On the Relevance of Probability Distortions in the Extended Warranties Market*

[Preliminary and incomplete]

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Abstract

We study the reasons for high profits in the extended warranties market. Using data from a big US consumer electronics retailer on extended warranty purchases between 1998 and 2004, we estimate a model in which a profit-maximizing monopolistic seller offers extended warranties to a population of risk-averse consumers who may distort failure probabilities. We find that overweighting of failure probabilities is a relevant factor in determining economic outcomes in this market: without probability overweighting, profits drop by 90% and consumer surplus more than doubles. We also find that probability overweighting is affected by the environment and is reduced with learning: there is less overweighting in online transactions than in in-store transactions, and the likelihood of the same household buying an extended warranty is reduced with experience.

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1 Introduction

The market for extended warranties is highly profitable. Analysts estimate that extended warranties accounted for almost half of BestBuy’s operating income in 2003, and that profit margins on these warranties were about 50% to 60%. These margins were nearly 18 times the profit margins on the products that the warranties covered.[1] To likely avoid attention, BestBuy gradually reduced the transparency of reporting on its extended warranty business since 2001. Around the same time, concern about high profit margins on extended warranties led to a UK Competition Commission investigation of their main consumer electronics retailers. Despite its efforts, the Commission did not find evidence of abuse of dominance and instead attributed high profit margins to a “complex monopoly situation,” the solution of which likely falls outside the scope of standard competition policy (Baker and Siegelman, 2013).

One factor that may contribute to the high profitability of extended warranties lies in the way these are marketed. In a brick and mortar store, a consumer is offered the extended warranty after making the decision to buy the main product. At this stage, the seller potentially benefits from close to monopoly pricing power because consumers may believe (or are convinced to believe) that they cannot buy the same warranty elsewhere. In addition to this pricing power, there are demand-related issues that potentially support high prices. An extended warranty is an insurance contract, and buyers may be willing to pay a high premium to insure themselves against product failures. Consumers’ high willingness-to-pay may be due to consumers’ aversion to risk, or due to mistakes in evaluating the cost or likelihood of a failure. The recent empirical findings of Barseghyan et al (2012) suggest that mistakes in the form of overweighting small probability events, rather than “standard” risk aversion, are an important ingredient in consumers’ decision making when buying insurance.[2]

Using extended warranty transactions from a large US consumer electronics retailer, we provide empirical evidence that demand-side probability distortions in the form of overweighting and low marginal sensitivity to changes in failure rate are important factors in driving the high profitability in this market. Moreover, we argue that there is rationale and scope for intervention in the form of well-designed consumer protection policies, and these have the potential to significantly improve consumer welfare.

Our approach to studying the extended warranties market begins with providing evidence that standard risk aversion is not likely to be a dominant factor in consumers’ decision to buy an extended warranty. If it were, we would expect consumers’ likelihood of buying an extended warranty to be significantly correlated with observables such as gender, age, and income (which to the best of our knowledge do not affect the price of insurance in this market). We do not find indications of such

[2] On the cost side, warranties cost very little to market, and fail very infrequently. It is possible, however, that failure rates among those who buy extended warranties are higher than average due to moral hazard (conditional on buying the warranty, consumers do not take good care of the product) and adverse selection (those with higher propensity to break the product buy extended warranties), which then puts upward pressure on extended warranty prices.
correlations in our dataset.

We then proceed to specify a structural model of demand and supply that captures the main features of the market. On the demand side, risk averse consumers decide whether to purchase the warranty after making the decision to buy the main product. The warranty is a contract that fully insures the buyer against the product failing. In deciding whether to buy the warranty, the buyer approximates the cost of failure using the price paid for the product, but may make mistakes in estimating the likelihood of failure and in incorporating this likelihood to the warranty’s value.

From the demand model, we separately identify and estimate the consumer’s degree of (standard) risk aversion and the distortion in evaluating failure rates. Our identification strategy relies on how a household’s willingness-to-pay for an extended warranty varies across products that have different costs of failure (i.e. loss from a product failure) but the same failure rates. We show that a single-crossing condition of the willingness-to-pay function is sufficient to separately identify standard risk aversion and probability distortions in this context. We provide examples of common utility functions that satisfy the single-crossing property, including the one that we will use for estimation.

On the supply side, we model the seller as a monopolist who prices the extended warranty to maximize profit (given the price of the main product). We endow the retailer with monopoly pricing power and investigate to what extent behavioral biases can influence monopoly prices. To get a measure of the (expected) marginal cost of providing a warranty, we combine our supply model with our demand estimates.

Our estimation results point to an important role of probability distortions in explaining extended warranty purchase behavior. First, we find substantial overweighting of failure rates below 15%. For example, a 5% failure rate is seen as if a product has a failure rate of 12% when an average household is evaluating the warranty. Second, our estimate of standard risk aversion implies an average willingness-to-pay that is close to actuarially fair rates, consistent with behavior of a risk neutral consumer. We show that estimating a model that ignores probability distortions requires extreme risk aversion to rationalize the data.

We perform counterfactual experiments to assess the impact of probability distortions on extended warranty prices, price-cost margins, and welfare. We find that the ratio of extended warranty price to the main product price declines from 17% to 16%, with price-cost margins going down from 31% to 24% when we remove the bias. Removing the bias drastically reduces the fraction insured from 39% to 7%.

The effect of removing the bias on welfare is ambiguous. Overweighting of failure rates inflates consumers’ willingness-to-pay for the warranty, potentially leading to overinsurance relative to the first best. On the other hand, market power leads to underinsurance. We estimate that the deadweight-loss from overinsurance is larger than the deadweight-loss from underinsurance, and so welfare increases when we remove the bias. Removing the bias leads to a welfare improvement of $9 million, or a 15% increase in welfare. More strikingly, consumer surplus improves by $219 million
(which represents more than a doubling of consumer surplus) when the retailer can no longer exploit
the bias. Finally profits go done from $267 million to $36 million, or an 85% decrease, in this case.

We conclude by exploring whether the bias is internal to the consumer or due to external
cues, and whether consumers adjust how they value the warranty based on past experience. If
probability distortions were influenced largely by one’s external environment and/or consumers
learn, then there is room and rationale for policy interventions to minimize the bias. Using our
panel data of households, we find substantially different purchasing behavior between online and
in-store transactions. Our best estimate suggests that the likelihood of purchasing an extended
warranty across all products increases from 12% to 29% when consumers interact with sales people
in the store. Moreover, prior experience with purchasing an extended warranty decreases the
likelihood of purchasing a warranty today from 29% to 4%, once we control for (unobserved)
persistent characteristics of the buyer.

