B Analysis of Actual Firm Pricing [For Online Publication]

Cream skimming effect Advantageous selection into monitoring may cream skim from the Firm's unmonitored pool. As a result, firms may choose to raise prices in the unmonitored pool. In addition, they may also want to surcharge the unmonitored pool to indirectly encourage monitoring participation. To test the effect of monitoring introduction on the unmonitored pool more formally, we take advantage of the staggered introduction of monitoring across states. This gives rise to a regression discontinuity strategy that evaluates how prices and average cost changed in the *unmonitored* pool. We focus on a year before and after monitoring introduction; our observable characteristics also include state fixed effects and flexible controls for trends and seasonality. We only focus on the first semester ($t = 0$) to avoid contamination from attrition[56]. We therefore drop the t subscript, and run the following regression

$$dep.\ var._i = \alpha + \gamma Qtr_i + \kappa \mathbf{1}_{post,i} + \theta \cdot Qtr_i \times \mathbf{1}_{post,i} + \mathbf{x}_i' \beta + \xi_{y,i} + \varepsilon_i \tag{16}$$

We use price p_i and claim count C_i as our dependent variable. Qtr is the running variable, which denotes the calendar quarter when driver i arrived at the Firm[57]. $\mathbf{1}_{post}$ is an indicator for whether i arrived at the Firm after the introduction of monitoring. $\mathbf{x}$ and a coverage fixed effect ξ_y soak up compositional changes in observable risk class and coverage plans. The coefficient θ reveals treatment effect of monitoring introduction on prices and claims in the unmonitored pool.

Estimates for $\hat{\theta}$ across various specifications are reported in figure B.2. The firm did not raise prices around monitoring introduction. We also find no evidence that the average cost of the unmonitored pool deteriorated by more than 2%.

In reality, monitoring is only a small fraction of the market. As our demand estimates will reveal in the next section, even when monitored drivers are significantly better, its influence on the unmonitored pool is significantly limited by its small size. Further, the Firm does not make follow-up offers to customers who initially opted out monitoring, which is necessary for unraveling to occur empirically. Lastly, monitoring programs are subject to approval by state commissioners. And a new program that affects baseline pricing may be subject to

[56]This regression does not include monitored drivers, so there is no contamination from moral hazard.

[57]It is normalized so that the quarter immediately after monitoring introduction is indexed as 0.

more regulatory scrutiny. On the flip side, this suggests that the current monitoring regime is largely welfare-neutral for unmonitored drivers.

Dynamic and non-uniform pricing Monitored drivers have 35% higher profitability overall, controlling for observables. On top of the risk reduction (during monitoring) and better risk rating, this can also be a result of higher profit margin and retention rate when information is revealed. We provide descriptive evidence on pricing and dynamic retention in this section.

First, the Firm faces a dynamic pricing problem as information is revealed at the end of the first period. It offers a opt-in discount to encourage all drivers to participate in monitoring. This averages to around 5% across states and time.

When monitoring information is revealed, the Firm can use it to set non-uniform prices. Here, the Firm's pricing schedule is based on a monitoring tier that measures how "surprising" a given driver's monitoring score is to the Firm. In figure B.6, we plot the empirical distribution of monitoring tier, which is realized monitoring score divided by firm's expected score given observables[58]. Consistent with our findings above, the average monitored driver performed much better than expected[59].

Figure B.3 presents the discount schedule the Firm uses given the percentile of monitoring tier as defined above. Surprisingly good drivers are on the left, who are offered the highest renewal discount, while around 25% of drivers that performed poorly (compared to firm's expectation) received a surcharge.

Figure B.4 plots the corresponding retention rate. It is clear that as discounts approach zero or negative, retention rate drops significantly. In fact, we can regress renewal choice (binary) on prices with monitoring discount, controlling for observables and price level without the discount. θ then measures the slope of the residual (retention) demand.

$$\mathbf{1}_{renew,i} = \alpha + \delta p_i + \theta disc_i + \mathbf{x}_i' \beta + \varepsilon_i \tag{17}$$

The estimates for $\hat{\theta}$ are reported in figure B.5. Without monitoring discount, a \$1 increase in

[58]For monitored driver i, the expected score is derived based on the average driver in i's observable (x_i) group. It also does not take into account the fact that i has selected into monitoring. The graph has a long right tail and is truncated at 200%.

[59]It is important to note that a driver with a monitoring tier of 30% is not necessarily 70% safer than the average person in her pool, especially in renewal period. This is because monitoring score does not capture risk perfectly, and it is also stochastic. Our structural model quantifies these effects more formally.

price (decrease in discount given) causes the retention rate to drop by 0.07 percentage points (7 basis points). When firms give discounts, however, the slope of the demand decreases, and by 56% when the discount given is larger than 10%. This suggests that

