD Bankruptcy Disutility	13.58	47.23

Table 8: Model-Implied Bankruptcy Impacts

Using the estimated model of Section 5, we calculate the impact of historical bankruptcies. The first column lists major historical bankruptcies. The second column lists the percent decline in market share each firm experienced because of its bankruptcy. The third column lists the percent change in price each firm chose in response to its bankruptcy. The fourth column lists the percent decline in producer surplus each firm experienced because of its bankruptcy. The fifth column lists the percent change in consumer welfare, averaged across all firms and markets over the bankruptcy period, that occurred because of the bankruptcy. All numbers are quantity-weighted averages across markets. The rows without firm names display average effects across markets impacted by any bankrupt firm in which the bankrupt firm had (i) a market share less than its median market share, or (ii) a market share greater than its median market share. Finally, the third panel considers the bankruptcy impacts in a counterfactual world where consumers understand the survival prospects of bankrupt car manufacturers. See Section 5.3 for details.

	Market Share	Price	Producer Surplus	Consumer Welfare
Airline Estimates				
American Airlines	-10.2	-0.4	-11.5	-3.4
Delta Airlines	-9.8	-0.2	-10.6	-2.4
United Airlines	-12.7	-0.2	-13.5	-2.7
$<$ Median Market Share	-12.4	-0.1	-12.9	-2
$>$ Median Market Share	-9.5	-0.5	-11.1	-4.1
Car Manufacturer Estimates				
General Motors	-22.6	-2	-27	-6.8
Chrysler	-30.8	-0.1	-31	-3.4
$<$ Median Market Share	-27.6	-1.2	-30	-6.2
$>$ Median Market Share	-17.9	-3	-23.8	-6.3
Car Manufacturer Estimates, Educated Consumers				
General Motors	-10.9	-1.4	-15.1	-3.3
Chrysler	-16.4	-0.4	-17.6	-1.9

Internet Appendix

A Hertz Experiment

A.1 Further Description of the Experiment

We received IRB approval from Harvard (protocol number IRB20-1634) and Boston College (protocol number 21.078.01e). We preregistered our experiment with the American Economic Association.[22]

Following our preregistration, we ran our survey until we collected data from 1200 participants that (i) passed our attention checks and (ii) gave monotonic price-list responses: we drop participants that prefer a \$X Enterprise gift card to a \$50 Hertz gift card and prefer a \$50 Hertz gift card to a \$Y > \$X Enterprise gift card. This required us to collect data in batches, leading to slightly more than 1200 responses.

While all participants complete the same price list, we randomize the information that accompanies the price list into four groups. One-third of participants are assigned to the control group. One-third of participants are assigned to the "basic" treatment group and are told that Hertz is currently in bankruptcy. The remaining third of participants are split into the third and fourth groups – the "survival" treatment group and the "DIP" treatment group. In these groups, participants are educated about Chapter 11 in addition to Hertz's bankruptcy status. The survival treatment group of participants is shown the following text: "Alamo Rent A Car, Budget, and National Car Rental all filed for bankruptcy in 2001 and 2002. All three are still in business today." The DIP treatment group is shown the following description of Hertz's DIP financing loan: "While in bankruptcy, Hertz obtained a \$1.65 billion loan to 'support the Company as it moves through its next stage of its Chapter 11 process'"[23] We summarize this information in Table A.1.

As described in the main text, in the next stage of our experiment, all participants are presented with a list of well-known firms and asked which firms are currently bankrupt.

In the final stage, we ask questions to understand consumer perceptions about bankrupt

[22] Our preregistration can be found at the following link: https://www.socialscienceregistry.org/trials/6406.

[23] See https://www.news-press.com/story/money/companies/2020/10/16/hertz-has-secured-1-65-billion-new-financing-fights-its-way-out-bankruptcy/3676571001/.

firms. These questions are in Table A.2. These questions help to identify the mechanisms behind consumers' choices. We also ask participants what fraction of large public companies that seek to remain in business through bankruptcy reorganization succeed. Additionally, we ask how many times the participant has used Hertz and Enterprise in the past (0, 1-5 times, or more than 6 times). Finally, we conclude by gathering demographic information about participants: age, gender, education, and income.

Table A.1: Information Provided to Experiment Participants

Immediately before completing the price list, experiment participants are randomly assigned to one of four groups: control, basic treatment, survival treatment, or DIP treatment. In this table, we show the information provided to participants in each of the four groups. In the third column, we list the proportion of experiment participants that we intended to assign to each group (before applying our preregistered filters).

Group	Information Displayed	Proportion
Control	Hertz and Enterprise are rental car companies.	1/3
Basic treatment	Control + "Hertz filed for Chapter 11 bankruptcy on May 22, 2020. Hertz is still in bankruptcy."	1/3
Survival treatment	Basic treatment + "Alamo Rent A Car, Budget, and National Car Rental all filed for bankruptcy in 2001 and 2002. All three are still in business today."	1/6
DIP treatment	Basic treatment + "While in bankruptcy, Hertz obtained a $1.65 billion loan to 'support the Company as it moves through its next stage of its Chapter 11 process' (Hertz Newsroom)."	1/6

Table A.2: Mechanism Questions

After completing the price list, participants are then asked "On a scale from 1 to 7, how much do you agree with the following statements?". The statements that they are presented with are displayed in this table.

Companies go bankrupt because their product is inferior.
Companies go bankrupt because they have engaged in fraudulent activities.
Companies go bankrupt because their products are overpriced.
Going bankrupt is synonymous with ceasing to operate.
Companies that go bankrupt have sale prices that reflect a greater bargain.
I worry that the cars will not be maintained well at a bankrupt car rental company.
I worry that bankrupt companies have limited inventory.
I worry that my gift card will not be honored if the company is bankrupt.

A.2 Data

The variable WTP_i is equal to participant i's willingness to pay, in Enterprise-gift-card dollars, for a \$50 Hertz gift card. After applying the filters described in our preregistration, we measure WTP_i for 1,238 participants. Our primary independent variable is an indicator $Aware_i$ that is equal to one if participant i is aware of Hertz's bankruptcy. We consider a participant to be aware of the bankruptcy if she selects Hertz when she is asked to indicate which firms are bankrupt.

In our empirical analysis, we instrument for the endogenous variable $Aware_i$ using the randomly assigned treatment status of participant i. We define an indicator $Treat_i$ that is equal to one if the participant is in one of the three treatment groups: basic treatment, survival treatment, or DIP treatment. We also define indicators $Survival\ treat_i$ and $DIP\ treat_i$ that are equal to one if participant i is in the survival or DIP-treatment groups, respectively.

In Table A.3, we report summary statistics. On average, control-group participants value Hertz and Enterprise equally, as shown by the mean of WTP_i being close to \$50. In the basic-treatment group, 90% of participants are aware of Hertz's bankruptcy, confirming that most participants pay attention to the text accompanying the price list in the experiment. Among basic-treatment-group participants, the average willingness to pay for a Hertz giftcard is roughly \$11 lower than the corresponding average among control participants. Participants in the survival-treatment group and DIP-treatment group also value Hertz less than control-group participants, but the difference is not as large.

A.3 Two-Stage Least Squares Setup

Table A.3 shows that the average willingness to pay for a Hertz gift card is roughly \$11 lower in the basic-treatment group than in the control group. This comparison of average willingness to pay underestimates the causal effect of Hertz's bankruptcy because some control-group participants knew of Hertz's bankruptcy before the experiment. To account for this, we use a two-stage least squares (2SLS) approach and estimate a local average treatment effect (LATE): the average causal effect of learning that Hertz is bankrupt among individuals that did not already know of the bankruptcy.

Our 2SLS approach requires an instrument that increases awareness of Hertz's bankruptcy (first-stage relevance) without otherwise impacting an individual's willingness to pay for Hertz (exclusion restriction). By construction, our randomly assigned experimental treatment is likely to meet these criteria.

In this context, the exclusion restriction requires that informing participants of Hertz's bankruptcy does not affect a participant's willingness to pay for Hertz other than through this information. Outside of our experiment, awareness of Hertz's bankruptcy might be correlated with unobservable consumer preferences. However, given that our instrument is a randomly assigned treatment status in a controlled laboratory experiment, we believe that the exclusion restriction is likely to hold.

The first-stage relevance condition requires that the randomly assigned treatment status is correlated with awareness of Hertz's bankruptcy. To show that this condition is satisfied, we estimate the following equation by ordinary least squares (OLS):

$$Aware_i = \phi + \gamma Treat_i + \Pi X_i + \epsilon_i. \tag{A.1}$$

In equation (A.1), ϕ is an intercept, ϵ_i is an error term, and γ is the cofficient on the treatment status $Treat_i$. In some specifications, we also estimate coefficients Π on a vector X_i of control variables. For control variables, we include: (i) an indicator equal to one if participant i has previously patronized Hertz; (ii) an indicator equal to one if participant i has previously patronized Enterprise; (iii) an indicator variable that is equal to one if the participant is male; (iv) the participant's age, proxied by a series of indicator variables that are equal to one if the age is in a particular interval (e.g., 35-44 years old); (v) the participant's income, proxied by a series of indicator variables that are equal to one if the income is in a particular interval (e.g., \$50,000 to \$74,999); and (vi) a series of indicator variables for different education levels (e.g., high-school graduate). In all of our analysis, we use robust standard errors to account for heteroskedasticity.

