Consumer Choice and Corporate Bankruptcy*

Samuel Antill† Megan Hunter‡

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Abstract: Using incentivized randomized experiments, we estimate the causal effect of a Chapter 11 bankruptcy filing on consumer demand for the bankrupt firm's products. Knowledge of a firm's bankruptcy reduces a consumer's willingness to pay by 18-35%, depending on the industry. We show evidence that consumers fear both (i) a liquidation preventing future relationships with a firm and (ii) a decline in quality while a firm reorganizes. Estimating a structural model of consumer demand, we quantify the large negative impact of bankruptcy on consumer welfare and a bankrupt firm's market share.

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†Harvard Business School, santill@hbs.edu

‡Boston College Carroll School of Management, megan.hunter@bc.edu

1 Introduction

Firms rely extensively on debt financing. While debt has many benefits, defaulting on debt can destroy firm value. For example, a bankruptcy filing can create the perception that a firm will liquidate, scaring off customers who derive utility from future interactions with a stable business. Likewise, a firm may be perceived as having low quality if it is reorganizing in Chapter 11 bankruptcy, deterring consumers. Fearing this consumer response, distressed firms may avoid an otherwise beneficial Chapter 11 reorganization to prevent such a loss of customers. While these indirect costs of bankruptcy have been studied for decades, they are notoriously difficult to quantify. In this paper, we use two incentivized experiments to estimate the causal effect of corporate bankruptcy on consumer demand for a bankrupt firm's products. We incentivize participants to honestly report their willingness to pay for a 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. Up to 48% of consumers are aware of major corporate bankruptcies. Estimating a structural model, we quantify the negative effects of historical bankruptcies on consumer and producer surplus.

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 — 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 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 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 a randomized experiment. We ask experiment participants to report their willingness to pay for various firms' products. Holding all other details fixed, we randomly vary the bankruptcy status of each firm across participants. We follow a recent methodology developed by Kessler, Low, and Sullivan (2019) to incentivize participants to honestly report their preferences in hypothetical choices. Because the decisions are hypothetical, we can vary the bankruptcy statuses of both real and fictional firms. We also vary other information about each firm's bankruptcy, allowing us to understand the mechanisms by which bankruptcy affects consumer decision making. By randomly disclosing the bankruptcy status of a firm to consumers, we estimate the causal effect of the bankruptcy on preferences for consumers that are aware of the bankruptcy. This turns out to be a relevant estimate - we provide the first evidence that many consumers are aware of major bankruptcies.

We consider three industries: airlines, car manufacturers, and retail stores. We focus on these consumer-facing industries because of the high number of large historical bankruptcies. 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 35%. 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 further document that a substantial fraction of consumers are aware when a large firm files for bankruptcy. We present experiment participants with a list of firms and ask them 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 credit ratings. Thus, while participants are aware of bankruptcy filings, they are not aware of pre-bankruptcy financial distress.

In a second experiment, consumers are directly incentivized to select between the gift cards of two real firms. One firm was in bankruptcy at the time of the experiment. Randomly disclosing this fact to consumers, we replicate all of the results of our primary experiment.

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 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 data from our experiment 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.

Finally, our experiment 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.

1.1 Contribution to the Literature

This paper's main contributions to the literature are 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) 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 (iii) educating consumers about the survival prospects of bankrupt firms can dampen the effects of a corporate bankruptcy.

We contribute to several literatures. First, we contribute to the literature studying demand for financially distressed firms' products. In earlier work, Hortaçsu, Matvos, Syverson, and Venkataraman (2013) and Hortaçsu, Matvos, Shin, Syverson, and Venkataraman (2011) find that used-car-auction prices for a particular vehicle decline when the vehicle's manufacturer approaches bankruptcy. The authors show that professional automobile dealers who participate in these auctions are less willing to pay for vehicles from a manufacturer that will not honor warranties or replace parts in the event of liquidation. We complement these studies by showing in a randomized controlled experiment that nonprofessional consumers (i) are aware of bankruptcy filings associated with businesses that they patronize and (ii) are far less willing to pay for goods of bankrupt firms. Additionally, we provide direct evidence on the mechanisms by which corporate bankruptcy reduces consumer demand. We also contribute by demonstrating that these indirect bankruptcy costs may be mitigated by educating consumers about bankrupt firm survival prospects; to the best of our knowledge, we are the first paper to experimentally manipulate what a consumer knows about bankruptcy.[1]

Second, we contribute to the literature studying how financially distressed firms optimally anticipate future bankruptcy-driven changes in consumer demand (Matsa, 2011; Phillips and Sertsios, 2013; Malshe and Agarwal, 2015).[2] We contribute novel estimates of how a firm should optimally change prices during bankruptcy. Our estimates are the first ones based on causal evidence from randomized experiments - our structural model infers optimal pricing decisions from the causal effect of bankruptcy on consumer demand. Our estimates suggest that optimal price changes are relatively small.

[1] In contemporaneous work, Bernstein, Colonnelli, Iverson, and Hoffman (2022) experimentally manipulate what small businesses know about bankruptcy. Their interesting experiment answers an entirely different set of questions about small-business decision making.

[2] Malshe and Agarwal (2015) quantify how advertising and R&D funding changes when a firm is highly leveraged. Phillips and Sertsios (2013) explore how product quality and pricing vary with airline financial distress. Matsa (2011) shows that highly leveraged grocery stores lower their quality.

