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The Cost of Legal Restrictions on Experience Rating

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We investigate the cost of legal restrictions on experience rating in auto and home insurance. The cost is an opportunity cost as experience rating can mitigate the problems associated with unobserved heterogeneity in claim risk, including mispriced coverage and resulting demand distortions. We assess this cost through a counterfactual analysis in which we explore how risk predictions, premiums, and demand in home insurance and two lines of auto insurance would respond to unrestricted multiline experience rating. Using claims data from a large sample of households, we first estimate the variance-covariance matrix of unobserved heterogeneity in claim risk. We then show that conditioning on claims experience leads to material refinements of predicted claim rates. Last, we assess how households' demand for coverage would respond to multiline experience rating. We find that the demand response would be large.

I. Introduction

In many insurance markets, there are variables that affect an insured's claim risk but are not observable by the insurer.[1] In other words, there is unobserved heterogeneity in claim risk. The problem with unobserved heterogeneity in claim risk is that it can lead to mispriced insurance, which in turn can impair the efficient operation of insurance markets, including by distorting the demand for insurance coverage.

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[1]Alternatively, there may be variables that are observable by the insurer but that the insurer is prohibited from using when it underwrites or rates the insured's policy (Salanié 1997; Avraham et al. 2014).

In theory, an insurer can mitigate these problems through experience rating. The logic is straightforward. Even if there is unobserved heterogeneity in claim risk at the time the insurer underwrites and rates an insured's policy, the insurer subsequently receives signals about the insured's latent risk type. In particular, the insurer observes the insured's claims experience. By conditioning on the insured's claims experience, the insurer can refine its initial prediction about the insured's claim risk, which is based solely on observables. The insurer can then use its refined prediction to adjust—or experience rate—the insured's premium to better reflect her true claim risk.[2]

In practice, however, U.S. law frequently imposes restrictions on an insurer's ability to engage in experience rating.[3] An example from federal law is the Affordable Care Act's community rating provisions, which forbid experience rating of premiums for heath insurance coverage offered in the individual or small-group market.[4] A state law example is New York's Insurance Law, which forbids experience rating of premiums for auto comprehensive or home insurance coverage and also prohibits using auto comprehensive claims to experience rate premiums in any other line of insurance coverage.[5]

In this article, we empirically investigate the cost of legal restrictions on experience rating in the context of auto and home insurance. The cost is an opportunity cost. As noted above, experience rating has the potential to mitigate the problems associated with unobserved heterogeneity in claim risk. When the law imposes restrictions on experience rating, insurers lose the opportunity to fully utilize their insureds' claims experience to refine their risk predictions and adjust their premiums to better reflect the true risks. We assess this opportunity cost through a counterfactual analysis in which we explore how risk predictions, premiums, and demand in two lines of auto coverage and one line of home coverage would respond to unrestricted experience rating within and across the three lines of coverage.

Our data comprise an unbalanced panel of 62,425 households that purchased auto and home policies from a single insurance company between 1998 and 2006. Among other things, the data record the number of claims filed by each household in three lines of coverage: auto collision, auto comprehensive, and home all perils. In addition, the data contain detailed information about the households and their auto and home policies.

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[2]Experience rating is not to be confused with classification rating. Under classification rating, an insured's premium is based on the collective loss experience of all insureds in the insured's risk class. Under experience rating, by contrast, an insured's premium is adjusted based on her individual loss experience.

[3]Advocates for legal restrictions on experience rating (and other forms of risk classification) generally rely on arguments from equity (distributional and deontological) (e.g., Abraham 1985; Avraham et al. 2014). For instance, they argue that such restrictions promote access to insurance for high-risk, low-income insureds (e.g., Meier 1991; Thiery & Van Schoubroeck 2006; Thomas 2007; Dionne & Rothschild 2014). That said, many consider efficiency questions as well (e.g., Abraham 1985; Avraham et al. 2014; Dionne & Rothschild 2014; Abraham & Chiappori 2015).

[4]See Patient Protection and Affordable Care Act § 2701, 42 U.S.C. § 300gg (2018).

[5]See N.Y. Ins. Law § 2334 (2018); N.Y. Comp. Codes R. & Regis. tit. 11, §§ 161.8, 169.1 (2018).

Our analysis proceeds in three steps. First, we use the data to estimate the variance-covariance matrix $\boldsymbol{\Sigma}$ of unobserved heterogeneity in claim risk and to generate the households' predicted claim rates based on observables. We model households' claim counts using a Poisson mixture model with correlated random effects. To estimate the model, we take a moments-based approach that uses generalized estimating equations based on marginal moments (Morris 2012). Unlike the standard approach—maximum likelihood estimation of a parametric mixture of Poisson distributions—our estimation approach is semi-parametric and unconstrained with respect to the parameters of the mixing distribution (Pinquet 2013). Among other things, the estimates reveal that unobserved heterogeneity in claim risk is positively correlated across lines of coverage.

Next, we demonstrate the value of the information contained in $\hat{\boldsymbol{\Sigma}}$—and, by implication, the value of the signals provided by the households' claims histories—by showing that conditioning on claims experience leads to material refinements of the households' predicted claim rates. For instance, we find that (1) among households with downward revisions, their predicted claim rates decrease on average by 7 percent in auto collision, 13 percent in auto comprehensive, and 14 percent in home, and (2) among households with upward revisions, their predicted claim rates increase on average by 10 percent in auto collision, 23 percent in auto comprehensive, and 28 percent in home. We also demonstrate the incremental value of conditioning across lines of coverage (in addition to conditioning within lines of coverage).

Finally, we investigate the extent to which the households' demand for coverage, as captured by their deductible choices, would respond to experience rating within and across lines of coverage (i.e., uniline and multiline experience rating). In so doing, we obtain a lower bound on the potential for unpriced heterogeneity in claim risk to distort demand. Our experience rating scheme is a simple bonus-malus system under which changes in premiums are proportional to changes in predicted claim risk. We model households' deductible choices according to standard expected utility theory. After calibrating the model with the risk aversion estimate reported by Barseghyan et al. (2013), we use the model to generate deductible choices for the households in our data assuming first that premiums are not experience rated and then that they are experience rated. We find that there would be large responses to experience rating. In particular, we find that the fraction of households that would change deductibles if premiums were experience rated is 7 percent in auto collision, 21 percent in auto comprehensive, and 15 percent in home, resulting in average changes in coverage of $247, $178, and $347, respectively, among policies with a change.

The article proceeds as follows. Section II discusses the related literature. Section III describes our data. Section IV presents the model and explains our estimation approach. Sections V–VII contain the three steps of our analysis. Section VIII offers concluding remarks.

II. Related Literature

The article contributes to two literatures. The first is the literature on experience rating in insurance markets. For surveys, see, for example, Pinquet (2000, 2013) and

Antonio and Valdez (2012).[6] Most closely related are the handful of papers on multiline experience rating, beginning with Jewell (1974). For example, Pinquet (1998) studies experience rating across auto claims at fault and not at fault; Desjardins et al. (2001) and Angers et al. (2006) study experience rating for fleets of vehicles; Frees (2003) studies experience rating across multiple lines within auto insurance; Englund et al. (2008, 2009) study experience rating across various types of commercial coverage; Frees et al. (2010) study experience rating across multiple perils within home insurance; and Antonio et al. (2011) study experience rating across multiple auto insurance policies. There are two main differences between these papers and ours. First, we study experience rating across home insurance (all perils) and two lines of auto insurance (collision and comprehensive).[7] Second, and more importantly, we also study the effects of multiline experience rating on the demand for coverage. This underscores a key difference in focus. Whereas these studies focus on the actuarial science of experience rating, we focus on the economics of legal restrictions on experience rating.

The second related literature is the empirical literature on the regulation of insurance markets, and in particular the strand that seeks to quantify the economic effects of legal restrictions on risk classification by insurers. For example, Buchmueller and DiNardo (2002), Simon (2005), and Bundorf and Simon (2006) study the effects of community rating in U.S. health insurance markets; Finkelstein et al. (2009) study the effects of a ban on gender-based pricing in the U.K. annuity market; and Bundorf et al. (2012) and Geruso (2017) study the effects of uniform contribution requirements in the U.S. employer-provided health insurance market.[8] Again, there are the two main differences between these papers and ours. First, we study regulation of the U.S. auto and home insurance markets. Second, whereas these papers study the effects of restrictions on ex ante risk classification (i.e., classification rating), we study the effects of restrictions on ex post risk classification (i.e., experience rating).

III. Description of the Data

The source of the data is a large U.S. property and casualty insurance company. The company offers auto and home insurance. The full dataset includes annual information on more than 400,000 households that purchased auto or home policies from the company

[6]For textbook treatments, see Lemaire (1995), Bühlmann and Gisler (2005), and Denuit et al. (2007).

[7]Thuring (2011) and Thuring et al. (2012) study auto and home insurance but with a focus on cross-selling.

[8]Though it is not their focus, Einav et al. (2010) also consider the effects of legal restrictions on risk classification in the U.S. employer-provided health insurance market. There also is a rich theoretical literature on insurance regulation and the social welfare implications of legal restrictions on risk classification (e.g., Hoy 1982, 2006; Crocker & Snow 1986, 2011; Thomas 2008; Rothschild 2011).

between 1998 and 2006. All the policies in the data are governed by New York law.[9] The data contain all the information in the company's records regarding the households and their policies. In addition, the data record the number of claims that each household filed with the company under each of its policies during the period of observation.

We focus our attention on three lines of coverage: auto collision, auto comprehensive, and home all perils. Auto collision coverage pays for damage to the insured vehicle caused by a collision with another vehicle or object, without regard to fault. Auto comprehensive coverage pays for damage to the insured vehicle from all other causes (e.g., theft, fire, flood, windstorm, glass breakage, vandalism, hitting or being hit by an animal or by falling or flying objects), without regard to fault. Home all perils coverage pays for damage to the insured home from all causes (e.g., fire, windstorm, hail, tornadoes, vandalism, or smoke damage), except those that are specifically excluded (e.g., flood, earthquake, or war). For simplicity, we often refer to home all perils merely as home.

In most of the analysis, we consider an unbalanced panel of 62,425 households that purchased all three coverages (auto collision, auto comprehensive, and home) in one or more years between 1998 and 2006. In all, this tricoverage sample comprises 294,917 household-years. Table A1 in the Appendix provides descriptive statistics for the tricoverage sample. Tables A2, A3, and A4 in the Appendix summarize the claims, premiums, and deductibles in the tricoverage sample. The mean number of claims per household-year is 0.107 in auto collision, 0.032 in auto comprehensive, and 0.079 in home.[10] On average, households paid annual premiums of $200 in auto collision, $127 in auto comprehensive, and $548 in home. The mean deductibles per household-year are $396, $273, and $350 in auto collision, auto comprehensive, and home, respectively. The modal deductibles are $500 in auto collision, $200 in auto comprehensive, and $250 in home.