We present the results of estimating equation (A.1) in Table A.4. Column (1) shows the results of a regression with no control variables estimated in our full sample. Unsurprisingly, we find that informing participants of Hertz's bankruptcy dramatically increases the likelihood that a participant is aware of Hertz's bankruptcy — by 64 percentage points. The F-statistic on the instrument, $Treat_i$, is 747. Column (2) confirms that this result is robust to the inclusion of the control variables in X_i. The sample size declines slightly because some participants do not respond to all demographics questions. Columns (3) and (4) confirm that our results are robust to excluding the DIP-treatment group and survival-treatment group.

A.4 Two-Stage Least Squares Results

Next, we evaluate the causal effect of bankruptcy awareness on consumers' willingness to pay. By comparing consumers that are aware of Hertz's bankruptcy to those that are not, we hold fixed any omitted variables related to the bankrupt firm. However, it could be that consumers who are aware of Hertz's bankruptcy are unobservably different from those that are not. To overcome this omitted-variables problem, we use a two-stage least squares (2SLS) approach. In the first stage, we instrument for bankruptcy awareness with the exogenous treatment status. In the second stage, we evaluate the impact of the instrumented bankruptcy-awareness value on willingness to pay.

Specifically, we estimate the following equation by 2SLS:

$$WTP_i = \phi + \gamma \widehat{Aware}_i + \Pi X_i + \epsilon_i. \tag{A.2}$$

In this equation, $\widehat{Aware}_i$ is the fitted value of $Aware_i$ from equation (A.1). The dependent variable is participant i's willingness to pay for Hertz (Section A.2). The other variables and coefficients are defined analogously to equation (A.1). The results are displayed in Table A.5. Column (5) shows the results of a 2SLS regression estimated using the control group and basic-treatment group. The LATE of learning that Hertz is bankrupt is a reduction in willingness to pay for a Hertz gift card by 35% of the control-group mean. Column (6) shows that this is robust to the inclusion of control variables. Individuals with prior experience with Hertz are more willing to pay for Hertz. Individuals with prior experience at Enterprise are less willing to pay (in Enterprise-gift-card dollars) for Hertz.

Column (4) shows the results of estimating equation (A.2) by OLS, using actual values of $Aware_i$ rather than instrumented values. We find that the correlation between awareness of Hertz's bankruptcy and willingness to pay for Hertz is smaller in magnitude than the LATE of learning that Hertz is bankrupt. This suggests that omitted variables such as financial sophistication might be correlated with both bankruptcy awareness and preferences for Hertz. The smaller magnitude for the negative OLS coefficient suggests that individuals who are endogenously aware of Hertz's bankruptcy have a higher willingness to pay for Hertz.

Columns (1)-(3) display the results of the same regressions using a different estimation sample: one that includes the DIP-treatment group and survival-treatment group. Including these groups, we find a LATE that is smaller in magnitude. This suggests that educating individuals about DIP financing and Chapter 11 survival prospects can mitigate consumer reactions to bankruptcy announcements.

A.5 Other Treatment Effects

Next, we examine the effect of educating consumers about Hertz and its bankruptcy. We estimate the following regression by OLS:

$$WTP_i = \phi + \gamma Treat_i + \delta Survival\ treat_i + \beta DIP\ treat_i + \Pi X_i + \epsilon_i. \tag{A.3}$$

Table A.6 displays the results. Consistent with the 2SLS estimates in the previous section, the randomized treatment reduces willingness to pay. The second row of Table A.6 shows that, conditional on learning Hertz is bankrupt, learning that similar companies survived bankruptcy increases willingness to pay. These educated participants still have a lower willingness to pay than control participants, who are not informed of Hertz's bankruptcy. Nonetheless, this result confirms that educating consumers about the survival prospects of bankrupt firms can reduce the impact of a bankruptcy filing. Educating consumers about Hertz's DIP loan has a small positive but statistically insignificant effect on willingness to pay.

A.6 Mechanisms

Finally, we ask consumers to report the extent to which various concerns about bankrupt firms affected their willingness to pay for Hertz's giftcards. Participants answer on a scale from one (not concerned) to seven (very concerned). Table A.7 shows the average answer for each concern. We see that the strongest concerns relate to maintenance (a bankrupt rental-car company will undermaintain its cars) and inventory (a bankrupt rental-car company will have poor inventory). Both of these suggest that concerns about the quality of a firm during bankruptcy can be as important as concerns that a bankrupt firm will liquidate.

A.7 Robustness

Lastly, we run the same experiment but without running the giftcard lottery. Therefore this experiment is unincentivized. The results hold and can be found in Table A.8.

A.8 Results

Table A.3: Summary Statistics

This table displays summary statistics. For each participant, *Aware* is an indicator variable that is equal to one if the participant is aware of Hertz's bankruptcy. *WTP* is the participant's willingness to pay for Hertz defined in Section A.2. We present summary statistics separately for the full sample, control group, basic-treatment group, DIP-treatment group, and survival-treatment group.

	Mean	SD	N
Full sample			
Aware	0.66	0.47	1,238
WTP	43.56	23.98	1,238
Control			
Aware	0.26	0.44	453
WTP	49.81	19.33	453
Basic treatment			
Aware	0.90	0.30	376
WTP	38.36	26.67	376
DIP treatment			
Aware	0.94	0.24	200
WTP	40.88	26.11	200
Survival treatment			
Aware	0.83	0.37	209
WTP	41.94	23.05	209

Table A.4: First Stage

This table displays ordinary least squares estimates of our first-stage equation (A.1). The dependent variable, *Aware*, is an indicator variable that is equal to one if the participant is aware of Hertz's bankruptcy. *Treat* is an indicator that is equal to one if the participant is in one of the three treatment groups. *Prior Hertz* and *Prior Enterprise* are indicators that are equal to one if the participant previously purchased from Hertz or Enterprise, respectively. In the regressions associated with columns (2) and (4), we include: (i) an indicator variable that is equal to one if the participant is male; (ii) the participant's age, proxied by a series of indicator variables that are equal to one if the age is in a particular interval (e.g., 35-44 years old); (iii) the participant's income, proxied by a series of indicator variables that are equal to one if the income is in a particular interval (e.g., \$50,000 to \$74,999); and (iv) a series of indicator variables for different education levels (e.g., high-school graduate). Columns (3) and (4) exclude both the DIP-treatment and survival-treatment groups. We report robust standard errors in parentheses.

	Aware			
	(1)	(2)	(3)	(4)
Treat	0.637***	0.642***	0.646***	0.653***
	(0.023)	(0.023)	(0.026)	(0.026)
Prior Hertz		0.011		0.019
		(0.022)		(0.028)
Prior Enterprise		0.005		0.026
		(0.022)		(0.029)
Sample	Full	Full	Basic Treat	Basic Treat
Demographics FE	N	Y	N	Y
Observations	1238	1223	829	822
F-Statistic	746.9	755.6	633.2	649.8
Adj. R^2	0.419	0.427	0.416	0.421

Table A.5: Instrumental-Variables Regressions

This table displays two-stage least squares (2SLS) estimates of our instrumental-variables regression (A.2). The dependent variable, *WTP*, is the participant's willingness to pay for Hertz defined in Section A.2. We instrument for the endogenous variable *Aware*, defined in Table A.4, using an indicator that is equal to one if the participant is in one of the three treatment groups. Columns (2), (3), (5), and (6) display 2SLS estimates. Columns (1) and (4) show estimates from ordinary least squares (OLS) regressions in which we regress *WTP* directly on the endogenous variable *Aware*. See Table A.4 for the other variable definitions and the demographic control variables. Columns (4)-(6) exclude both the DIP-treatment and survival-treatment groups. We report robust standard errors in parentheses.

	WTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Aware	-10.565***	-15.476***	-15.199***	-11.142***	-17.734***	-17.680***
	(1.333)	(2.059)	(1.992)	(1.575)	(2.560)	(2.432)
Prior Hertz			9.455***			10.525***
			(1.481)			(1.762)
Prior Enterprise			-7.880***			-8.497***
			(1.554)			(1.893)
Estimator	OLS	IV	IV	OLS	IV	IV
Sample	Full	Full	Full	Basic Treat	Basic Treat	Basic Treat
Demographics FE	N	N	Y	N	N	Y
Observations	1238	1238	1223	829	829	822

Table A.6: Subtreatments

This table displays ordinary least squares estimates. The dependent variable is willingness to pay. The independent variables are indicators for treatment groups. See Table A.4 for the other variable definitions and the demographic control variables. Column (1) excludes the DIP-treatment group and column (2) excludes the survival-treatment group. We report robust standard errors in parentheses.

	WTP			
	(1)	(2)	(3)	(4)
Treat	-11.448***	-11.448***	-11.448***	-11.372***
	(1.648)	(1.648)	(1.649)	(1.604)
Survival treat	3.573*		3.573*	3.947*
	(2.105)		(2.105)	(2.048)
DIP treat		2.511	2.511	2.285
		(2.301)	(2.301)	(2.255)
Prior Hertz				9.306***
				(1.497)
Prior Enterprise				-7.970***
				(1.566)
Estimator	OLS	OLS	OLS	OLS
Excluded Treatment	DIP	Survival	None	None
Demographics FE	N	N	N	Y
Observations	1038	1029	1238	1223
Adj. R^2	0.0471	0.0468	0.0396	0.0865

Table A.7: Summary Statistics, Mechanisms

We ask participants to report the extent to which various concerns about bankrupt firms affected their willingness to pay for Hertz's giftcards. Participants answer on a scale from one (not concerned) to seven (very concerned). For each concern, this table shows the average response, the standard deviation of responses, and the p-value from a t-test of whether the average response exceeds four (a neutral response).