Third, we contribute to the literature showing how bankruptcy filings impact product-market competition. A large literature examines correlations between airline bankruptcies, airline quality, and airline pricing (Borenstein and Rose, 1995, 2003; Ciliberto and Schenone, 2012a,b). Examining airlines close to bankruptcy, Busse (2002) shows that levered airlines are more likely to start price wars. In the marketing literature, Ozturk, Chintagunta, and Venkataraman (2019) find that the bankruptcy of one firm can have negative spillover effects on the firm's competitors because consumers worry that the firm's financial distress may be representative of the entire industry. Again, we contribute novel estimates of equilibrium price responses to bankruptcies. Our experiment-driven estimates show that firms opportunistically increase prices in response to a competitor's bankruptcy, but these changes are quite small in equilibrium.

Methodologically, our paper builds on Exley (2016), who precedes this work in using a price list to estimate consumer valuations, and Kessler, Low, and Sullivan (2019), who develop a methodology for incentivizing hypothetical choices. We also contribute to the literature using structural estimations to quantify bankruptcy inefficiencies.[3] Similarly, our experimental approach complements the long reduced-form literature quantifying bankruptcy costs.[4]

Finally, this paper relates more broadly to the literature exploring the relationship between firm reputation and consumer demand (Dodds, Monroe, and Grewal, 1991; Burke, Dowling, and Wei, 2018; Mainardes, Mota, and Moreira, 2020). In the accounting literature, Noh, So, and Zhu (2022) examine how consumers respond to financial reports.

[3] See Eraslan (2008); Jenkins and Smith (2014); Davydenko, Strebulaev, and Zhao (2012); Glover (2016); Dou, Taylor, Wang, and Wang (2021); Antill (2021, 2022).

[4] See, for example, Weiss (1990); Andrade and Kaplan (1998); Iverson (2018); Bernstein, Colonnelli, Giroud, and Iverson (2019); Bernstein, Colonnelli, and Iverson (2019); Iverson, Madsen, Wang, and Xu (2020); Wang (2022).

2 Experimental Design

We aim to measure the causal effect of a Chapter 11 bankruptcy filing on consumer demand for the bankrupt firm's products. The ideal experiment for this purpose would measure consumer demand for both a firm A and a firm B that is bankrupt but otherwise identical to firm A. Comparing consumer demand for firm A to demand for firm B would identify the desired causal effect. This ideal experiment is infeasible using observational data because bankrupt firms are inherently different from nonbankrupt firms. We overcome this challenge with an experimental design that considers demand for two identical firms, in which we randomly vary the bankruptcy status of one firm holding all other characteristics fixed. Our experiment addresses concerns that unobservable firm characteristics might affect both a firm's bankruptcy status and demand for its products.

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 4, we combine these estimates with a structual model to estimate the overall causal effect of bankruptcy on producer and consumer surplus.

We now briefly summarize our experiment. We conclude the section with a description of the final experiment-participant sample. Appendix A provides details.

2.1 Attention Tests

In the first stage of the experiment, we ask questions unrelated to bankruptcy, which include attention tests. We exclude participants that fail attention tests.

2.2 Incentivizing Participants

In the second stage of the experiment, we incentivize participants to honestly report their preferences. To measure willingness to pay for actual goods and services in an incentivized manner, we follow the methodology of Kessler, Low, and Sullivan (2019). 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. Participants that simply type answers as quickly as possible would likely be removed from the survey before this point by the attention tests.

We obtain qualitatively similar results in another experiment with more traditional incentives: participants choose between the gift cards of two firms and have a chance of winning one of their chosen gift cards.[5] This second experiment, which shows our results are robust to using different incentive schemes, is discussed in Section 5.

[5] We randomly inform participants that one of the two firms is bankrupt (which was true at the time of the experiment). We focus on the current experiment, which relies on the Kessler, Low, and Sullivan (2019) approach, because (i) gift cards are not an ideal incentive given their treatment in bankruptcy and (ii) hypothetical purchase decisions give us more freedom to manipulate prices and bankruptcy statuses of actual firms without deceiving participants.

2.3 Randomizing Information and Measuring Willingness to Pay

In the third 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.

2.3.1 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 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.[6]

Table 1 describes the ten willingness-to-pay questions, listing firm B, firm A, and the firm-A reference price for each question. Every participant answers these same ten willingness-to-pay questions. Appendix A provides details.

2.3.2 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 2.

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 1). The remaining information groups see text similar to the above quote in all ten questions. However, there are small differences in the text. 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

[6] We chose these particular firms because they have never been in bankruptcy.

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.

2.4 No Deception

It is important to note that we are not deceiving participants in any way. We inform participants that all purchase decisions and facts about firms are hypothetical. Our IRB reviewers agreed there is no deception.

2.5 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. Each participant answers these questions for one industry, which corresponds to their final willingness-to-pay question. We conclude by asking for demographic information.

2.6 Final Experiment-Participant Sample

We ran our experiment online from January - February 2022 using a survey marketplace called Lucid.[7] Lucid tracks demographic information for millions of survey takers, allowing us to run our survey on a representative sample of US adults.[8] Following our preregistered

[7]We preregistered our experiment prior to running the survey. See Appendix A.

[8]Table B.2 compares the demographic composition of our sample to that of the US.

sample-selection criteria, our final sample consists of 1,749 participants. Our final dataset contains 17,490 willingness-to-pay-question responses for these 1,749 participants. Appendix A provides further details on the preregistered distribution of participants across information groups.