IV. Model and Estimation Approach

A standard regression model for longitudinal univariate count data is the Poisson random effects model. We extend this model to multivariate count data—here, claim counts under three types of insurance coverage—by allowing for correlated random effects.[11]

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[9]As noted above, New York forbids experience rating of premiums for auto comprehensive or home insurance coverage and also prohibits using auto comprehensive claims to experience rate premiums in any other line of insurance coverage. See N.Y. Ins. Law § 2334 (2018); N.Y. Comp. Codes R. & Regis. tit. 11, §§ 161.8, 169.1 (2018).

[10]In the data, we observe the frequency of claims but not their severity. Hence, we focus on and define claim risk in terms of claim frequency. In our model of deductible choice, we assume that the loss associated with every claim exceeds the maximum deductible option; see Section VII.

[11]By allowing for random effects, our model accounts for overdispersion, including due to excess zeros, in a similar way as the (pooled) negative binomial model (see, e.g., Wooldridge 2002:Ch. 19). An alternative approach would be a zero-inflated model. However, Vuong (1989) and likelihood ratio tests select the negative binomial model over the zero-inflated model, suggesting that adjustment for excess zeros is not necessary once we allow for random effects.

Let y_{itk} denote the number of claims for household i in year t under coverage k, where $i = 1, ..., N$, $t = 1, ..., T_i$, and $k \in \{c, m, h\}$. In the set of coverages, c denotes auto collision, m denotes auto comprehensive, and h denotes home. Similarly, let $\mathbf{x}_{itk}$ denote a vector of observables (plus a constant) for household i in year t under coverage k.[12] Let λ_{itk} denote household i's baseline claim rate in year t under coverage k, and let ϵ_{ik} denote a time-constant random effect for household i under coverage k. Both λ_{itk} and ϵ_{ik} are unobserved.

We assume that claims for household i in year t under coverage k follow a Poisson arrival process with rate $\lambda_{itk}\epsilon_{ik}$. Specifically, we assume:

$$y_{itk} \mid \mathbf{x}_{itk} \sim Poisson(\lambda_{itk}\epsilon_{ik}),$$

where

$$\lambda_{itk} = \exp(\mathbf{x}'_{itk}\boldsymbol{\beta}_k)$$

and $\boldsymbol{\epsilon}_i \equiv [\epsilon_{ic}\ \epsilon_{im}\ \epsilon_{ih}]'$ is iid with $E(\boldsymbol{\epsilon}_i) = [1\ 1\ 1]'$ and $V(\boldsymbol{\epsilon}_i) = \boldsymbol{\Sigma}$.

The parameters to be estimated are:

$$\boldsymbol{\beta} \equiv \begin{bmatrix} \boldsymbol{\beta}_c \\ \boldsymbol{\beta}_m \\ \boldsymbol{\beta}_h \end{bmatrix} \quad \text{and} \quad \boldsymbol{\Sigma} \equiv \begin{bmatrix} \sigma_c^2 & \rho_{mc}\sigma_m\sigma_c & \rho_{hc}\sigma_h\sigma_c \\ \rho_{cm}\sigma_c\sigma_m & \sigma_m^2 & \rho_{hm}\sigma_h\sigma_m \\ \rho_{ch}\sigma_c\sigma_h & \rho_{mh}\sigma_m\sigma_h & \sigma_h^2 \end{bmatrix}.$$

Of principal interest is the variance-covariance matrix, $\boldsymbol{\Sigma}$, which captures both the within-coverage variance of unobserved heterogeneity in claim risk, $\boldsymbol{\sigma}^2 \equiv (\sigma_c^2, \sigma_m^2, \sigma_h^2)$, and its cross-coverage correlation structure, $\boldsymbol{\rho} \equiv (\rho_{cm}, \rho_{ch}, \rho_{mh})$.

The likelihood function may be written as:

$$\mathcal{L}_i = \int_{\epsilon_{ih}} \int_{\epsilon_{im}} \int_{\epsilon_{ic}} \left\{ \prod_k \prod_t \exp(-\lambda_{itk}\epsilon_{ik}) \frac{(\lambda_{itk}\epsilon_{ik})^{y_{itk}}}{y_{itk}!} \right\} f(\epsilon_{ic}, \epsilon_{im}, \epsilon_{ih})\, d\epsilon_{ic}\, d\epsilon_{im}\, d\epsilon_{ih},$$

where $f(\epsilon_{ic}, \epsilon_{im}, \epsilon_{ih})$ is the trivariate density of $\boldsymbol{\epsilon}_i$. A standard parametric approach is to specify f and estimate the model by maximum likelihood. Typical specifications of f include the lognormal distribution and the gamma distribution (in which case $\mathcal{L}_i$ reduces to the product of negative binomial densities). In our case, however, the standard approach is computationally intractable. The likelihood function not only involves a multidimensional integral, but, depending on f, it also may not have a closed-form expression.

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[12]The variables that comprise $\mathbf{x}_{itk}$ are listed in Tables A5 (auto) and A6 (home) in the Appendix. In auto, they include the age, gender, and insurance score (which is based on information contained in credit reports) of the primary driver, the age and gender of each additional driver, and the age, use, location, and safety features of each vehicle. In home, they include the insurance score of the primary owner, the age, value, use, location, type of construction, and safety features of the dwelling, whether the dwelling is owner occupied, and the number of families that occupy the dwelling.

We adopt a semi-parametric, moments-based approach, which provides a computationally tractable method for consistent estimation of $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$ for all possible densities f. Under this approach, estimation is via generalized estimating equations (GEE) based on marginal moments.[13] Given the assumptions of our model, we can derive the first and second marginal moments and use them to construct estimating equations for $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$. More specifically, we use the first marginal moment to define a quasi-score equation, where the associated estimating equation for $\boldsymbol{\beta}$ is based on a weighted least squares estimator with the weight matrix defined by the covariance structure derived from the second marginal moment. The estimating equation for $\boldsymbol{\Sigma}$ is based on the relation between the empirical variance estimate and the model-defined covariance structure. The two estimating equations are solved iteratively to obtain $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\Sigma}}$. For further details about the estimation approach, see the Appendix.[14]

V. Estimation Results

V.A. Regression Estimates

Table 1 presents the estimates of the association parameters, $\boldsymbol{\sigma}^2$ and $\boldsymbol{\rho}$, implied by $\hat{\boldsymbol{\Sigma}}$. The estimates reveal that the variance of unobserved heterogeneity is lowest in auto collision ($\hat{\sigma}_c^2 = 0.11$) and is roughly four times higher in auto comprehensive ($\hat{\sigma}_m^2 = 0.40$) and home ($\hat{\sigma}_h^2 = 0.41$). More importantly, the estimates also reveal that unobserved heterogeneity is correlated across coverages—each pairwise correlation is positive and statistically significant. Perhaps not surprisingly, the strongest correlation is between auto collision and auto comprehensive ($\hat{\rho}_{cm} = 0.66$). There is also a fairly strong correlation between auto comprehensive and home ($\hat{\rho}_{mh} = 0.56$). The weakest correlation is between auto collision and home ($\hat{\rho}_{ch} = 0.29$). Even this correlation, however, is economically significant, as we demonstrate in Sections VI and VII.

Our primary interest in these correlations is their instrumental value in terms of predicting claim risk and experience rating, which we explore in Sections VI and VII. However, they are also interesting in their own right because they suggest that, even after controlling for observable characteristics, there exists a latent, domain-general component to risk type. We elaborate on this point in our concluding discussion in Section VIII.

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[13]GEE were introduced by Liang and Zeger and co-authors in the 1980s (see, e.g., Liang & Zeger 1986; Zeger & Liang 1986; Zeger et al. 1988). For a textbook treatment of GEE, see, e.g., Ziegler (2011).

[14]See also Morris (2012) and Pinquet (2013). This approach is an extension of quasi-generalized pseudo maximum likelihood (QGPML) estimators developed by Gouriéroux et al. (1984a, 1984b) and the extended GEE approach developed by Prentice (1988). The QGPML method can be characterized as first-order GEE with a specific association structure. Prentice introduced an extension of first-order GEE that utilizes a second set of estimating equations to jointly estimate the association parameters. QGPML can be embedded in the GEE framework, resulting in commonly studied consistency and asymptotic results for simultaneous inference on both the regression parameters and the association parameters.

Table 1: Association Parameter Estimates – Tricoverage Sample (294,917 household-years)

	Estimate	*95 percent confidence interval*	
Variances:			
Auto collision	0.107	0.065	0.149
Auto comprehensive	0.399	0.221	0.577
Home	0.405	0.383	0.428
Covariances:			
Auto collision and auto comprehensive	0.137	0.101	0.173
Auto collision and home	0.061	0.022	0.099
Auto comprehensive and home	0.225	0.179	0.271
Correlations:			
Auto collision and auto comprehensive	0.663	0.399	0.926
Auto collision and home	0.293	0.099	0.486
Auto comprehensive and home	0.559	0.389	0.729

The estimates of the regression parameters, $\boldsymbol{\beta}$, are reported in Tables A5 (auto) and A6 (home) in the Appendix. Because $\boldsymbol{\beta}$ is not the object of primary interest, we relegate our comments about the regression parameter estimates to the Appendix as well.

V.B. Robustness Checks

Alternative Samples

As a check of the sensitivity of the association parameter estimates to our sample restrictions, we reestimate the model on two alternative samples of the data: (1) a balanced panel of 8,731 households (78,579 household-years) that purchased all three coverages (auto collision, auto comprehensive, and home); and (2) an unbalanced panel of 203,731 households (1,019,170 household-years) that purchased both auto coverages (collision and comprehensive). The association parameter estimates for both alternative samples are reported in Table A7 in the Appendix.[15] They are largely consistent with the estimates for the tricoverage sample. If anything, they suggest that our baseline estimates are conservative.