	Mean	SD	p-value for Mean > 4
Inferior product	3.16	1.66	1
Fraud	3.12	1.75	1
Overpriced	3.74	1.7	1
Cease to operate	3.51	1.86	1
Bargain prices	4.22	1.55	0
Maintenance	4.43	1.77	0
Inventory	4.51	1.67	0

Table A.8: Motivating Evidence from Hertz's Bankruptcy, Including Unincentivized Version

This table shows the results of our first experiment (Section 2). Let $Aware_i$ denote an indicator equal to one for participants i who are aware of Hertz's bankruptcy. Let $Treat_i$ be an indicator for i being randomly selected to learn Hertz is bankrupt. Let WTP_i denote the willingness to pay for the Hertz \$50 gift card. Columns (1)-(2) show the results of an ordinary-least-squares (OLS) regression of $Aware_i$ on $Treat_i$. Columns (3)-(4) shows the results of a two-stage-least-squares (2SLS) regression of WTP_i on $Aware_i$, where we instrument for $Aware_i$ using $Treat_i$. Columns (1) and (3) use data from our incentivized price-list experiment, while columns (2) and (4) use data from an equivalent but unincentivized experiment. We report robust standard errors in parentheses. In our main experiment, we use participant-clustered standard errors because we include multiple observations for each participant; since the analysis for this table includes one observation for each participant, we opt for robust standard errors only in this table.

	Aware		WTP	
	(1)	(2)	(3)	(4)
Treat	0.646***	0.648***		
	(0.026)	(0.027)		
Aware			-17.734***	-10.105***
			(2.560)	(2.183)
Incentivized	Y	N	Y	N
Estimator	OLS	OLS	2SLS	2SLS
Observations	829	762	829	762
F-Statistic	633.2	561.9		

B Instant Brands Experiment

This appendix presents details on our second experiment. We received IRB approval from Harvard (IRB protocol number IRB23-1040) and Boston College (protocol number 24.024.01e). We preregistered our experiment with the American Economic Association before running the experiment. Our preregistration can be found at the following link: https://www.socialscienceregistry.org/trials/11632. The "Study 3" in the title refers to the fact that, while we call this study two for expositional purposes, it was run after our first two studies.

B.1 Preregistered Sample Criteria

Following our preregistration, we ran our survey until we collected data from 900 participants that passed our two initial attention checks. Further following our preregistration, we drop participants that (i) failed the attention check in the middle of our survey, (ii) already own an Instant Pot or similar product, or (iii) gave nonmonotonic price-list responses: we drop participants that prefer \$X to an Instant Pot and prefer an Instant Pot to \$Y > \$X.

B.2 Additional Treatment Arm and Results

In addition to the treatment and control groups described in the main text, we included a third treatment group, Debtor-In-Possession (DIP) Treatment, which provided further information about Instant Pot's financing. This is analogous to the DIP treatment group in the Hertz experiment. This group sees the following additional quote in addition to the bankruptcy information from the main treatment group:

> After filing for bankruptcy, Instant Brands obtained a new loan for \$30 million from existing lenders. "We are making important progress in our court-supervised process, and the commitment for additional financing reflects our lenders' confidence in our business and our ability to achieve a successful outcome," said Mr. Gadbois.

There is no statistically significant difference in willingness to pay between the DIP treatment group and the control group.

Table B.1: Subtreatments

This table displays ordinary least squares estimates. The dependent variable is willingness to pay. The independent variables are indicators for treatment groups. See Table 1 for the other variable definitions and the demographic control variables. We report robust standard errors in parentheses.

	WTP
	(1)
Treat	-9.506*
	(5.145)
DIP Treat	-1.704
	(4.974)
Experiment	Instant
Estimator	OLS
Control Variables	Y
Observations	226
Control-Group Mean	53.48

C Third Experiment Details

This appendix presents details on our third experiment. We received IRB approval from Harvard (modification MOD20-1634-02 of protocol number IRB20-1634) and Boston College (protocol number 21.078.01e). We preregistered our experiment with the American Economic Association before running the experiment. Our preregistration can be found at the following link: https://www.socialscienceregistry.org/trials/8411. The "Study 2" in the title refers to the fact that this study was conducted after our first study, which is described in Section 2.

C.1 Attention Tests

We present each participant with a picture and ask them to identify the object in the picture. We also present participants with a long block of text. In the middle of the text, we tell participants they must select a particular answer from a list to continue to the survey. We exclude participants that fail these commonly used attention tests.

C.2 Willingness-to-Pay Questions

All of our willingness-to-pay questions have the following format:

> This question is hypothetical. You will not pay anything in reality.
>
> Please imagine that you need to purchase a (flight/shirt/car). You are deciding between two (airlines/retailers/car manufacturers): Firm A or Firm B.
>
> (Fact about Firm B corresponding to information group).
>
> Your desired (flight/shirt/car) costs (Firm A Price) at Firm A. What is the most that you would be willing to pay for an equivalent (flight/shirt/car) on Firm B? Please enter a whole number.

For example, the following is the exact text of one willingness-to-pay question for the "bankruptcy" information group:

> This question is hypothetical. You will not pay anything in reality.

> Please imagine that you need to purchase a round-trip economy-fare airline ticket. Your flight departs in one month. You are deciding between two airlines: Airline A or Airline B.
>
> Please imagine that Airline B filed for Chapter 11 bankruptcy and is still in bankruptcy.
>
> Your desired flight costs $300 on Airline A. What is the most that you would be willing to pay for an equivalent flight on Airline B? Please enter a whole number.

The following is the exact text of a question for the quality information group.

> This question is hypothetical. You will not pay anything in reality.
>
> Please imagine that you need to purchase a shirt. You are deciding between two retail stores: Express or American Eagle Outfitters.
>
> Please imagine that American Eagle filed for Chapter 11 bankruptcy and is still in bankruptcy. During the bankruptcy, the Better Business Bureau assessed that American Eagle's quality was not affected by the bankruptcy.
>
> Your desired shirt costs $35 from Express. What is the most that you would be willing to pay for an equivalent shirt from American Eagle? Please enter a whole number.

C.3 Preregistered Sample-Size Criteria

After all of the willingness-to-pay questions, we ask each participant to rate the extent to which various concerns affected their willingness-to-pay decisions. We also assess each participant's knowledge of actual historical bankruptcies. Each participant answers these questions for one industry, which corresponds to their final willingness-to-pay question.

To ensure that each industry has a sufficient number of participants answering these follow-up questions, we randomize participants into bins based on both the information group and the follow-up-question industry. We define sixteen bins. We define seven car-follow-up-question bins corresponding to the seven information groups. We similarly define seven airline-follow-up-question bins. We define fewer retail-follow-up bins - just one for bankruptcy and one for control. Table C.1 lists bin definitions. Following our preregistration, we ran the experiment until we had at least 100 participants in each bin after excluding participants who fail attention tests. This required running the experiment in batches, leading to a sample size of 1749 that is larger than 1600. Statistically, our criteria made it extremely likely that the final sample size would meaningfully exceed 1600.

Note that the follow-up questions are answered after the information for each information group is presented and after all willingness-to-pay questions are answered. Participants cannot go backward in the survey. This implies that the particular follow-up questions a participant sees cannot possibly violate the exclusion restriction for our main analysis.

Table C.1: Sample-Selection Criteria

We randomize participants into seven information groups. In the final stage of the experiment, participants answer follow-up survey questions. The follow-up questions relate to the last industry for which the participant answered willingness-to-pay questions. We randomize participants into sixteen bins corresponding to information groups and follow-up-question industries. This table lists the bins and minimum observation counts.

Arm #	Follow-Up-Questions Industry	Information Group	Minimum Observation Count
1	Retail	Bankruptcy	100
2	Retail	Control	100
3	Car	Bankruptcy	100
4	Car	Pre-Bankruptcy	100
5	Car	Survival 100	100
6	Car	Survival 50	100
7	Car	Quality	100
8	Car	Post-Bankruptcy	100
9	Car	Control	100
10	Airline	Bankruptcy	100
11	Airline	Pre-Bankruptcy	100
12	Airline	Survival 100	100
13	Airline	Survival 50	100
14	Airline	Quality	100
15	Airline	Post-Bankruptcy	100
16	Airline	Control	100

C.4 Incentives

Participants in this third experiment make hypothetical purchase decisions. We loosely follow the approach of Kessler, Low, and Sullivan (2019) to make it incentive compatible to answer these hypothetical questions in a manner consistent with actual preferences. Specifically, we present participants with the following information:

> In each of the following questions, you will be asked to imagine that you are making a purchase decision. These decisions are hypothetical: you will not pay the reported amount or receive the good or service described. However, you

> will be entered into a lottery for a prize. If you win the lottery, a computer program will determine the prize based on your reported answers. Answering these hypothetical questions in a manner consistent with your actual preferences will thus lead to a lottery prize that more closely matches your preferences.