3 Reduced-Form Results

3.1 The Causal Effect of Bankruptcy on Consumer Demand

For each participant i in each of $q = 1, 2, ..., 10$ questions, we measure the participant's willingness to pay WTP_{iq} for some firm B's product or service. There are four airline questions, three retail questions, and three car questions, leading to a larger sample for airlines. In each question, we tell the participant how much an equivalent product costs at another firm A. We define the 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:

$$WTP_{iq}^{norm} \equiv \left(\text{WTP at Firm B} \right) / \left(\text{Given Price at Firm A} \right).$$

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 $WTP_{iq} \geq 0$.

We define mutually exclusive binary indicator variables for information groups. For example, $\text{Control}_i = 1$ implies i is provided no information about firm B in all questions. $\text{Bankruptcy}_i = 1$ 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 regressions at the participant-question level, clustering standard errors by participant.

First, we consider a sample of participants in the following four information groups: Control, Pre-Bankruptcy, Bankruptcy, and Post-Bankruptcy. Within this sample, we estimate the following regression separately for each industry:

$$WTP_{iq}^{norm} = \alpha + \delta\text{Pre-Bankruptcy}_i + \beta\text{Bankruptcy}_i + \gamma\text{Post-Bankruptcy}_i + \epsilon_{iq}. \quad (1)$$

We omit the indicator for Control-group participants. Because of this, the coefficient α on the constant term may be interpreted as the average normalized willingness to pay for Control-group participants. Similarly, the coefficients on Pre-Bankruptcy$_i$, Bankruptcy$_i$ and Post-Bankruptcy$_i$ may be interpreted as differences in average normalized willingness to pay, relative to the Control group.

Table 3 shows that 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 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.

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). This effect is especially pronounced for car manufacturers, where a prior bankruptcy only reduces willingness to pay by 5.5% of the Control-group average.

Finally, Table 3 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 3.6 that consumers are not aware which firms are close to bankruptcy. In contrast, Section 3.5 shows that a substantial fraction of consumers are aware when a firm files for bankruptcy.

3.2 Causal Evidence on Mechanisms

Table 3 shows that knowledge of a corporate bankruptcy substantially reduces a consumer's willingness to pay for the bankrupt firm's products. We next examine the mechanisms by which a bankruptcy affects consumer demand.

To examine mechanisms, we study the sample of participants in the following five information groups: Control, Bankruptcy, Quality, Survival 50, Survival 100. Within this sample, we estimate the following regression separately for each industry:

$$WTP_{iq}^{norm} = \alpha + \beta \text{Bankruptcy}_i + \delta \text{Quality}_i + \gamma \text{Survival } 50_i + \rho \text{Survival } 100_i + \epsilon_{iq}. \quad (2)$$

As in Table 3, the first row of Table 4 shows that knowledge of a corporate bankruptcy causally reduces a consumer's willingness to pay for the firm's products. To understand why consumers respond in this way, we first examine 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%.

Next, we examine 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.[9] 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 a durable good for which warranties and future part purchases are likely to be important for consumers.

3.3 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 6, 7, and 8 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 for car purchases relate to losing a warranty and not being able to find replacement parts. For retail bankruptcies,

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

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.

3.4 Implied Survival Probabilities and Consumer Education

As described in Section 3.2, 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. Table 5 shows the implied survival beliefs for each industry using the regression in Table 4. 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.[10]

We find that consumers act as if they believe 78% of airlines survive bankruptcy. This is surprisingly accurate: Table 5 shows that, 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 and retail 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.

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

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. We explore this further using our structural model in Section 4.4.4.

3.5 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.[11] 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 9 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 5, 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, we define Bankruptcy Awareness as the fraction of participants reporting a 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-

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

level regression of Bankruptcy Awareness on Actual Bankruptcy. Table 10 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.

3.6 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 3 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. 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 10 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 10 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.

3.7 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 real-world behavior for four reasons. First, our experiment participants have a real incentive to truthfully report their preferences (Kessler, Low, and Sullivan, 2019). Second, Table B.2 confirms that our experiment participants comprise a demographically representative sample of US adults. Third, Table B.3 shows that our experiment participants regularly make the types of purchases that we ask about in our experiment. Fourth, Table B.4 shows that our results are robust to focusing on those participants who most frequently make these purchases.

4 Structural Model Estimation

Next, we estimate a structural model to infer how historical bankruptcies impacted market shares, consumer welfare, pricing, and producer surplus. We estimate a model of consumer choice in which consumers might care if a service provider or good producer is bankrupt. Firms in the model compete for customers through endogenous pricing decisions. We use our 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. Specifically, we obtain datasets containing historical prices and market shares for motor vehicles and flights.[12]

4.1 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: vehicles or flights. 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 Appendix C.

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:

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

In this equation, δ_{jt} is a parameter capturing the average taste for good j in market t. The

[12] Measuring prices and market shares, or even defining markets, is extremely difficult for retail goods. We leave this exercise for future work.

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. 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. We explain the distribution of awareness A_{ijt} below.

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^* satisfying the following equation for any f:

$$\{p_{jt}^*\}_{j \in G_{ft}} \in \text{argmax}_{\{p_{jt}\}_{j \in G_{ft}}} \sum_{j \in G_{ft}} S_{jt}^{model} \Bigg((\{p_{jt}\}_{j \in G_{ft}}, \{p_{kt}^*\}_{k \notin G_{ft}}) \Bigg) \times \Bigg(p_{jt} - c_{jt} \Bigg). \quad (6)$$

In words, firm f chooses prices for all the goods G_{ft} it provides. Firm f accounts for how its market shares depend 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.