Moral Hazard

Our approach implicitly assumes that a household's claim risk is not a function of its choice of deductible. That is, we assume households do not suffer from moral hazard. In

[15]To ease the computational burden of the reestimations, we obtain estimates of the regression parameters from a generalized linear model (GLM) assuming the random effects follow a lognormal distribution. In the tricoverage sample, the semi-parametric and GLM estimates for $\boldsymbol{\beta}$ are nearly identical ($R^2 = 0.9998$). Thus, we are confident that using the GLM estimates for $\boldsymbol{\beta}$ does not corrupt the semi-parametric estimates of the association parameters in the reestimations.

particular, we assume there is neither ex ante moral hazard (deductible choice does not influence the frequency of claimable events) nor ex post moral hazard (deductible choice does not influence the decision to file a claim). The empirical evidence on moral hazard in auto insurance markets is mixed (Cohen & Siegelman 2010), and we are not aware of any empirical evidence on moral hazard in home insurance markets. Because deductibles are small relative to the overall level of coverage, it seems reasonable to assume there is no ex ante moral hazard. However, because the damage from a claimable event may occasionally be less than the chosen deductible (at least for "high deductible" households), it may be less reasonable to assume there is no ex post moral hazard. As a check of the sensitivity of the association parameter estimates to our assumption on moral hazard, we reestimate the model separately for "low deductible" and "high deductible" households. We define a household as "low deductible" if none of its deductibles is greater than $250. Conversely, we define a household as "high deductible" if at least one of its deductibles is greater than $250. Table A8 in the Appendix reports the association parameter estimates for low and high deductible households.[16] They are largely consistent with each other and with the estimates for the tricoverage sample, suggesting that moral hazard is not an issue.[17]

VI. Signaling Value of Claims Experience

In this section, we demonstrate the value of the information contained in the estimated variance-covariance matrix $\hat{\boldsymbol{\Sigma}}$—and, by implication, the signaling value of the households' claims histories—by showing that conditioning on claims experience leads to material refinements of the predicted claim rates in the tricoverage sample. We also demonstrate the incremental value of utilizing the information on the cross-coverage correlation structure of unobserved heterogeneity ($\boldsymbol{\rho}$), as opposed to utilizing only the information on the within-coverage variance of unobserved heterogeneity ($\boldsymbol{\sigma}^2$), by showing that conditioning across lines of coverage (in addition to conditioning within lines of coverage) leads to material incremental refinements of the predicted claim rates.

Throughout this section and beyond, we distinguish among three types of predicted claim rates. The first are *prior claim rates*, $\hat{\lambda}_{itk} \equiv \exp\left(\mathbf{x}'_{itk}\hat{\boldsymbol{\beta}}_k\right)$. These are a priori predicted claim rates based on ex ante observables. The second are *uniline posterior claim rates*, $\hat{\vartheta}_{itk} \equiv \hat{\lambda}_{itk} E^{UL}\left(\epsilon_{ik}|\mathbf{y}_{ik}\right)$ for each coverage $k \in \{c, m, h\}$, where $\mathbf{y}_{ik} \equiv \left(y_{i1k}, ..., y_{iT_ik}\right)$ and $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ is calculated assuming $\epsilon_{ik} \overset{iid}{\sim}$ *lognormal* with $E(\epsilon_{ik}) = 1$ and $V(\epsilon_{ik}) = \hat{\sigma}_k^2$. These are

[16]As before, the reestimations use GLM estimates of the regression parameters assuming the random effects follow a lognormal distribution.

[17]Our test of moral hazard is also a test of adverse selection, as adverse selection also implies a correlation between deductible choice and claim frequency (Chiappori & Salanié 2000). Accordingly, the results reported in Table A8 in the Appendix also suggest that our estimates are robust to the possibility of adverse selection.

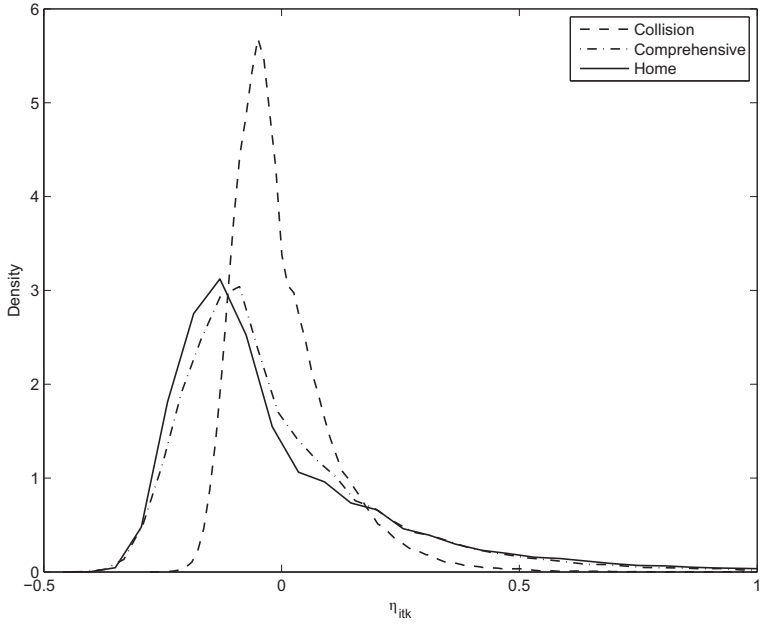
a posteriori predicted claim rates conditional on within-coverage ex post claims experience. The third are *multiline posterior claim rates*, $\hat{\theta}_{itk} \equiv \hat{\lambda}_{itk} E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$, where $\mathbf{y}_i \equiv (\mathbf{y}_{ic}, \mathbf{y}_{im}, \mathbf{y}_{ih})$ and $E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$ is calculated assuming $\boldsymbol{\epsilon}_i \equiv [\epsilon_{ic}\ \epsilon_{im}\ \epsilon_{ih}]' \overset{iid}{\sim}$ *lognormal* with $E(\boldsymbol{\epsilon}_i) = [1\ 1\ 1]'$ and $V(\boldsymbol{\epsilon}_i) = \hat{\boldsymbol{\Sigma}}$. These are a posteriori predicted claim rates conditional on ex post claims experience both within and across lines of coverage. The derivations of $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ and $E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$ are set forth in the Appendix.

Our approach to updating the prior claim rates accords with standard Bayesian credibility theory. In actuarial parlance, *credibility* refers to statistical methods that combine individual and class estimates of the *risk premium* (i.e., the expected number of claims). *Bayesian credibility* refers to credibility approaches that utilize Bayes's theorem. The *Bayesian credibility premium* is the a priori predicted claim rate (the class estimate) multiplied by an a posteriori correction—also known as a bonus-malus coefficient—that reflects idiosyncratic claim risk (the individual estimate). In particular, $\hat{\vartheta}_{itk} \equiv \hat{\lambda}_{itk} E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ corresponds to the textbook Bayesian credibility premium—where $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ is the bonus-malus coefficient—for the single-line Poisson-lognormal credibility model, and $\hat{\theta}_{itk} \equiv \hat{\lambda}_{itk} E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$ is the extension to the multiple-line case. A noteworthy property of the Bayesian credibility approach is that it is balanced: $E(E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})) = 1$ and $E(E^{ML}(\epsilon_{ik}|\mathbf{y}_i))) = 1$ for each coverage $k \in \{c, m, h\}$, so the bonus-malus corrections average to unity. For more on Bayesian credibility theory, see generally, for example, Denuit et al. (2007:Ch. 3).

To demonstrate that conditioning on claims experience leads to material refinements of the predicted claim rates, we compare the empirical distribution of the prior claim rates, $\hat{\lambda}_{itk}$, with that of the multiline posterior claim rates, $\hat{\theta}_{itk}$. Figure 1 plots, for each coverage k, the kernel density of $\eta_{itk} \equiv (\hat{\theta}_{itk} - \hat{\lambda}_{itk})/\hat{\lambda}_{itk}$. Further details are set forth in Table 2. For households with negative values of η_{itk}, the mean value of η_{itk} is −7 percent in auto collision, −13 percent in auto comprehensive, and −14 percent in home. For a quarter of these households, η_{itk} is less than −9 percent in auto collision, −19 percent in auto comprehensive, and −20 percent in home. For a tenth, η_{itk} is less than −12 percent in auto collision and −24 percent in both auto comprehensive and home. The numbers are even more striking for households with positive values of η_{itk}. For these households, the mean value of η_{itk} is +10 percent in auto collision, +23 percent in auto comprehensive, and +28 percent in home. For a quarter of these households, η_{itk} exceeds +14 percent in auto collision, +31 percent in auto comprehensive, and +37 percent in home. For a tenth, η_{itk} exceeds +23 percent in auto collision, +53 percent in auto comprehensive, and +65 percent in home. The numbers are similar for households with low, medium, and high prior claim rates,[18] suggesting that the value of the information in $\hat{\boldsymbol{\Sigma}}$ is robust to differences in baseline claim risk.

[18]A prior claim rate is "low" when it is in the bottom quartile and "high" when it is in the top quartile. It is "medium" otherwise. In the tricoverage sample, the respective low and high cutoffs are 0.078 and 0.127 in auto collision, 0.016 and 0.044 in auto comprehensive, and 0.054 and 0.096 in home.

Figure 1: Kernel density of η_{itk}.



To show the incremental value of conditioning across lines of coverage, we compare the empirical distribution of the multiline posterior claim rates, $\hat{\theta}_{itk}$, with that of the uniline posterior claim rates, $\hat{\vartheta}_{itk}$. Figure 2 plots, for each coverage k, the kernel density of $\zeta_{itk} \equiv (\hat{\theta}_{itk} - \hat{\vartheta}_{itk})/\hat{\vartheta}_{itk}$. Further details are set forth in Table 3. For households with negative values of ζ_{itk}, the mean value of ζ_{itk} is −3 percent in auto collision, −10 percent in auto comprehensive, and − 4 percent in home, and for a tenth ζ_{itk} is less than −6 percent in auto collision, −17 percent in auto comprehensive, and − 8 percent in home. Again, the numbers are more striking for households with positive values of η_{itk}. For these households, the mean value of ζ_{itk} is +7 percent in auto collision, +16 percent in auto comprehensive, and + 9 percent in home, and for a tenth ζ_{itk} exceeds +15 percent in auto collision, +36 percent in auto comprehensive, and + 21 percent in home. As before, the numbers are similar for households with low, medium, and high prior claim rates, suggesting that the incremental value of the information in $\hat{\boldsymbol{\rho}}$ is robust to duifferences in baseline claim risk.

