The Effect of Product Misperception on Economic Outcomes: Evidence from the Extended Warranty Market *

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Abstract

Panel and survey data are used to analyze the economic outcomes in the extended warranty market. We establish that the strong demand and high profits in this market are driven by consumers distorting the failure probability of the insured product, rather than standard risk aversion or sellers’ market power. Providing information to consumers about failure probabilities significantly reduces their willingness to pay for warranties, indicating the important role of information, or lack of, in driving consumers’ purchase behavior. Such information provision is shown to be more effective in enhancing consumer welfare than additional market competition.

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1 Introduction

An extended warranty is an insurance contract that protects against the failure of a durable good such as a consumer electronic. The extended warranty market is highly profitable[^1] and has caught the attention of consumer protection and competition authorities in different countries. In the UK, the Office of Fair Trading observed that “there is insufficient competition and information to ensure that consumers get good value” in the extended warranty market, and that “many electrical retailers may make considerable profits on the sale of extended warranties” (UK Competition Commission, 2003). The UK Competition Commission has consequently conducted a comprehensive investigation of this market. Its report expressed concerns about the lack of market competition due to the way warranties are sold, and the lack of available information at the point of sale about the reliability of the insured product and the cost of repair (UK Competition Commission, 2003). The Federal Trade Commission in the US has also looked into this market, and is advising consumers to obtain information about the likelihood of product failure and the potential cost of repair before buying an extended warranty.[^2]

This paper uses panel and survey data to analyze market competition and consumer behavior in the extended warranty market. The first takeaway from the analysis is that the strong demand and high profits in this market are driven by consumers distorting the failure probability of the insured product, rather than standard risk aversion or sellers’ market power. The second takeaway is that providing information to consumers about failure probabilities significantly reduces their willingness to pay for warranties, indicating the important role of information, or lack of, in driving consumers’ purchase behavior. The third takeaway is that such information provision is more effective in enhancing consumer welfare than additional market competition, highlighting the relevance of policies that guide consumers’ decision making directly.

The starting point of our analysis is that the market for extended warranties is characterized by market power on the supply side and high willingness to pay on the demand side. On the supply side, sellers have market power because the warranty is an add-on product. It is usually offered to consumers immediately after they finalize their decision to buy the insured product, at a stage in which searching for another product or switching to another seller is costly. This search and switching cost implies significant market power à la Ellison’s (2005) add-on pricing model.[^4]

[^1]: The UK Competition Commission (2003) estimates that the top five consumer electronics retailers in the UK earned 116 to 152 million pounds annually on the sale of extended warranties in the early 2000s. Similarly, analysts in the US estimate extended warranties accounted for almost half of BestBuy’s operating income in 2003, and that profit margins on warranties ranged from 50% to 60% ("The Warranty Windfall," Business Week (December 19, 2004)).

[^2]: See https://www.consumer.ftc.gov/articles/0240-extended-warranties-and-service-contracts

[^3]: For example, BestBuy trains its sales people to offer warranties to consumers only after they finalize their decision to buy the insured product at a stage in which searching for another product or switching to another seller is costly. This search and switching cost implies significant market power à la Ellison’s (2005) add-on pricing model.[^4]

[^4]: According to the UK Competition Commission (2003), "Most customers shop around for electronic goods; the retail price is a major factor in their choice. However, extended warranty buyers do not often plan to buy an extended warranty (less than half of consumers who bought an extended warranty said that they had planned to do so before they went into the store), and many are unaware of the existence of alternatives to taking the EW offered at the
On the demand side, about one in four TV buyers in our panel data purchases an extended warranty. On average, this buyer pays $90 or more to insure against a loss of at most $400 with 7% probability. What drives this high willingness to pay? Sydnor (2010) uses data on home insurance deductible choices to show standard risk aversion in the form of diminishing marginal utility for wealth cannot explain consumers’ high willingness to pay for reductions in deductibles. Sydnor (2010) proposes several alternative explanations for the high willingness to pay, including misperception of claim probabilities and reference-dependent preferences. Barseghyan et al. (2013) examine several alternatives to standard risk aversion, and conclude that upward distortion of claim probabilities plays a key role in explaining deductible choices in home and auto insurance.

Our first objective is to quantify the importance of probability distortions and standard risk aversion on the demand side relative to market power on the supply side in determining demand, prices, and profits in the extended warranty market.

To do so, we consider a model of market competition based on Ellison’s (2005) add-on pricing game to which we incorporate Barseghyan et al.’s (2013) decision-making model, in which consumers are assumed to be risk-averse expected utility maximizers who may distort failure probabilities. We then use panel data on household-level product and extended warranty purchases from a large US electronics retailer to estimate consumers’ risk-aversion and probability-distortion parameters and the retailer’s cost of selling and servicing the warranty. The panel data documents approximately 45,000 transactions made by almost 20,000 households between 1998 and 2004. Almost 30% of the transactions involved the purchase of an extended warranty. Our structural estimation focuses on TVs, which constitute about 11% of the data, due to the availability of TV failure rates from Consumer Reports.

Variation in repair costs for different products with the same failure rate enables us to separately identify the risk-aversion and probability-distortion parameters. Intuitively, either parameter can explain the willingness to pay for a warranty to any given product. But they have different predictions regarding the rate at which willingness to pay changes in response to a change in the repair cost. In particular, probability distortion implies a slower rate than risk aversion. Thus, fixing the failure rate, changes in willingness to pay in response to changes in repair costs enable us to separately identify the two parameters.

Our estimation indicates there is a substantial upward distortion of failure probabilities. For example, a 5% objective failure probability is perceived as a 13% failure probability. This estimate is similar to the estimate of Barseghyan et al. (2013) and to our survey results described below. Standard risk aversion, on the other hand, plays an insignificant role in consumers’ decision making. The estimated risk-aversion parameter implies willingness to pay is close to actuarially fair rates in the absence of probability distortion.

We use counterfactual analysis to quantify the effect of probability distortions on market outcomes. Specifically, we compare outcomes in the existing market with outcomes in a counterfactual point of sale.”
market in which retailers have the same market power but the distortion is “shut down” in the sense that consumers use objective failure probabilities in decision making. A key assumption in the analysis is that TVs are priced similarly whether consumers distort failure probabilities or not. As discussed in section 7, this assumption is supported by comparing TV prices between retailers who offer extended warranties and retailers who do not, institutional details, and Ellison’s (2005) results.

The counterfactual analysis demonstrates that probability distortions drive the strong demand and high profits, whereas market power drives the high prices and margins. Specifically, when shutting down probability distortions, volume and profit decrease by more than 90%, but price and margin decrease by only 4% and 11%, respectively.

Our second objective is to better understand the mechanism for the distortion. One possible mechanism is that consumers know the objective probabilities but overweight them as predicted by Prospect Theory (Kahneman and Tversky (1979)). Another possible mechanism — which seems to fit the concerns of competition authorities — is that consumers lack information about the objective probabilities and overestimate them. Bordalo et al.’s (2015) theory of attention proposes a possible reason for overestimation: consumers are surprised when reminded by the sales person that TVs can break, and overreact to this information.

Understanding the mechanism is welfare- and policy-relevant. If the distortion stems from lack of information about failure probabilities, as postulated by the second mechanism, consumer welfare should be evaluated with respect to the objective probabilities, and room exists for policies that inform consumers about these probabilities. On the other hand, if consumers know the probabilities and distort them in their decision making, deciding whether objective or distorted probabilities should be used in welfare analysis depends on whether one interprets overweighting as a deliberate process or as a mistake in decision making.

To study the mechanism, we conducted controlled experiments. In a pre-test with approximately 500 participants, we found the failure rate in the pool of participants was about 5%. This rate is similar to the failure rates reported by Consumer Reports.

In the first main experiment with approximately 1,000 participants who did not participate in the pre-test, we randomly assigned participants to one of three treatments. In two treatments, we elicited participants’ perceived TV failure probability and their willingness to pay for an extended warranty, and in the third, we first informed participants about the objective probability and then elicited their willingness to pay. We found that average perceived TV failure probability among uninformed participants was about 14%, which is almost three times larger than the objective

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5 Possible support for Bordalo et al.’s (2015) theory comes from the comparison of the strong in-store demand with the weak online demand in the data (see section 2.3). Indeed, making TV failures salient and triggering overreaction seems harder in the online marketplace than in the store, where the salesperson has the buyer’s attention, and can press the buyer to make a quick decision.

6 This mechanism-based approach to welfare analysis is based on Rubinstein and Salant (2008, 2012) who argue behavioral welfare analysis should rely on understanding the mechanism that maps the decision maker’s preferences to his choices.
failure rate. Moreover, the average willingness to pay among informed participants was much lower than among uninformed participants. For example, the median willingness to pay among informed participants was about half of the median willingness to pay among uninformed participants. We interpret these findings as suggesting that lack of information about failure probabilities is a relevant factor in creating the distortion, and that information provision reduces the distortion.

In the second experiment with another 900 participants, we examined whether traces of probability distortion were present among informed participants. Specifically, we elicited informed participants' willingness to pay for TVs with the same failure rate but with different repair costs, and used the identification strategy of the empirical analysis to separately identify the risk aversion and probability distortion parameters from the reported willingness to pay. We found that most participants displayed modest or no probability distortion as well as no risk aversion. We interpret these findings as indicating information provision either eliminates or significantly reduces the distortion.

Equipped with the experimental findings, our third objective is to evaluate consumer welfare and the effectiveness of various policy interventions based on the panel data. We first observe that welfare in the existing market is negative, i.e., consumer welfare would increase if the market for warranties did not exist. This is because any positive welfare generated by consumers with true willingness to pay above the price is dominated by the decrease in welfare due to consumers with true willingness to pay below the price mistakenly buying warranties as a result of overestimation.

As for policy, Armstrong (2008) discusses two broad categories of policies competition authorities use to enhance market performance and consumer welfare. The first and more prominent category includes competition policies, which target the supply side of the market and aim to intensify competition. The second category includes consumer policies, which target the demand side and aim to enhance consumers’ decision making directly.