Participants are thus incentivized to honestly report their preferences in order to receive a lottery prize suited to their tastes. Importantly, there is no incentive for a participant to misreport her willingness to pay.[24]

As in Kessler, Low, and Sullivan (2019), we do not tell participants how we map their responses into a prize. In practice, we use responses to determine whether a lottery-winning participant receives a Delta Airlines gift card or an American Eagle gift card. As we describe in Section 3.2.1, participants report their willingness to pay for flights, shirts, and cars. We rank participants by their average reported willingness to pay for flights and for shirts. If a participant has a higher rank (relative willingness to pay) for flights than for shirts, the participant's lottery prize is a gift card for Delta Airlines. Otherwise, it is an American Eagle gift card. There is thus no deception when we tell participants their prize is based on their reported answers. Critically, participants do not know that their lottery prize is a gift card. Participants are thus incentivized to give honest answers about purchase decisions without any conflating concerns about the viability of a bankrupt firm's gift cards.

[24]Participants that simply type answers as quickly as possible would likely be removed from the survey before this point by the attention tests.

D Additional Results from the Third Experiment

Table D.1: Time Until Purchased Airline Flight

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups for the airline questions. All regressions include all participants: those in the control group and all treatment groups. The first column includes responses to all four airline-willingness-to-pay questions. The second column contains only responses to the questions in which the purchased flight departs in one month. The third column contains only responses to the question in which the purchased flight departs in three months. See Table 4 for variable definitions. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Pre-Bankruptcy	-0.196***	-0.186***	-0.225***
	(0.024)	(0.024)	(0.027)
Bankruptcy	-0.218***	-0.208***	-0.249***
	(0.021)	(0.021)	(0.024)
Post-Bankruptcy	-0.076***	-0.070***	-0.093***
	(0.019)	(0.020)	(0.021)
Quality	-0.081***	-0.072***	-0.107***
	(0.021)	(0.022)	(0.024)
Survival 50	-0.310***	-0.303***	-0.332***
	(0.026)	(0.025)	(0.029)
Survival 100	-0.146***	-0.138***	-0.169***
	(0.022)	(0.022)	(0.025)
Constant	0.898***	0.890***	0.920***
	(0.011)	(0.012)	(0.013)
Industry	Airline	Airline	Airline
Time Frame	Overall	One Month	Three Months
Observations	6996	5247	1749

Table D.2: Demographics

This table displays summary statistics on age, education, ethnicity, and income. The first column displays the percentage of participants in our sample with a given demographic characteristic. The second column contains the corresponding statistics for the United States population. The statistics in the second column come from the 2020 American Comunity Survey. Note that some Census percentages do not add to 100% due to excluded categories.

	Percent of Population	
Age	Our Sample	U.S. Population
18 - 24 years old	8.6	9.3
25 - 34 years old	14.6	13.9
35 - 44 years old	15.9	12.7
45 - 54 years old	13.5	12.7
55 - 64 years old	19.9	12.9
65 - 74 years old	22.7	9.4
75 years or older	4.8	6.7
Education	Our Sample	U.S. Population
Some high school or less	2.9	8.9
High school graduate	21.1	27.9
Some college/technical school	31	14.9
College graduate	32.9	23.5
Post graduate or higher	12.1	14.4
Ethnicity	Our Sample	U.S. Population
African American	8.7	12.6
Asian	3.6	5.6
Hispanic	5.9	5.1
Other, please specify	1.5	6.2
White/Caucasian	80.3	70.4
Income	Our Sample	U.S. Population
0 to 14,999	10.1	9.9
15,000 to 24,999	11.1	8.5
25,000 to 34,999	11.6	8.6
35,000 to 49,999	16.4	12
50,000 to 74,999	20.3	17.2
75,000 to 99,999	14.3	12.8
100,000 to 149,999	10.7	15.6
150,000 and over	5.5	15.4

Note: The data comes from the 2020 American Community Survey.
https://www.socialexplorer.com/tables/ACS2020$_5$yr/R13321678

Table D.3: Purchase Frequency

Near the end of our experiment, participants are asked a series of questions about their purchase frequencies in the three industries. The first column displays responses to questions of the form “Before the pandemic, how often did you purchase X?” The second column displays the percentage of participants in our sample selecting a given response.

Purchase Clothing	Percentage
Once a year	11.3
Once every 4-6 months	25.7
Once every 2-3 months	32.2
1-2 times a month	21.3
3+ times a month	9.5
Purchase Flights	Percentage
Less than once every 2 years	49.5
Once every other year	8.6
Once a year	18.8
Once every 4-6 months	15.2
Once every 2-3 months	6.3
Once a month	1.7
Last Car Purchase	Percentage
more than 5 years ago	37.9
4-5 years ago	15.2
1-3 years ago	31.2
In the past year	15.7

Table D.4: Experiment-Three Regression By Purchase Frequency

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups. The odd columns include all participants: those in the control group and all treatment groups. The even columns include only those participants who make frequent purchases in the relevant industry. Specifically, even columns include only those participants who did not select the lowest purchase frequency, see Table D.3 for details on potential purchase frequencies. See Table 4 for variable definitions. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-Bankruptcy	-0.196***	-0.228***	-0.101***	-0.120***	-0.173***	-0.145***
	(0.024)	(0.035)	(0.026)	(0.028)	(0.025)	(0.031)
Bankruptcy	-0.218***	-0.256***	-0.179***	-0.190***	-0.193***	-0.181***
	(0.021)	(0.031)	(0.021)	(0.023)	(0.022)	(0.030)
Post-Bankruptcy	-0.076***	-0.083***	-0.070***	-0.073***	-0.048**	-0.026
	(0.019)	(0.027)	(0.023)	(0.025)	(0.024)	(0.032)
Quality	-0.081***	-0.106***	-0.069***	-0.085***	-0.080***	-0.074**
	(0.021)	(0.030)	(0.024)	(0.027)	(0.025)	(0.033)
Survival 50	-0.310***	-0.291***	-0.123***	-0.133***	-0.208***	-0.189***
	(0.026)	(0.033)	(0.027)	(0.027)	(0.025)	(0.033)
Survival 100	-0.146***	-0.176***	-0.114***	-0.105***	-0.074***	-0.067*
	(0.022)	(0.033)	(0.023)	(0.024)	(0.027)	(0.038)
Constant	0.898***	0.924***	0.962***	0.972***	0.879***	0.872***
	(0.011)	(0.017)	(0.015)	(0.016)	(0.015)	(0.020)
Industry	Airline	Airline	Retail	Retail	Car	Car
Sample	Overall	Frequent	Overall	Frequent	Overall	Frequent
Observations	6996	3536	5247	4653	5247	3261

Table D.5: Experiment-Three Regression By Previous Purchase from Airlines

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups. The first column is same as the first column in Table 4 and includes all participants: those in the control group and all treatment groups. The second column includes only participants who have ever purchased from JetBlue. Column three includes only participants who have ever purchased from Southwest. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Pre-Bankruptcy	-0.196***	-0.177***	-0.226***
	(0.024)	(0.065)	(0.034)
Bankruptcy	-0.218***	-0.282***	-0.221***
	(0.021)	(0.051)	(0.028)
Post-Bankruptcy	-0.076***	-0.071*	-0.071***
	(0.019)	(0.040)	(0.025)
Quality	-0.081***	-0.110***	-0.097***
	(0.021)	(0.042)	(0.029)
Survival 50	-0.310***	-0.308***	-0.293***
	(0.026)	(0.050)	(0.032)
Survival 100	-0.146***	-0.159***	-0.166***
	(0.022)	(0.051)	(0.031)
Constant	0.898***	0.925***	0.909***
	(0.011)	(0.028)	(0.016)
Industry	Airline	Airline	Airline
Sample	Overall	JetBlue Customers	Southwest Customers
Observations	6996	1760	3936

Table D.6: Experiment-Three Regression By Previous Purchase from Retailers

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups. The first column is same as the second column in Table 4 and includes all participants: those in the control group and all treatment groups. The second column includes only participants who have ever purchased from American Eagle Outfitters. Column three includes only participants who have ever purchased from Express. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Pre-Bankruptcy	-0.101***	-0.127***	-0.151***
	(0.026)	(0.039)	(0.049)
Bankruptcy	-0.179***	-0.202***	-0.225***
	(0.021)	(0.030)	(0.038)
Post-Bankruptcy	-0.070***	-0.081***	-0.046
	(0.023)	(0.031)	(0.048)
Quality	-0.069***	-0.106***	-0.101**
	(0.024)	(0.033)	(0.040)
Survival 50	-0.123***	-0.137***	-0.174***
	(0.027)	(0.032)	(0.040)
Survival 100	-0.114***	-0.110***	-0.101**
	(0.023)	(0.032)	(0.043)
Constant	0.962***	0.994***	1.013***
	(0.015)	(0.021)	(0.026)
Industry	Retail	Retail	Retail
Sample	Overall	AE Customers	Express Customers
Observations	5247	2724	1890

Table D.7: Experiment-Three Regression By Previous Purchase from Car Manufacturer

This table shows ordinary least squares regressions of willingness to pay on indicators for treatment groups. The first column is same as the third column in Table 4 and includes all participants: those in the control group and all treatment groups. The second column includes only participants who have ever purchased from Ford. Column three includes only participants who have ever purchased from Tesla. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Pre-Bankruptcy	-0.173***	-0.151***	0.023
	(0.025)	(0.033)	(0.225)
Bankruptcy	-0.193***	-0.160***	0.056
	(0.022)	(0.030)	(0.143)
Post-Bankruptcy	-0.048**	-0.070**	0.164
	(0.024)	(0.032)	(0.345)
Quality	-0.080***	-0.054*	0.181
	(0.025)	(0.030)	(0.470)
Survival 50	-0.208***	-0.199***	-0.197
	(0.025)	(0.033)	(0.240)
Survival 100	-0.074***	-0.069*	0.121
	(0.027)	(0.039)	(0.120)
Constant	0.879***	0.877***	0.878***
	(0.015)	(0.020)	(0.115)
Industry	Car	Car	Car
Sample	Overall	Ford Customers	Tesla Customers
Observations	5247	2907	96

Table D.8: Mechanism Questions for the Airline Industry

Participants rank the importance of various concerns on a scale from one (not important) to seven (important), where four indicates a neutral response. This table shows the average response, calculated within the bankruptcy-treatment group, for each concern. The second column shows the standard deviation across participants. This table shows responses for questions related to airline-flight purchases. See Internet Appendix C for an explanation of how our preregistered sample-size criteria led to the displayed number of participants answering these questions.