4.2 Estimating 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.[13]

Each willingness-to-pay question in our experiment corresponds to a hypothetical market t with two goods, $j = A, B$.[14] 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

[13]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 4.4.1, we describe our method for using historical data to estimate good-specific tastes.

[14]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.

imply the following market share for good B:

$$\text{B share}^{data}_{control}(p_{Bt}) = \left[\sum_{i=1}^{N} \text{Control}_i \times \mathbf{1}\left(WTP_{it} > p_{Bt} \right)\right] / \left[\sum_{i=1}^{N} \text{Control}_i\right]. \tag{7}$$

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:

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

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):

$$\text{B share}^{data}_{bank}(p_{Bt}) = \left[\sum_{i=1}^{N} \text{Bankruptcy}_i \times \mathbf{1}\left(WTP_{it} > p_{Bt} \right)\right] / \left[\sum_{i=1}^{N} \text{Bankruptcy}_i\right] \tag{9}$$

$$\text{B share}^{model}_{bank}(p_{Bt}) = \mathbb{E}_{\alpha_{id},\beta_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\bar{\delta}^d_t + \alpha_{id} (p_{Bt} - p_{At}) + \beta_{id} + (\epsilon_{iBtd} - \epsilon_{iAtd}) > 0 \right)\right]. \tag{10}$$

We estimate the parameters $\theta^{Experiment}_d \equiv \left(\bar{\delta}^d_t, \bar{\alpha}^d, \sigma^d_\alpha, \bar{\beta}^d, \sigma^d_\beta \right)$ by the Generalized Method of Moments. Using our experimental data, we define a vector M^{data}_d containing moments of the form (7) and (9) for various prices p_{Bt}. Appendix C provides detailed moment definitions and explains how, by design, M^{data}_d identifies $\theta^{Experiment}_d$. For each candidate set of parameters, we use equations (8) and (10) to calculate the model-implied equivalent M^{model}_d of the empirical vector M^{data}_d. Using the efficient weighting matrix W_d, we estimate $\theta^{Experiment}_d$ to minimize the weighted difference between model-implied and experiment-implied moments:

$$\hat{\theta}_d^{Experiment} = \text{argmin}_{\theta_d^{Experiment}} \left(M_d^{data} - M_d^{model} \right) W_d \left(M_d^{data} - M_d^{model} \right)'. \tag{11}$$

Appendix C provides details on our standard approach for constructing the weighting matrix W_d and asymptotic participant-clustered standard errors. We estimate $\hat{\theta}_d^{Experiment}$ separately for flight purchases and vehicle purchases to capture heterogeneous preferences across industries. Table 11 displays estimates and standard errors for the key parameters $\{\bar{\alpha}^d, \sigma_\alpha^d, \bar{\beta}^d, \sigma_\beta^d\}$. We interpret these parameters and magnitudes in Appendix C.

4.3 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 9).

4.4 Estimating Historical Bankruptcy Impacts

Finally, we use observational data to estimate good-taste parameters δ_{jt} and marginal costs c_{jt} for each historical market. We then turn to our key model counterfactual: What if various historical bankruptcies had never occurred?

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).[15] The D1B1

[15]See https://www.transtats.bts.gov/tables.asp?QO_VQ=EFI&QO_anzr=Nv4yv0r.

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.[16] We provide details in Appendix C.

4.4.1 Estimating Good-Taste Parameters

In each historical market t, we observe a vector of prices p_t^{data} and market shares S_t.[17] 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 4.2, 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 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 equation (5). We estimate taste parameters δ_{jt} in each historical market to equate S_{jt} and $S_{jt}^{model}(p_t^{data})$ for all j.[18]

[16]See `https://fred.stlouisfed.org/series/CPALTT01USQ657N`.

[17]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%.

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

4.4.2 Estimating Marginal Costs

Given our estimates of $\{\delta_{jt}\}$, we can simulate $S_{jt}^{model}(p_t^{data})$ and its partial derivatives. We estimate marginal costs $\{c_{jt}\}$ to make observed prices satisfy the first-order conditions associated with the pricing equilibrium condition (6) for all j:

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

4.4.3 Estimating the Costs of Historical Bankruptcies

Finally, we 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).[19] Finally, we simulate to calculate counterfactual market shares, producer surplus, and consumer welfare. We provide details in Appendix C.

Table 12 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

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

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%.

Table 12 shows that the bankruptcies of Delta Airlines and United Airlines had similar effects. 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 car-manufacturer bankruptcies had larger effects for two reasons. First, after accounting for heterogeneous consumer tastes, car bankruptcies cause more consumer disutility than airline bankruptcies (Table 11). Second, consumers are more aware of car-manufacturer bankruptcies than airline bankruptcies (Table 9).

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. We report the results in Table 13. 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 13. 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.

4.4.4 Can Consumer Education Help?

Finally, we use the estimated model to explore the effects of educating consumers about corporate bankruptcy. Table 5 shows that, on average, consumers (i) have correct beliefs about bankrupt-airline-survival prospects, and (ii) incorrectly underestimate the likelihood that a car manufacturer will survive bankruptcy. What if consumers were educated about car-manufacturer bankruptcy survival prospects?[20]

To answer this question, we hold each bankruptcy status B_{jt} fixed and consider a counterfactual world in which consumers hold the rational belief (Table 5) that large car manufacturers survive bankruptcy. We adjust the distribution of bankruptcy sensitivities β_{id} to reflect this belief. Specifically, 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 $\{\beta_{id}\}$. Finally, we compare these values to the corresponding values in the no-bankruptcy counterfactual. That is, we examine how each bankruptcy would impact counterfactually educated consumers, relative to the counterfactual of the bankruptcy not occurring. Appendix C provides details.