An example of a competition policy in the extended warranty market is the UK Competition Commission’s (2003) proposal that retailers advertise and post the price of the warranty alongside the price of the product it insures. This policy is expected to drive down prices because it reduces the search and switching costs of consumers. If the demand for warranties were driven solely by consumers’ risk aversion, such a price reduction would have a positive effect on consumer welfare. It would increase the utility of existing warranty buyers as well as the utility of new buyers, who now purchase the warranty because of the lower prices. But with overestimation, the utility of new buyers may be negative, and so the effect of price reduction on consumer welfare is unclear. On the other hand, a consumer policy that reduces overestimation increases consumer welfare, assuming no price change, because consumers make better choices, but may trigger a price change, and so its effect is also unclear. An example of a consumer policy is to demand retailers to disclose failure probabilities to consumers, similar to what we did in the experiment.

Counterfactual analysis demonstrates that consumer policies that reduce overestimation are more effective in enhancing consumer welfare than competition policies that lead to price reduction.
Intuitively, when warranty prices go down but overestimation still exists, consumer welfare decreases because the welfare gain due to lower prices is dominated by the welfare loss generated by more consumers buying warranties due to overestimation. On the other hand, when overestimation goes down, consumer welfare increases because the welfare gain due to consumers making better choices dominates any other effect. Thus, our findings indicate competition policies may lead to suboptimal results in markets with uninformed or biased consumers relative to consumer policies that aim to improve consumers’ decision making directly.

The rest of the paper is organized as follows. Section 1.1 reviews the related literature. Section 2 presents the panel data and reports empirical regularities on household purchase behavior. Section 3 presents the model and the identification strategy. Section 4 describes the estimation procedure. Section 5 reports the results of the estimation. Section 6 studies the mechanism for the distortion. Section 7 studies the importance of probability distortions relative to market power in determining demand, prices, profit, and consumer welfare. Section 8 concludes with a discussion of policy implications.

### 1.1 Related literature

This paper is related to the empirical literature on estimating risk preferences (see Barseghyan et al. (forthcoming) for a recent survey.) Cohen and Einav (2007) use data on auto insurance deductible choices to estimate a structural model of individual choice with standard risk aversion. They find unobserved heterogeneity in risk aversion is greater than unobserved heterogeneity in risk (claim rates), and that the two are positively correlated. Barseghyan et al. (2011) compare households’ degree of standard risk aversion in auto and home insurance. They find risk preferences are not stable across contexts, and that many households exhibit greater risk aversion in their home deductible choices than in their auto deductible choices.

Sydnor (2010) uses home insurance deductible choices to demonstrate that consumers’ willingness to pay for insurance is very high. For example, many consumers pay $100 to lower their deductible from $1,000 to $500 when their (ex-post) claim rate is less than 5%. Sydnor (2010) shows that fitting such choices to a standard model of risk aversion yields extreme levels of risk aversion, and proposes several alternative explanations for the high willingness to pay, including misperception of claim rates and reference-dependent preferences.

Our paper is closest to Barseghyan et al. (2013), who develop a structural model of individual choice with standard risk aversion and probability distortions, and estimate it using data on auto and home insurance deductible choices. Barseghyan et al. (2013) find upward distortion of claim probabilities plays a key role in explaining deductible choices. Moreover, the shape of the probability-distortion function fits the shape predicted by Prospect Theory (Kahneman and Tversky (1979)). Several other papers incorporate probability distortions to the estimation of risk preferences, and find evidence of their relevance in various contexts, including financial markets (Kliger and Levy (2009)) and betting markets (Jullien and Salanié (2000), Snowberg and Wolfers...
We make three contributions to this literature. First, we quantify the effect of probability distortions, relative to market power and risk aversion, on prices, volume, and profit. We are able to make progress on this question because electronics retailers have (1) monopolistic power when selling warranties, which facilitates cost estimation, and (2) little flexibility in cutting TV prices below cost, which facilitates the counterfactual analysis. Second, we use survey data to show the distortion stems from lack of information about failure probabilities. This contribution is important for welfare analysis and the evaluation of policy interventions. Third, we demonstrate that consumer policies are more effective than competition policies in improving consumer welfare.

Another related literature is the marketing and experimental literature on why consumers buy extended warranties (Chen et al. (2009), Huysentruyt and Read (2010), Jindal (2014)). Chen et al. (2009) use purchase data of about 600 households from an unspecified US electronics retailer over the period November 2003 to October 2004 to study how the insured product characteristics (hedonic vs. utilitarian) and marketing actions by retailers affect the likelihood of purchasing an extended warranty. Huysentruyt and Read (2010) use survey data to demonstrate that participants overestimate the likelihood of washing-machine breakdowns and their cost of repair. Jindal (2014) uses different survey data to highlight the role of loss aversion in the context of extended warranties for washing machines. The four-year failure probability of washing machines is 20% to 30%, so probability distortions are expected to have a less significant role in this context. We contribute to this literature by demonstrating that lack of information about failure probabilities is a relevant factor in creating the distortion, and that information provision significantly reduces the distortion.

2 Data

This section describes the panel data. Section 6 describes the survey data.

We use the INFORMS Society of Marketing Science Durables Dataset 1, which is a panel data of household durable-goods transactions from a major US electronics retailer. The full sample contains approximately 140,000 product-level transactions made by almost 20,000 households across the retailer’s 1,176 outlets and its online store. Prices across outlets and the online store are essentially identical. Transactions took place between December 1998 and November 2004.

The data contains four main types of transactions. About 117,000 transactions involve the purchase of a specific product other than an extended warranty. About 15,000 transactions involve the purchase of an extended warranty. About 5,000 transactions involve the return of a product other than an extended warranty, and about 1,000 transactions involve the return of an extended warranty. For each transaction, we observe the product ID, the price of the product, the brand, and the category and subcategory of the product.

A shopping trip is a collection of transactions made by a given household at a given store at a given date and time. For each household and shopping trip, we observe the buyer’s gender, the
age and gender of the head of the household, income group and whether there are children in the household.

There are three data issues that we have to deal with. First, the data only tells us the product subcategory (e.g., 9-16 inch TVs) the warranty is for. We restrict our sample to shopping trips in which a one-to-one mapping exists between the extended warranty and the corresponding product. For example, we drop shopping trips involving a purchase of two 9-16 inch TVs but only one extended warranty purchased for this subcategory. We lose approximately 2,000 observations for this reason.

Second, if a household did not purchase an extended warranty for a given product, we do not observe the warranty’s price. To identify the warranty price in such cases, we match the non-warranty transaction with a corresponding warranty transaction for the same product ID from the closest transaction date. After dropping transactions for which we cannot find a corresponding warranty transaction, we end up with a sample of approximately 45,000 observations.

Third, for the structural estimation, we need information about the insured product failure probability, which is the likelihood that the product will need a repair within three to four years of purchase. We focus on TVs in the estimation, because we are able to obtain TV failure rates from Consumer Reports, which publishes TV failure rates by brand and size every year based on surveys of tens of thousands of TV owners. We use the failure rates from the 2004 report, which is based on the responses of more than 100,000 TV owners between 1998 and 2002.
Table 2: EW information for TVs

<table>
<thead>
<tr>
<th>Attach rate</th>
<th>TV price</th>
<th>EW-TV price ratio</th>
<th>Fail rate</th>
<th>Margin</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>9-16in</td>
<td>0.149</td>
<td>122.99</td>
<td>0.284</td>
<td>0.072</td>
<td>0.729</td>
</tr>
<tr>
<td>19-20in</td>
<td>0.176</td>
<td>173.97</td>
<td>0.240</td>
<td>0.065</td>
<td>0.710</td>
</tr>
<tr>
<td>25in</td>
<td>0.270</td>
<td>245.33</td>
<td>0.220</td>
<td>0.069</td>
<td>0.643</td>
</tr>
<tr>
<td>27in</td>
<td>0.299</td>
<td>354.06</td>
<td>0.197</td>
<td>0.059</td>
<td>0.681</td>
</tr>
<tr>
<td>&gt;30in</td>
<td>0.348</td>
<td>812.53</td>
<td>0.219</td>
<td>0.076</td>
<td>0.619</td>
</tr>
<tr>
<td>OVERALL (TV)</td>
<td>0.268</td>
<td>400.07</td>
<td>0.223</td>
<td>0.067</td>
<td>0.672</td>
</tr>
</tbody>
</table>

Notes: Fail rates are from Consumer Reports. Overall numbers are sales-weighted averages. Margin is computed as \((\text{EW price} - \text{fail rate} \times \text{TV price})/\text{EW price}\).

2.1 Attachment rates, prices, and approximate profit margins

Table 1 shows the fraction of consumers who bought extended warranties (henceforth, the attachment rate) and the extended-warranty-to-product price ratio for each product category. Attachment rates range from about 20% for items such as VCRs (VIDEO HDWR), music CDs, and video games (MUSIC), to as high as 40% for items such as car stereos and speakers (MOBILE). Warranties are priced on average at 24% of the price of the insured product, and the standard deviation of the warranty-to-product price ratio is 11% (see Panel A in Figure 1 for the distribution of ratios.)

No significant correlation at the product level exists between variations in the product price and variations in the warranty price.\(^9\)

Table 2 reports TV attachment rates, prices, warranty-to-product price ratios, and failure rates broken down by TV subcategory. Attachment rates range from 15% to 35%, with higher attachment rates for more expensive categories. The average price ratio for TVs is about 22% with a standard deviation of 8% (see Panel B in Figure 1).

Using the TV price multiplied by the TV failure rate as a rough estimate of the expected cost of servicing a TV warranty, Table 2 also reports a “back of the envelope” profit margin on TV warranties. This margin ranges from 62% to 73% for different TV subcategories, which is close to what is cited in the popular press. We expect the seller in our dataset to have lower margins due to revenue sharing with warranty providers and commissions to sales people.