The paper is organized as follows. The next section introduces the data and provides reduced-
form evidence against the view that risk aversion is the main driver for extended warranty purchase.
Section 3 presents the model and our identification strategy. Section 4 discusses estimation and
section 5 contains the results. We perform counterfactuals in section 6 and section 7 explores
whether there is rationale and scope for intervention.

2 Data

We use the INFORMS Society of Marketing Science (ISMS) Durables Dataset 1 which is a panel
data of household durable goods transactions from a major U.S. electronics retailer. The full sample
contains around 170,000 transactions made by almost 20,000 households across the retailer’s 1,176
outlets and its online store. Of these transactions, about 117,000 correspond to a specific product
that the household purchased in a given shopping trip. An extended warranty purchase is recorded
as a separate transaction. Transactions took place between December 1998 to November 2004. The
data also contains household characteristics including 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 two data issues that we have to deal with. First, the data only tells us the product
subcategory (e.g. 9-16 inch TVs) for which the warranty is for. We restrict our sample to shopping
trips in which there is a clear one-to-one mapping between the extended warranty and the corre-
sponding 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. At the end, we lose about 2,000
observations for this reason.

Second, if a household does 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

\footnote{Income group is a number from 1-9 where 9 is the highest income group. The data documentation does not provide
information on how these groups are defined.}
Table 1: By product category

<table>
<thead>
<tr>
<th>Product Category</th>
<th>% Bought EW</th>
<th>EW-Product price ratio</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUDIO</td>
<td>0.281</td>
<td>0.232</td>
<td>6450</td>
</tr>
<tr>
<td>DVS</td>
<td>0.295</td>
<td>0.207</td>
<td>1439</td>
</tr>
<tr>
<td>IMAGING</td>
<td>0.377</td>
<td>0.199</td>
<td>3001</td>
</tr>
<tr>
<td>MAJORS</td>
<td>0.356</td>
<td>0.197</td>
<td>864</td>
</tr>
<tr>
<td>MOBILE</td>
<td>0.398</td>
<td>0.249</td>
<td>5176</td>
</tr>
<tr>
<td>MUSIC</td>
<td>0.208</td>
<td>0.169</td>
<td>1189</td>
</tr>
<tr>
<td>P<em>S</em>T</td>
<td>0.245</td>
<td>0.237</td>
<td>3765</td>
</tr>
<tr>
<td>PC HDWR</td>
<td>0.258</td>
<td>0.274</td>
<td>8773</td>
</tr>
<tr>
<td>TELEVISION</td>
<td>0.311</td>
<td>0.217</td>
<td>6307</td>
</tr>
<tr>
<td>VIDEO HDWR</td>
<td>0.206</td>
<td>0.240</td>
<td>5828</td>
</tr>
<tr>
<td>WIRELESS</td>
<td>0.245</td>
<td>0.317</td>
<td>1485</td>
</tr>
<tr>
<td></td>
<td>0.287</td>
<td>0.239</td>
<td>44277</td>
</tr>
</tbody>
</table>

nonwarranty transaction with a corresponding warranty transaction based on product ID and we
assign the observable price from the closest transaction date. We end up with a sample of about
45,000 observations.

2.1 Attachment rates, prices, and approximate margins

Table 1 shows the fraction of consumers who bought extended warranties (henceforth, the attach-
ment rate), and the ratio of the extended warranty price to the product price for each product
category. Attachment rates range from about 20% for items such as VCRs (VIDEO HDWR), mu-
sic CDs and video games (MUSIC), to as high as about 40% for items like car stereos and speakers
(MOBILE). Warranties are priced at about 24% of the price of the insured product, on average.

We restrict our analysis to TVs due to availability of published failure rates from Consumer
Reports. Table 2 provides attachment rates, prices, ratio of extended warranty to product price,
published failure rates, and approximate price-cost margins, broken down by TV subcategory.
Attachment rates range from about 15% to 35%, with larger attachment rates for TVs that are 30
inches or higher (most expensive category). Similar to the other product categories, the warranty to
product price ratio is about 24% on average. To provide a rough estimate of the expected marginal
cost of servicing a warranty, we multiply the failure rates from Consumer Reports by the price of
the product. This estimate implies a price-cost margin of about 62 to 73%, which is close to what
is cited in the popular press. Note that we expect the seller in our dataset to have lower margins
due to issues like profit-sharing with third party providers of the warranty and commissions to sales
people.

\[\text{We also drop observations where the price of the good is significantly less than the price of the warranty (less than 1,000 observations).}\]

\[\text{These failure rates come from Consumer Reports (see also table 6 (p. 22 ) of Wang, Ata and Islegen (2012)) which gives the likelihood that a repair has to be made within 3 to 4 years of using the product. We construct lifetime failure rates assuming the product lasts for 3.5 years.}\]
Table 2: By TV product type

<table>
<thead>
<tr>
<th>% bought</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>122.989</td>
<td>0.284</td>
<td>0.072</td>
<td>0.729</td>
</tr>
<tr>
<td>19-20in</td>
<td>0.176</td>
<td>173.973</td>
<td>0.240</td>
<td>0.065</td>
<td>0.710</td>
</tr>
<tr>
<td>25in</td>
<td>0.269</td>
<td>244.923</td>
<td>0.220</td>
<td>0.069</td>
<td>0.643</td>
</tr>
<tr>
<td>&gt;30in</td>
<td>0.348</td>
<td>812.533</td>
<td>0.219</td>
<td>0.076</td>
<td>0.619</td>
</tr>
<tr>
<td></td>
<td>0.253</td>
<td>421.092</td>
<td>0.235</td>
<td>0.070</td>
<td>0.667</td>
</tr>
</tbody>
</table>

Notes: Fail rates are from Consumer Reports, assuming a 3-year lifetime and constant fail rate.
Margin = (EW price - CR fail rate × TV price)/EW price

2.2 Attachment rates by buyers’ characteristics

We examine the relationship between attachment rates and buyers’ characteristics in tables 3 and 4. Table 3 shows attachment rates broken down according to buyers’ (and households’) characteristics, while table 4 contains the results from a regression of extended warranty purchase on these characteristics. All in all, these two tables suggest that buyers’ characteristics are not strong predictors of extended warranties purchases.

Table 3 shows attachment rates broken down by gender of the buyer, gender and age of the head of the household, whether income is above or below the median income category in the data, and finally whether there is a child present in the household. Attachment rates do not significantly differ across these groups. For example, around 27% of female buyers purchase the warranty compared to 25% of male buyers. In terms of income, 25% of above median income households purchase the warranty compared to 27% of below median income households. Although having a child seem to decrease the likelihood of purchasing a warranty by 8 percentage points, this difference goes away once we introduce controls.