Table 12 shows the results. 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

[20]We focus on car manufacturers in this counterfactual because consumers hold roughly correct beliefs about airline survival prospects.

educated about bankruptcy. 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 12 shows that this counterfactual consumer education would dramatically reduce the negative effects of bankruptcy on producer and consumer welfare.

5 Experiment Robustness

A second experiment confirms that our results are robust. This experiment has two attractive features. First, participants choose between real gift cards at Hertz and Enterprise, so they are directly incentivized to reveal their demand for these firms. Second, we exogenously vary the perceived bankruptcy status of Hertz: Hertz was in Chapter 11 at the time of the experiment (November - December 2020) and we randomly inform participants of this fact. We thus observe how exogenous variation in a consumer's awareness of Hertz's bankruptcy affects demand for Hertz, measured with a real choice between gift cards.

In a randomly assigned treatment group, we informed participants that Hertz was currently bankrupt. In both the Control and the treatment group, we measure which participants are aware of Hertz's bankruptcy by providing a list of firms and asking them to select which are bankrupt. We find that 26% of Control participants were aware of Hertz's bankruptcy. Roughly 90% of treated participants were aware of Hertz's bankruptcy. Instrumenting for awareness of Hertz's bankruptcy using the randomly assigned treatment, we find that learning Hertz is bankrupt causally reduces willingness to pay by 35% (Table D.5).

To determine the mechanism by which bankruptcy affects consumer demand, we ask follow-up survey questions. We also add additional randomly assigned treatments which provide further information about Hertz. One group is told about Hertz's debtor-in-possession financing loan. Another is told that similar rental car companies survived bankruptcy. We find that consumers fear both (i) a liquidation preventing future relationships with a firm and (ii) a decline in quality while a firm reorganizes. Specifically, consumers express concerns about the maintenance and inventory of rental cars during bankruptcy. Further details on this experiment and the results can be found in Appendix D.

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 substantial 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.[21]

[21] Of course, these are ex-post losses. It is possible that higher deadweight losses in bankruptcy can improve ex-ante welfare by solving commitment problems (Antill and Grenadier, 2019), mitigating externalities associated with inefficient continuation (Antill and Clayton, 2021), or discouraging inefficient overinvestment associated with unsecured debt (Donaldson, Gromb, and Piacentino, 2020).

Our results have additional marketing implications. Previous research shows that switching costs between brands are substantial and play an important role in consumer decision making (Klemperer, 1995). If consumers switch away from a firm because of its bankruptcy status, the firm may struggle to regain those customers. Such a permanent loss of customers could explain why many firms that emerge from bankruptcy perform poorly and subsequently refile for bankruptcy (Hotchkiss, 1995). Our work also points to actions that marketing managers can take in bankruptcy. For example, they can change their communication with consumers and associated advertising. While managers might not want to explicitly mention the bankruptcy (to ensure that unaware consumers remain unaware), they can change communication to ease potential concerns.[22] Similarly, consumer-facing firms might benefit from out-of-court restructurings, rather than formal bankruptcy filings, given that consumers are unaware of which nonbankrupt firms are financially distressed.

Our results also imply a role for policy intervention. If consumers stop shopping at a store that is attempting to reorganize, this could accelerate the store's liquidation. Such a closure gives consumers fewer choices when shopping. Consumers deciding against shopping at a bankrupt firm can thus harm both the firm and future consumers. Indeed, our estimation shows that policymakers were wise to ensure that General Motors had an expedited bankruptcy.

Additionally, while we show that educating consumers about bankruptcy survival prospects can improve producer and consumer surplus, we cannot speak to education about bankrupt-firm quality. It is difficult to disentangle the impact of a bankruptcy on quality from the unobserved quality problems that led to the bankruptcy. We thus cannot estimate whether consumers are correct in their quality concerns that lead to lower willingness to pay. Nonethe-

[22] For example, "Our shelves are fully stocked" or, "As always, our planes are checked after every flight."

less, given our estimates of how strongly consumers care about corporate bankruptcy, it is important to help consumers make decisions with accurate information about bankruptcy and the survival prospects of bankrupt firms.[23]

[23] 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: 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.

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 2: 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 1 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 nonbankrupt company.

Table 3: Causal Effects of Current and Historical Bankruptcies on 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 indicator variable "Bankruptcy" is equal to one for participants in the Bankruptcy-treatment group, who are told that each firm B is currently in Chapter 11 bankruptcy. The indicator variable "Post-Bankruptcy" is equal to one for participants in the Post-Bankruptcy-treatment group, who are told that firm B filed for Chapter 11 bankruptcy but has already emerged. The indicator variable "Pre-Bankruptcy" is equal to one for participants in the Pre-Bankruptcy-treatment group, who are told that firm B has a 50% chance of filing for bankruptcy in the next 6 months. This table includes observations at the participant-question level for participants in either the Control group, the Bankruptcy-treatment group, the Pre-Bankruptcy-treatment group, or the Post-Bankruptcy-treatment group. We regress normalized willingness to pay on indicator variables for the three treatment groups, estimating a separate regression for each industry. Standard errors, clustered at the participant level, are shown in parentheses.