2.2 Buyers’ characteristics

Tables 3 and 4 examine the relationship between attachment rates and buyers’ characteristics for all product categories and for TVs. In Table 3, attachment rates are broken down by buyer gender, gender and age of the head of the household, income, and whether there is a child in the household. Income is the only characteristic that is strongly correlated with attachment rates for TVs and

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\(^7\)Income group is a number from 1 to 9, where 9 is the highest income group. We do not have additional information on income within each group.

\(^8\)We also drop the less than 1,000 observations in which the price of the good is significantly less than the price of the warranty.

\(^9\)We regress the log of the product price on the log of the warranty price for each product, and estimate an average coefficient equal to 0.046 with an average p-value of 0.26.
all other product categories. For example, when moving from the highest to the lowest income category, TV attachment rates increase by almost 11 percentage points in TV attachment rates. Having a child seems to decrease TV attachment rates by 7 percentage points, but this effect goes away once we introduce controls in a regression analysis.

Table 4 presents the results of regressing an extended warranty purchase dummy on buyers’ and households’ characteristics and their interactions with gender. The regressions include brand and subcategory fixed effects to account for average differences in purchasing behavior across these dimensions. Consistent with most of the raw means in Table 3, the only characteristic that is statistically and economically significant is income when all product categories are included. Adjusted $R^2$'s are very small despite including subcategory and brand fixed effects. All in all, the two tables indicate that other than income, the above characteristics are not strongly correlated with warranty purchases.

### Table 3: Attachment rates by buyer and household characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Attach rate</th>
<th>Obs</th>
<th>Attach rate</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>0.305</td>
<td>13976</td>
<td>0.286</td>
<td>1534</td>
</tr>
<tr>
<td>Male</td>
<td>0.280</td>
<td>26228</td>
<td>0.261</td>
<td>2768</td>
</tr>
<tr>
<td>Female (head of hh)</td>
<td>0.308</td>
<td>12412</td>
<td>0.285</td>
<td>1380</td>
</tr>
<tr>
<td>Male (head of hh)</td>
<td>0.280</td>
<td>24760</td>
<td>0.260</td>
<td>2620</td>
</tr>
<tr>
<td>Below median income (category &lt; 5)</td>
<td>0.321</td>
<td>10404</td>
<td>0.310</td>
<td>1170</td>
</tr>
<tr>
<td>Above median income (category ≥ 5)</td>
<td>0.276</td>
<td>33900</td>
<td>0.253</td>
<td>3547</td>
</tr>
<tr>
<td>Lowest income category (category = 1)</td>
<td>0.343</td>
<td>2656</td>
<td>0.340</td>
<td>300</td>
</tr>
<tr>
<td>Highest income category (category = 9)</td>
<td>0.253</td>
<td>6452</td>
<td>0.233</td>
<td>660</td>
</tr>
<tr>
<td>Over 50 (head of hh)</td>
<td>0.293</td>
<td>23259</td>
<td>0.282</td>
<td>2717</td>
</tr>
<tr>
<td>Under 50 (head of hh)</td>
<td>0.280</td>
<td>20882</td>
<td>0.250</td>
<td>1975</td>
</tr>
<tr>
<td>Has child in hh</td>
<td>0.282</td>
<td>13940</td>
<td>0.248</td>
<td>1279</td>
</tr>
<tr>
<td>No child in hh</td>
<td>0.296</td>
<td>6234</td>
<td>0.323</td>
<td>779</td>
</tr>
</tbody>
</table>

2.3 In-store versus online transactions

About 1% of the transactions in the data were made online. The attachment rate for these transactions is about 4%, which is one seventh of the in-store attachment rate. In Table 5 we use regression analysis to examine what drives this difference and its robustness. The first model does not include any controls, so it gives numbers that are very similar to the raw attachment rates. The other models turn on various fixed effects. Subcategory and brand fixed effects allow us to soak up any differences in mean purchasing behavior induced by the nature of the product. We also include household, month, and year fixed effects as further controls.

We see a drop in the effect of in-store purchases as we add fixed effects. Including a household fixed effect reduces the effect by about 5 percentage points. Including product-related fixed effects reduces the effect by additional 2.5 percentage points. Including all the fixed effects leads to a
Table 4: Regression of EW purchase dummy on buyer and household characteristics

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th></th>
<th>Coeff</th>
<th>SE</th>
<th>TV</th>
<th>Coeff</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>-0.064</td>
<td>(0.039)</td>
<td>-0.069</td>
<td>(0.101)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (head)</td>
<td>0.001*</td>
<td>(0.0004)</td>
<td>0.001</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>-0.014***</td>
<td>(0.003)</td>
<td>-0.013*</td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has child in hh</td>
<td>&lt; 10^{-5}</td>
<td>(0.014)</td>
<td>-0.017</td>
<td>(0.038)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male × Age</td>
<td>0.001</td>
<td>(0.001)</td>
<td>0.001</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male × Income</td>
<td>0.002</td>
<td>(0.003)</td>
<td>&lt; 10^{-4}</td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male × Child</td>
<td>0.004</td>
<td>(0.017)</td>
<td>-0.006</td>
<td>(0.045)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.08</td>
<td></td>
<td>0.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. obs (good-hh-trip)</td>
<td>19375</td>
<td></td>
<td>1973</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Both regressions include brand and subcategory fixed effects. Standard errors in parentheses are clustered at shopping-trip level. Significance levels: ***1%, **5%, *10%.

Table 5: Regression of extended warranty purchase dummy on shopping mode

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-store?</td>
<td>0.247***</td>
<td>0.200***</td>
<td>0.180***</td>
<td>0.175***</td>
<td>0.166***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Household FE</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Subcategory FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Brand FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>No. obs (good-hh-trip)</td>
<td>44304</td>
<td>44304</td>
<td>44304</td>
<td>44304</td>
<td>44304</td>
</tr>
<tr>
<td>No. HHs</td>
<td>17158</td>
<td>17158</td>
<td>17158</td>
<td>17158</td>
<td>17158</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses are clustered at shopping-trip level.

reduction in the effect from 25 to 17 percentage points. That is, the likelihood of purchasing an extended warranty jumps from 12% to 29% when the product is purchased in the store.

2.4 Warranty returns

The data contains 1,239 warranty return transactions. About 67% of them are returns that accompany the insured product return. These returns are probably made due to the add-on feature of the warranty – it has no value if the insured product is returned. But 33% of the warranty returns are made without returning the main product. We run regressions similar to Table 4 and find that none of the buyer or household characteristics in the data are strongly correlated with this return behavior.
3 Theory

We consider an add-on pricing model à la Ellison (2005) and Ellison and Ellison (2009) to which we incorporate the consumer model of Barseghyan et al. (2013).

There are several sellers of a main product $M$ and an extended warranty $EW$ for the product $M$. Each seller sets a price $p$ for the product that is observable to buyers, and a price $t$ for the warranty that is not.

The assumption that the product price is observable and the warranty price is not seems to be the case in practice. For example, BestBuy advertises product prices but not warranty prices, and trains its sales people to offer warranties and other add-ons to buyers only after they finalize their decision to purchase the product.

Buyers decide which seller to visit after observing the price of the product across sellers and forming rational expectations about warranty prices. Buyers visit the seller of their choice at a cost $s$ and learn the price of the warranty. The cost $s$ corresponds to the hassle or time involved in visiting a store and going through the purchase process. Buyers then decide whether to buy the main product, the main product and the warranty, or visit another store at a cost of $s$, where they will face the same decision.

Relevant equilibrium properties. As Ellison (2005) shows, any pure strategy sequential equilibrium of the above game has two properties. The first is that the price of the warranty set by any seller is the monopoly price relative to the demand for warranties among buyers of the product. Otherwise, as in Diamond (1971), the seller can raise the price of the warranty by some $\epsilon < s$, and buyers will not switch to another seller. We use the first-order condition of the monopoly pricing problem to estimate the seller’s cost.

The second property is that buyers visit only one seller and always buy the product in equilibrium, because buyers incur a cost of visiting a seller. Thus, if they anticipate they will not buy the main product, they will not visit the store. We therefore focus below on buyers’ decision to buy the warranty conditional on already purchasing the product.

Warranty purchase decision. Following Barseghyan et al. (2013), we model buyers as risk-averse expected utility maximizers who may distort failure probabilities.

Let $W$ denote the buyer’s wealth after buying the main product, $t$ the price of the warranty, and $u(\cdot, r)$ the buyer’s concave utility over wealth levels that is parameterized by $r$, the buyer’s degree of risk aversion around $W$.

A buyer’s utility if he purchases the warranty is $V_{EW} = u(W - t; r)$. If he does not purchase the warranty, his utility is $V_{NW} = \omega(\phi)E(u(W - X; r)) + (1 - \omega(\phi))u(W; r)$, where $\phi$ is the failure probability.

\begin{footnotesize}
10. The assumption that buyers form rational expectations about warranty prices is not necessary for our empirical analysis. One could alternatively assume, as in Gabaix and Laibson (2006), that buyers do not plan to purchase a warranty prior to visiting the seller, and decide which seller to visit based solely on the price of the main product. In this alternative specification, buyers form rational expectations about warranty prices of other sellers after visiting the first seller and being offered the warranty.

11. This assumes that there is no deductible associated with using the warranty as is often the case in practice.
\end{footnotesize}
probability of the product, \( \omega(\phi) \) is the probability-distortion function, which increases in \( \phi \), and \( X \) is the random cost of repair. This specification implies buyers consider failure probabilities sequentially in the sense that they first consider the total probability of failure \( \omega(\phi) \) and then the probability of each failure type conditional on a failure occurring.