Table 4 presents the results of regressing an extended warranty purchase dummy on buyers’ characteristics. The regressions include brand and subcategory fixed effects to account for average differences in purchasing behavior across these dimensions. Focusing on the specification without interaction terms (i.e. columns 2 and 3), none of the buyers’ characteristics are statistically significant predictors of extended warranty purchase, consistent with most of the raw means in table 3. For example, the estimated effect of gender is just about 1% and is not statistically significant. Turning to the estimates with interaction terms (i.e. columns 3 and 4), we again see that none of the coefficients are statistically significant.

A wide literature in psychology and economics provides evidence that the above characteristics we examine are correlated with risk aversion. (See Cohen and Einav (2007) and Dohmen et al (2011) for recent studies, and Byrnes et al (1999) and Croson and Gneezy (2009) for surveys of the literature.) For example, studies point to greater risk aversion among women than men. Read through these lens, our results suggest that risk aversion is not the main factor driving extended warranty purchase behavior.

There is a concern that our coefficient estimates in table 4 confound the effect of risk aversion and risk type on
Table 3: Proportion of people who bought EW (TV)

<table>
<thead>
<tr>
<th>Category</th>
<th>% bought</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>0.274</td>
<td>1076</td>
</tr>
<tr>
<td>Male</td>
<td>0.246</td>
<td>1860</td>
</tr>
<tr>
<td>Female (head of hh)</td>
<td>0.274</td>
<td>972</td>
</tr>
<tr>
<td>Male (head of hh)</td>
<td>0.245</td>
<td>1765</td>
</tr>
<tr>
<td>Above median income (category ≥5)</td>
<td>0.247</td>
<td>2446</td>
</tr>
<tr>
<td>Below median income (category &lt;5)</td>
<td>0.271</td>
<td>792</td>
</tr>
<tr>
<td>Over 50 (head of hh)</td>
<td>0.264</td>
<td>1865</td>
</tr>
<tr>
<td>Under 50 (head of hh)</td>
<td>0.239</td>
<td>1350</td>
</tr>
<tr>
<td>Has child in hh</td>
<td>0.234</td>
<td>881</td>
</tr>
<tr>
<td>No child in hh</td>
<td>0.316</td>
<td>531</td>
</tr>
</tbody>
</table>

Table 4: Regression of extended warranty purchase (TV) on household characteristics

Dependent variable: EW purchase dummy

<table>
<thead>
<tr>
<th></th>
<th>Coeff</th>
<th>SE</th>
<th>Coeff</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male (head)</td>
<td>-0.010</td>
<td>(0.026)</td>
<td>-0.050</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Age (head)</td>
<td>0.001</td>
<td>(0.001)</td>
<td>0.001</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Income</td>
<td>-0.004</td>
<td>(0.006)</td>
<td>-0.005</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Has child in HH</td>
<td>-0.042</td>
<td>(0.030)</td>
<td>-0.002</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Male × Age</td>
<td>0.001</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male × Income</td>
<td>0.001</td>
<td>(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male × Child</td>
<td>-0.061</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subcategory FE</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand FE</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

No. obs (good-hh-trip) 1189 1189

Notes: Standard errors in parentheses are clustered at shopping trip level.
Significance level: ***1%, **5%, *10%
3 Model and identification

We proceed to study a model of the extended warranty market and estimate some of its parameters. In the model, each consumer first decides which main product to buy, not taking into account the potential purchase of the warranty. After finalizing this decision, the seller “surprises” the buyer, and offers him to add-on an extended warranty to his purchase. The consumer then decides whether to do so or not.

The timing of the model and its sequential structure are motivated by how extended warranties are sold in practice. In actual store settings, sales people usually offer this warranty to the buyer after he finalizes his decision to purchase the corresponding product and is about to pay for it. It seems unlikely that the buyer will revisit the costly decision to purchase the main product at this stage. It also seems unlikely that when shopping for the main product, buyers seriously consider the potential purchase of the extended warranty as no information about the warranty or its price is usually provided before the decision to buy the product has been reached.

We focus on the second stage of the purchase process. At this stage, buyers decide whether to purchase the warranty or not, which will be driven by their degree of risk aversion and probability distortions. We can then solve for aggregate demand, and estimate the monopolist’s marginal cost from his profit-maximizing pricing decision.

Starting with the buyer’s decision, a buyer’s value from purchasing the warranty is

\[ V_{EW} = u(W - t; r) \]

where \( W \) is the buyer’s wealth after buying the main product, \( t \) is the price of the warranty, and \( u(\cdot, r) \) is the consumer’s concave utility over wealth levels that is parameterized by \( r \), the buyer’s degree of risk aversion around \( W \). Note that there is no deductible associated with using the warranty, as is usually the case in extended warranty contracts.
The buyer’s value without the warranty is

\[ V_{NW} = \omega(\phi)E(u(W - X; r)) + (1 - \omega(\phi))u(W; r) \]

where \( \omega(\phi) \) is the buyer’s perception of the objective failure probability \( \phi \), which increases in \( \phi \), and \( X \) is the random cost of repair. Clearly, \( X \leq A \), where \( A \) is the price of the main product, because the buyer can always buy a new product instead of fixing the existing one. Thus, the buyer’s value without the warranty is bounded below by \( \omega(\phi)u(W - A; r) + (1 - \omega(\phi))u(W; r) \). In what follows, we will identify \( V_{NW} \) with this lower bound, i.e., we will have:

\[ V_{NW} = \omega(\phi)u(W - A; r) + (1 - \omega(\phi))u(W; r) \]

The non-standard component in the model is the probability distortion function \( \omega(\cdot) \) that reflects how the buyer assesses objective failure probabilities and how he uses them in making decisions. There are at least two reasons for probability distortions. First, estimating failure probabilities is not straightforward. This is because buyers usually have limited personal experience about the failure of durable goods, and at the point of sale, the only other readily available information source is the sales person whose incentives are to sell the warranty. Second, even if individuals estimate failure probabilities correctly, Prospect Theory proposes that individuals incorporate these probabilities in decision making by using decision weights. In particular, individuals tend to put too much weight on low probability events, like the failure probability of a durable, hence increasing the attractiveness of purchasing a warranty.

Individual heterogeneity is captured by choice shocks, \( \epsilon_{EW} \) and \( \epsilon_{NW} \), that additively affect \( V_{EW} \) and \( V_{NW} \). Assuming these shocks are iid Type I Extreme Value with scale parameter \( \sigma \), we can write the demand for extended warranties \( D(t; r, \omega(\phi), \sigma) \), in a unit mass population as follows:

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

where

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

Moving to the seller, he is a risk-neutral monopolist who prices the warranty to maximize profit taking into account the demand for warranties and the cost of selling and servicing the warranty.

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9This implies that we likely underestimate \( \omega \) and \( r \) because using a higher repair cost makes the purchase of the warranty more attractive even without appealing to risk aversion and probability distortion.