	Mean	SD
Signal Past Low Quality	3.06	1.88
Signal Past Fraud	3.08	1.95
Signal Past Overpricing	3.40	1.81
Cease to Operate	4.81	2.10
Bargain Deals	4.02	1.80
Not Maintained Well	4.23	2.26
Delays and Cancellations	4.61	1.98
Don't Want to Build Reward Points	4.38	2.21
Safety Concerns	4.27	2.17
Observations	111	

Table D.9: Mechanism Questions for the Car Industry

Participants rank the importance of various concerns on a scale from one (not important) to seven (important), where four indicates a neutral response. This table shows the average response, calculated within the bankruptcy-treatment group, for each concern. The second column shows the standard deviation across participants. This table shows responses for questions related to car purchases. See Internet Appendix C for an explanation of how our preregistered sample-size criteria led to the displayed number of participants answering these questions.

	Mean	SD
Signal Past Low Quality	2.94	1.95
Signal Past Fraud	2.91	2.00
Signal Past Overpricing	3.19	1.99
Bargain Deals	4.43	1.71
Not Produced Well	4.17	1.92
Lose Warranty	5.04	1.87
Not Find Parts	4.57	2.08
Lack of Inventory	4.26	1.89
Observations	110	

Table D.10: Mechanism Questions for the Retail Industry

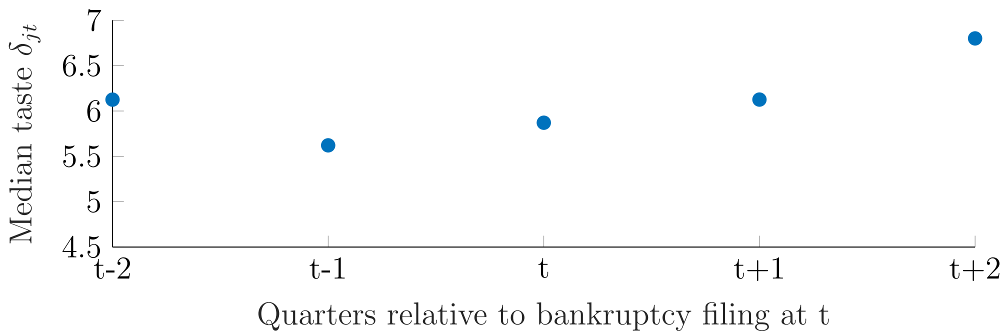
Participants rank the importance of various concerns on a scale from one (not important) to seven (important), where four indicates a neutral response. This table shows the average response, calculated within the bankruptcy-treatment group, for each concern. The second column shows the standard deviation across participants. This table shows responses for questions related to retail purchases. See Internet Appendix C for an explanation of how our preregistered sample-size criteria led to the displayed number of participants answering these questions.

	Mean	SD
Signal Past Low Quality	3.23	1.92
Signal Past Fraud	3.20	1.76
Signal Past Overpricing	3.40	1.72
Bargain Deals	4.71	1.65
Not Produced Well	3.73	2.19
Cannot Return	4.50	2.26
Don't Want to Build Reward Points	4.25	2.23
Lack of Inventory	4.41	1.77
Observations	113	

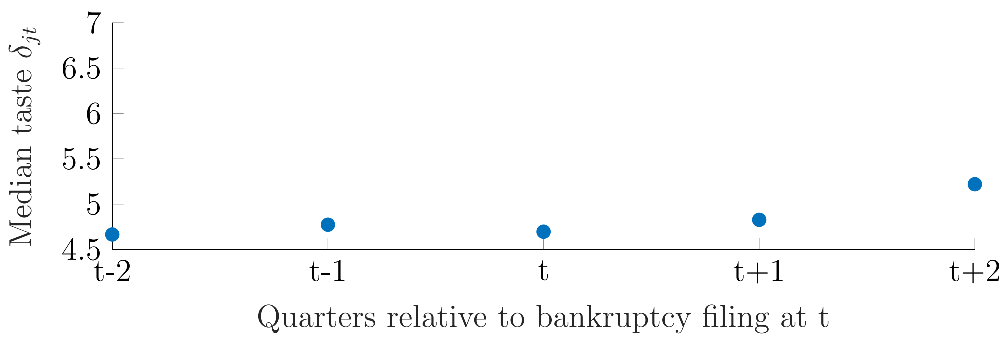
Figure D.1: Median taste for bankrupt airlines

Estimating our structural model, we estimate the average taste parameter δ_{jt} for each airline j in each market t. In each quarter for each of the largest three airlines, we calculate the median δ_{jt} across all routes. We plot this median for each quarter in a five quarter window around each airline's bankruptcy.

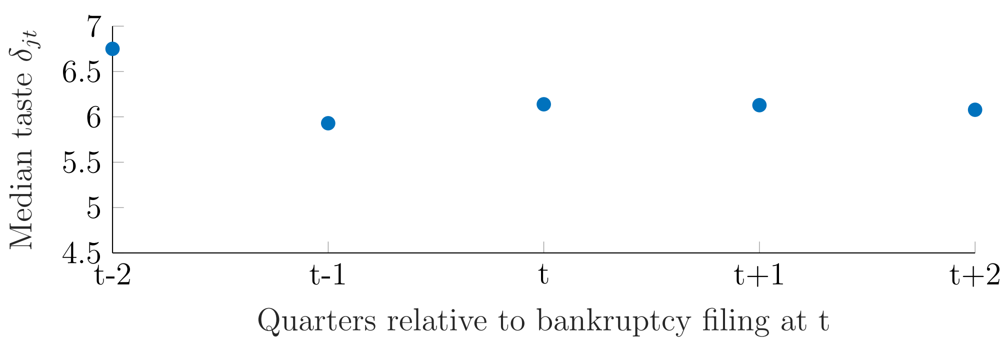
(a) American Airlines, bankrupt at t = 2011Q4



(b) Delta Airlines, bankrupt at t = 2005Q3



(c) United Airlines, bankrupt at t = 2002Q4



E Details on Structural Estimation

This appendix provides details on the structural estimation described in Section 5.

E.1 Estimating Consumer Taste Parameters Using Experimental Data

We first estimate price-sensitivity and bankruptcy-sensitivity parameters using our experimental data. We estimate model parameters to make model-implied market shares match experiment-implied market shares in hypothetical markets defined in our experiment.[25]

Each willingness-to-pay question in our experiment corresponds to a hypothetical market t with two goods, $j = A, B$.[26] The price p_{At} of good A is fixed. If the price of good B were p_{Bt} and neither good provider were bankrupt (control group), the experiment data would imply the following market share for good B:

$$\text{B share}^{data}_{control}(p_{Bt}) = \left[\sum_{i=1}^{N} Control_i \times \mathbf{1}\left(WTP_{it} > p_{Bt} \right)\right] / \left[\sum_{i=1}^{N} Control_i\right]. \tag{E.1}$$

For any fixed parameters, equation (3) gives a corresponding model-implied market share for Firm B – if the price of good B were p_{Bt} and neither good provider were bankrupt, then:

$$\text{B share}^{model}_{control}(p_{Bt}) = \mathbb{E}_{\alpha_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}^d_t + \alpha_{id}\ (\ p_{Bt} - p_{At}\ ) + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0 \right)\right], \tag{E.2}$$

where $\bar{\delta}^d_t \equiv \delta_{Bt} - \delta_{At}$. We can similarly calculate model-implied and experiment-implied market shares in a hypothetical market where Firm B is bankrupt (bankruptcy treatment):

$$\text{B share}^{data}_{bank}(p_{Bt}) = \left[\sum_{i=1}^{N} Bankruptcy_i \times \mathbf{1}\left(WTP_{it} > p_{Bt} \right)\right] / \left[\sum_{i=1}^{N} Bankruptcy_i\right] \tag{E.3}$$

$$\text{B share}^{model}_{bank}(p_{Bt}) = \mathbb{E}_{\alpha_{id},\beta_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}^d_t + \alpha_{id}\ (\ p_{Bt} - p_{At}\ ) + \beta_{id} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0 \right)\right]. \tag{E.4}$$

[25] Since a given consumer has the same price and bankruptcy sensitivities across all goods in an industry, there is no harm in focusing on specific markets in our experiment. In Section E.3, we describe our method for using historical data to estimate good-specific tastes.

[26] Unlike the historical markets we turn to next, participants in these hypothetical markets do not have an outside option, which allows for cleaner identification of parameters.