We assume the sum of the conditional probabilities is 1. We also assume the cost of repair is less than the main product price, because the buyer can always buy a new product instead of fixing the existing one. Thus, the buyer’s utility if he does not purchase the warranty is bounded below by 
\[
\omega(\phi)u(\omega(W - p; r) + (1 - \omega(\phi))u(W; r))
\]
We will identify \( V_{NW} \) with this lower bound in our estimation, i.e., we will have 
\[
V_{NW} = \omega(\phi)u(\omega(W - p; r) + (1 - \omega(\phi))u(W; r)).
\]

**Demand for warranties.** Observationally equivalent households may make different purchase decisions based on various unobserved factors such as technical skills to “do it yourself.” We account for this unobserved heterogeneity by incorporating additively separable individual choice shocks, \( \epsilon_{EW} \) and \( \epsilon_{NW} \), to \( V_{EW} \) and \( V_{NW} \). Assuming these shocks are iid Type I Extreme Value with scale parameter \( \sigma \) and normalizing the buyer population to 1, we can derive the demand for warranties:

\[
D(t; r, \omega(\phi), p, \sigma) = \Pr(\epsilon_{NW} - \epsilon_{EW} \leq \Omega(t; r, \omega(\phi), p, \sigma))
\]
\[
= \frac{\exp \Omega(t; r, \omega(\phi), p, \sigma)}{1 + \exp \Omega(t; r, \omega(\phi), p, \sigma)},
\]

(1)

where
\[
\Omega(t; r, \omega(\phi), p, \sigma) \equiv \frac{V_{EW} - V_{NW}}{\sigma} \]

(2)

**Identification.** We rely on the identification assumptions and results of Barseghyan et al. (2013, forthcoming) to uniquely identify the risk-aversion and probability-distortion parameters.

Consider a product \( M \) with price \( p_M \) and the failure probability \( \phi \). Let \( \omega = \omega(\phi) \) denote the distorted probability. The willingness to pay (WTP) of buyers with risk aversion \( r \) and the distorted probability \( \omega \) for a warranty to product \( M \) is the price \( t \) that solves 
\[
V_{EW}(t; r) = V_{NW}(p_M, r, \omega).
\]
This WTP can be inferred from choice probabilities given enough variation in extended warranty prices for product \( M \).

The identification challenge is that this WTP can be explained by a continuum of pairs \( (r, \omega(r)) \), where \( r \) is the degree of risk aversion and \( \omega(r) \) is the distorted probability as a function of \( r \). This is because any increase in the degree of risk aversion \( r \) can be undone by a decrease in the probability distortion \( \omega \).

Suppose now that we observe another product \( M' \) with the same failure probability but a different price \( p_{M'} \). Because the failure probability is the same, the same pair \( (r, \omega) \) should explain the different WTPs for warranties to products \( M \) and \( M' \). The pair \( (r, \omega) \) can then be identified uniquely if the two iso-WTP “curves”, i.e., the two continuums of pairs \( (r, \omega(r)) \) that explain the

---

\(^{12}\)Section 5 discusses the robustness of our estimates to alternative cost specifications.

\(^{13}\)The utility specification we use in estimation imposes a specific normalization so we can identify the scale parameter \( \sigma \). This scale parameter is the inverse of the marginal utility of income.
different WTPs, cross each other exactly once.

Figure 2 provides graphical intuition. The solid curve is the iso-WTP curve for product \( M \) with price \( p_M \). Without additional variation, we cannot uniquely identify the pair \((r, \omega)\) against the pair \((r', \omega')\), because the two pairs lie on the same iso-WTP curve, and so can rationalize the same WTP. However, if we also observe the WTP for product \( M' \), the pair \((r, \omega)\) can be uniquely identified as long as the iso-WTP curve for product \( M' \) (the dashed curve in Figure 2) crosses the iso-WTP curve for product \( M \) exactly once.

Barseghyan et al. (forthcoming) establish this single-crossing property holds under what they call Assumption 1. Assumption 1 essentially requires that for any three wealth levels \( W_0 > W_1 > W_2 \), the ratio \( \frac{u(W_1; r) - u(W_2; r)}{u(W_0; r) - u(W_1; r)} \) is strictly increasing in \( r \). This condition holds for CARA, CRRA, and the utility specification we use in the estimation.

4 Estimation

This section describes the estimation strategy, which is composed of two stages. In the first stage, we use choice data to estimate the risk-aversion and probability-distortion parameters. In the second stage, we use the demand elasticities implied by the first-stage estimation to back out the retailer’s marginal cost \( c_j \) of selling and serving a warranty for product \( j \). Specifically, we back out \( c_j \) from the first-order condition of the retailer’s profit-maximization problem, which is given by

\[
\frac{t_j - c_j}{t_j} = \frac{1}{|E(t_j; r, \omega(\phi), p_j, \sigma)|},
\]

where \( E(t_j; r, \omega(\phi), p_j, \sigma) \) is the price elasticity of demand for warranties for product \( j \). The rest of this section focuses on describing the demand-side estimation in detail.

In specifying the utility of consumers, we follow Cohen and Einav (2007), Barseghyan et al. (2011), and Barseghyan et al. (2013), and use a second-order Taylor approximation of consumers’ utility function \( u(\cdot) \). The main benefit of using this specification is that it does not require data on wealth.

The second-order Taylor approximation of \( u(\cdot) \) around \( W \) for some wealth deviation \( \Delta \) is given by

\[
u(W + \Delta) \approx u(W) + u'(W)\Delta + \frac{u''(W)}{2} \Delta^2.
\]

Dividing by \( u'(W) \) and letting \( r = -u''(W)/u'(W) \) denote the Arrow-Pratt coefficient of absolute risk aversion\(^{14}\), we obtain that

\[
u(W + \Delta) \approx \frac{u(W)}{u'(W)} + \Delta - \frac{r}{2} \Delta^2.
\]

\(^{14}\)Strictly speaking, the Arrow-Pratt coefficient of absolute risk aversion can vary with income if the utility specification is not CARA.
Using this specification to evaluate the utility difference $\Omega_j$ between purchasing and not purchasing a warranty for product $j$ (equation (2)), we obtain that

$$\Omega_j = \frac{\omega_j p_j - t_j + \frac{r}{2} (\omega_j p_j^2 - t_j^2)}{\sigma}.$$ 

We consider both a parametric and a non-parametric specification of the probability-distortion function.

**Parametric specification.** A common way to model a single-parameter probability-distortion function is to use the Prelec (1998) functional form

$$\omega(\phi) = \exp\left[-(-\log(\phi))^\alpha\right],$$

where $\alpha \in (0, 1)$ is the parameter of interest, and larger values of $\alpha$ reflect a smaller distortion.\(^{15}\)

In this specification,

$$\Omega_j = \Omega_j(\alpha, r, \sigma) = \frac{\omega(\phi_j)p_j - t_j + \frac{r}{2} (\omega(\phi_j)p_j^2 - t_j^2)}{\sigma}.$$ 

Following Berry (1994), we add to $\Omega_j(\alpha, r, \sigma)$ a product-specific error term $\nu_j$ with $E(\nu_j|p_j, t_j) = 0$. This error term can be thought of as reflecting product-specific variation in the value of purchasing a warranty that is unobserved to the econometrician and is orthogonal to the product and warranty prices. Letting $D_j$ denote the attachment rate for product $j$, we can now invert the structural equation (1) that relates the observed “market share” $D_j$ and the theoretical market share $\Omega_j(\alpha, r, \sigma) + \nu_j$ to obtain the estimating equation

$$\log \frac{D_j}{1-D_j} = \Omega_j(\alpha, r, \sigma) + \nu_j,$$

and use nonlinear least squares to estimate the parameters $(\alpha, r, \sigma)$.

Note the estimating equation has a single product price $p_j$ and a single warranty price $t_j$ for every product $j$. The data, however, has within-product variation in these prices. Because there is insufficient data to create market shares for every pair of prices, we do not use the within-product variation in the estimation. Rather, we use the highest TV price $p_j$ and the lowest extended warranty price $t_j$ for product $j$.\(^{16}\)

**Nonparametric distortion.** The nonparametric specification assumes the probability distortion has the form

$$\omega_j = \omega(\phi_j) + \xi_j,$$ \hfill (4)

\(^{15}\)Note that the Prelec function is used in the literature to model situations in which consumers know the relevant probabilities, whereas in our setting they may not.

\(^{16}\)An alternative estimation method that uses the within-product variation in prices is Maximum Likelihood (ML). We consider ML estimation in section \[\text{5}\].
where $\phi_j$ is the failure probability of product $j$, $\omega(\cdot)$ is some unknown function, and $\xi_j$ is a product-specific noise in the probability distortion. We assume the expected value of $\xi_j$ is zero conditional on a given failure probability and TV and extended warranty prices in the same subcategory.

Using the same inversion strategy as in Berry (1994) and rearranging, we express the $\omega_j$ as a function of the unknown parameters $(r, \sigma)$ and the data:

$$
\omega_j = \frac{\sigma \log \left( \frac{D_j}{1-D_j} \right) + t_j + \frac{r}{2} t_j^2}{p_j + \frac{r}{2} p_j^2}.
$$

The estimation then proceeds in two steps. We first construct moment conditions involving $\omega_j$ and use them to estimate $r$ and $\sigma$. We then use the estimated $r$ and $\sigma$ and the data to back out the nonparametric estimates of $\omega_j$ from equation (5).

To construct the moment conditions, we fix a product subcategory, for example, 30” or larger TVs, and consider two products $j$ and $j'$ in this subcategory with the same failure probability. The difference between the respective $\omega$’s is $\omega_j - \omega_{j'} = \xi_j - \xi_{j'}$. Because the expected value of $\xi$ is zero, we obtain the moment condition

$$
E[\omega_j - \omega_{j'}| \phi_j = \phi_{j'}, p_j, p_{j'}, t_j, t_{j'}] = 0.
$$

Moreover, because prices are assumed to be orthogonal to the difference between $\omega$’s in the subcategory, we also obtain the expected value of $(\omega_j - \omega_{j'})P$ where $P \in \{p_j, p_{j'}, t_j, t_{j'}\}$ is also zero.