10“...The company selling the warranty has the information on failure rates. You don’t....That’s not easy to find out. Companies aren’t in the habit of telling you that their products fail 4 percent or 12 percent of the time. Failure rates are usually low. Warranty companies know that. And they know, too, that consumers tend to think the failure rate is higher.” ("Should I Buy an Extended Warranty", New York Times, August 28, 2014).

11The utility specification we will use in estimation imposes a specific normalization so we can identify a scale parameter. This scale parameter is the inverse of the marginal utility of income.
This is motivated by consumers’ belief that searching for another main product or buying the extended warranty elsewhere is costly.

Given a product priced at $A$ with a failure probability $\phi$, the seller’s expected marginal cost of selling and servicing the warranty is $c(A, \phi)$. The seller chooses a price $t$ to solve:

$$\max_{t \geq 0} (t - c(A, \phi)) \cdot D(t; r, \omega(\phi), \sigma)$$

This is a standard monopoly pricing problem with the first-order condition:

$$\frac{t - c(A, \phi)}{t} = \frac{1}{|\mathcal{E}(t; r, \omega(\phi), \sigma)|}$$

where $\mathcal{E}(t; r, \omega(\phi), \sigma)$ is the price elasticity of demand for extended warranties.

### 3.1 Identification

The main challenge in identification is separately identifying risk aversion and the probability weighting function given choice data on extended warranty purchases. Choice probabilities can be inverted to get a measure of willingness-to-pay for the warranty and so we focus on how to uniquely get $(r, \omega(\cdot))$ from willingness-to-pay.

Define a consumer by a pair $(r, \omega(\phi))$. The identification question boils down to whether variation in willingness-to-pay allows us to differentiate consumers along the dimensions of $(r, \omega(\phi))$. Our strategy relies on how willingness-to-pay vary with the loss that the consumer faces for different products that have the same failure rate.

Fix the failure rate $\phi$ and let $\omega = \omega(\phi)$. Consider a buyer characterized by $(r, \omega)$ and define her willingness-to-pay for an extended warranty on a good with underlying value $A_1$ as $t(A_1, r, \omega)$, where $t(A_1, r, \omega)$ is the extended warranty price $t$ that solves

$$V_{EW}(t, r) = V_{NW}(A_1, r, \omega).$$

Consider a second buyer $(r', \omega')$ such that $r' \neq r$ (or equivalently $\omega' \neq \omega$) but

$$t(A_1, r', \omega') = t(A_1, r, \omega).$$

We say that $r$ and $\omega$ are separately identified if there exists a second product with the same failure rate but $A_2 \neq A_1$ that satisfies

$$t(A_2, r', \omega') \neq t(A_2, r, \omega).$$

The following property ensures this:

**Property 1 (Single-crossing)** For a utility function $u(\cdot)$, the implied willingness-to-pay $t(\cdot, r, \omega)$
satisfies the single-crossing property if

\[ \frac{\partial h(A, r, \omega)}{\partial r} - \frac{\partial h(A, r, \omega)}{\partial \omega} \]

strictly increases in \( A \).

Figure 1: Identification: Single-crossing of willingness-to-pay

Figure 1 graphically provides the intuition for sufficiency of single-crossing for identification. The curve \( WTP(A_1, \phi) \) is the combination of risk aversion parameters and probability weights that give the same willingness-to-pay for a product with value \( A_1 \). If we only observed \( WTP(A_1, \phi) \), then we cannot separately identify \( r \) and \( \omega \) since infinitely many pairs would rationalize the data. Now, identification requires that if we look at a second good with value \( A_2 \neq A_1 \) but with the same failure rate, then it must be that the willingness-to-pay curve \( WTP(A_2, \phi) \) crosses \( WTP(A_1, \phi) \) only at a single point. We prove in the appendix that single-crossing holds for the Constant Absolute Risk Aversion (CARA) case and for the second order Taylor approximation of any utility function. We use the latter functional form in our estimation.

4 Estimation

Following Cohen and Einav (2007) and Barseghyan et al (2012), we use a second order Taylor approximation of the utility function \( u(\cdot) \) in estimating the model. 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
\[ u(W + \Delta) \approx u(W) + u'(W)\Delta + \frac{u''(W)}{2}\Delta^2. \]

Normalizing by \( u'(W) \) and letting \( r = -u''(W)/u'(W) \), we obtain\(^{12}\)
\[ \frac{u(W + \Delta)}{u'(W)} \approx \frac{u(W)}{u'(W)} + \Delta - \frac{r}{2}\Delta^2. \]

Using this specification to evaluate the difference in utility between purchasing an extended warranty (equation 1), we obtain that:
\[ \Omega_j = \frac{\omega_j A_j - t_j + \frac{r}{2}(\omega_j A_j^2 - t^2)}{\sigma}. \]

Let \( q_j \) be the observed attachment rate for product \( j \). Our choice model implies\(^{13}\)
\[ \log \frac{q_j}{1-q_j} = \Omega_j = \frac{\omega_j A_j - t_j + \frac{r}{2}(\omega_j A_j^2 - t^2)}{\sigma}. \tag{3} \]

The decision weight \( \omega_j \) acts like a (non-additive) product effect. We decompose this effect as follows:
\[ \omega_j = \omega(\phi_j) + \xi_{\text{k}(j)} + \eta_j. \tag{4} \]

where \( \omega(\cdot) \) is some unknown function of \( \phi \), \( \xi_{\text{k}(j)} \) is a subcategory-level effect, and \( \eta_j \) is a random shock. The parameters \( \xi_{\text{k}(j)} \) allow decision weights to vary between subcategories, thus capturing the possibility that consumers may apply different decision weights for TVs of different sizes, different projection technology, etc.

Using equation 3, we can express \( \omega_j \)'s as functions of the unknown parameters \((r, \sigma)\) and the data:
\[ \omega_j = \frac{\sigma \Omega_j + t_j + \frac{r}{2}t_j^2}{A_j + \frac{r}{2}A_j^2}. \tag{5} \]

We construct moment conditions involving \( \omega_j \) to estimate \( r \) and \( \sigma \).\(^{14}\) Once we have these parameters, we calculate \( \omega_j \) using equation 5. Our assumption regarding the error structure in equation 4 implies the following moment condition
\[ E[\omega_j - \omega_{j'}|\phi_j = \phi_{j'}, k(j) = k(j'), A_j, A_{j'}, t_j, t_{j'}] = 0 \]

\(^{12}\)Strictly speaking, the Arrow-Pratt coefficient of risk aversion does not vary with income only for CARA utility.