We estimate the parameters $\theta_d^{Experiment} \equiv \left(\bar{\delta}_t^d, \bar{\alpha}^d, \sigma_\alpha^d, \bar{\beta}^d, \sigma_\beta^d \right)$ by the Generalized Method of Moments. Using our experimental data, we define a vector M_d^{data} containing moments of the form (E.1) and (E.3) for various prices p_{Bt}. For each candidate set of parameters, we use equations (E.2) and (E.4) to calculate the model-implied equivalent M_d^{model} of the empirical vector M_d^{data}. Our estimation procedure chooses model parameters to equate M_d^{model} and M_d^{data}. We now provide detailed moment definitions and explain how, by design, M_d^{data} identifies $\theta_d^{Experiment}$. We then explain the details of our GMM estimation.

E.1.1 Experiment-Moment Definitions and Identification

In one question from our third experiment, participants give their willingness to pay for a hypothetical flight from Southwest (Firm B), given that an equivalent flight costs \$300 on JetBlue (Firm A). This corresponds to a hypothetical market with two goods $j = A, B$ in which $p_{At} = \$300$. We identify consumer-preference parameters for flight purchases using responses to this question. Crucially, we only estimate consumer-specific parameters that apply to all airlines, like price sensitivity and bankruptcy sensitivity. We do not assume that a consumer's taste specifically for Southwest will in any way reflect their specific taste for another airline such as Delta. Instead, after we estimate the parameters governing consumer-specific tastes, we use historical data on each airline's flights to estimate airline-specific tastes, as described below.

In another question from our third experiment, participants give their willingness to pay for a hypothetical car from Tesla (Firm B), given an equivalent car from Ford (Firm A) costs \$28,000. This corresponds to a hypothetical market with two cars $j = A, B$ in which $p_{At} = \$28,000$. We identify consumer-preference parameters for motor-vehicle purchases using responses to this question. We do not assume that a consumer's taste specifically for Tesla will in any way reflect their specific taste for another car manufacturer like Chrysler. Instead, after we estimate the parameters governing consumer-specific tastes, we use historical data on each car manufacturer's sales to estimate car-specific tastes, as described below.

Unlike the historical markets we study in Section E.3, participants in these hypothetical markets do not have an outside option, which allows for cleaner identification of parameters.

In each hypothetical market, we define a 5×1 vector M_d^{data} of five empirical moments. The first moment is B $\text{share}_{control}^{data}(p_{At})$, the experiment-implied market share for Firm B if Firm B were solvent and charged the same amount as Firm A. This moment is defined following equation (E.1).[27] For cars, we use $p_{Bt} = p_{At} = \$28,000$. For flights, we use $p_{Bt} = p_{At} = \$300$. This first moment is ideal for identifying the difference in average tastes $\bar{\delta}_t^d$. Specifically, since $p_{Bt} = p_{At}$, the corresponding model moment simplifies to:[28]

$$\text{B share}_{control}^{model}(p_{At}) = \mathbb{E}_{\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}_t^d + (\epsilon_{iBtd} - \epsilon_{iAtd}) > 0\right)\right]. \tag{E.5}$$

Since we have fixed the distribution of ϵ_{ijtd}, this equation implies that there is exactly one value of $\bar{\delta}_t^d$ that equates B $\text{share}_{control}^{data}(p_{At})$ and B $\text{share}_{control}^{model}(p_{At})$. For both cars and flights, the first element of M_d^{data} thus pins down the value of the parameter $\bar{\delta}_t^d$.

The next two moments in M_d^{data} are defined by keeping Firm B solvent and varying the price of Firm B's good. Specifically, the second moment is B $\text{share}_{control}^{data}(1.15p_{At})$, the experiment-implied market share for Firm B if Firm B were solvent and charged 15% more than Firm A. For flights, we have $p_{Bt} = 1.15P_{At} = \$345$ and for cars we have $p_{Bt} = 1.15P_{At} = \$32,200$. The third moment is B $\text{share}_{control}^{data}(1.2p_{At})$, Firm B's market share if it charged 20% more than Firm A. Together, these two moments pin down the price-sensitivity parameters $\bar{\alpha}^d$ and σ_α^d. Specifically, the corresponding model moments are:

$$\text{B share}_{control}^{model}(1.15p_{At}) = \mathbb{E}_{\alpha_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}_t^d + 0.15\alpha_{id}p_{At} + (\epsilon_{iBtd} - \epsilon_{iAtd}) > 0\right)\right] \tag{E.6}$$

$$\text{B share}_{control}^{model}(1.2p_{At}) = \mathbb{E}_{\alpha_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}_t^d + 0.2\alpha_{id}p_{At} + (\epsilon_{iBtd} - \epsilon_{iAtd}) > 0\right)\right]. \tag{E.7}$$

Recall that the first element of M_d^{data} pins down $\bar{\delta}_t^d$. Our estimation varies $\bar{\alpha}^d$ and σ_α^d until these two model moments match the empirical counterparts. Intuitively, there should be a unique pair ($\bar{\alpha}^d$,σ_α^d) that achieves this: the average price sensitivity $\bar{\alpha}^d$ pins down how one price increase (e.g., 15%) affects market share while the volatility of price sensitivities across consumers σ_α^d pins down the impact of the other price increase (e.g., 20%).

The final two moments in M_d^{data} are defined using bankruptcy-treatment-group partic-

[27] In all empirical moment calculations, we exclude participants who are exactly indifferent between goods B and A at prices p_{Bt}, p_{At}. For example, in the calculation of this first moment, we exclude participants whose willingness to pay for Firm B's good is exactly p_{At}.

[28] We calculate model moments by simulating 10,000 draws of $\{\alpha_{id}, \beta_{id}, \epsilon_{ijtd}\}$.

ipants for whom Firm B is bankrupt. Specifically, the fourth moment is B $\text{share}^{data}_{bank}(p_{At})$, the experiment-implied market share for Firm B if Firm B were bankrupt and charged the same price as Firm A. The fifth moment is B $\text{share}^{data}_{control}(0.5p_{At})$, Firm B's market share if it were bankrupt and charged 50% less than Firm A. Together, these two moments pin down the bankruptcy-sensitivity parameters $\bar{\beta}^d$ and σ^d_β. Specifically, the corresponding model moments are:

$$\text{B share}^{model}_{bank}(p_{At}) = \mathbb{E}_{\beta_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\ \bar{\delta}^d_t + \beta_{id} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0\ \right)\right] \tag{E.8}$$

$$\text{B share}^{model}_{bank}(0.5p_{At}) = \mathbb{E}_{\alpha_{id},\beta_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\ \bar{\delta}^d_t - 0.5\alpha_{id}p_{At} + \beta_{id} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0\ \right)\right]. \tag{E.9}$$

Recall that the first three elements of M^{data}_d pin down $\bar{\delta}^d_t, \bar{\alpha}^d, \sigma^d_\alpha$. Our estimation varies $\bar{\beta}^d$ and σ^d_β until these final two model moments match the empirical counterparts. Intuitively, there should be a unique pair ($\bar{\beta}^d$,σ^d_β) that achieves this: the average bankruptcy sensitivity $\bar{\alpha}^d$ pins down how bankruptcy affects market shares at one price point (e.g., $p_{Bt} = p_{At}$) while the volatility of bankruptcy sensitivities across consumers σ^d_β pins down the impact of bankruptcy at the other price point (e.g., $p_{Bt} = 0.5p_{At}$).

E.1.2 Covariance and GMM Weighting Matrices

Separately examining experiment responses for car purchases and flight purchases, we measure the 5×1 vectors $\{M^{data}_d\}$ defined above. For each industry, we then construct the covariance matrix C_d of M^{data}_d by bootstrapping 500 participant-clustered samples from our data and taking covariances of elements of M^{data}_d across bootstrapped samples. We use the efficient weighting matrix $W_d = C_d^{-1}$ and estimate $\theta^{Experiment}_d$ separately for car purchases and flight purchases. Specifically, we estimate $\theta^{Experiment}_d$ to minimize the weighted difference between model-implied and experiment-implied moments:

$$\hat{\theta}^{Experiment}_d = \text{argmin}_{\theta^{Experiment}_d}\left(\ M^{data}_d - M^{model}_d\ \right) W_d \left(\ M^{data}_d - M^{model}_d\ \right)'. \tag{E.10}$$

We construct asymptotic participant-clustered standard errors for the estimates $\theta^{Experiment}_d$ by the usual formula. Let GRD_d be the 5×5 matrix defined such that the jth column of row

i is equal to the partial derivative of model moment $M_{d,j}^{model}$ with respect to model parameter $\theta_{d,i}^{Experiment}$.[29] Let $N = 664$ denote the number of participants in the control and bankruptcy-treatment groups - the number of participants used to calculate the data moments M_d^{data}. By the usual formula, the asymptotic covariance matrix for our parameter estimates is then:

$$\text{Asymptotic participant-clustered parameter covariance} = \frac{1}{N}\left(GRD_d \times C_d^{-1} \times GRD_d' \right)^{-1}, \tag{E.11}$$

where $\times$ denotes matrix multiplication.

We estimate $\hat{\theta}_d^{Experiment}$ separately for flight purchases and vehicle purchases to capture heterogeneous preferences across industries.

E.1.3 Interpreting Parameter Estimates

Table 7 displays estimates and standard errors for the key parameters $\{\bar{\alpha}^d, \sigma_\alpha^d, \bar{\beta}^d, \sigma_\beta^d\}$, estimated and displayed separately for car purchases and flight purchases.