Thus, we have five moment conditions. In each of them, we replace the $\omega$’s with the RHS of equation (5) and use the generalized method of moments to estimate $r$ and $\sigma$. The estimation requires that each pair of products we consider is from the same subcategory and shares the same failure probability. We have 2,040 such pairs in the data.

## 5 Results

This section reports the estimates of the probability-distortion function, the risk-aversion parameter, and the seller’s cost.

### 5.1 The relevance of probability distortions

Figure 3 plots of the estimated one-parameter Prelec (1998) function $\omega(\phi) = \exp[\alpha(-\log(\phi))]$. The parameter $\alpha$ is estimated to be 0.6894 with a 95% confidence interval of $(0.6887, 0.6902)$. The figure also includes a scatter plot of the estimated non-parametric $\omega_j$’s and a local linear fit based on the non-parametric values with a bootstrapped 95% pointwise confidence band around it.

Table 6 presents the non-parametric estimates from a different perspective. It partitions failure probabilities to bins of 2%. For each bin, it reports the average failure probability and the average estimated distorted probability in the bin. It also reports the convexity measure $(\omega(\phi') - \omega(\phi))/\phi'$.
Table 6: Estimate of probability distortion

<table>
<thead>
<tr>
<th>Fail prob intervals</th>
<th>Average fail prob</th>
<th>Average distorted prob</th>
<th>Convexity measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>4–6</td>
<td>5.0</td>
<td>13.5</td>
<td>—</td>
</tr>
<tr>
<td>6–8</td>
<td>6.8</td>
<td>16.5</td>
<td>1.69</td>
</tr>
<tr>
<td>8–10</td>
<td>9.3</td>
<td>17.5</td>
<td>0.40</td>
</tr>
<tr>
<td>≥10</td>
<td>13.4</td>
<td>17.9</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Notes: Columns 1, 2, and 3 are in %. In column 1, the upper bound is not included in the bin.

φ, where φ' > φ are two adjacent average failure probabilities in the Table. This convexity measure is the increment in the average distortion divided by the increment in the average failure probability.

Two patterns emerge in the Figure and the Table. First, there is substantial upward distortion of failure probabilities, as illustrated in Figure 3 by the estimated Prelec function, most of the estimated \( w_j \)'s, the local linear fit, and the 95% confidence band, all lying above the 45-degree line. The distortion is also illustrated in Table 6 where, for example, products with an average failure probability of 5% are perceived as products with a 13.5% failure probability. Second, the degree of the upward distortion decreases as the failure probability increases. This is illustrated in Figure 3 by the concavity of the local linear fit, and in Table 6 by the decrease in the convexity measure. These two patterns are in line with the findings of Barseghyan et al. (2013).

5.2 The irrelevance of risk aversion

The estimate of the risk-aversion parameter \( r \) is close to zero in both the parametric and non-parametric specifications of the distortion function. In both specifications, it is approximately \( 10^{-6} \) with a 95% confidence interval that has a width of less than \( 10^{-6} \).

To interpret the relative importance of the estimated parameters, Table 7 presents the implied WTP for an extended warranty to a TV that costs $400 under various failure probabilities. In column 2, we calculate WTP with the estimated one-parameter distortion function and the estimated risk-aversion parameter. In column 3, we calculate WTP using the same risk-aversion parameter while imposing \( \omega(\phi) = \phi \). The comparison of WTPs across the two columns indicates the contribution of probability distortion to WTP is significantly larger than that of standard risk aversion. Moreover, when the probability distortion is turned off (column 3), WTP is essentially equal to the actuarially fair rate.

The estimation “favors” the probability distortion explanation over the risk-aversion explanation, because probability distortion implies — in line with the data — smaller variations in WTP in response to variations in repair cost than the variations in WTP implied by risk aversion. To see this, consider a situation in which the repair cost increases at a constant rate while the failure probability remains fixed. Probability distortion without risk aversion implies WTP increases at a constant rate, whereas risk aversion without probability distortion implies WTP increases at an increasing rate. For example, if the failure probability is 5%, the repair cost is $400, and the WTP

\[17\] In calculating WTP, all the error terms are set to zero.
Table 7: WTP for EW on a good that costs $400

<table>
<thead>
<tr>
<th>Failure prob</th>
<th>Model estimates</th>
<th>Model estimates imposing $\omega(\phi) = \phi$ in WTP calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.04</td>
<td>42.63</td>
<td>16.00</td>
</tr>
<tr>
<td>0.06</td>
<td>51.99</td>
<td>24.00</td>
</tr>
<tr>
<td>0.08</td>
<td>60.18</td>
<td>32.00</td>
</tr>
<tr>
<td>0.10</td>
<td>67.65</td>
<td>40.00</td>
</tr>
<tr>
<td>0.12</td>
<td>74.63</td>
<td>48.00</td>
</tr>
<tr>
<td>0.14</td>
<td>81.26</td>
<td>56.00</td>
</tr>
</tbody>
</table>

for a warranty is $60, then the WTP can be explained by either $\omega = 0.15$ and no risk aversion or by $r = 0.018$ and no probability distortion. As the repair cost increases, the WTP in the model with probability distortion increases at a constant rate of $\omega$. So if the repair cost increases to $500, WTP increases to $75$, and if the repair cost increases to $600, WTP increases to $90$. The WTP in the model with risk aversion increases at a faster rate. If the repair cost increases to $500, WTP increases to $79$, and if the repair cost increases to $600, WTP increases to $101$. Thus, although either probability distortion or risk aversion can explain the WTP for a single product, the rate at which WTP changes in response to a change in repair cost favors probability distortion.

Another source of variation that favors probability distortion over risk aversion is the variation in WTP in response to changes in failure probability. Recall that we assume in the parametric specification — and infer from the estimates in the non-parametric specification — that the distortion function is concave for the relevant range of failure probabilities. Now consider a situation in which the repair cost is fixed and the failure probability increases at a constant rate. Probability distortion without risk aversion implies WTP increases at a decreasing rate, whereas risk aversion without probability distortion implies WTP increases at a constant rate. Thus, similarly to the repair cost, the slower rate at which WTP changes in response to changes in the failure probability in the data favors probability distortion.

5.3 Robustness of demand-side estimates

We consider the robustness of the demand-side estimates to the utility specification, estimation procedure, and repair-cost specification.

**CARA utility.** An alternative utility specification that does not require data on wealth is CARA:

$$u(W + \Delta) = \frac{1 - \exp(-r(W + \Delta))}{r}.$$ 

We reestimate the parametric version of the model for this alternative specification. We obtain that $\alpha$ is equal to 0.721 with a 95% confidence interval of (0.510, 0.932), and that the risk-aversion parameter is not statistically different from 0. These estimates are similar to those of the main specification.

**Maximum Likelihood.** An alternative estimation method that uses both within-product and
between-product variation in prices is Maximum Likelihood (ML).

Consider a consumer \( i \) who faces a price \( p_{ij} \) for product \( j \), a price \( t_{ij} \) for a warranty to product \( j \), and choice shocks to \( V_{EW} \) and \( V_{NW} \) that are iid Type I Extreme Value with scale parameter \( \sigma \).

The probability that consumer \( i \) purchases a warranty for product \( j \) is given by

\[
L_{ij} = \frac{\exp \Omega_{ij}}{1 + \exp \Omega_{ij}},
\]

where

\[
\Omega_{ij} = \frac{\omega(\phi_j)p_{ij} - t_{ij} + \frac{r}{2}(\omega(\phi_j)p_{ij}^2 - t_{ij}^2)}{\sigma}.
\]

Letting \( d_{ij} \) denote whether consumer \( i \) purchased a warranty to product \( j \) \((d_{ij} = 1)\) or not \((d_{ij} = 0)\), and summing over all pairs \((i, j)\), where consumer \( i \) bought product \( j \), we obtain the log-likelihood function,

\[
\sum_{(i,j)} \{d_{ij} \log L_{ij} + (1 - d_{ij}) \log (1 - L_{ij})\},
\]

that we maximize.

The ML estimate of the distortion parameter \( \alpha \) is somewhat smaller than in the main specification at 0.6141 with a 95\% confidence interval of \((0.5980, 0.6301)\). This estimate reflects a larger distortion of failure probabilities. The estimate of the risk-aversion parameter remains close to zero, reflecting its insignificance.

The ML estimate of the distortion parameter reflects a larger distortion than the estimate in the main specification because of the choice of prices. ML uses variation in both the product price and the warranty price, whereas the main specification uses the highest product price and the lowest warranty price, thus making warranty purchases more attractive even without referring to probability distortion or risk aversion.

**Repair cost.** The utility from not buying a warranty, \( V_{NW} \), depends on the distribution of the repair cost \( X \). The main specification assumes away this dependence by bounding \( X \) from above with the main product price, thus making the purchase of a warranty more attractive without referring to risk aversion or probability distortion. However, this assumption may affect the estimates of the probability-distortion and risk-aversion parameters differently. We now consider alternative cost specifications to verify this is not the case.

Assume the repair cost \( X \) is distributed on the interval \([0, p]\), where \( p \) is the main product price. Without loss of generality, let \( X \) be equal to \( \kappa p \), where \( \kappa \) is a random variable with support in \([0, 1]\). Taking advantage of the second-order specification of consumers’ utility, we can write \( V_{NW} \) as a function of the first two moments of the repair-cost distribution (ignoring the constant term \( u(W) \)):

\[
V_{NW} = \omega(\phi)pE(\kappa) + \frac{r}{2}\omega(\phi)p^2[Var(\kappa) + E(\kappa)^2].
\]

Thus, knowing the mean and variance of \( \kappa \) is sufficient to compute the utility difference \( \Omega \).
Letting $\mu$ denote the expected value of $\kappa$, the variance $\sigma^2_\mu$ of $\kappa$ is bounded above by $\mu(1 - \mu)$ because $\kappa$ is distributed on $[0, 1]$ and the largest variance is obtained when the probability mass is concentrated at the end points of the interval. Thus, to check the robustness of the estimates to the cost specification, it suffices to re-estimate the model for all combinations of $\mu \in [0, 1]$ and $\sigma^2_\mu \in [0, \mu(1 - \mu)]$.