VII. Experience Rating and Deductible Choices

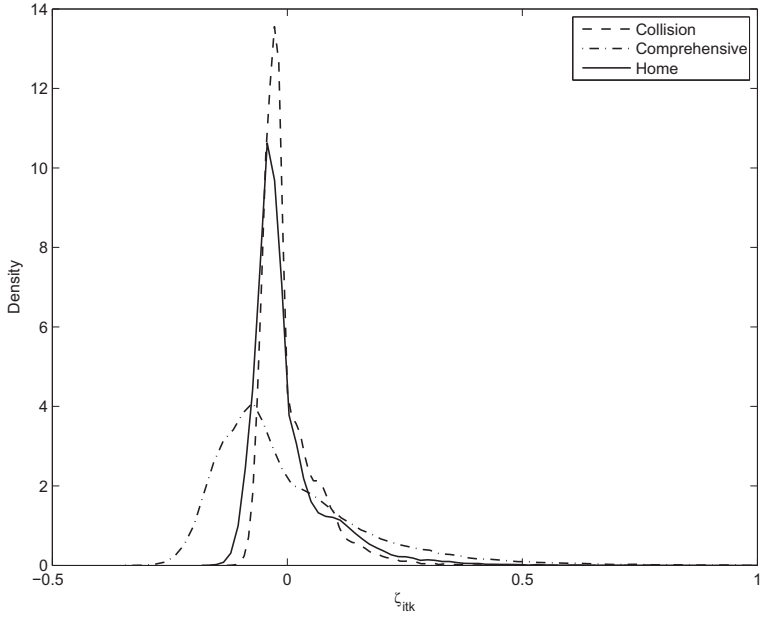
The previous section demonstrates the signaling value of the households' claims experience. In this section, we investigate the extent to which the households' demand for

Table 2: Descriptive Statistics for $\eta = (\theta-\lambda)/\lambda$ – Tricoverage Sample (294,917 household-years)

Coverage	Prior claim rates	$\eta < 0$ Obs	Mean	10th percentile	25th percentile	$\eta > 0$ Obs	Mean	75th percentile	90th percentile
Auto collision	All	180,909	−0.066	−0.121	−0.093	114,008	0.101	0.140	0.227
	Low	46,914	−0.055	−0.100	−0.080	26,815	0.094	0.129	0.213
	Medium	89,988	−0.066	−0.120	−0.094	57,471	0.100	0.139	0.223
	High	44,007	−0.078	−0.143	−0.110	29,722	0.110	0.152	0.249
Auto comprehensive	All	188,792	−0.132	−0.236	−0.186	106,125	0.231	0.310	0.531
	Low	47,384	−0.111	−0.198	−0.157	26,345	0.198	0.270	0.455
	Medium	94,742	−0.131	−0.233	−0.186	52,717	0.231	0.307	0.533
	High	46,666	−0.155	−0.273	−0.220	27,063	0.264	0.353	0.593
Home	All	196,205	−0.142	−0.241	−0.198	98,712	0.280	0.367	0.646
	Low	51,136	−0.120	−0.207	−0.166	22,593	0.273	0.350	0.630
	Medium	97,208	−0.146	−0.238	−0.200	50,251	0.277	0.365	0.642
	High	47,861	−0.159	−0.271	−0.227	25,868	0.292	0.390	0.663

Notes: A prior claim rate is "low" if it is in the bottom quartile and "high" if it is in the top quartile. It is "medium" otherwise. In the tricoverage sample, the respective low and high cutoffs are 0.078 and 0.127 in auto collision, 0.016 and 0.044 in auto comprehensive, and 0.054 and 0.096 in home.

Figure 2: Kernel density of ζ_{itk}.



insurance coverage, as captured by their deductible choices, would respond to experience rating. As noted above, this yields a lower bound on the potential for unpriced heterogeneity to distort their demand for insurance coverage, which in turn sheds light on the potential for experience rating to reduce market inefficiency due to unobserved heterogeneity in claim risk.

VII.A. Experience Rating

In each coverage, the company uses the same basic procedure to generate a household's pricing menu of premium-deductible combinations. The company first determines a household's base price $\bar{p}$ according to a coverage-specific rating function, which takes into account the household's coverage-relevant characteristics and any applicable discounts. Using the base price, the company then generates the household's pricing menu $\mathcal{M} = \{(p(d), d) : d \in \mathcal{D}\}$, which associates a premium $p(d)$ with each deductible d in the coverage-specific set of deductible options $\mathcal{D}$, according to a coverage-specific multiplication rule, $p(d) = (g(d) \cdot \bar{p}) + \delta$, where $g(\cdot)$ is a decreasing positive function and $\delta > 0$. The multiplicative factors $\{g(d) : d \in \mathcal{D}\}$ are known as the deductible factors and δ is a small markup known as the expense fee. The deductible factors and the expense fee are coverage specific but household invariant.

Table 3: Descriptive Statistics for $\zeta = (\theta - \vartheta)/\vartheta$ – Tricoverage Sample (294,917 household-years)

Coverage	*Prior claim rates*	$\zeta < 0$				$\zeta > 0$			
		Obs	*Mean*	*10th percentile*	*25th percentile*	*Obs*	*Mean*	*75th percentile*	*90th percentile*
Auto collision	All	198,557	−0.034	−0.059	−0.046	96,360	0.069	0.093	0.153
	Low	51,883	−0.030	−0.052	−0.041	21,846	0.067	0.092	0.148
	Medium	99,078	−0.034	−0.059	−0.047	48,381	0.069	0.093	0.153
	High	47,596	−0.038	−0.065	−0.052	26,133	0.070	0.095	0.157
Auto comprehensive	All	183,662	−0.098	−0.173	−0.139	111,255	0.157	0.217	0.357
	Low	46,521	−0.095	−0.171	−0.135	27,208	0.163	0.224	0.370
	Medium	91,981	−0.099	−0.175	−0.140	55,478	0.159	0.220	0.359
	High	45,160	−0.098	−0.173	−0.139	28,569	0.149	0.207	0.334
Home	All	202,137	−0.044	−0.079	−0.059	92,780	0.093	0.132	0.211
	Low	51,610	−0.040	−0.074	−0.055	22,119	0.093	0.135	0.213
	Medium	101,001	−0.046	−0.082	−0.062	46,458	0.095	0.134	0.214
	High	49,526	−0.044	−0.080	−0.059	24,203	0.090	0.126	0.203

Notes: A prior claim rate is "low" if it is in the bottom quartile and "high" if it is in the top quartile. It is "medium" otherwise. In the tricoverage sample, the respective low and high cutoffs are 0.078 and 0.127 in auto collision, 0.016 and 0.044 in auto comprehensive, and 0.054 and 0.096 in home.

We assume that the company's experience rating scheme is a simple bonus-malus system under which base prices are adjusted in proportion to changes in predicted claim risk. Let $\bar{p}_{ik}^{UL}$ denote household i's experience-rated base price in coverage k in the case of uniline experience rating (i.e., when premiums are experience rated only within coverages), and let $\bar{p}_{ik}^{ML}$ denote household i's experience-rated base price in coverage k in the case of multiline experience rating (i.e., when premiums are experience rated both within and across coverages). We assume that:

$$\bar{p}_{ik}^{UL} = \frac{\hat{\vartheta}_{ik}}{\hat{\lambda}_{ik}} \times \bar{p}_{ik} \quad \text{and} \quad \bar{p}_{ik}^{ML} = \frac{\hat{\theta}_{ik}}{\hat{\lambda}_{ik}} \times \bar{p}_{ik},$$

where $\hat{\lambda}_{ik}$, $\hat{\vartheta}_{ik}$, and $\hat{\theta}_{ik}$ denote household i's prior claim rate, uniline posterior claim rate, and multiline posterior claim rate, respectively, in coverage k. Recall that $\hat{\vartheta}_{ik} = \hat{\lambda}_{ik} E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ and $\hat{\theta}_{ik} = \hat{\lambda}_{ik} E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$. Hence:

$$\bar{p}_{ik}^{UL} = E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik}) \times \bar{p}_{ik} \quad \text{and} \quad \bar{p}_{ik}^{ML} = E^{ML}(\epsilon_{ik}|\mathbf{y}_i) \times \bar{p}_{ik},$$

where $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ and $E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$ are the bonus-malus coefficients in the single-line and multiple-line Poisson-lognormal credibility models, respectively (see, e.g., Denuit et al. 2007:Ch. 3; Pinquet 2013). Table 4 summarizes the uniline and multiline bonus-malus coefficients. Note that the uniline and multiline experience rating schemes are balanced in that the bonus-malus coefficients average to unity in each coverage.

VII.B. Deductible Choices

We proceed in two steps to investigate how households' deductible choices would respond to experience rating. First, we assume that households make deductible choices according to standard expected utility theory. Second, we investigate how deductible choices would

Table 4: Summary of Bonus-Malus Coefficients – Tricoverage Sample (294,917 household-years)

	Uniline			*Multiline*		
	Coll	*Comp*	*Home*	*Coll*	*Comp*	*Home*
Mean	1.00	1.00	1.00	1.00	1.00	1.00
Standard deviation	0.08	0.17	0.26	0.11	0.24	0.27
5th percentile	0.91	0.86	0.79	0.87	0.75	0.75
10th percentile	0.92	0.89	0.81	0.89	0.78	0.78
25th percentile	0.94	0.92	0.85	0.93	0.85	0.83
Median	0.97	0.96	0.91	0.97	0.93	0.91
75th percentile	1.04	0.98	1.08	1.05	1.08	1.08
90th percentile	1.11	1.23	1.29	1.14	1.28	1.32
95th percentile	1.16	1.32	1.50	1.20	1.45	1.53

change when we move from prior premiums to uniline premiums and multiline premiums.[19]

A Model of Deductible Choice

A household i faces a menu of premium-deductible pairs $\{(p_i(d), d) : d \in \mathcal{D}\}$. The household experiences at most one claim during the policy period, and it believes the probability of experiencing a claim is μ_i. In the event of a claim, the loss exceeds the maximum deductible option and payment of the deductible is the only cost associated with the claim. Under these assumptions, the household's choice of deductible involves a choice among lotteries of the form $L_i(d) \equiv (-p_i(d), 1-\mu_i; -p_i(d) - d, \mu_i)$.

Under the standard expected utility model, the utility of lottery $L_i(d)$ is given by:

$$U_i(L_i(d)) = (1 - \mu_i)u_i(w_i - p_i(d)) + \mu_i u_i(w_i - p_i(d) - d), \tag{1}$$

where $u_i(\cdot)$ is the household's Bernoulli utility function and w_i is its wealth. We assume that household i chooses a deductible $d \in \mathcal{D}$ to maximize $U_i(L_i(d))$.

We assume that every household has the same utility function: $u_i(\cdot) = u(\cdot)$ for all i.[20] For $u(\cdot)$, we consider a second-order Taylor expansion. Also, because $u(\cdot)$ is unique only up to an affine transformation, we normalize the scale of utility by dividing by $u'(\cdot)$. With this specification, Equation (1) becomes:

$$U_i(L_i(d)) = -\left[p_i(d) + \mu_i d\right] - \frac{r}{2}\left[(1 - \mu_i)(p_i(d))^2 + \mu_i(p_i(d) + d)^2\right], \tag{2}$$

where $r = -u''(\cdot)/u'(\cdot)$ is the coefficient of absolute risk aversion.