	Normalized WTP		
	(1)	(2)	(3)
Pre-Bankruptcy	-0.196***	-0.101***	-0.173***
	(0.024)	(0.026)	(0.025)
Bankruptcy	-0.218***	-0.179***	-0.193***
	(0.021)	(0.021)	(0.022)
Post-Bankruptcy	-0.076***	-0.070***	-0.048**
	(0.019)	(0.023)	(0.024)
Constant	0.898***	0.962***	0.879***
	(0.011)	(0.015)	(0.015)
Industry	Airline	Retail	Car
Observations	4436	3327	3327

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

Table 4: Causal Evidence on Mechanisms by which Bankruptcies Affect Consumer Demand

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 indicator variable "Bankruptcy" is equal to one for participants in the Bankruptcy-treatment group, who are told that each firm B is currently in Chapter 11 bankruptcy. The indicator variable "Quality" is equal to one for participants in the Quality-treatment group, who are told that firm B filed for Chapter 11 bankruptcy but an independent agency has assessed that the bankruptcy has not affected firm B's quality. The indicator variables "Survival 50" and "Survival 100" are equal to one for participants in the Survival-50 and Survival-100-treatment groups, respectively. Participants in these groups are told that firm B is currently bankrupt but has a 50% (100%) chance of surviving bankruptcy. This table includes observations at the participant-question level for participants in either the Control group or one of the following treatment groups: Bankruptcy, Quality, Survival 50, Survival 100. We regress normalized willingness to pay on indicator variables for the four treatment groups, estimating a separate regression for each industry. 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)
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	5216	3912	3912

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

Table 5: Implied Survival Beliefs

Using the regression coefficients in Table 4, we infer the implied beliefs that consumers have about the survival prospects of bankrupt firms. This table shows the average implied survival belief for each industry. We compare these to historical bankruptcy survival rates by industry, for bankruptcies with at least $1 billion in assets, using data from Bankruptcydata.com. Section 3.4 provides details.

Industry	Implied Survival Belief	Actual Survival Rate
Airlines	78%	76%
Car Manufacturers	56%	100%
Retail	0%	64%

Table 6: 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 Appendix A 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 7: 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 Appendix A 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 8: 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 Appendix A 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	

Table 9: 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 10: 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 11: Model-Parameter Estimates

We estimate the consumer price-sensitivity and bankruptcy-sensitivity parameters from the model of Section 4 using our experimental data, according to the procedure described in Section 4.2. 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 12: Model-Implied Bankruptcy Impacts

We estimate the model of Section 4 using our experimental data and historical prices and market shares, according to the procedure described in Sections 4.2 - 4.4. Using the estimated model, 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 third panel considers the bankruptcy impacts in a counterfactual world where consumers understand the survival prospects of bankrupt car manufacturers. See Section 4.4 for details.

Bankruptcy	Market Share	Own 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
Car Manufacturer Estimates				
General Motors	-22.6	-2	-27	-6.8
Chrysler	-30.8	-0.1	-31	-3.4
Car Manufacturer Estimates, Educated Consumers				
General Motors	-10.9	-1.4	-15.1	-3.3
Chrysler	-16.4	-0.4	-17.6	-1.9

Table 13: Heterogeneous Model-Implied Bankruptcy Impacts

We estimate the model of Section 4 using our experimental data and historical prices and market shares, according to the procedure described in Sections 4.2 - 4.4. Using the estimated model, we calculate the impact of historical bankruptcies. In each market affected by a bankruptcy, we calculate the impact of the bankruptcy on market shares, prices, producer surplus, and consumer welfare in that market. This table displays average effects across markets in which the bankrupt firm had (i) a market share less than its median market share, and (ii) a market share greater than its median market share. See Table 12 for column definitions and Section 4.4 for details.

Sample	Market Share	Own Price	Producer Surplus	Consumer Welfare
Airline Estimates				
$<$ Median Market Share	-12.4	-0.1	-12.9	-2
$>$ Median Market Share	-9.5	-0.5	-11.1	-4.1
Car Manufacturer Estimates				
$<$ Median Market Share	-27.6	-1.2	-30	-6.2
$>$ Median Market Share	-17.9	-3	-23.8	-6.3

A Experiment Details

This appendix presents details on our experiment. We received IRB approval and preregistered our experiment with the American Economic Association before running the 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 5.

A.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.

A.2 Incentivizing Participants

In the second stage of the experiment, we incentivize participants to honestly report their preferences. To measure willingness to pay for actual goods and services in an incentivized manner, we follow the methodology of Kessler, Low, and Sullivan (2019). 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.

We use reported answers to select whether the lottery prize is a gift card for a retailer or an airline. Critically, participants are never told that their prize will be 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.

A.3 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) on 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.

A.4 Preregistered Sample-Size Criteria

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. 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 A.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 A.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

B Additional Results

Table B.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

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

Table B.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_5yr/R13321678

Table B.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 B.4: Main Regression By Real-World 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 B.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

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

C Details on Structural Estimation

This appendix provides details on the structural estimation described in Section 4.

C.1 Experiment-Moment Definitions and Identification

In one question from our 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 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 4.4, 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 (7).[24] 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:[25]

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

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:

[24] 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}.