\(^{13}\)A complication in linking \( \Omega_j \) to product-level attachment rates arises because \( A \) and \( t \) varies at the product level. If we had infinite data, we can compute \( q_j|A,t = \text{Pr}(d_i = 1|j(i) = j, A, t) \) and then invert this equation to get \( \Omega_j \) for each pair \((A, t)\). However, this is not our case. The best we can do is to aggregate across all price pairs \((A, t)\) within each product: \( q_j = \sum_{(A,t)} \text{Pr}(d_i = 1|j(i) = j, A, t) \text{Pr}(A, t|j(i) = j) \) and then use the observed maximum value for \( A \) and minimum value for \( t \).

\(^{14}\)Because of the large variation in prices across categories, we estimate separate scale parameters for each subcategory, and we allow for heteroskedasticity. Specifically we let \( \sigma_k(A) = \sigma_k \sqrt{A} \) for subcategory \( k \).
since \( \omega_j - \omega_{j'} = \eta_j - \eta_{j'} \) for \( j, j' \) such that \( \phi_j = \phi_{j'} \) and \( k(j) = k(j') \). As long as failure rates for any two products \( j \) and \( j' \) belonging in the same subcategory are the same, decision weights associated with extended warranties for these products will be equal, on average.

The last component we need to estimate is the marginal cost of the seller, \( c(A, \phi) \). We assume that \( c(A, \phi) = \mu \phi A \) and estimate the parameter \( \mu \). The parameter \( \mu \) absorbs factors that affect cost such as sales commission, repair cost paid to a third party, the potential effect of moral hazard, etc.

5 Results

5.1 Probability weighting and risk aversion

Figure 2 plots our estimate of the probability weighting function \( \omega(\cdot) \). We include a scatter plot of the estimated product effects \( \omega_j \)'s and a local linear fit. We also include a fit based on the one-parameter Prelec (1998) function,

\[
\omega(\phi) = \exp\left[-(-\log(\phi))^{\alpha}\right]
\]

which is close but slightly less concave than the local linear fit. We estimate \( \alpha = 0.685 \) with bootstrapped standard error equal to 0.097.

Our estimates are in line with Prospect Theory. First, there is substantial overweighting of small probabilities. For example, a product with a 5\% failure rate is perceived as a product with a 12\% failure rate. Second, the degree of overweighting declines as failure rates increase.

Figure 2: Estimated weighting function
We estimate the risk aversion parameter $r$ to be practically zero ($\approx 10^{-5}$ with SE = $5 \times 10^{-3}$). We also estimate a risk aversion parameter under what we refer to as the standard model in which $\omega(\phi) = \phi$. We estimate this parameter to be equal to 0.013 (SE = 0.002).

To interpret our estimates, Table 5 presents the average willingness-to-pay (WTP\textsuperscript{15}) for an extended warranty for a product worth $100 under various failure rates. Columns 2 and 3 present the WTP using the estimated risk aversion parameter from the full model. In column 2, we compute the WTP with our estimated weighting function, and in column 3, we impose $\omega(\phi) = \phi$. Column 4 uses the estimated risk aversion parameter from the standard model in which $\omega(\phi) = \phi$.

Columns 2, 3, and 4 illustrate that in the full model, the contribution of probability distortions is much more significant than that of standard risk aversion. As column 3 shows, willingness-to-pay when there are no probability distortions is equal to the actuarially fair rate. In contrast, the risk aversion parameter in Column 4 that comes from the standard model (i.e. without probability distortions) requires a very high degree of aversion to risk in order to fit the data well. For example, a consumer with this risk aversion parameter will only accept a 50-50 gamble with a loss of $30 if the gain is at least $55.

<table>
<thead>
<tr>
<th>Failure rate</th>
<th>Model est $\omega$</th>
<th>Model est $\omega(\phi) = \phi$</th>
<th>Standard est $\phi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>5.805</td>
<td>1.000</td>
<td>1.621</td>
</tr>
<tr>
<td>0.02</td>
<td>7.844</td>
<td>2.001</td>
<td>3.209</td>
</tr>
<tr>
<td>0.03</td>
<td>9.427</td>
<td>3.001</td>
<td>4.767</td>
</tr>
<tr>
<td>0.04</td>
<td>10.785</td>
<td>4.002</td>
<td>6.297</td>
</tr>
<tr>
<td>0.05</td>
<td>12.003</td>
<td>5.002</td>
<td>7.799</td>
</tr>
<tr>
<td>0.06</td>
<td>13.123</td>
<td>6.003</td>
<td>9.276</td>
</tr>
<tr>
<td>0.07</td>
<td>14.173</td>
<td>7.003</td>
<td>10.728</td>
</tr>
<tr>
<td>0.08</td>
<td>15.166</td>
<td>8.004</td>
<td>12.157</td>
</tr>
<tr>
<td>0.09</td>
<td>16.116</td>
<td>9.004</td>
<td>13.563</td>
</tr>
<tr>
<td>0.10</td>
<td>17.029</td>
<td>10.004</td>
<td>14.949</td>
</tr>
</tbody>
</table>

5.2 Retailer’s cost

Expected marginal cost for an extended warranty for product $j$ is $\mu \phi_j A_j$. We estimate $\mu = 1.622$ (SE = 0.479). This implies a back-of-the-envelope seller’s profit margin of 43%, because an extended warranty is priced at about 20% of the price of the good, and the marginal cost of selling and servicing the warranty is the product of $\mu = 1.623$, the average failure rate 0.07 and the price of the good. Estimates from the popular press indicate that BestBuy transfers about 40% of the price

\textsuperscript{15}The average WTPs are computed by setting the choice shocks, $\epsilon_{EW}$ and $\epsilon_{NW}$, and the shock that enters the weighting function, $\eta_j$, to zero.
of the warranty to the company that handles service, suggesting that BestBuy’s cost of selling the warranty, mostly in the form of sales commission, is about 17%.

5.3 Robustness against different expected loss of the consumer

Our benchmark model uses the upper bound loss $A$ to compute the value of not buying the extended warranty. In table 6, we present the estimates of probability weighting and risk aversion when we allow the expected loss to vary as a fraction of $A$. Clearly, by using the upper bound, we underestimate the extent of the bias since the estimate of the Prelec parameter $\alpha$ decreases as we decrease the loss. The estimate of standard risk aversion only becomes non-negligible once the explanatory power of $\alpha$ is exhausted.