We find that across all combinations of mean and variance, the effect of the variance on the parameter estimates is negligible, suggesting that it suffices to examine specifications in which consumers perceive the repair as a deterministic fraction of the product price. Table 8 reports the estimates of the risk-aversion parameter $r$ and the Prelec parameter $\alpha$ for various fractions. As the table shows, the risk-aversion parameter continues to be economically irrelevant, whereas the probability distortion becomes larger in the sense that $\alpha$ decreases. Put differently, as the repair cost decreases and thus purchasing a warranty becomes less attractive, the estimated magnitude of the distortion increases until its explanatory power is exhausted, but the risk-aversion parameter continues to be irrelevant.

<table>
<thead>
<tr>
<th>% of product price</th>
<th>$r$</th>
<th>Prelec $\alpha$</th>
<th>$\omega(0.05)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>$\approx 10^{-6}$</td>
<td>0.689</td>
<td>0.119</td>
</tr>
<tr>
<td>90%</td>
<td>$\approx 10^{-6}$</td>
<td>0.639</td>
<td>0.133</td>
</tr>
<tr>
<td>80%</td>
<td>$\approx 10^{-6}$</td>
<td>0.579</td>
<td>0.151</td>
</tr>
<tr>
<td>70%</td>
<td>$\approx 10^{-6}$</td>
<td>0.507</td>
<td>0.175</td>
</tr>
<tr>
<td>60%</td>
<td>$\approx 10^{-6}$</td>
<td>0.416</td>
<td>0.206</td>
</tr>
<tr>
<td>50%</td>
<td>$\approx 10^{-6}$</td>
<td>0.297</td>
<td>0.250</td>
</tr>
<tr>
<td>40%</td>
<td>$\approx 10^{-6}$</td>
<td>0.128</td>
<td>0.316</td>
</tr>
<tr>
<td>30%</td>
<td>0.0339</td>
<td>0.368</td>
<td></td>
</tr>
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Notes: The Prelec parameter is constrained to be weakly greater than 0, at which stage its explanatory power is exhausted. This happens between 30% and 40%.

5.4 Retailer’s cost

Figure 4 presents a scatter plot of the non-parametric cost estimates divided by the corresponding TV prices, and a local linear fit with a bootstrapped 95% confidence band. For the purpose of the counterfactual analysis, we also fit the non-parametric cost ratios with the polynomial $\mu_0 + \mu_1 \phi + \mu_2 \phi^2$. As Figure 4 illustrates, the fitted polynomial $0.04 + 1.32\phi - 2.48\phi^2$ is essentially identical to the local linear fit. Using the quadratic fit, we estimate that the retailer’s cost, which includes commissions to sales people and revenue sharing with warranty providers, is about 54% of the price of the warranty and that the retailer’s profit margin is about 46%.
5.5 Model fit

We examine how well the model and the estimates fit the data by comparing attachment rates and warranty prices predicted by the model to those in the data. The prices used in the comparison are the ones used in the main specification, namely, the highest TV price and the lowest warranty price.

To compute predicted attachment rates at the product level, we plug into equation (1) the non-parametric estimate of the probability-distortion function, the estimated risk-aversion and scale parameters, and the observed TV and warranty prices from the data. The model predicts a mean attachment rate of 0.276, which is similar to the 0.268 mean attachment rate in the data. Figure 5 depicts that the distributions of the predicted and observed attachment rates are also similar.

To compute the predicted warranty prices, we construct the demand for warranties at the product level based on the non-parametric estimates of the distortion function, estimated risk-aversion and scale parameters, and the observed TV prices from the data. Using this demand and the non-parametric cost estimate, we derive the retailer's profit-maximizing warranty price.

The model predicts a mean warranty-to-product price ratio of 0.175, which is similar to the 0.171 price ratio in the data. Figure 6 depicts that the distributions of the predicted and observed price ratios are also similar.

6 What Drives Probability Distortions?

This section studies the mechanism for the upward distortion of failure probabilities, an important step in evaluating consumer welfare and various policy tools that aim to improve consumer welfare.

One possible mechanism is misperception of unknown probabilities. Uniformed consumers overestimate failure probabilities, and hence are willing to pay for warranties more than they would if they knew these probabilities. Another possible mechanism is overweighting of known small probabilities. Prospect Theory (Kahneman and Tversky (1979)) proposes that individuals incorporate probabilities in decision making by using decision weights, and in particular, assign high decision weights to low probability events. Of course, a combination of the two mechanisms might also drive the distortion.

We use experiments to study the mechanism. A pretest elicits TV failure rates in the population of participants. The two main experiments elicit participants’ perceived failure probabilities and compare them to the failure rate from the pretest, examine how participants’ WTP for warranties changes when they receive information about the objective rate, and studies whether traces of probability distortion are present among informed participants.

In all experiments, we use the Mechanical-Turk (M-Turk) platform. We recruited participants who performed at least 500 tasks on M-Turk prior to each experiment, and had an approval rating

18 Note these price ratios are smaller than the 0.223 attachment rate in Table 2 because of the choice of observed prices.
of 90% or more. About 56% of the participants were males, 43% were females, and 1% preferred not to specify their gender. The median age bracket in the sample was 25-34 years and the median household annual income bracket was $40,000-49,999. The distributions of age and household income brackets appear in Figure 7. Each participant participated in one study and was randomly assigned to one treatment in the study.

6.1 Pretest

This survey elicits failure rates in the population of participants.

Participants (N = 504) were invited to participate in a survey about TVs. We expected the survey would take up to two minutes to complete and promised a payment of 25 cents for participation.

We first asked participants if they had bought a TV in the past three years. Those who responded positively were asked to report, for each TV they bought, the year they bought it (2015, 2016, or 2017) and whether it had needed a repair by a technician.

About 72% of the participants reported they had bought a TV in the past three years. From among them, about 64% reported they had bought one TV, 28% that they had bought TVs, and the rest three or more.

Table 9 indicates failure rates across years range between 4% and 6%, and that the average failure rate is 4.9%. This number is similar to the failure rates in Consumer Reports. Consumer Reports surveyed the performance of 23 major TV brands in early 2017 based on a sample of more than 100,000 TV owners between 2011 and 2016. The mean and the median three-year failure rates by brand are 5%, with 17 out of the 23 brands having a failure rate of 2% to 5%, 5 brands having failure rates of 6% to 7%, and the remaining brand (Spectre) having a failure rate of 10%.

6.2 Study 1

This study elicited perceived failure probabilities and WTP in the population of participants. We expected the study would take up to three minutes to complete, and promised a payment of 40 cents for participation.

At the beginning of the study, participants (N=1001) were asked to “Imagine you just bought a TV for $600. The TV is by LG, and has a 50” screen and Ultra HD technology.”

---

Table 9: TV Repair rates

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td># Bought</td>
<td>193</td>
<td>206</td>
<td>116</td>
<td>—</td>
</tr>
<tr>
<td># Needed repair</td>
<td>8</td>
<td>12</td>
<td>5</td>
<td>—</td>
</tr>
<tr>
<td>Implied fail rate</td>
<td>4.1%</td>
<td>5.8%</td>
<td>4.3%</td>
<td>4.9%</td>
</tr>
</tbody>
</table>

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19LG is one of the brands with a 5% failure rate according to Consumer Reports. We selected the TV attributes and price based on online offerings at BestBuy and Costco at the time of the experiment.
then randomly assigned to one of three treatments.

In Treatment 1, participants were first asked to complete the following sentence:

“The maximum amount in dollars that I am willing to pay for a protection plan that will cover all the repair costs of this TV in the next three years is ________”.

They were then asked: “In your opinion, what is the likelihood in percentages (%) that this TV will need a repair in the next three years?”.

We incentivized the second question by promising participants 10 additional cents if their response was among the 10 most accurate responses.

In Treatment 2, the order of the questions was reversed.

In Treatment 3, participants were first informed that “You are told by an expert friend that the likelihood the TV will need a repair within the next three years is 5%.”

They were then asked to report the maximum amount they would be willing to pay for a three-year protection plan, as in the other treatments.

After completing one of the three sets of questions above, participants were asked how many TVs they had bought in the past five years and how many of these TVs they had bought online, whether any of the TVs they had bought in the past five years had needed a repair, and how many protection plans for TVs and other electronic devices they had bought in the past. They then reported their age bracket, income bracket and gender.

First finding: Failure probabilities are overestimated. The mean reported beliefs in Treatments 1 and 2 are 13.49% (standard error of 0.81) and 15.12% (standard error of 0.86), respectively. The median reported belief in both treatments is 10%. These numbers are much higher than the objective three-year failure rate reported above. Thus, participants overestimated the failure probabilities. Moreover, the magnitude of the overestimation as reflected in the mean belief is similar to that of our non-parametric structural analysis, in which a failure probability of 5% is perceived as a 13.5% failure probability.

Figure provides a finer description of the reported beliefs by means of Cumulative Distribution Functions (CDFs). For each treatment, the CDF assigns for every 0 ≤ x ≤ 100 the proportion of participants in the treatment who estimated the failure probability to be weakly less than x%. The CDFs are similar (the Kolmogorov–Smirnov (KS) test statistic for the equality of the CDFs is 0.086 (p = 0.151)). In each of them, more than 60% of the participants reported beliefs that were at least two-fold larger than the objective probability.