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

$$\text{B share}_{control}^{model}(1.15p_{At}) = \mathbb{E}_{\alpha_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\ \bar{\delta}_t^d + 0.15\alpha_{id}p_{At} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0\ \right)\right] \tag{C.2}$$

$$\text{B share}_{control}^{model}(1.2p_{At}) = \mathbb{E}_{\alpha_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\ \bar{\delta}_t^d + 0.2\alpha_{id}p_{At} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0\ \right)\right]. \tag{C.3}$$

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 participants for whom firm B is bankrupt. Specifically, the fourth moment is B $\text{share}_{bank}^{data}(p_{At})$, 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 $\text{share}_{control}^{data}(0.5p_{At})$, 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_β^d. Specifically, the corresponding model moments are:

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

$$\text{B share}_{bank}^{model}(0.5p_{At}) = \mathbb{E}_{\alpha_{id},\beta_{id},\epsilon_{ijtd}}\left[\mathbf{1}\left(\ \bar{\delta}_t^d - 0.5\alpha_{id}p_{At} + \beta_{id} + (\ \epsilon_{iBtd} - \epsilon_{iAtd}\ ) > 0\ \right)\right]. \tag{C.5}$$

Recall that the first three elements of M_d^{data} pin down $\bar{\delta}_t^d, \bar{\alpha}^d, \sigma_\alpha^d$. Our estimation varies $\bar{\beta}^d$ and σ_β^d until these final two model moments match the empirical counterparts. Intuitively, there should be a unique pair ($\bar{\beta}^d$,σ_β^d) 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_β^d pins down the impact of bankruptcy at the other price point (e.g., $p_{Bt} = 0.5p_{At}$).

C.2 Covariance and Weighting Matrices

Separately examining experiment responses for car purchases and flight purchases, we measure the 5×1 vectors $\{M_d^{data}\}$ defined above. For each industry, we then construct the covariance matrix C_d of M_d^{data} by bootstrapping 500 participant-clustered samples from our data and taking covariances of elements of M_d^{data} across bootstrapped samples. We use the efficient weighting matrix $W_d = C_d^{-1}$ and estimate $\theta_d^{Experiment}$ separately for car purchases and flight purchases according to equation (11). Finally, we construct asymptotic participant-clustered standard errors 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 $\theta_{d,i}^{Experiment}$.[26] Let $N = 664$ denote the number of participants in the Control and Bankruptcy-treatment group - 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:

$$\text{Asymptotic participant-clustered parameter covariance} = \frac{1}{N} \left(GRD_d \times C_d^{-1} \times GRD_d' \right)^{-1}, \tag{C.6}$$

where $\times$ denotes matrix multiplication.

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

C.3 Interpreting Parameter Estimates

Table 11 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 3, 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.

C.4 Historical Data and Market and Good Definitions

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).[27] The D1B1 is a 10% sample of all domestic purchased airline itineraries. We focus on the market file, which

[27] See https://www.transtats.bts.gov/tables.asp?QO_VQ=EFI&QO_anzr=Nv4yv0r.

contains directional market characteristics of each domestic itinerary in the D1B1, such as the airline, origin and destination airport, prorated market fare, and number of passengers. We adjust market fares to 2021 dollars using the Federal Reserve Bank of St Louis consumer price index[28] and exclude observations in which the market fare is zero. We use this data to construct market shares and average prices at the airline-route-quarter level, where 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.

We obtain vehicle manufacturer suggested retail prices and sale volumes from WARDS Intelligence. The 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. We adjust prices to 2021 dollars as described above.

Finally, when analyzing bankruptcies, we focus on markets in which the bankrupt firm

[28]See https://fred.stlouisfed.org/series/CPALTT01USQ657N.

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.[29] 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).

C.5 Estimating Good-Taste Parameters and Marginal Costs

Once we have estimated $\theta_d^{Experiment}$ and calibrated $\{\kappa_j\}$, we estimate $\{\delta_{jt}\}$ in each market t. Specifically, 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 $S_{jt}^{model}(p_t^{data}) = S_{jt}(p_t^{data})$.

Given our estimates of $\{\delta_{jt}\}$, we use the 10,000 simulated draws of $\alpha_{id}, \beta_{id}, \{\epsilon_{ijtd}\}, \{A_{ijt}\}$ 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):

$$S_{jt}^{model}\left(p_t^{data}\right) + \sum_{k \in G_{ft}} \left(p_{kt}^{data} - c_{kt}\right) \times \frac{\partial}{\partial p_{jt}} S_{kt}^{model}\left(\left(p_{jt}, \{p_{nt}^{data}\}_{n \neq j}\right)\right)\Big|_{p_{jt}=p_{jt}^{data}} = 0. \tag{C.7}$$

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

C.6 Counterfactual Simulations

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 (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.

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 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:

$$100\times \left(-1 + \frac{\sum_{j \in G_{ft}} S_{jt}^{model}(p_t^{data}) \times (p_{jt}^{data} - c_{jt})}{\sum_{j \in G_{ft}} S_{jt}^{model}(p_t^{counter}) \times (p_{jt}^{counter} - c_{jt})} \right). \tag{C.8}$$

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).

D Hertz Experiment

D.1 Further Description of Experiment

We conducted this experiment during Hertz'z bankruptcy. 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 before running the experiment. Our preregistration can be found at the following link: https://www.socialscienceregistry.org/trials/6406.