<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>$\approx 10^{-5}$</td>
<td>0.685</td>
<td>0.120</td>
</tr>
<tr>
<td>90%</td>
<td>$\approx 10^{-5}$</td>
<td>0.631</td>
<td>0.135</td>
</tr>
<tr>
<td>80%</td>
<td>$\approx 10^{-5}$</td>
<td>0.567</td>
<td>0.155</td>
</tr>
<tr>
<td>70%</td>
<td>$\approx 10^{-5}$</td>
<td>0.489</td>
<td>0.181</td>
</tr>
<tr>
<td>60%</td>
<td>$\approx 10^{-5}$</td>
<td>0.396</td>
<td>0.213</td>
</tr>
<tr>
<td>50%</td>
<td>$\approx 10^{-5}$</td>
<td>0.284</td>
<td>0.255</td>
</tr>
<tr>
<td>40%</td>
<td>$\approx 10^{-5}$</td>
<td>0.175</td>
<td>0.296</td>
</tr>
<tr>
<td>30%</td>
<td>$\approx 10^{-5}$</td>
<td>0.105</td>
<td>0.326</td>
</tr>
<tr>
<td>20%</td>
<td>$\approx 10^{-5}$</td>
<td>0.071</td>
<td>0.339</td>
</tr>
<tr>
<td>10%</td>
<td>$\approx 10^{-5}$</td>
<td>0.063</td>
<td>0.343</td>
</tr>
</tbody>
</table>

6 Counterfactuals

We are interested in quantifying the profit and welfare implications of probability distortions in the extended warranty market. We thus focus on a counterfactual exercise in which we fix the strategic environment, and study how optimal prices and quantities change when consumers do not exhibit the bias. To the extent that the bias is triggered in part by the store environment or can be alleviated with learning and experience, this exercise gives us quantitative insight on the effectiveness of consumer protection policies, and informational campaigns.

We compare two settings. In the first, we use the estimated weighting function and estimated risk aversion, and in the second we turn off the bias, i.e. set $\omega(\phi) = \phi$ but keep the same risk aversion parameter. In each setting, we construct demand based on these estimates, on the product price $A$, and on the failure rate $\phi$, and derive optimal prices. This gives us two distributions of optimal prices: one for biased consumers and another for unbiased consumers. In calculating optimal prices, we use the risk aversion parameter estimated from the full model and also the one-parameter Prelec (1998) function (i.e. equation 6 with estimated $\alpha = 0.685$) as our weighting function whenever relevant (biased consumers). These numbers depend on the product price $A$ and failure rates.
φ. First, we take the set of observed product prices and failure rates in our data, and generate counterfactual distributions for the extended warranty-to-product price ratio, price-cost margins and fraction insured. Second, we compute the price ratio, price-cost margins, fraction insured and welfare measures for each $\phi \in \{0.01, 0.02, \ldots, 0.15\}$, using the median TV price in our estimating sample ($499.99$).

6.1 Prices and profit margins

Figure 3 plots the density and cdf of the extended warranty price-to-product ratio with and without the bias. Our model (with bias) predicts an average and median ratio of 17.03% and 14.31%, which are slightly below the average and median ratio of 17.66% and 16.67% in the data. Removing the bias shifts the distribution to the left and decreases the mean and median ratios to 15.58% and 12.78%, respectively.

Figure 4 plots the ratios as a function of failure rate. Ratios increase as failure rate increases because marginal cost is increasing in failure rates. The ratio with the bias ranges from about 6.79% to 27.68% and without the bias, from 5.33% to 27.38%. The gap between the two ratios tends to decrease as the failure rate increases because the ratio with the bias increases at a decreasing rate due to the concavity of the weighting function in the relevant region.

Figure 3: Counterfactual: Densities and cdfs of the ratio of EW and TV price
Figure 5 presents the effect of the bias on price-cost margins. With the bias, average and median price-cost margins are 31.47% and 29.86%. The average and median price-cost margins from the data (i.e. computed using our estimate of $\mu$ but with observed prices) are 31.09% and 39.11%. Similar to extended warranty-to-product price ratio, removing the bias shifts the distribution to the left, decreases the mean price-cost margin to 23.63%, and decreases the median to 19.24%. These represent about a 25% and 36% reduction in the average and median price-cost margins.

The left panel of figure 6 plots the price-cost margins with and without the bias for various failure rates. The right panel shows the percent reduction in price-cost margins from removing the bias. With the bias, price-cost margins range from 12.08% to 76.09%, while without the bias, the range is from 11.11% to 69.55%. The percent reduction in price-cost margins has an inverted U-shape which peaks at about a failure rate of 6%. At this failure rate, removing the bias reduces price-cost margins by about 26%.
Figure 5: Counterfactual: Densities and cdfs of price-cost margins

Figure 6: TV price-cost margins
6.2 Quantity

The effect of the bias on the fraction of insured individuals is even more profound. Figure 7 plots the density and cdf of the fraction insured with and without the bias. With the bias, the average and median fraction insured are 38.59% and 41.10%, while the corresponding numbers in the data are 32.42% and 31.58%. Without the bias, the average and median fraction of insured decreases to 6.75% and 5.92%. This reflects an 83% and 86% reduction in the average and median fraction of consumers who buy the extended warranty.

![Figure 7: Counterfactual: Densities and cdfs of fraction insured](image)

6.3 Welfare

When consumers overweight failure probabilities, demand for extended warranties goes up. We assume that the bias is “non-welfare-relevant”\(^{16}\) in the sense that the increase in consumers’ willingness-to-pay for the warranty due to the bias does not reflect a true increase in consumer surplus and so will not be counted in computing welfare. The first best level of insurance is characterized by the intersection of the demand curve of unbiased consumers with the retailer’s marginal cost \( t = \mu \phi A \).

Figure 8 compares the fraction of insured individuals with and without the bias to the first-best fraction insured. Clearly, there is substantial overinsurance with the bias relative to the first-best. On the other hand, there is underinsurance without the bias relative to the first best, which is a

\(^{16}\)We borrow this term from Handel and Kolstad (2014).
consequence of monopoly pricing. The degree of overinsurance is non monotonic in the failure rate, while the degree of underinsurance is decreasing.

Figure 8: Fraction insured

To get a realistic dollar equivalent measure for consumer surplus, profits and total welfare, we assume that there are 30 million potential buyers of TV extended warranties.\footnote{US TV shipments ranged from 37 million to 40 million over 2010 to 2013 \cite{CNN}.}

Consumer surplus increases when the bias is removed. There are two channels for this increase. First, holding the extended warranty price constant, removing the bias shifts the demand curve to the left and reduces the fraction insured. Consumers who now forgo buying the warranty are exactly those who pay more than their unbiased willingness-to-pay, hence increasing consumer surplus. We refer to this as the ripoff effect. Second, since extended warranty prices go down without the bias, additional consumers would now like to buy the warranty, increasing the fraction insured and consumer surplus. We refer to this as the price effect. Figure 9 illustrates these two effects.
Figure 9: Two effects of removing the bias on Consumer Surplus