To examine the robustness of the reported beliefs to changes in incentives, we re-ran Treatments 1 and 2 with a different group of 209 participants. We promised participants a bonus of 20 cents, which is twice as large as the original incentive, if their estimate was among the 10 most accurate ones. We found no significant difference in the reported beliefs relative to a bonus of 10 cents. The mean reported belief in Treatment 1 is 14.28 (standard error of 1.39) and in Treatment 2 is 16.36 (standard error of 1.78). The two CDFs of Treatment 1 with 10-cent and 20-cent incentives are
Table 10: WTP with and without information

<table>
<thead>
<tr>
<th></th>
<th>T1 (N = 334)</th>
<th>T2 (N = 330)</th>
<th>T3 (N = 337)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean WTP (std error)</td>
<td>73.01 (5.88)</td>
<td>53.69 (2.68)</td>
<td>42.73 (4.15)</td>
</tr>
<tr>
<td>Mean WTP Truncated (std error)</td>
<td>56.33 (2.19)</td>
<td>47.26 (1.73)</td>
<td>30.86 (1.5)</td>
</tr>
<tr>
<td>Median WTP</td>
<td>50</td>
<td>50</td>
<td>25</td>
</tr>
</tbody>
</table>

Note: Second row mean is truncated to eliminate the top and bottom 5% of the WTP distribution.

similar (p = 0.36), as are the two CDFs of Treatment 2 (p = 0.50). Thus, the reported beliefs are robust to this change in incentives.

Second finding: WTP drops when information is provided. Table 10 summarizes participants’ reported WTP for a three-year warranty. The mean and the median WTP in Treatment 3 are significantly smaller than in Treatment 1, indicating that providing participants with information about the objective failure probability reduced their WTP significantly. Stronger evidence for this assertion is given in Figure 9, which draws the CDFs of WTP by treatment. The CDF for Treatment 3 is essentially first-order-stochastically dominated by the CDF for Treatment 1, indicating that WTP for warranties was reduced with information (the KS statistic for the equality of the CDFs is 0.309 (p < 0.001)).

Two forces are potential drivers of the reduction in WTP. First, Treatment 3 reminded participants about failure probabilities prior to reporting WTP. Merely reminding participants about failure probabilities (independently of whether the objective probability was specified or not) prior to reporting WTP could have driven the reduction in WTP. Second, Treatment 3 informed participants about the objective failure probability. It is possible that informing participants about this low probability is what drove the reduction in WTP. To examine the relevance of these two forces, comparing the WTP in Treatment 2 with the WTP in Treatments 1 and 3 is instructive, because the first force but not the second one was present in Treatment 2.

The data provides strong evidence for the presence of the second force. The CDF for Treatment 3 in Figure 9 is essentially first-order stochastically dominated by the CDF for Treatment 2 (the KS statistic is 0.238 (p < 0.001)). The mean and median WTPs are also significantly different.

The evidence for the first force is weaker and stems in part from differences in the tail of the WTP distributions. Although the CDF for Treatment 2 in Figure 9 seem to be first-order stochastically dominated by the CDF for Treatment 1, the statistical evidence for the difference is weak (the KS statistic is 0.087 (p=0.14)). The median WTP is identical across conditions. Note, however, that a significant difference exists in the mean WTP. One of the sources of this difference is the tail of the WTP distributions. Indeed, the gap between the mean WTPs shrinks by half when the top and bottom 5% of the WTP distributions are truncated.

To summarize, survey participants displayed two patterns. First, they overestimated failure probabilities. Second, their WTP decreased significantly when they received information about the objective failure probabilities.
Table 11: WTP for different TVs with information

<table>
<thead>
<tr>
<th></th>
<th>T1 (N = 451)</th>
<th>T2 (N = 465)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean WTP (std error)</td>
<td>46.89 (3.43)</td>
<td>66.22 (3.96)</td>
</tr>
<tr>
<td>Mean WTP Truncated (std error)</td>
<td>36.04 (1.49)</td>
<td>54.90 (2.21)</td>
</tr>
<tr>
<td>Median WTP</td>
<td>25</td>
<td>50</td>
</tr>
</tbody>
</table>

Note: Second row mean is truncated to eliminate the top and bottom 5% of the WTP distribution.

6.3 Study 2

This study elicited WTP for warranties for TVs of different values after participants were informed about objective failure probabilities. We expected the study would take up to three minutes to complete, and promised a payment of 40 cents for participation.

Participants (N = 916) were randomly assigned to one of two treatments. The first and main question of Treatment 1 was identical to the first and main question of Treatment 3 in Study 1. The first and main question in Treatment 2 differed from Treatment 1 only in asking participants to “Imagine you just bought a TV for $1000. The TV is by LG, and has a 70” screen and Ultra HD technology.” That is, we changed the price of the TV, and to make sure the $1000 price was realistic, we also changed the screen size. Changing the product across treatments, while fixing the failure probability, enables us to use the identification strategy from the previous sections.

After answering the first question, participants in both treatments were asked whether they had bought a TV in the past three years, and reported their age bracket, income bracket, and gender.

First finding: WTP changes significantly with price. Table 11 illustrates that the mean and median of the WTP distribution are much higher for $1000 TVs than for $600 TVs. Figure 10 illustrates this ranking extends to the CDFs as the one for the $600 TV is first-order stochastically dominated by the one for $1000 (the KS statistic for the equality of the CDFs is 0.199 (p < 0.001)).

Main finding: Probability distortions are significantly reduced when information is provided. After truncating the top and bottom 5% of the WTP distribution, we estimate the degree of probability distortion and standard risk aversion among participants under two scenarios.

In the first scenario, we assume participants share the same distortion w and the same risk-aversion parameter r, but may differ from one another in various unobserved factors. As a result, participants’ reported WTP does not equate the utility difference Ω to 0 precisely. Rather, it equates Ω to an error parameter ε, which is equal to 0 in expectation. We estimate this model using nonlinear least squares to find r and w.

The estimated value of w is 5.6%, which is very close to the objective probability of 5%. The estimate of the risk-aversion parameter is negligible.

In the second scenario, we divide participants into quartiles based on WTP. We match the corresponding quartiles across treatments, and assume participants in each combined quartile share the same w and r. We repeat the above estimation procedure for each quartile separately.
We find that neither risk aversion nor probability distortions is required to explain WTP for the lower half of the WTP distribution. The 50-75 quartile has a distortion of 2.5% upward. This upward distortion is much smaller than the upward distortion of about 9.5% among the 50-75 quartile in Study 1. The 75-100 quartile has an upward distortion of 8%, which is again much smaller than the 24% distortion for the corresponding quartile in Study 1.

Overall, we conclude that providing information to participants reduces probability distortions significantly. Because the distortion provides an upper bound on the degree of probability overweighting, we conclude that the role of overweighting in driving consumers' purchase behavior is not significant once they become informed about the objective failure probability.

7 The Effect of Probability Distortions on Economic Outcomes

This section uses counterfactual analysis to quantify the effect of probability distortions relative to market power on economic outcomes.

We consider four scenarios in the analysis. The first scenario, “Market power with Biased consumers” (scenario MB), corresponds to the existing market in which the retailer has monopolist market power and buyers distort failure probabilities. In the second scenario, “Market power with Unbiased consumers” (scenario MU), the retailer continues to benefit from the same market power but buyers do not distort failure probabilities. Comparing the second scenario with the first enables us to study the importance of probability distortions while fixing the existing market environment. In the third scenario, “Competitive market with Unbiased consumers” (scenario CU), unbiased consumers purchase warranties in a competitive market. Because of competition, market prices are equal to the retailers’ marginal cost and retailers make zero profit. Comparing this scenario with the second scenario enables us to study the importance of market power in the absence of probability distortions. In the fourth scenario, “Competitive market with Biased consumers” (scenario CB), retailers price at marginal cost and buyers distort failure probabilities. Comparing this scenario with scenario CU enables us to study the importance of probability distortions in a counterfactual competitive environment.

We assume that any change in the main product’s price across the four scenarios is negligible. To motivate this assumption, we first observe that little differentiation exists between electronics retailers, and that TV prices are easily observable. Thus, in the absence of extended warranties and other add-ons, TVs would have been priced close to marginal cost. The introduction of extended warranties implies retailers may have incentives to cut TV prices below cost in order to increase the demand for warranties.

There are several reasons to believe such price cutting, if it happens, is insignificant. First, on the theoretical side, Ellison’s (2005) analysis indicates the incentive to cut prices below cost is mitigated by an “adverse selection” effect, i.e., cutting the prices of TVs will attract a disproportionate volume

\footnote{We truncate the top and bottom 5% of the distribution in Study 1 for the purpose of this comparison.}
of consumers with low WTP who will not buy warranties. Second, on the institutional side, TV manufacturers have tight controls on the pricing and marketing practices of retailers in order to prevent such price cutting. Two examples of controls are the Minimum Advertised Price (MAP) policy, whereby retailers cannot advertise below the manufacturer’s suggested retail price, and the Unilateral Manufacturer’s Retail Price (UMRP) policy, which imposes a penalty when retailers set prices below the UMRP. Third, on the empirical side, we hand collected and compared 40 TV prices from BestBuy and Target in 2003. BestBuy offered extended warranties in 2003, whereas Target did not. To the extent that Target and BestBuy face similar TV wholesale prices, we would expect TV prices at BestBuy to be lower than at Target if BestBuy’s warranty business affected their TV pricing. We find, however, that TV prices are very similar across retailers. On average, TV prices at BestBuy are 0.4 percentage points higher than at Target (standard error of 0.9 percentage points), and the median price difference is 0.

In the four counterfactual scenarios, cost and demand for warranties depend on the TV price $p$ and the failure rate $\phi$. We use the average TV price of $400 and consider the failure rates $\{0.04, 0.05, \ldots, 0.15\}$. For the cost specification, we use the parametric estimate of $c(p_j, \phi)$ with $p_j = 400$. To construct demand in scenarios MB and CB, we use the estimated $\alpha$ and $r$ from the parametric estimation. In the two other scenarios, we turn off the distortion by setting $\omega(\phi) = \phi$ but keep the same $r$.