We calibrate the model with the estimate for r reported by Barseghyan et al. (2013) (hereafter, BMOT). BMOT estimate Equation (2) using a cross-section of 4,170 households in the tricoverage sample. They arrive at their estimation sample by imposing two restrictions. First, they restrict attention to households who first purchased their auto and home policies in the same year, in either 2005 or 2006. This is meant to avoid temporal issues, such as changes in household characteristics and in the economic environment. Second, they consider only the initial deductible choices of each household. This is meant to increase confidence that they are working with active choices; one might be concerned that some households renew their policies without actively reassessing their deductible choices. To account for observationally equivalent households choosing different deductibles, BMOT assume random utility with additively separable choice noise.

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[19]In the Appendix, we also consider a generalization of the expected utility model that allows for probability distortions.

[20]Despite the simplistic assumption of homogeneous preferences, the model fits the data reasonably well. It correctly predicts 53 percent of the deductible choices in home, 37 percent in auto collision, and 27 percent in auto comprehensive.

Specifically, they assume that the utility from deductible $d \in \mathcal{D}$ is $\mathcal{U}(d) \equiv U(L_i(d)) + \varepsilon_{i,d}$, where $\varepsilon_{i,d}$ follows a type 1 extreme value distribution with scale parameter σ. In addition, they assume that $\mu_i = 1 - \exp(-\hat{\vartheta}_i)$. Estimating the model by maximum likelihood, they report $\hat{r} = 0.0129$.

VII.C. Results

We use the calibrated model to investigate the extent to which the households' deductible choices would change if premiums were experience rated. In particular, we examine how the distribution of model-predicted deductible choices changes when we counterfactually move from prior premiums (i.e., premiums generated using non-experience-rated base prices, $\bar{p}_{ik}$) to uniline premiums and multiline premiums (i.e., premiums generated using uniline experience-rated base prices, $\bar{p}_{ik}^{UL}$, and multiline experience-rated base prices, $\bar{p}_{ik}^{ML}$). In each case, we assume that households believe their claim probability is $\mu_i = 1 - \exp(-\hat{\theta}_i)$.

Table 5 presents the results. In addition to displaying the distributions, the table reports the percentage of policies in which the deductible choice changes when we move from prior premiums to uniline and multiline premiums, as well as the resulting (absolute) changes in coverage. The main takeaway is that the response of deductible choices to experience rating would be substantial. When we move from prior premiums to uniline premiums, the deductible choice changes in 5 percent of auto collision policies, 12 percent of auto comprehensive policies, and 14 percent of home policies, resulting in average changes in coverage of \$247, \$164, and \$343, respectively, among policies with a change, and of \$13, \$20, and \$47, respectively, among all policies. When we move from prior premiums to multiline premiums, the deductible choice changes in 7 percent of auto collision policies, 21 percent of auto comprehensive policies, and 15 percent of home policies, resulting in average changes in coverage of \$247, \$178, and \$347, respectively, among policies with a change and of \$17, \$38, and \$51, respectively, among all policies.[21]

VIII. Conclusion

We examine the cost of legal restrictions on experience rating in auto and home insurance. Using data on claims histories, we first estimate the variance-covariance matrix of unobserved heterogeneity in claim risk. We find, inter alia, that unobserved heterogeneity in claim risk is positively correlated across coverages. As noted above, this suggests that there is a latent, domain-general component to risk type. This finding adds to a growing

[21]The results for the model with probability distortions are reported in the Appendix. The main takeaway is the same.

Table 5: Response of Deductible Choices to Experience Rating – Tricoverage Sample (62,425 policies)

Panel A: Auto collision

Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
$100	2,374	2,389	2,409
$200	0	0	0
$250	34,564	34,723	34,751
$500	24,004	23,872	23,808
$1,000	1,483	1,441	1,457
Policies with change in deductible (percent)	-	5.3	6.8
Aggregate changes in coverage (dollars), gross	-	820,750	1,046,450
Per policy change in coverage (dollars), policies with change	-	246.99	246.86
Per policy change in coverage (dollars), all policies	-	13.15	16.76

Panel B: Auto comprehensive

Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
$50	7	4	4
$100	3,633	3,723	3,633
$200	10,444	10,643	10,822
$250	15,144	15,359	15,636
$500	27,979	27,530	27,276
$1,000	5,218	5,166	5,054
Policies with change in deductible (percent)	-	12.4	20.9
Aggregate changes in coverage (dollars), gross	-	1,276,800	2,348,350
Per policy change in coverage (dollars), policies with change	-	164.47	179.91
Per policy change in coverage (dollars), all policies	-	20.45	37.62

Panel C: Home

Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
$100	85	69	70
$250	31,871	32,851	32,993
$500	18,440	17,972	17,847
$1,000	11,632	11,160	11,139
$2,500	318	304	303
$5,000	79	69	73
Policies with change in deductible (percent)	-	13.5	14.7
Aggregate changes in coverage (dollars), gross	-	2,902,500	3,187,200
Per policy change in coverage (dollars), policies with change	-	343.45	347.45
Per policy change in coverage (dollars), all policies	-	46.50	51.06

body of evidence that riskiness is a trans-substantive characteristic of individuals (e.g., Barksy et al. 1997; Dohmen et al. 2011; Golden et al. 2016). It also complements existing research suggesting that risk aversion, though not completely stable across

contexts (Barseghyan et al. 2011), also has a latent, domain-general component (e.g., Einav et al. 2012; Barseghyan et al. 2016).[22]

Next, we show that conditioning on claims experience leads to material refinements of predicted claim rates, with the average downward revisions ranging from 7 percent to 14 percent and the average upward revisions ranging from 10 percent to 28 percent. Accordingly, for the average household—which has prior predicted claim rates of 10.7 percent in auto collision, 3.2 percent in auto comprehensive, and 7.9 percent in home—such conditioning implies posterior predicted claim rates of 10.0 percent, 2.8 percent, and 6.8 percent, respectively, in the case of downward revisions, and of 11.8 percent, 3.9 percent, and 10.1 percent, respectively, in the case of upward revisions.

Last, we assess how insureds' demand for coverage would respond to experience rating assuming that households make deductible choices according to standard expected utility theory. We find that the demand response to experience rating would be large. Across the three coverages, we find that anywhere from 7 percent to 21 percent of households would change their deductible in response to multiline experience rating, resulting in average changes in coverage ranging from $178 to $347 among policies with a change.

The main takeaway from our analysis is that in the absence of experience rating there would be considerable unpriced heterogeneity in claim risk that in turn would lead to sizable distortions in households' demand for insurance coverage. In other words, our analysis suggests that the cost of legal restrictions on experience rating can be substantial. We believe this is important for policymakers to keep in mind. As noted above, regulation of experience rating is widespread in the United States. In auto and home insurance, New York is just one of many states that limit insurers' ability to engage in experience rating.[23] For instance, California and Oklahoma prohibit increasing an insured's premium for auto collision insurance on the basis of an accident for which the insured was not at fault;[24] Florida and Pennsylvania prohibit increasing an insured's premium for auto comprehensive insurance on the basis of an accident regardless of whether the insured was at fault;[25] and Oklahoma and Texas prohibit increasing an insured's premium for home insurance on the basis of a weather-related claim or the first non-weather-related claim.[26]

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[22]But see Barseghyan et al. (2018).

[23]As noted above, New York forbids experience rating of premiums for auto comprehensive or home insurance coverage and also prohibits using auto comprehensive claims to experience rate premiums in any other line of insurance coverage. See N.Y. Ins. Law § 2334 (2018); N.Y. Comp. Codes R. & Regis. tit. 11, §§ 161.8, 169.1 (2018).

[24]See Cal. Ins. Code §§ 1861.02–1861.025 (2018); Cal. Code Regs. tit. 10, §§ 2632.12–2632.13.1 (2018); Okla. Stat. tit. 36, § 941 (2018).

[25]See Fla. Stat. ch. 626.9541(o)(10) (2018); 31 Pa. Code § 67.33(b)(3) (2018).

[26]See Okla. Stat. tit. 36, § 3691.1 (2018); Okla. Admin. Code § 365:15-7-26 (2018); 28 Tex. Admin. Code § 21.1004 (2018).

Of course, in order to determine whether any particular legal restriction on experience rating is worth the cost, a policymaker would need to conduct a full-fledged welfare analysis (assuming she takes a welfarist approach to policymaking). Although such an analysis is beyond the scope of this article, we can sketch out what it would entail. First and foremost, one would have to specify a social welfare function, which presumably would take into account the utility of both insureds and insurers. In addition, one would have to model and predict not only the behavior of insureds on the intensive margin (as we do), but also the behavior of insureds on the extensive margin and the behavior of insurers. This is because legal restrictions on experience rating can have long-term market effects beyond the short-term demand effects that we consider. For instance, they can lead to risk-based adverse selection and higher insurance costs. Indeed, several studies of the auto insurance market find that insurance costs are higher when rate regulation generates cross-subsidies from low- to high-risk insureds (e.g., Weiss et al. 2010; Derrig & Tennyson 2011). Needless to say, one would have to make difficult normative judgments in specifying the social welfare function. Moreover, the positive analysis would be sensitive to the assumptions that one makes about behavior. This is a topic that we hope to explore in future research.

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APPENDIX

A. Descriptive Statistics

Table A1 provides descriptive statistics for the tricoverage sample. Tables A2, A3, and A4 summarize the claims, premiums, and deductibles in the tricoverage sample.

Table A1: Descriptive Statistics – Tricoverage Sample (294,917 household-years)

	Mean	*Std Dev*	*Min*	*Max*
Auto:				
Driver 1 age (years)	56.10	14.70	19	99
Driver 1 female	0.33	0.47	0	1
Driver 1 single	0.22	0.41	0	1
Driver 1 married	0.63	0.48	0	1
Driver 1 insurance score	789.51	106.50	297	996
Driver 2	0.48	0.50	0	1
Driver 2 age (years)	50.28	12.93	16	94
Driver 2 female	0.91	0.28	0	1
Driver 3+	0.04	0.21	0	1
Young driver	0.01	0.10	0	1
Vehicle 1 age (years)	4.43	3.59	-1	46
Vehicle 1 personal use	0.47	0.50	0	1
Vehicle 1 passive restraint	0.99	0.10	0	1
Vehicle 1 anti-theft	0.57	0.49	0	1
Vehicle 1 anti-lock brakes	0.79	0.41	0	1
Vehicle 2	0.53	0.50	0	1
Vehicle 2 age (years)	5.94	5.53	-1	83
Vehicle 2 personal use	0.55	0.50	0	1
Vehicle 2 passive restraint	0.94	0.24	0	1
Vehicle 2 anti-theft	0.46	0.50	0	1
Vehicle 2 anti-lock brakes	0.70	0.46	0	1
Vehicle 3+	0.05	0.22	0	1
Home:				
Home age (years)	45.05	27.20	0	206
Insured value (thousands of dollars)	153.31	75.63	1	3,250
Farm or business	0.02	0.15	0	1
Primary residence	1.00	0.04	0	1
Owner occupied	0.98	0.14	0	1
Number of families	1.16	1.89	1	99
Masonry construction	0.07	0.25	0	1
Distance to fire hydrant (feet)	401.83	514.82	0	30,000
Alarm or other protection	0.95	0.22	0	1

Note: Insurance score is based on information contained in credit reports.