In a series of questions, participants are asked if they would prefer a \$50 gift card at Hertz or a gift card at Enterprise. For each participant, we vary the value of the Enterprise gift card in \$5 increments starting at \$0 and ending at \$95. This price list reveals each participant's willingness to pay in "Enterprise dollars" for \$50 at Hertz. To incentivize participants to accurately report their preferences, 1% of participants are randomly selected to receive one of their preferred gift cards from the price list, selected at random. Participants are informed of this lottery before making their selections. As indicated in the preregistration for our experiment, we drop participants that indicate nonmonotonic preferences: a preference for \$Y dollars at Enterprise over \$50 at Hertz and a preference for \$50 at Hertz over \$Y' > \$Y at Enterprise. We also follow our preregistered design by dropping participants that prefer a \$0 gift card at Enterprise to \$50 at Hertz.

While all participants complete the same price list, we randomize the information that accompanies the price list. Immediately before completing the price list, participants are randomized into one of four groups. One-third of participants are assigned to the Control group. Control participants are presented with the price list and told they must choose between Hertz and Enterprise, which are car rental companies. In the second group, participants are informed that Hertz is in Chapter 11 bankruptcy. One-third of participants are assigned to this group, which we refer to this as the "Basic" treatment group.

In the third and fourth groups, participants are educated about Chapter 11 when they are informed that Hertz is in Chapter 11 bankruptcy. When informed of Hertz's bankruptcy, the third 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." We refer to this third group as the "Survival" treatment group. When the fourth group of participants is informed of Hertz's bankruptcy, the participants are also 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'"[30] We refer to this fourth group as the "DIP" treatment group. The third of participants not assigned to either Control or Basic treatment are evenly split between the third and fourth groups. We summarize this information in Table D.1.

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. This allows us to identify participants in the Control group that are aware of Hertz's bankruptcy. We also verify which treated participants retain the knowledge that Hertz is bankrupt. In our empirical analysis, the awareness of Hertz's bankruptcy that we measure in this stage is instrumented by the randomized treatment status from the previous stage of our experiment.

In the final stage, we ask questions to understand consumer perceptions about bankrupt firms. These questions are in Table D.2. This helps 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

[30] 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/.

how many times the participant has used Hertz and Enterprise in the past (0, 1-5 times, more than 6 times). Finally, we conclude by gathering demographic information about participants: age, gender, education, and income.

Table D.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 D.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.

D.2 Data

For each participant, we identify the largest value \$Y such that the participant prefers \$50 at Hertz to \$Y at Enterprise. We define the willingness-to-pay variable WTP_i to equal \$Y / \$50. The variable WTP_i is thus equal to participant i's willingness to pay, in Enterprise-gift-card dollars, for one Hertz-gift-card dollar. 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 D.3, we report summary statistics. Within the Control group ($Treat_i = 0$), 26% of participants are aware of Hertz's bankruptcy. On average, Control-group participants value Hertz and Enterprise equally, as shown by the mean of WTP_i. 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 23% lower than the corresponding average among Control participants. Participants in the DIP treatment and Survival-treatment groups also value Hertz less than Control-group participants, but the difference is not as large.

The summary statistics in Table D.3 suggest that exogenously informing participants of Hertz's bankruptcy makes those participants less willing to pay for Hertz's services. The summary statistics also suggest that educating consumers about DIP financing or Chapter 11 survival rates can lessen the impact of bankruptcy filings on consumer demand.

D.3 Two-Stage Least Squares Setup

Table D.3 shows that the average willingness to pay for a Hertz giftcard is 23% 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):

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

In equation (D.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 (D.1) in Table D.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.

D.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:

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

In this equation, $\widehat{Aware}_i$ is the fitted value of $Aware_i$ from equation (D.1). The dependent variable is participant i's willingness to pay for Hertz (Section D.2). The other variables and coefficients are defined analogously to equation (D.1). The results are displayed in Table D.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 \$0.36 reduction in willingness to pay for a Hertz-gift-card dollar. 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 (D.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.

D.5 Other Treatment Effects

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

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

Table D.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 D.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.

D.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 D.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.

D.7 Results

Table D.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 D.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	0.87	0.48	1,238
Control			
Aware	0.26	0.44	453
WTP	1.00	0.39	453
Basic treatment			
Aware	0.90	0.30	376
WTP	0.77	0.53	376
DIP treatment			
Aware	0.94	0.24	200
WTP	0.82	0.52	200
Survival treatment			
Aware	0.83	0.37	209
WTP	0.84	0.46	209

Table D.4: First Stage

This table displays ordinary least squares estimates of our first-stage equation (D.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

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

Table D.5: Instrumental-Variables Regressions

This table displays two-stage least squares (2SLS) estimates of our instrumental-variables regression (D.2). The dependent variable, WTP, is the participant's willingness to pay for Hertz defined in Section D.2. We instrument for the endogenous variable Aware, defined in Table D.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 D.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	-0.211***	-0.310***	-0.304***	-0.223***	-0.355***	-0.354***
	(0.027)	(0.041)	(0.040)	(0.031)	(0.051)	(0.049)
Prior Hertz			0.189***			0.211***
			(0.030)			(0.035)
Prior Enterprise			-0.158***			-0.170***
			(0.031)			(0.038)
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

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

Table D.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 D.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	-0.229***	-0.229***	-0.229***	-0.227***
	(0.033)	(0.033)	(0.033)	(0.032)
Survival treat	0.071*		0.071*	0.079*
	(0.042)		(0.042)	(0.041)
DIP treat		0.050	0.050	0.046
		(0.046)	(0.046)	(0.045)
Prior Hertz				0.186***
				(0.030)
Prior Enterprise				-0.159***
				(0.031)
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

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

Table D.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