### 7.1 Prices, volume, and profit

Given cost and demand, we calculate optimal prices, attachment rates, and profit margins in the different scenarios. To derive a yearly dollar equivalent measure of profit, we assume 30 million people buy TVs every year.\(^{21}\)

Panel A in Figure 11 plots the warranty-to-TV price ratio as a function of failure probabilities for the different scenarios. The price ratios are increasing and concave in the failure probability. They are highest in scenario MB, lower in scenario MU, and lowest in scenarios CU and CB. The gap between scenarios MB and MU is smaller than the gap between scenario MU and the two competitive market scenarios CU and CB.

Thus, probability distortions lead to a price increase, but this price increase is smaller than the price increase due to market power. For example, at the average failure rate of 7%, the price ratio in scenario MB is about 20% higher than in scenarios CU and CB. About three quarters of this gap is attributed to market power (the gap between MU and the competitive-market scenarios), and the rest to probability distortions. Because prices in the competitive-market scenarios are equal to marginal cost (which includes payments to third-party providers), the same conclusion applies to profit margins: pricing power is responsible for three quarters of retailers’ margin.

Panel B in Figure 11 plots attachment rates as a function of failure probabilities. Attachment

\(^{21}\)This number is somewhat smaller than the yearly TV shipments in the US between 2010 to 2013, which ranged from 37 million to 40 million. [CNN, “With new TVs, size matters,” June 26, 2013](https://www.cnn.com/2013/06/26/business/television/shipping/)
rates in scenario MB are 30% or larger, whereas attachment rates in scenario MU are around 5%. That is, fixing the existing competitive environment with market power, the introduction of probability distortions leads to a five-fold or larger increase in volume. Attachment rates in scenario MB are about three times larger than in scenario CU. That is, any rationing that takes place due to market power is insignificant relative to the volume increase due to the distortion.

Panel C in Figure 11 plots profits as a function of failure rates. More than 90% of retailers’ profit is due to probability distortions.

To sum up, probability distortions drive the strong demand for warranties and the high profits, whereas market power drives the high prices and margins.

7.2 Consumer and total welfare

Evaluating consumer welfare requires taking a stance as to whether probability distortions are welfare-relevant in the sense that the distorted probabilities should be part of consumer welfare. We interpret the results of the experiment, especially those of study 2, as suggesting they should not, because the results demonstrate that providing information to consumers about objective failure probabilities triggers most of them to use the objective or slightly distorted probabilities in their decision making. Put differently, information provision “reveals” that consumers prefer to use the objective probabilities in decision making. We thus evaluate welfare with respect to the objective failure probabilities.

Figure 12 plots consumer welfare as a function of failure rates. Consumer welfare is highest in scenario CU. This is because consumers evaluate failure probabilities correctly and prices are lowest. Consumer welfare is lower in scenario MU. This is because prices are higher due to retailers’ market power leading to lower attachment rates. In both scenarios, consumer welfare is positive because only consumers with true WTP above price buy warranties.

Consumer welfare is negative in scenario MB, which is identical to the existing market. Put differently, consumer welfare would increase if the market for extended warranties did not exist. This is because probability distortions are sufficiently large, so that any positive surplus generated by purchases of buyers with true WTP above price is dominated by the decrease in consumer welfare due to purchases of buyers with true WTP below price.

Consumer welfare is even lower in scenario CB. This is because the increase in consumer welfare (relative to scenario MB) due to existing consumers paying lower prices and the entry of new consumers with true WTP above price is dominated by the decrease in consumer welfare due to the entry of new consumers with true WTP below price buying warranties because of the distortion.

Figure 12 illustrates that the reduction in consumer welfare due to probability distortions in the existing competitive environment, i.e., the gap between MU and MB, and in the alternative competitive environment, i.e., the gap between CU and CB, are much larger than the reduction in consumer welfare in the existing market.

\[22\] The comparison between scenarios CU and CB also highlights the large effect of the distortion on volume while fixing the competitive environment, as volume more than doubles when moving from scenario CU to scenario CB.
consumer welfare due to market power (the gap between CU and MU or the gap between CB and MB). For example, at a 7% failure probability, consumer welfare increases by $140 million when moving from MB to CU, and more than 95% of this increase is due to shutting down the distortion, i.e., due to the transition from MB to MU.

To illustrate the forces at play, consider the two positive welfare effects when moving from scenario MB to scenario MU (see Figure 13 for a graphical illustration). First, holding the warranty price fixed, a shift inward of the demand curve occurs when shutting down probability distortions. Consumers who now forgo buying the warranty are exactly those who overpaid for warranties based on their true WTP for it, thus increasing consumer welfare. We refer to this effect as the ripoff effect. Second, warranty prices go down when shutting down the distortion. Existing buyers pay lower prices, and new consumers, who estimate failure probabilities correctly, buy warranties. As a result, attachment rates and consumer welfare increase. We refer to this effect as the price effect. Figure 14 plots the dollar-equivalent value of the two effects for various failure rates. The ripoff effect clearly dominates the price effect for all failure rates.

The effect of probability distortions on total welfare is ex-ante ambiguous. The first-best level of insurance is the one in scenario CU, because all consumers with true WTP above cost are insured. In scenario MU, there is under-insurance relative to the first-best, because retailers price warranties above cost, and thus consumers with true WTP above cost but below market prices are not insured. In scenarios MB and CB, there is over-insurance relative to the first-best, because consumers with true WTP below cost purchase insurance due to probability distortions. See Figure 15 for a graphical illustration.

Figure 16 plots total welfare as a function of failure rates. Total welfare in scenario MU is larger than in scenario MB. Put differently, the adverse welfare effect of market power (the gap between CU and MU) is smaller than the adverse welfare effect of the distortion (the gap between MU and MB). The adverse welfare effect of the distortion is so large that total welfare in scenario CB is lower than in all other scenarios.

### 8 Conclusion

This paper analyzed the effect of probability distortions on economic outcomes in the extended warranty market. We established that the distortion is a dominant factor in driving the strong demand and high profit in this market. We also established that when consumers receive information about failure probabilities, their willingness to pay for warranties reflects a much smaller distortion, indicating the distortion is a mistake in decision making due to lack of information. We conclude with a short discussion of the policy implications of these findings.

In its 2003 report, the UK Competition Commission (2003) proposed that electronics retailers “display the price of an applicable EW (extended warranty) alongside the DEG (domestic electrical good) in store and in press advertisement and other publicity.” This proposal is an example of a
competition policy that aims to intensify competition and lead to lower prices. But lower prices do not necessarily increase consumer welfare, because lower prices imply additional consumers with willingness to pay below price buy warranties due to the distortion. Our findings suggest consumer policies that aim to improve consumers’ decision making may be more effective in increasing consumer welfare. An example of such policy, which may have an effect similar to the information-provision treatments in our experiment, is to demand that retailers display the failure probability of the product next to its price.

To illustrate this point, we return to our counterfactual scenarios. We can think about scenario MB as corresponding to the existing market, scenario CB as corresponding to the market outcome following a competition policy that eliminates market power, and scenario MU as corresponding to the market outcome following a consumer policy that eliminates overestimation.

Panel B in Figure 11 illustrates market volume will more than double if warranties are priced at cost as we move from MB to CB. However, Figure 12 illustrates consumer welfare will decrease. Total welfare will also decrease, because firms make zero profit in this scenario. On the other hand, both consumer welfare and total welfare are positive in scenario MU.

Figure 17 provides additional evidence that consumer policies that lead to a reduction — and not necessarily the elimination — of the distortion are welfare-superior to competition policies that lead to price reduction. In the figure, we assume TVs are priced at $400, and the failure probability is 7%.

In solid blue, we plot for every $0 \leq \lambda \leq 1$ how consumer welfare (Panel A) and total welfare (Panel B) change when consumers distort failure probabilities and warranty prices are a convex combination of competitive prices with weight $\lambda$ and monopoly prices with weight $1 - \lambda$. As $\lambda$ increases, i.e., as the market becomes more competitive, both consumer and total welfare decrease. In dashed red, we plot how welfare changes when consumers perceive failure probabilities as a convex combination of the objective probability with weight $\lambda$ and the distorted probability with weight $1 - \lambda$, and the retailer prices optimally with respect to the resulting demand. Clearly, welfare increases in $\lambda$, and for any $\lambda$, welfare is larger than following any price reduction.

Thus, policies that aim to intensify price competition may lead to suboptimal results in markets with uninformed or biased consumers relative to consumer policies that aim to improve consumers’ decision making.

References


UK Competition Commission (2003), “Extended warranties on domestic electrical goods: A report on the supply of extended warranties on domestic electrical goods within the UK – Volumes 1, 2 and 3.”
Figures

Figure 1: Histograms of extended-warranty-to-product price ratios

(A) All Products

(B) TVs

Figure 2: Identification: Single-crossing of willingness to pay
Figure 3: Estimated distortion function

Notes: For presentation purposes, the graph is truncated at 0.25. The largest value of $\omega$ is about 0.34.

Figure 4: Retailer’s cost

Notes: For presentation purposes, the graph is truncated at 0.25. The largest value of the normalized cost is about 0.35.
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Figure 6: Model fit: Warranty-to-TV price ratios
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(B) Income

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Figure 9: CDFs of WTP in USD in study 1

Figure 10: CDFs of WTP in USD in study 2
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(A) Warranty-to-TV price ratios

(B) Attachment rates

(C) Profits
Figure 12: Counterfactuals: Consumer welfare

Figure 13: Ripoff and price effects of shutting down distortion
Figure 14: Counterfactuals: Magnitude of ripoff and price effects

Figure 15: Sources of welfare loss

Welfare loss:
- MU relative to CU
- MB relative to CU
- CB relative to MB

Demand with distortion
- Demand without distortion

Welfare loss:
- Under-insurance in MU
- Over-insurance

MC

40
Figure 16: Counterfactuals: Total welfare

Figure 17: Comparing policy interventions as function of $\lambda$

(A) Consumer welfare  
(B) Total welfare