Table A2: Claims – Tricoverage Sample (294,917 household-years)

	Auto collision		*Auto comprehensive*		*Home*	
Count	*Frequency*	*Percent*	*Frequency*	*Percent*	*Frequency*	*Percent*
0	265,692	90	285,923	97	273,984	93
1	27,186	9	8,495	3	18,886	6
2	1,890	1	467	0	1,872	1
3	140	0	30	0	159	0
4	6	-	0	-	12	-
5	3	-	2	-	2	-
6					2	-

Note: Dash indicates less than 0.01 percent.

Table A3: Premiums – Tricoverage Sample (294,917 household-years)

	Auto collision	*Auto comprehensive*	*Home*
Mean	200	127	548
Standard deviation	104	70	309
Minimum	20	6	50
1st percentile	60	34	204
5th percentile	82	48	265
10th percentile	97	58	296
25th percentile	129	81	359
Median	178	113	466
75th percentile	243	157	638
90th percentile	327	210	891
95th percentile	393	250	1,110
99th percentile	560	358	1,683
Maximum	2,520	2,524	10,224

Note: Amounts in dollars.

Table A4: Deductibles – Tricoverage Sample (294,917 household-years)

	Auto collision		*Auto comprehensive*		*Home*	
Deductible	*Frequency*	*Percent*	*Frequency*	*Percent*	*Frequency*	*Percent*
$50	-	-	34,007	12	-	-
$100	7,846	3	18,502	6	11,577	4
$200	65,672	22	128,599	44	-	-
$250	51,644	18	31,556	11	197,100	67
$500	159,702	54	78,098	26	70,567	24
$1,000	10,053	3	4,155	1	14,537	5
$2,500	-	-	-	-	1,044	0
$5,000	-	-	-	-	92	0

Note: Dash indicates deductible option not available.

B. Estimation Approach

Let y_{itk} denote the number of claims for household i in year t under coverage k, where $i = 1, ..., N$, $t = 1, ..., T_i$, and $k \in \{c, m, h\}$. Similarly, let $\mathbf{x}_{itk}$ denote a vector of observables (plus a constant) for household i in year t under coverage k. Let λ_{itk} denote household i's baseline claim rate in year t under coverage k, and let ϵ_{ik} denote a time-constant random effect for household i under coverage k. Also, let $\mathbf{y}_{ik} \equiv \left(y_{i1k}, ..., y_{iT_ik}\right)$ and $\mathbf{y}_i \equiv (\mathbf{y}_{ic}, \mathbf{y}_{im}, \mathbf{y}_{ih})$, and let $\boldsymbol{\lambda}_{ik} \equiv (\lambda_{i1k}, ..., \lambda_{iT_ik})$ and $\boldsymbol{\lambda}_i \equiv (\boldsymbol{\lambda}_{ic}, \boldsymbol{\lambda}_{im}, \boldsymbol{\lambda}_{ih})$.

The first two marginal moments for the class of models used in this research—longitudinal multivariate count models with multiplicative correlated random effects—are:

$$E\left(y_{itk}|\mathbf{x}_{itk}\right) = \exp\left(\mathbf{x}'_{itk}\boldsymbol{\beta}_k\right) = \lambda_{itk}$$

and

$$\mathbf{V}_i \equiv Var\left(\mathbf{y}_i|\mathbf{x}_i\right) = diag\left(\boldsymbol{\lambda}'_i\right) + \boldsymbol{\Sigma}\otimes\mathbf{1}_{T_i}\mathbf{1}'_{T_i} \circ \boldsymbol{\lambda}_i\boldsymbol{\lambda}'_i,$$

where $\circ$ is element-wise multiplication, $\otimes$ is the Kronecker product, and $\mathbf{1}_{T_i}$ is a T_i-dimensional vector of ones.

The moment-based approach for fitting this model relies on the moment conditions implied by the marginal mean and variance along with the basic assumptions for multiplicative correlated random effects models. The estimator $\left(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\Sigma}}\right)$ for $\boldsymbol{\beta} \equiv [\boldsymbol{\beta}_c\ \boldsymbol{\beta}_m\ \boldsymbol{\beta}_h]'$ and $\boldsymbol{\Sigma}$ is defined as the solution to:

$$\sum_i \begin{pmatrix} \mathbf{D}'_i & 0 \\ 0 & \mathbf{E}'_i \end{pmatrix} \begin{pmatrix} \mathbf{V}_i & 0 \\ 0 & \mathbf{I} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{y}_i - \boldsymbol{\lambda}_i \\ \mathbf{R}^*_i - \mathbf{V}^*_i \end{pmatrix} = 0,$$

where $\mathbf{D}_i \equiv \frac{\partial \boldsymbol{\lambda}_i}{\partial \boldsymbol{\beta}} = diag\left[\mathbf{x}'_{ic}\boldsymbol{\lambda}_{ic}\ \mathbf{x}'_{im}\boldsymbol{\lambda}_{im}\ \mathbf{x}'_{ih}\boldsymbol{\lambda}_{ih}\right]'$, $\mathbf{V}_i$ is the model based variance-covariance matrix as defined above, $\mathbf{E}_i \equiv \frac{\partial \mathbf{V}^*_i}{\partial \boldsymbol{\Sigma}^*} = diag\left[\left(\boldsymbol{\lambda}_{ic}\boldsymbol{\lambda}'_{ic}\right)^* \left(\boldsymbol{\lambda}_{im}\boldsymbol{\lambda}'_{im}\right)^* \left(\boldsymbol{\lambda}_{ih}\boldsymbol{\lambda}'_{ih}\right)^* \left(\boldsymbol{\lambda}_{ic}\boldsymbol{\lambda}'_{im}\right)^* \left(\boldsymbol{\lambda}_{ic}\boldsymbol{\lambda}'_{ih}\right)^* \left(\boldsymbol{\lambda}_{im}\boldsymbol{\lambda}'_{ih}\right)^*\right]$, $\mathbf{I}$ is the identity matrix, and $\mathbf{R}_i$ is the cross product of residuals $r_{itk} \equiv y_{itk} - \lambda_{itk}$. Also, let * indicate a half-vectorization operator, such that $\mathbf{R}^*_i$, $\mathbf{V}^*_i$, and $\boldsymbol{\Sigma}^*$ are the vectors of the upper triangular elements of the matrices $\mathbf{R}_i$, $\mathbf{V}_i$, and $\boldsymbol{\Sigma}$, respectively. The roots of the set of estimating equations are obtained via an iterative procedure, updated at each iteration with the consistent estimator of $\boldsymbol{\beta}$ given $\hat{\boldsymbol{\Sigma}}$ and the consistent estimator of $\boldsymbol{\Sigma}$ given $\hat{\boldsymbol{\beta}}$, until convergence. See Morris (2012) for more details on the estimation algorithm and asymptotic results for joint inference.

C. Regression Estimates

Tables A5 (auto) and A6 (home) report the estimates of the regression parameters, $\boldsymbol{\beta}$. Although $\boldsymbol{\beta}$ is not the object of principal interest, the estimates reveal several noteworthy

Table A5: Regression Parameter Estimates, Auto – Tricoverage Sample (294,917 household-years)

	Collision		*Comprehensive*	
	Estimate	*Std Err*	*Estimate*	*Std Err*
Intercept	−0.998*	0.135	−2.675*	0.248
Driver 1 age (years)	−0.011*	0.004	0.039*	0.008
Driver 1 age squared (hundreds of years)	0.013*	0.003	−0.048*	0.007
Driver 1 female	0.067*	0.021	−0.084*	0.041
Driver 1 married	0.048	0.025	0.125*	0.046
Driver 1 separated, divorced, or widowed	0.000	0.023	0.058	0.045
Driver 1 insurance score (tens)	−0.018*	0.001	−0.013*	0.001
Has 2 drivers	0.063	0.123	−0.135	0.214
Has 3+ drivers	0.529*	0.158	0.058	0.255
Young driver	0.020	0.049	0.019	0.082
Driver 2 age (years)	0.012*	0.005	0.006	0.009
Driver 2 age squared (hundreds of years)	−0.013*	0.005	−0.002	0.008
Driver 2 female	0.097*	0.034	−0.064	0.060
Driver 2 married	−0.207*	0.047	−0.121	0.087
Driver 2 separated, divorced, or widowed	0.088	0.164	0.000	0.302
Vehicle 1 age (years)	−0.012	0.005	−0.028*	0.006
Vehicle 1 age squared (hundreds of years)	−0.015	0.044	0.143*	0.036
Vehicle 1 personal use	−0.010	0.014	−0.034	0.025
Vehicle 1 passive restraint	−0.078	0.062	−0.114	0.102
Vehicle 1 anti-theft	0.011	0.015	0.018	0.027
Vehicle 1 anti-lock brakes	0.026	0.016	0.039	0.030
Has 2 vehicles	0.281*	0.056	0.689*	0.095
Has 3+ vehicles	0.293*	0.107	0.930*	0.156
Vehicle 2 age (years)	−0.023*	0.003	−0.020*	0.005
Vehicle 2 age squared (hundreds of years)	0.031*	0.010	0.019	0.018
Vehicle 2 personal use	−0.019	0.015	−0.035	0.027
Vehicle 2 passive restraint	0.075	0.039	−0.033	0.062
Vehicle 2 anti-theft	0.029	0.018	0.009	0.033
Vehicle 2 anti-lock brakes	−0.003	0.019	−0.023	0.032
Year dummies	Yes		Yes	
Territory codes	Yes		Yes	

Notes: Insurance score is based on information contained in credit reports. Territory codes indicate rating territories, which are based on actuarial risk factors, such as traffic and weather patterns, population demographics, wildlife density, and the cost of goods and services.
*Significant at the 5 percent level.

facts. First, auto claim rates (collision and comprehensive) are negatively related to insurance score (which is based on information contained in credit reports) but positively related to the age and number of vehicles. However, they are not correlated with vehicle safety features (passive restraint, anti-theft, and anti-lock brakes). Second, collision claim rates are negatively related to the age of the primary driver and are higher for households in which the primary driver is female. Conversely, comprehensive claim rates are positively related to the age of the primary driver and are lower for households in which the primary driver is female. Third, collision claim rates are higher for households with

three or more drivers. Finally, home claim rates are negatively related to insurance score but positively related to the age and insured value of the home. In addition, they are higher for homes that are used for farming or business and for homes that are not the owner's primary residence. Home claim rates, however, are not correlated with home safety features (masonry construction, distance to fire hydrant, and alarm or other protection).