Figure 10 plots consumer surplus as a function of failure rate for the first best, and with and without the bias. In the first best, consumer surplus ranges from $20 million to $268 million. Without the bias, consumer surplus ranges from $7 million to $95 million and with the bias, it ranges from -$193 million to -$48 million. At the mean failure rate of 7%, removing the bias increases consumer surplus from -$185 million to $34 million, an improvement of $219 million. Decomposing this increase in terms of the two effects, the ripoff effect is $207 million while the price effect is $13 million.
Figure 10 plots profits as a function of failure rates. Profits are zero in the first best while profits range from $7 million to $106 million when there is no bias. When there is bias, profits range from $52 million to $352 million. At the mean failure rate, profits fall from $246 million with the bias, to $36 million without the bias, a decrease of about 85%. Most of the profits when consumers are biased comes from the surplus extracted from consumers who would not have bought the warranty otherwise, i.e. the ripoff effect.
We now turn to the effect of removing the bias on total welfare. The effect depends on whether the quantity insured with the bias, $q^{bias}$, is below or above the first best quantity, $q^{FB}$. Welfare unambiguously decreases when we remove the bias if $q^{FB} \geq q^{bias}$ since the bias actually brings us closer to the first best quantity from below. On the other hand, if $q^{FB} < q^{bias}$, the effect of removing the bias is ambiguous. In this case, one needs to compare the deadweight-loss from overinsurance with the deadweight-loss from underinsurance. Figure 12 illustrates the comparison of deadweight-losses for $q^{FB} < q^{bias}$.
Figure 13 plots total welfare as a function of failure rates. For failure rates below 6%, removing bias decreases welfare by about $0.9 million to $65 million. However for failure rates above 6%, removing the bias increases welfare by about $9 million to $22 million. At the mean failure rate, welfare with the bias is $61 million while without the bias, welfare is $70 million. This reflects an improvement of $9 million from removing the bias, or a 15% increase in welfare. Deadweight-loss due to overinsurance is $111 million while deadweight-loss due to underinsurance is $82 million.
To summarize our welfare analysis, although the effect of the bias on welfare is a priori ambiguous, we do find that policies that can successfully reduce the bias are welfare-enhancing. Moreover, there is overwhelming reason to adopt such policies as the impact of the bias on consumer welfare is substantial.

7 Is there room for intervention?

The counterfactual margin analysis in the previous section quantifies the potential role of consumer protection policy to reduce margins in the extended warranties market. However, efficacy of such an intervention depends on what drives consumer bias in the first place. Is the bias inherent to the decision maker or is it mostly influenced by her external environment, say, due to manipulations or sales tactics implemented by the seller? Is the bias intrinsic and deeply built-in in consumer behavior, or can experience and education about the product decrease the extent of the bias? If the source of bias is external and/or consumers learn, then there is room for well-designed consumer protection policy\textsuperscript{18}.

To gain insight on the source of the bias, we first examine consumer behavior in transactions made online and in the store. We use the full dataset in the succeeding analysis to increase our sample size and range of products. Table\textsuperscript{7} compares raw attachment rates online vs in-store. The in-store attachment rates are close to the overall attachment rate (29%), while online attachment

\textsuperscript{18}Baker and Siegelman (2013) explore some regulatory responses in this market.
Table 7: Online vs In-store extended warranty purchases

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std dev</th>
<th>No obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.287</td>
<td>0.452</td>
<td>44304</td>
</tr>
<tr>
<td>In-store</td>
<td>0.289</td>
<td>0.453</td>
<td>43876</td>
</tr>
<tr>
<td>Online</td>
<td>0.042</td>
<td>0.201</td>
<td>428</td>
</tr>
</tbody>
</table>

Notes: Observation are at the good-hh-trip level

Table 8: Regression of extended warranty purchase on shopping mode

Dependent variable: EW purchase dummy

<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>
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</tr>
<tr>
<td>Year FE</td>
<td>N</td>
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</tr>
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<td>No. HHs</td>
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<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.
Significance level: ***1%, **5%, *10%

rates are significantly lower at 4%. Taken as is, this represents a sevenfold (an increase of about 25 percentage points) nudge to buy extended warranties when in the store. The number of transactions is way lower online than in the store so one might worry that the difference is driven by other factors such as which consumers buy online, what products are bought, etc.

Exploiting the panel data structure of our dataset, we explore various regressions in Table 8 to examine the robustness of the in-store effect on purchases. The first model (I) does not include any controls so it gives the same numbers as table 7. The next 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 of the effect of in-store purchases as we include more fixed effects. Including just a household fixed effects reduces the effect by about 5 percentage points. The reduction in the effect is much larger when including product-related fixed effects. Including all of the fixed effects lead to a reduction in the effect from 25 percentage points to 17. Being in the store leads to a jump in attachment rates from 12% to 29%, which is more than a twofold nudge.

As an additional robustness check, table 9 contains the result of regressing the extended warranty purchase dummy on shopping mode but broken down by product category. The first two columns come from a simple OLS regression without additional controls. The middle two columns include the household characteristics in the data as controls. Finally the last two columns include a household
Table 9: Regression of extended warranty purchase on shopping mode broken down by product category

<table>
<thead>
<tr>
<th>Dependent variable: EW purchase dummy</th>
<th>OLS</th>
<th>se</th>
<th>Obs</th>
<th>OLS with char</th>
<th>se</th>
<th>Obs</th>
<th>FE (HH)</th>
<th>se</th>
</tr>
</thead>
<tbody>
<tr>
<td>Television</td>
<td>0.31*** (0.08)</td>
<td>6307</td>
<td>0.32** (0.14)</td>
<td>2360</td>
<td>0.22 (0.20)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio</td>
<td>0.16*** (0.05)</td>
<td>6450</td>
<td>0.12* (0.07)</td>
<td>2517</td>
<td>0.07 (0.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mobile</td>
<td>0.40* (0.19)</td>
<td>5176</td>
<td>0.37 (0.28)</td>
<td>1883</td>
<td>. .</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P<em>S</em>T</td>
<td>0.23*** (0.06)</td>
<td>3765</td>
<td>0.23*** (0.08)</td>
<td>1519</td>
<td>0.19* (0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imaging</td>
<td>0.36*** (0.07)</td>
<td>3001</td>
<td>0.39*** (0.12)</td>
<td>1197</td>
<td>. .</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Hardware</td>
<td>0.18*** (0.05)</td>
<td>8773</td>
<td>0.09 (0.08)</td>
<td>3471</td>
<td>0.03 (0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Music</td>
<td>0.16* (0.09)</td>
<td>1189</td>
<td>0.20 (0.15)</td>
<td>469</td>
<td>0.30 (0.24)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Video</td>
<td>0.21*** (0.04)</td>
<td>5828</td>
<td>0.22*** (0.07)</td>
<td>2151</td>
<td>0.17* (0.09)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DVS</td>
<td>0.05 (0.23)</td>
<td>1439</td>
<td>0.34 (0.46)</td>
<td>586</td>
<td>0.50* (0.28)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wireless</td>
<td>0.25 (0.18)</td>
<td>1485</td>
<td>0.27 (0.31)</td>
<td>483</td>
<td>0.57** (0.25)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
Significance level: ***1%, **5%, *10%

fixed effect. There is significant variation in the effect of in-store purchases across the product categories but overall, the effect remains large. The effect survives even if we include household characteristics. Although we lose statistical significance once we include household fixed effects due to a small number of observations, the magnitudes are roughly the same across the different regression models.