To interpret model parameters, it is helpful to note that the average effect of an airline bankruptcy on consumer indirect utility is the same as the average effect of a \$60 price increase ($-\bar{\beta}^d/\bar{\alpha}^d$), which is 20% of the reference price \$300. The average effect of a car-manufacturer bankruptcy on consumer indirect utility is the same as the average effect of a \$11,687 price increase ($-\bar{\beta}^d/\bar{\alpha}^d$), which is 42% of the reference price \$28,000.

While the above estimates are loosely related to the reduced-form coefficients in Table 4, these model estimates are not directly comparable. This is because the Generalized-Method-of-Moments approach targets market shares. The effect of bankruptcy on consumer utility must be large enough to produce the shift in market share implied by the experimental data. This shift does not depend on the average effect of bankruptcy on willingness to pay; instead, it depends on the prevalence of marginal consumers whose utility for solvent Firm A's good is such that they prefer good B if and only if Firm B is solvent. This is a nonlinear function of all model parameters.

There is relatively little variation in price sensitivities and bankruptcy sensitivities across consumers.

[29] We calculate partial derivates numerically by first-order forward-step finite difference with a step size of 0.01.

E.2 Calibrating Bankruptcy Awareness

In our experiment, all participants in the bankruptcy group are aware of a bankruptcy by definition of the treatment group. In reality, not all consumers are aware when a firm files for bankruptcy. To account for this, we model the awareness A_{ijt} of consumer i as a Bernoulli random variable with mean κ_j. We calibrate κ_j for each historically bankrupt firm f_j to match the fraction of experiment participants aware of firm f_j's bankruptcy (Table 5).

E.3 Estimating Average Good-Taste Parameters in Historical Markets

Next, we turn to observational data on historical markets to estimate the average good-taste parameters δ_{jt}.

E.3.1 Data Details

We obtain average prices and market shares for airlines on US flight routes from the Department of Transportation's Airline Origin and Destination Survey (DB1B).[30] The DB1B is a 10% sample of all domestic purchased airline itineraries. We use this data to construct market shares and average prices at the airline-route-quarter level. We obtain manufacturer suggested retail prices and vehicle sale volumes from Wards Intelligence. We use this data, which covers all new vehicle sales in the US, to construct market shares and average prices at the model-vehicle-class-year level. We adjust prices to 2021 dollars using the Federal Reserve Bank of St Louis consumer price index.[31]

Specifically, in the DB1B, we focus on the market file, which contains directional market characteristics of each domestic itinerary in the DB1B, such as the airline, origin and destination airport, prorated market fare, and number of passengers. We exclude observations in which the market fare is zero. A route is defined as an origin-airport-destination-airport pair. A market is defined as a route in a given quarter. We aggregate flights on a given airline such that each airline has only one good in a given market: its flights on that route in that quarter. We exclude route-quarters in which one airline has a 100% market share or in which there are fewer than 1,000 passengers. Our final dataset only contains observations with positive market shares.

[30]See https://www.transtats.bts.gov/tables.asp?QO_VQ=EFI&QO_anzr=Nv4yv0r.
[31]See https://fred.stlouisfed.org/series/CPALTT01USQ657N.

The WARDS dataset covers all new motor-vehicle purchases in the US, aggregated to the vehicle-class-year level. A "vehicle class" is defined as a specific (i) vehicle type (e.g., car or light truck), (ii) vehicle segment (e.g., luxury car or middle car), (iii) vehicle subsegment (e.g., large SUV or small pickup), and (iv) power type (hybrid or gas). A market is defined as a given vehicle class in a given year. A good is defined as a model and make (e.g., Hyundai Tucson). We average the price across all available trims of a make and model. One company (e.g., GM) can thus have multiple goods in a given market. We define a dataset at the good-vehicle-class-year level with the market share and price of each good. We drop vehicle-class-years in which the total sales volume is less than 50,000 units or one company (e.g., GM) has 100% market share. Our final dataset only contains observations with positive market shares.

Finally, when analyzing bankruptcies, we focus on markets in which the bankrupt firm had meaningful market share. Specifically, we focus on markets in which the bankrupt firm had a market share of at least 10% one year (or four quarters for airlines) prior to the bankruptcy in that route or vehicle class.[32] We call an airline (car manufacturer) bankrupt in a given quarter (year) if it is in Chapter 11 reorganization in any day of that quarter (year).

E.3.2 Estimating Average Good-Taste Parameters

In each historical market t, we observe a vector of prices p_t^{data} and market shares S_t.[33] We also observe indicators B_{jt} for historical bankruptcies. We follow the literature in assuming that the consumer-taste parameters, which we estimate separately in each industry in Section 5.2, do not vary across goods or markets within an industry. Given these consumer-taste-parameter estimates, we estimate the good-taste parameters $\{\delta_{jt}\}$ for each historical market t to make model-implied market shares match observed market shares S_t.

Specifically, using our experimental estimates of $\{\bar{\alpha}^d, \sigma_\alpha^d, \bar{\beta}^d, \sigma_\beta^d\}$ and the calibrated average-awareness values κ_j, we can fix any candidate taste parameters $\{\delta_{jt}\}$ and simulate good j's model-implied market share $S_{jt}^{model}(p_t^{data})$ at the observed prices p_t^{data} according to equa-

[32]Note, we assume the outside option has a market share of 50%, so this corresponds to an observed market share of 20%.

[33]We assume that 50% of consumers who consider flying or purchasing a vehicle ultimately do not make a purchase. We thus assume the outside option has a market share of 50%, reducing each good's observed market share by 50%.

tion (5). To be precise, we take a candidate vector $\{\delta_{jt}\}$ and simulate 10,000 draws of $\alpha_{id}, \beta_{id}, \{\epsilon_{ijtd}\}, \{A_{ijt}\}$ to calculate model-implied market shares $S_{jt}^{model}(p_t^{data})$ at the observed prices. Using the standard contraction mapping, (Berry, Levinsohn, and Pakes, 1995; Nevo, 2000) we use $S_{jt}^{model}(p_t^{data})$ to update to a new candidate vector $\{\delta_{jt}\}'$, repeating until $S_{jt}^{model}(p_t^{data}) = S_{jt}$.[34]

E.4 Estimating Marginal Costs

Given our estimates of $\{\delta_{jt}\}$, we use the 10,000 simulated draws of α_{id}, β_{id}, $\{\epsilon_{ijtd}\}, \{A_{ijt}\}$ to calculate $S_{jt}^{model}(p_t^{data})$ and its partial derivatives in each market t. We estimate marginal costs $\{c_{jt}\}$ to make observed prices satisfy the first-order conditions associated with the pricing equilibrium condition (6):

$$S_{jt}^{model}\left(p_t^{data}\right) + \sum_{k\in G_{ft}}\left(p_{kt}^{data} - c_{kt}\right) \times \frac{\partial}{\partial p_{jt}} S_{kt}^{model}\left(\left(p_{jt}, \{p_{nt}^{data}\}_{n\neq j}\right)\right)\Bigg|_{p_{jt}=p_{jt}^{data}} = 0. \tag{E.12}$$

E.5 Counterfactual Simulations: Estimating Historical Bankruptcy Impacts

We now turn to our key model counterfactual: What if various historical bankruptcies had never occurred?

For each bankruptcy and each market, we simulate 10,000 draws of $\alpha_{id}, \beta_{id}, \{\epsilon_{ijtd}\}, \{A_{ijt}\}$. We calculate u_{ijtd} for each good by equation (3) and calculate each simulated consumer i's chosen good j in each market t. Then, holding the simulated draws fixed, we assume counterfactually that B_{jt} is zero. We solve numerically for a new pricing equilibrium $p_t^{counter}$ satisfying (6). Specifically, we search numerically for a pricing equilibrium $p_t^{counter}$ satisfying the first-order conditions (E.12). When calculating these first-order conditions for a candidate $p_t^{counter}$, we use the same simulated draws of $\alpha_{id}, \beta_{id}, \{\epsilon_{ijtd}\}, \{A_{ijt}\}$ to calculate market shares and market-share derivatives, but we set $B_{jt} = 0$ in these calculations. For simplicity, we assume firms do not change the products they offer in bankruptcy (Seim, 2006).

Given the counterfactual price vector $p_t^{counter}$, we use the same draws of $\alpha_{id}, \beta_{id}, \{\epsilon_{ijtd}\}, \{A_{ijt}\}$ to calculate u_{ijtd} for each good by equation (3). In this calculation, we use the counterfactual

[34] It is a well-known result that there is exactly one vector $\{\delta_{jt}\}$ that achieves this (Nevo, 2000).

prices and set $B_{jt} = 0$. We calculate each simulated consumer i's counterfactual chosen good j in each market t. In each market, we then calculate consumer welfare, producer surplus, and market shares using the counterfactual prices and counterfactual chosen goods. In a given market, the average own-price change is the average of $100 \times (\frac{p_{jt}}{p_{jt}^{counter}} - 1)$ across all goods j provided by the bankrupt firm f_j. The change in producer surplus is:

$$100\times \left(-1 + \frac{\sum_{j \in G_{ft}} S_{jt}^{model}(p_t^{data}) \times (p_{jt}^{data} - c_{jt})}{\sum_{j \in G_{ft}} S_{jt}^{model}(p_t^{counter}) \times (p_{jt}^{counter} - c_{jt})} \right). \tag{E.13}$$

Finally, let Q_t denote the total number of passengers (or cars sold) in a market t. Let Y_t denote some causal effect of bankruptcy in market t: e.g., the percentage change in producer surplus caused by the bankruptcy. We calculate a weighted average effect as $(\sum_t Y_t Q_t)/\sum_t Q_t$, where we sum over all markets affected by the bankruptcy (e.g., during route-quarters of an airline's bankruptcy).