D. Derivations of $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$ and $E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$

Let y_{itk} denote the number of claims for household i in year t under coverage k, where $i = 1, ..., N$, $t = 1, ..., T_i$, and $k \in \{c, m, h\}$. Similarly, let $\mathbf{x}_{itk}$ denote a vector of observables (plus a constant) for household i in year t under coverage k. Let λ_{itk} denote household i's baseline claim rate in year t under coverage k, and let ϵ_{ik} denote a time-constant random effect for household i under coverage k. Also, let $\mathbf{y}_{ik} \equiv \left(y_{i1k}, ..., y_{iT_ik}\right)$ and $\mathbf{y}_i \equiv (\mathbf{y}_{ic}, \mathbf{y}_{im}, \mathbf{y}_{ih})$.

D.1. Derivation of $E^{ML}(\epsilon_{ik}|\mathbf{y}_i)$

We assume

$$y_{itk} \mid \mathbf{x}_{itk} \sim Poisson(\lambda_{itk}\epsilon_{ik}),$$

where

$$\lambda_{itk} = \exp\left(\mathbf{x}'_{itk}\boldsymbol{\beta}_k\right)$$

and $\boldsymbol{\epsilon}_i \equiv [\epsilon_{ic}\ \epsilon_{im}\ \epsilon_{ih}]' \overset{iid}{\sim} lognormal$ with $E(\boldsymbol{\epsilon}_i) = [1\ 1\ 1]'$ and $V(\boldsymbol{\epsilon}_i) = \boldsymbol{\Sigma}$. This leads to the following probability distribution functions:

$$\begin{aligned} f\left(\mathbf{y}_i|\boldsymbol{\epsilon}_i\right) &= \prod_k \prod_t Poisson(\lambda_{itk}\epsilon_{ik}) \\ &= \prod_k \prod_t \frac{(\epsilon_{ik}\lambda_{itk})^{y_{itk}}}{y_{itk}!} e^{-\epsilon_{ik}\lambda_{itk}} \\ &= \left(\prod_k \epsilon_{ik}^{\sum_t y_{itk}} e^{-\epsilon_{ik}\sum_t \lambda_{itk}}\right)\left(\prod_k \prod_t \frac{\lambda_{itk}^{y_{itk}}}{y_{itk}!}\right), \end{aligned}$$

$$\begin{aligned} f\left(\tilde{\epsilon}_i\right) &= Normal\left(\tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\Sigma}}\right) \\ &= \frac{1}{(2\pi)^{3/2}}\left|\tilde{\boldsymbol{\Sigma}}\right|^{-1/2} e^{-\frac{1}{2}(\tilde{\epsilon}_i - \tilde{\boldsymbol{\mu}})'\tilde{\boldsymbol{\Sigma}}^{-1}(\tilde{\epsilon}_i - \tilde{\boldsymbol{\mu}})}, \end{aligned}$$

where $\tilde{\epsilon}_i \equiv \ln(\epsilon_i)$, $\tilde{\boldsymbol{\mu}} \equiv -\frac{diag(\tilde{\boldsymbol{\Sigma}})}{2}$, and $\tilde{\boldsymbol{\Sigma}} \equiv \ln(\boldsymbol{\Sigma} + 1)$, and

Table A6: Regression Parameter Estimates, Home – Tricoverage Sample (294,917 household-years)

	Estimate	*Std Err*
Intercept	−1.968*	0.250
Insurance score (tens)	−0.018*	0.001
Home age (years)	0.003*	0.001
Home age squared (years)	0.000	0.000
Insured value (tens of thousands of dollars)	0.015*	0.001
Farm or business	0.098*	0.047
Primary residence	0.631*	0.228
Owner occupied	0.121	0.077
Number of families	−0.011	0.007
Masonry construction	0.048	0.029
Distance to fire hydrant (feet)	0.001	0.001
Alarm or other protection	0.019	0.036
Year dummies	Yes	
Territory codes	Yes	
Protection classes	Yes	

Notes: Insurance score is based on information contained in credit reports. Territory codes indicate rating territories, which are based on actuarial risk factors, such as traffic and weather patterns, population demographics, wildlife density, and the cost of goods and services. Protection classes gauge the effectiveness of local fire protection and building codes.
*Significant at the 5 percent level.

$$
\begin{aligned}
f(\mathbf{y}_i) &= \int_{\tilde{\epsilon}_{ic}}\int_{\tilde{\epsilon}_{im}}\int_{\tilde{\epsilon}_{ih}} f(\mathbf{y}_i|\tilde{\epsilon}_i) f(\tilde{\epsilon}_i)\, d\tilde{\epsilon}_{ih} d\tilde{\epsilon}_{im} d\tilde{\epsilon}_{ic} \\
&= \int_{\tilde{\epsilon}_{ic}}\int_{\tilde{\epsilon}_{im}}\int_{\tilde{\epsilon}_{ih}} \prod_k \prod_t Poisson\left(\lambda_{itk} e^{\tilde{\epsilon}_{ik}}\right) MVN\left(\tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\Sigma}}\right) d\tilde{\epsilon}_{ih} d\tilde{\epsilon}_{im} d\tilde{\epsilon}_{ic} \\
&= \frac{1}{(2\pi)^{3/2}} \left|\tilde{\boldsymbol{\Sigma}}\right|^{-1/2} \left(\prod_k \prod_t \frac{\lambda_{itk}^{y_{itk}}}{y_{itk}!}\right) \int_{\tilde{\epsilon}_{ic}}\int_{\tilde{\epsilon}_{im}}\int_{\tilde{\epsilon}_{ih}} g^{ML}(\tilde{\epsilon}_i)\, d\tilde{\epsilon}_{ih} d\tilde{\epsilon}_{im} d\tilde{\epsilon}_{ic},
\end{aligned}
$$

where $g^{ML}(\tilde{\epsilon}_i) \equiv \left(\prod_k e^{\tilde{\epsilon}_{ik}\sum_t y_{itk}} e^{-e^{\tilde{\epsilon}_{ik}}\sum_t \lambda_{itk}}\right) e^{-\frac{1}{2}(\tilde{\epsilon}_i - \tilde{\mu})' \tilde{\boldsymbol{\Sigma}}^{-1} (\tilde{\epsilon}_i - \tilde{\mu})}$.

Taken together, the posterior distribution is defined as:

$$
\begin{aligned}
f(\tilde{\epsilon}_i|\mathbf{y}_i) &= \frac{f(\mathbf{y}_i|\tilde{\epsilon}_i) f(\tilde{\epsilon}_i)}{f(\mathbf{y}_i)} \\
&= \frac{g^{ML}(\tilde{\epsilon}_i)}{\int_{\tilde{\epsilon}_{ic}}\int_{\tilde{\epsilon}_{im}}\int_{\tilde{\epsilon}_{ih}} g^{ML}(\tilde{\epsilon}_i)\, d\tilde{\epsilon}_{ih} d\tilde{\epsilon}_{im} d\tilde{\epsilon}_{ic}},
\end{aligned}
$$

and the expectation is:

$$
E^{ML}(\epsilon_i|\mathbf{y}_i) = \int_{\tilde{\epsilon}_{ic}}\int_{\tilde{\epsilon}_{im}}\int_{\tilde{\epsilon}_{ih}} \begin{bmatrix} e^{\tilde{\epsilon}_{ic}} \\ e^{\tilde{\epsilon}_{im}} \\ e^{\tilde{\epsilon}_{ih}} \end{bmatrix} f(\tilde{\epsilon}_i|\mathbf{y}_i)\, d\tilde{\epsilon}_{ih} d\tilde{\epsilon}_{im} d\tilde{\epsilon}_{ic}.
$$

D.2. Derivation of $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$

The univariate expectation, $E^{UL}(\epsilon_{ik}|\mathbf{y}_{ik})$, is a special case of the multivariate expectation, $E^{ML}(\epsilon_i|\mathbf{y}_i)$. Replacing the conditional and marginal distribution functions with their univariate counterparts, the univariate posterior distribution is:

$$\begin{aligned} f\left(\tilde{\epsilon}_{ik}|\mathbf{y}_{ik}\right) &= \frac{f\left(\mathbf{y}_{ik}|\tilde{\epsilon}_{ik}\right)f(\tilde{\epsilon}_{ik})}{f\left(\mathbf{y}_{ik}\right)} \\ &= \frac{g^{UL}(\tilde{\epsilon}_{ik})}{\int_{\tilde{\epsilon}_{ik}} g^{UL}(\tilde{\epsilon}_i)\, d\tilde{\epsilon}_{ik}}, \end{aligned}$$

where $g^{UL}(\tilde{\epsilon}_{ik}) \equiv \left(e^{\tilde{\epsilon}_{ik}\sum_t y_{itk}} - e^{e^{\tilde{\epsilon}_{ik}}\sum_t \lambda_{itk}} \right) e^{-\frac{1}{2\sigma_k^2}(\tilde{\epsilon}_{ik}-\tilde{\mu}_k)'(\tilde{\epsilon}_{ik}-\tilde{\mu}_k)}$ and $k \in \{c, m, h\}$, and the univariate expectation is

$$E^{UL}\left(\epsilon_{ik}|\mathbf{y}_{ik}\right) = \int_{\tilde{\epsilon}_{ik}} e^{\tilde{\epsilon}_{ik}} f\left(\tilde{\epsilon}_{ik}|\mathbf{y}_{ik}\right) d\tilde{\epsilon}_{ik}$$

for $k \in \{c, m, h\}$.

Table A7: Association Parameter Estimates – Alternative Samples

	Tricoverage sample (62,525 households; 294,917 household-years)			*Alternative sample 1* (8,731 households; 78,579 household-years)			*Alternative sample 2* (203,731 households; 1,019,170 household-years)		
	Estimate	*95 percent confidence interval*		*Estimate*	*95 percent confidence interval*		*Estimate*	*95 percent confidence interval*	
Variances:									
Auto collision	0.107	0.065	0.149	0.114	0.049	0.180	0.093	0.070	0.116
Auto comprehensive	0.399	0.221	0.577	0.342	0.068	0.616	0.402	0.300	0.505
Home	0.405	0.383	0.428	0.401	0.260	0.541			
Covariances:									
Auto collision and auto comprehensive	0.137	0.101	0.173	0.123	0.064	0.182	0.131	0.112	0.151
Auto collision and home	0.061	0.022	0.099	0.121	0.081	0.161			
Auto comprehensive and home	0.225	0.179	0.271	0.209	0.135	0.282			
Correlations:									
Auto collision and auto comprehensive	0.663	0.399	0.926	0.622	0.195	1.049	0.680	0.522	0.838
Auto collision and home	0.293	0.099	0.486	0.564	0.298	0.830			
Auto comprehensive and home	0.559	0.389	0.729	0.563	0.247	0.880			

Notes: The tricoverage sample comprises an unbalanced panel of households who purchased all three coverages (auto collision, auto comprehensive, and home) in one or more years between 1998 and 2006. Alternative sample 1 comprises a balanced panel of households who purchased all three coverages (auto collision, auto comprehensive, and home). Alternative sample 2 comprises an unbalanced panel of households who purchased both auto coverages (collision and comprehensive).