We now explore how experience with buying extended warranties in the past affects the likelihood of purchasing a warranty in the present. Table 10 contains the results of regressions of extended warranty purchase for a given product on whether an extended warranty was purchased in prior transactions on any other products. Our most preferred specification includes household, subcategory, brand, month and year fixed effects. Our results provide evidence of learning. Experience with extended warranties in the past decreases the likelihood of buying a warranty in the present by 25 percentage points, i.e. attachment rates go down from 29% to just 4%. We also measure experience in terms of the number of extended warranties bought in the past for any other good. We find that buying one extended warranty in the past decreases likelihood of buying an extended warranty today by 7 percentage points.

To conclude, we find that distortions in the online market place are much smaller suggesting that some of the distortion must come from external forces. This finding is consistent with the view that aggressive sales tactics in the store is a major factor driving purchasing behavior and consumer bias. Moreover, we find that experience with extended warranties in the past has a significant impact on the likelihood of purchase in the present, which is a sign of learning about the value of the extended warranty.

19Interestingly, when household fixed effects are not included, we estimate a positive effect of past purchasing behavior on the likelihood of buying today, contrary to learning. This reflects the classic problem of disentangling unobserved persistent heterogeneity and state dependence.
Table 10: Regression of current EW purchase behavior on past EW purchase
Dependent variable: Buy EW today?

<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>Bought EW before?</td>
<td>0.238***</td>
<td>0.235***</td>
<td>-0.253***</td>
<td>-0.253***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td></td>
</tr>
<tr>
<td>No. of EW bought before</td>
<td>-0.068***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>In-store?</td>
<td>0.180***</td>
<td>0.173***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.036)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Subcat &amp; brand FE</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month &amp; Yr FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>No. obs</td>
<td>18811</td>
<td>18811</td>
<td>18811</td>
<td>18811</td>
<td>18811</td>
</tr>
<tr>
<td>(good-hh-trip)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. HHs</td>
<td>7842</td>
<td>7842</td>
<td>7842</td>
<td>7842</td>
<td>7842</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses are clustered at shopping trip level. Dependent variable refers to a given product while “Bought” dummy regressor refers to buying an EW for any product in the past. Model V uses the number of extended warranties bought on any other product before as a regressor. Significance level: ***1%, **5%, *10%

References

[[TBD]]
Appendix

Utility functions that satisfy property \([\star]\) (single-crossing)

The following lemma is a useful extension for determining whether single-crossing holds for a given function. We use it throughout when we show that a given utility function satisfies property \([\star]\).

**Lemma 1** The function \(t(A,r,\omega)\) satisfies the single-crossing property if and only if for any function \(g(\cdot)\) such that \(\frac{dg(t(A,r,\omega))}{dt} \neq 0\),

\[
\begin{align*}
t(A_1, r, \omega) &= t(A_1', r', \omega'), \\
t(A_2, r, \omega) &= t(A_2', r', \omega'),
\end{align*}
\]

for some \(A_1\) and \(A_2\) such that \(A_1 \neq A_2\), then

\[
\frac{-\partial g(t(A,r,\omega))}{\partial \omega} \frac{\partial g(t(A,r,\omega))}{\partial r} = \frac{dg(t(A,r,\omega))}{dt} \frac{dT(A,r,\omega)}{dr} \frac{dT(A,r,\omega)}{d\omega}
\]

is strictly increasing in \(A\) for any transformation \(g(\cdot)\) such that

\[
\begin{align*}
g(t(A_1, r, \omega)) &= g(t(A_1', r', \omega')) \\
g(t(A_2, r, \omega)) &= g(t(A_2', r', \omega'))
\end{align*}
\]

and \(\frac{dg(t(A,r,\omega))}{dt} \neq 0\).

**Proof.** Note:

\[
\begin{align*}
\frac{\partial g(t(A,r,\omega))}{\partial r} &= \frac{dg(t(A,r,\omega))}{dt} \frac{\partial t(A,r,\omega)}{dr} = \frac{\partial t(A,r,\omega)}{dr} \\
\frac{\partial g(t(A,r,\omega))}{\partial \omega} &= \frac{dg(t(A,r,\omega))}{dt} \frac{\partial t(A,r,\omega)}{d\omega} \frac{\partial t(A,r,\omega)}{d\omega} = \frac{\partial t(A,r,\omega)}{d\omega}
\end{align*}
\]

by chain-rule. The rest follows from the single-crossing property.

**CARA utility**

Suppose

\[u(C) = -e^{-rC} .\]

Here, we have

\[
\Omega = V_{EW} - V_{NW} \\
= -e^{-r(W-t)} + \omega e^{-r(W-A)} + (1 - \omega)e^{-rW}.
\]

Willingness-to-pay is given by

\[
t(A, r, \omega) = \frac{\log(\omega e^{rA} + 1 - \omega)}{r} .
\]
Define the transformation
\[ g(t(A,r,\omega)) = \frac{\partial t(A,r,\omega)}{\partial A} \frac{\partial t(A,r,\omega)}{\partial t(A,r,\omega)}. \]  

(8)

Using this transformation and the formula for willingness-to-pay (equation 7), we can compute
\[
\frac{\partial}{\partial A} \left[ \frac{\partial g(t(A,r,\omega))}{\partial \omega} \frac{\partial g(t(A,r,\omega))}{\partial r} \right] = -\frac{r^2 e^{rA}(1 - \omega + \omega e^{rA})}{(1 - \omega)[1 - \omega(1 - e^{rA}(1 - rA))]^2} < 0
\]

and therefore the CARA utility function satisfies property 1 after applying lemma 1.

**Second order Taylor approximation**

For the 2nd order Taylor approximation, willingness-to-pay is given by
\[
t(t(A,r,\omega)) = \frac{1}{r} \left\{ -1 + \left[ 1 + 2r\omega \left( A + \frac{r}{2}A^2 \right) \right]^{1/2} \right\}.
\]

We use the same transformation as in the CARA case (i.e. equation 8). This gives
\[
\frac{\partial}{\partial A} \left[ \frac{\partial g(t(A,r,\omega))}{\partial \omega} \frac{\partial g(t(A,r,\omega))}{\partial r} \right] = -\frac{3 (1 + Ar)^2 (1 + 2Ar\omega + A^2r^2\omega)}{r^2 (1 - \omega)^3} < 0
\]

and thus, property 1 is satisfied after using lemma 1.