F Capital Structure Implications

In this appendix, we follow Antill (2021) and calibrate a standard dynamic-capital-structure model (Goldstein, Ju, and Leland, 2001; Strebulaev and Whited, 2012) to study the ex-ante implications of indirect bankruptcy costs. Using the model, we show that increasing creditor payoffs in bankruptcy can significantly reduce the cost of credit for non-bankrupt firms. Specifically, in Table 8, we show that the indirect costs of bankruptcy range from 10.6% to 31% of producer surplus. We use the dynamic model to consider the ex-ante impact of removing these indirect costs. We show that increasing creditor recovery by 10.6% of firm value increases ex-ante optimal leverage by six percentage points. The lower cost of credit increases ex-ante firm value by 2.6%. We show that increasing creditor recovery by 31% of firm value increases leverage by 15 percentage points and ex-ante firm value by 6.5%.

We now briefly outline the model and calibration, which follow the simplified approach of Antill (2021).

The infinite-horizon model consists of two alternating phases. In the "ex-ante" phase, the equity holders of a firm issue a perpetual callable bond. The equity holders choose the coupon C to maximize the sum of the debt proceeds and the equity value of the levered firm. Once the value C is chosen, the ex-ante phase ends and the next "ex-post" phase begins. In the ex-post phase, equity holders solve a continuous-time optimal stopping problem to determine, in each instant, whether to default on the debt or refinance it. If equity holders refinance the debt, they call the bond and enter a new ex-ante phase. If equity holders default, the game ends.

We now describe the ex-post phase, in which the coupon C is fixed. Time is continuous and all agents are risk neutral. The firm has assets that produce earnings before interest and taxes (EBIT) of $\delta_t dt$ per unit time, where δ_t follows a geometric Brownian motion:

$$d\delta_t = \mu \delta_t dt + \sigma \delta_t dB_t. \tag{F.1}$$

In equation (F.1), B_t is a standard Brownian motion, $\sigma > 0$ is a volatility parameter, and μ is a drift parameter that is strictly lower than the risk-free rate $r > 0$. The firm pays taxes at a constant rate τ and coupons are deductible, leading to a cashflow of $(1 - \tau)(\delta_t - C)dt$ per unit time.

If equity holders default at time t, they receive 0 and the game ends. If equity holders refinance at time t, they receive a payoff $\mathcal{R}_t$ for a process $\{\mathcal{R}_t\}_{t\geq 0}$ that is described shortly. Equity holders choose a default time $\mathcal{T}^D$ and refinancing time $\mathcal{T}^R$ to maximize the equity value:

$$\mathbb{E}(\delta) \equiv \sup_{\mathcal{T}^D,\mathcal{T}^R} \mathbb{E}^{\delta}\left[\int_0^{\mathcal{T}^D\wedge\mathcal{T}^R} e^{-rt}(1-\tau)(\delta_t - C)dt + \mathbf{1}\left(\mathcal{T}^D > \mathcal{T}^R\right)e^{-r\mathcal{T}^R}\mathcal{R}_{\mathcal{T}^R}\right], \tag{F.2}$$

where $\mathbb{E}^{\delta}$ refers to the expectation under the probability law of δ_t given $\delta_0 = \delta$.

In the ex-ante phase, equity holders choose a coupon C to maximize the sum of the debt proceeds and the equity value of the levered firm. The value of the debt proceeds is equal to the value of the debt times $(1-q)$, where $q > 0$ is a refinancing-cost parameter. The value of the debt is equal to the sum of three components. The first component is the expected discounted sum of the coupons prior to default or refinancing. The second component is the expected discounted value of the creditor recovery in the event of bankruptcy. If equity holders default at time t, we assume that creditors recover $(1-\alpha)(1-\tau)\delta_t/(r-\mu)$ for a parameter $\alpha > 0$. This recovery represents the value of receiving $(1-\tau)\delta_s$ in perpetuity, given a fraction α of the starting value δ_t is lost. The third component is the expected discounted value of receiving the par value P of the debt in the event of refinancing.

Given these assumptions, an equilibrium is given by constants $\theta, P, C, \delta_B, \delta_R, \delta_0$ satisfying the following:

1. If the refinancing payoff process $\mathcal{R}_t$ is given by $\mathcal{R}_t \equiv \theta\delta_t - P$, then the first hitting times $\mathcal{T}^{\delta_B} \equiv \inf\{t : \delta_t \leq \delta_B\}$, $\mathcal{T}^{\delta_R} \equiv \inf\{t : \delta_t \geq \delta_R\}$ solve the equity holders' problem:

$$\begin{aligned}(\mathcal{T}^{\delta_R}, \mathcal{T}^{\delta_D}) = \operatorname{argmax}_{\mathcal{T}^D,\mathcal{T}^R} \mathbb{E}^{\delta}\Bigg[\int_0^{\mathcal{T}^D\wedge\mathcal{T}^R} & e^{-rt}(1-\tau)(\delta_t - C)dt \\ & + \mathbf{1}\left(\mathcal{T}^D > \mathcal{T}^R\right)e^{-r\mathcal{T}^R}\left(\theta\delta_{\mathcal{T}^R} - P\right)\Bigg].\end{aligned} \tag{F.3}$$

2. If equity holders use the strategy $(\mathcal{T}^{\delta_R}, \mathcal{T}^{\delta_D})$, then P is the par value of the debt at

issuance given the starting value δ_0:

$$P = \mathbb{E}^{\delta_0}\Bigg[\int_0^{\mathcal{T}^{\delta_D}\wedge\mathcal{T}^{\delta_R}} e^{-rt}Cdt + \mathbf{1}\,(\,\mathcal{T}^{\delta_D} > \mathcal{T}^{\delta_R})e^{-r\mathcal{T}^{\delta_R}}P \tag{F.4}$$
$$+ \mathbf{1}\,(\,\mathcal{T}^{\delta_D} \leq \mathcal{T}^{\delta_R})e^{-r\mathcal{T}^{\delta_D}}\frac{(1-\alpha)(1-\tau)\delta_D}{r-\mu}\Bigg].$$

3. If the refinancing payoff process $\mathcal{R}_t$ is given by $\mathcal{R}_t \equiv \theta\delta_t - P$, the par value of debt is P, and equity holders use the strategy $(\mathcal{T}^{\delta_R}, \mathcal{T}^{\delta_D})$, then the equity holder's ex-ante value is $\theta\delta_0$:

$$\theta\delta_0 = (1-q)P + \mathbb{E}^{\delta_0}\Bigg[\int_0^{\mathcal{T}^{D}\wedge\mathcal{T}^{R}} e^{-rt}(1-\tau)(\delta_t - C)dt \tag{F.5}$$
$$+ \mathbf{1}\,(\,\mathcal{T}^{\delta_D} > \mathcal{T}^{\delta_R})e^{-r\mathcal{T}^{\delta_R}}\Bigg(\,\theta\delta_R - P\,\Bigg)\Bigg].$$

4. Given δ_0, there are no values $(\theta', C', \delta_B', \delta_R', P')$ consistent with 1-3 such that $\theta' > \theta$.

In an equilibrium, equity holders rationally anticipate that their ex-ante value is a linear function $\theta\delta_{\mathcal{T}^R}$ of the EBIT $\delta_{\mathcal{T}^R}$ at the time of refinancing. Equity holders must call the debt at par, paying P, to issue new debt and receive this value. Given this rational expectation, equity holders optimally use the specified strategy given by first hitting times $\mathcal{T}^{\delta_R}, \mathcal{T}^{\delta_D}$. Given this strategy and the coupon C, the value P at which debt is called is equal to the par value at issuance. The conjectured ex-ante value of equity is self consistent, in that $\theta\delta_0$ is the ex-ante value given that equity holders receive $\theta\delta_R$ if they refinance at δ_R. Finally, the level of debt C is optimal, in that condition 4 ensures there is no alternative coupon that leads to a higher ex-ante firm value. Given the definition of an equilibrium, the model is stationary: when equity holders refinance for the mth time, they will optimally issue a coupon $\delta_R^m C/\delta_0$ with par value $\delta_R^m P/\delta_0$, and subsequently use hitting-time strategies with thresholds $\delta_R^m\delta_R/\delta_0$ and $\delta_R^m\delta_B/\delta_0$.

To calibrate the model, we use the benchmark values of r, σ, μ, q, τ given in Table 5 of Strebulaev and Whited (2012). First, we lower α from 0.14 to 0.14-.106 = .034. This represents an increase in creditor recovery of 10.6% of firm value, which corresponds to our lowest estimate of indirect bankrupty costs (Table 8). We find that the equilibrium value of θ increases 2.6% and equilibrium leverage (P/θ) increases by six percentage points. Next, we repeat this exercise lowering α from 0.32 to 0.32-0.31 = .01. This represents an increase in creditor recovery of 31% of firm value, our highest estimate of indirect bankrupty costs (Table 8). We find that the equilibrium value of θ increases 6.5% and equilibrium leverage (P/θ) increases by 15 percentage points.