Table A8: Association Parameter Estimates – Low and High Deductible Households

	Tricoverage sample (62,425 households; 294,917 household-years)			*All deductibles $250* (22,072 households; 120,213 household-years)			*Any deductible > $250* (40,353 households; 174,704 household-years)		
	Estimate	*95 percent confidence interval*		*Estimate*	*95 percent confidence interval*		*Estimate*	*95 percent confidence interval*	
Variances:									
Auto collision	0.107	0.065	0.149	0.094	0.038	0.150	0.108	0.051	0.166
Auto comprehensive	0.399	0.221	0.577	0.337	0.086	0.587	0.450	0.201	0.698
Home	0.405	0.383	0.428	0.388	0.281	0.496	0.246	0.038	0.454
Covariances:									
Auto collision and auto comprehensive	0.137	0.101	0.173	0.138	0.085	0.192	0.129	0.081	0.178
Auto collision and home	0.061	0.022	0.099	0.088	0.055	0.120	0.058	0.021	0.094
Auto comprehensive and home	0.225	0.179	0.271	0.224	0.157	0.290	0.217	0.152	0.282
Correlations:									
Auto collision and auto comprehensive	0.663	0.399	0.926	0.776	0.300	1.252	0.586	0.272	0.900
Auto collision and home	0.293	0.099	0.486	0.458	0.230	0.686	0.352	0.066	0.639
Auto comprehensive and home	0.559	0.389	0.729	0.619	0.312	0.926	0.652	0.270	1.034

E. Robustness Checks

Table A7 reports the association parameter estimates for alternative samples 1 and 2. Alternative sample 1 comprises a balanced panel of households that purchased all three coverages (auto collision, auto comprehensive, and home). Alternative sample 2 comprises an unbalanced panel of households that purchased both auto coverages (collision and comprehensive).

Table A8 reports the association parameter estimates for low and high deductible households. A low deductible household is a household with no deductible greater than $250. A high deductible household is a household with at least one deductible greater than $250.

F. Deductible Choices: Probability Distortion Model

In the main text, we investigate how households' deductible choices would respond to experience rating under the assumption that households make deductible choice according to standard expected utility theory. Here, we investigate how households' deductible choices would respond to experience rating under the assumption that households make deductible choices according to a generalization of the expected utility model that allows for probability distortions. We refer to this model as the probability distortion model.

As before, a household i faces a menu of premium-deductible pairs $\{(p_i(d), d) : d \in \mathcal{D}\}$. The household experiences at most one claim during the policy period, and it believes the probability of experiencing a claim is μ_i. In the event of a claim, the loss exceeds the maximum deductible option and payment of the deductible is the only cost associated with the claim. Under these assumptions, the household's choice of deductible involves a choice among lotteries of the form $L_i(d) \equiv (-p_i(d), 1-\mu_i; -p_i(d)-d, \mu_i)$.

Under the probability distortion model, the utility of lottery $L_i(d)$ is given by:

$$U_i(L_i(d)) = (1-\Omega_i(\mu_i))u_i(w_i - p_i(d)) + \Omega_i(\mu_i)u_i(w_i - p_i(d) - d), \tag{A1}$$

where $u_i(\cdot)$ is the household's Bernoulli utility function, w_i is its wealth, and $\Omega_i(\cdot)$ is its probability distortion function. Given our setting, this model is quite general in that it includes several others as special cases, including models of subjective beliefs, rank-dependent probability weighting (Quiggin 1982; Tversky & Kahneman 1992), loss aversion (Kőszegi & Rabin 2006, 2007), and disappointment aversion (Gul 1991). For further details about the probability distortion model, see Barseghyan et al. (2013) (hereafter, BMOT).

We assume that every household has the same utility and probability distortion function: $u_i(\cdot) = u(\cdot)$ and $\Omega_i(\cdot) = \Omega(\cdot)$ for all i.[27] For $u(\cdot)$, we consider a second-order Taylor expansion. Also, because $u(\cdot)$ is unique only up to an affine transformation, we normalize the scale of utility by dividing by $u'(\cdot)$. With this specification, Equation (A1) becomes

$$U_i(L_i(d)) = -\left[p_i(d) + \Omega(\mu_i)d\right] - \frac{r}{2}\left[(1-\Omega(\mu_i))(p_i(d))^2 + \Omega(\mu_i)(p_i(d)+d)^2\right], \tag{A2}$$

where $r = -u''(\cdot)/u'(\cdot)$ is the coefficient of absolute risk aversion.

We calibrate the model with the estimates for r and $\Omega(\cdot)$ reported by BMOT. They estimate Equation (A2) using a cross-section of 4,170 households in the tricoverage sample. They arrive at their estimation sample by imposing two restrictions. First, they restrict attention to households that first purchased their auto and home policies in the same year, in either 2005 or 2006. This is meant to avoid temporal issues, such as changes in household characteristics and in the economic environment. Second, they consider only the initial deductible choices of each household. This is meant to increase confidence that they are working with active choices; one might be concerned that some households renew their policies without actively reassessing their deductible choices. To account for observationally equivalent households choosing different deductibles, BMOT assume random utility with additively separable choice noise. Specifically, they assume that the utility from deductible $d \in \mathcal{D}$ is $\mathcal{U}(d) \equiv U(L_i(d)) + \varepsilon_{i,d}$, where $\varepsilon_{i,d}$ follows a type 1 extreme value

[27]Despite the simplistic assumption of homogeneous preferences, the model fits the data reasonably well. It correctly predicts 62 percent of deductible choices in home, 42 percent in auto collision, and 34 percent in auto comprehensive.

distribution with scale parameter σ. In addition, they assume that $\Omega(\mu_i) = \exp(\delta_0 + \delta_1\mu_i + \delta_2\mu_i^2)$ and $\mu_i = 1 - \exp(-\hat{\vartheta}_i)$. Estimating the model by maximum likelihood, they report $\hat{r} = 0.00064$ and $\hat{\Omega}(\mu_i) = \exp(-2.71 + 12.03\mu_i - 35.15\mu_i^2)$.

We use the calibrated model to investigate the extent to which the households' deductible choices would change if premiums were experience rated. In particular, we examine how the distribution of model-predicted deductible choices changes when we counterfactually move from prior premiums (i.e., premiums generated using non-experience-rated base prices, $\bar{p}_{ik}$) to uniline premiums and multiline premiums (i.e., premiums generated using uniline experience-rated base prices, $\bar{p}_{ik}^{UL}$, and multiline experience-rated base prices, $\bar{p}_{ik}^{ML}$). In each case, we assume that households believe their claim probability is $\mu_i = 1 - \exp(-\hat{\theta}_i)$.

Table A9 presents the results. In addition to displaying the distributions, the table reports the percentage of policies in which the deductible choice changes when we move from prior premiums to uniline and multiline premiums, as well as the resulting (absolute) changes in coverage. The main takeaway here is the same as it is under the expected utility model—the response of deductible choices to experience rating would be substantial. When we move from prior premiums to uniline premiums, the deductible choice changes in 5 percent of auto collision policies, 14 percent of auto comprehensive policies, and 12 percent of home policies, resulting in average changes in coverage of \$262, \$144, and \$336, respectively, among policies with a change, and of \$14, \$21, and \$39, respectively, among all policies. When we move from prior premiums to multiline premiums, the deductible choice changes in 7 percent of auto collision policies, 25 percent of auto comprehensive policies, and 13 percent of home policies, resulting in average changes in coverage of \$262, \$149, and \$337, respectively, among policies with a change and of \$18, \$38, and \$43, respectively, among all policies.

Table A9: Response of Deductible Choices to Experience Rating – Tricoverage Sample (62,425 policies)

Panel A: Auto collision

	Expected utility model			*Probability distortion model*		
Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
\$100	2,374	2,389	2,409	1,194	1,273	1,279
\$200	0	0	0	0	0	0
\$250	34,564	34,723	34,751	29,379	29,428	29,524
\$500	24,004	23,872	23,808	30,194	30,018	29,925
\$1,000	1,483	1,441	1,457	1,658	1,706	1,697
Policies with change in deductible (percent)	-	5.3	6.8	-	5.3	6.8
Aggregate changes in coverage (dollars), gross	-	820,750	1,046,450	-	864,850	1,111,950

Table: A9 *Continued*

Panel A: Auto collision

	Expected utility model			*Probability distortion model*		
Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
Per policy change in coverage (dollars), policies with change	-	246.99	246.86	-	262.47	261.64
Per policy change in coverage (dollars), all policies	-	13.15	16.76	-	13.85	17.81

Panel B: Auto comprehensive

	Expected utility model			*Probability distortion model*		
Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
$50	7	4	4	20	19	21
$100	3,633	3,723	3,633	11,919	12,363	12,829
$200	10,444	10,643	10,822	16,976	16,949	16,862
$250	15,144	15,359	15,636	12,317	12,236	12,024
$500	27,979	27,530	27,276	19,910	19,565	19,371
$1,000	5,218	5,166	5,054	1,283	1,293	1,318
Policies with change in deductible (percent)	-	12.4	20.9	-	14.4	25.3
Aggregate changes in coverage (dollars), gross	-	1,276,800	2,348,350	-	1,295,500	2,351,000
Per policy change in coverage (dollars), policies with change	-	164.47	179.91	-	143.70	148.69
Per policy change in coverage (dollars), all policies	-	20.45	37.62	-	20.75	37.66

Panel C: Home

	Expected utility model			*Probability distortion model*		
Deductible choice	*Prior premiums*	*Uniline premiums*	*Multiline premiums*	*Prior premiums*	*Uniline premiums*	*Multiline premiums*
$100	85	69	70	91	100	98
$250	31,871	32,851	32,993	40,640	40,903	40,975
$500	18,440	17,972	17,847	14,529	14,201	14,122
$1,000	11,632	11,160	11,139	7,085	7,132	7,142
$2,500	318	304	303	64	72	69
$5,000	79	69	73	16	17	19
Policies with change in deductible (percent)	-	13.5	14.7	-	11.6	12.8
Aggregate changes in coverage (dollars), gross	-	2,902,500	3,187,200	-	2,437,850	2,692,850
Per policy change in coverage (dollars), policies with change	-	343.45	347.45	-	335.56	337.49
Per policy change in coverage (dollars), all policies	-	46.50	51.06	-	39.05	43.14