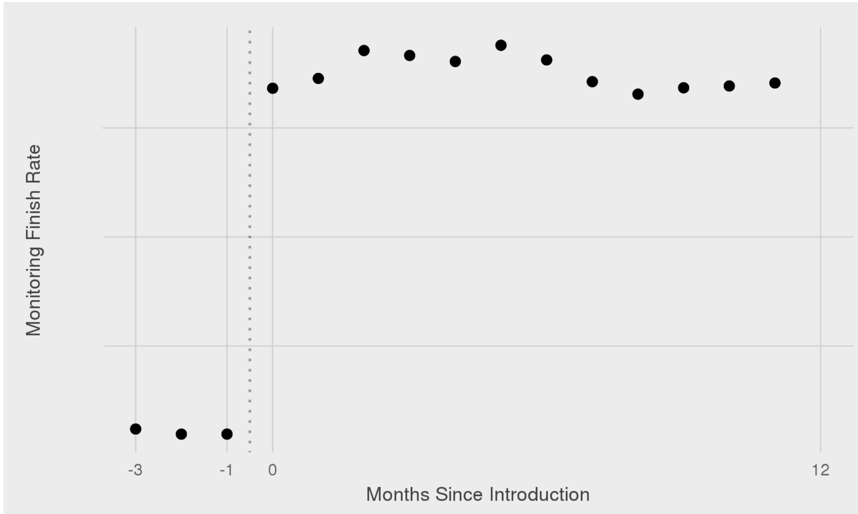

Figure B.1: Monthly monitoring finish rate around monitoring introduction

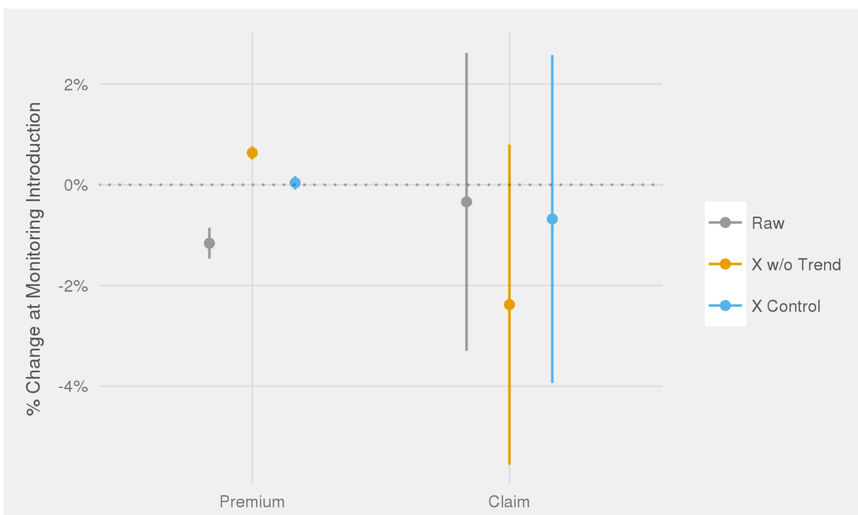

Figure B.2: Event Study: treatment effect of monitoring introduction on the unmonitored pool

Notes: figure B.1 the progression of monthly monitoring finish rate around the introduction of monitoring. The monthly finish rate are below 0.1% in all months before monitoring introduction. The reason why it is not exactly zero before monitoring introduction is due to small-scale trial and experimentation. We throw out states that introduced monitoring in the first three months or the last 12 months of our research window. This ensures that the trend we see do not pick up changes in state composition.
figure B.2 reports regression-discontinuity estimate θ of equation (16), where the horizontal axis distinguishes dependent variable used. These effects are translated in percentage terms by dividing the average of the dependent variable in the period immediately before monitoring introduction. We look at only first period outcomes, and include all *unmonitored* drivers arriving at the Firm a year before or after the Firm. States that introduced monitoring within a year after the beginning or a year before the end of our research window are excluded. The running variable is quarter since monitoring introduction. Different colors and positions represent different specifications of control variables (x_{it}). The grey (left-most) series represents estimates from regressions with the full set of x_{it}; the orange (middle) one includes a full set of observables, including flexible controls for trend and seasonality.

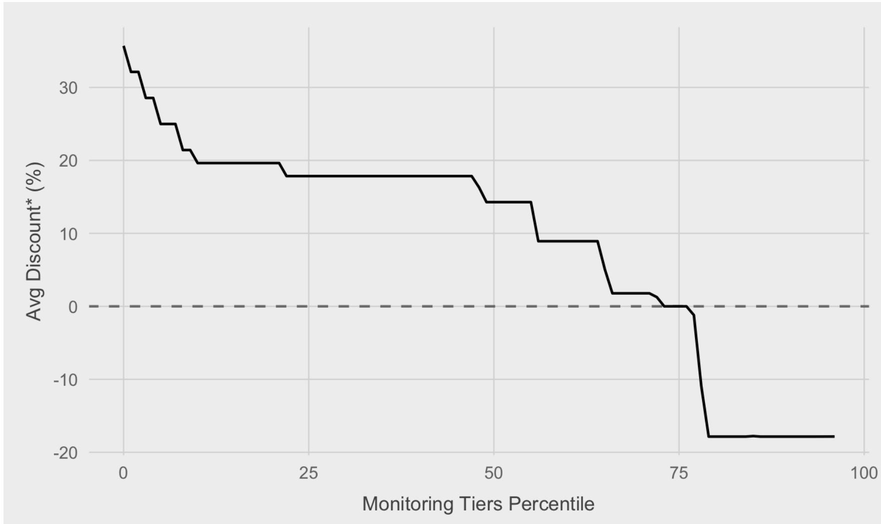

Figure B.3: Monitoring Discount Schedule

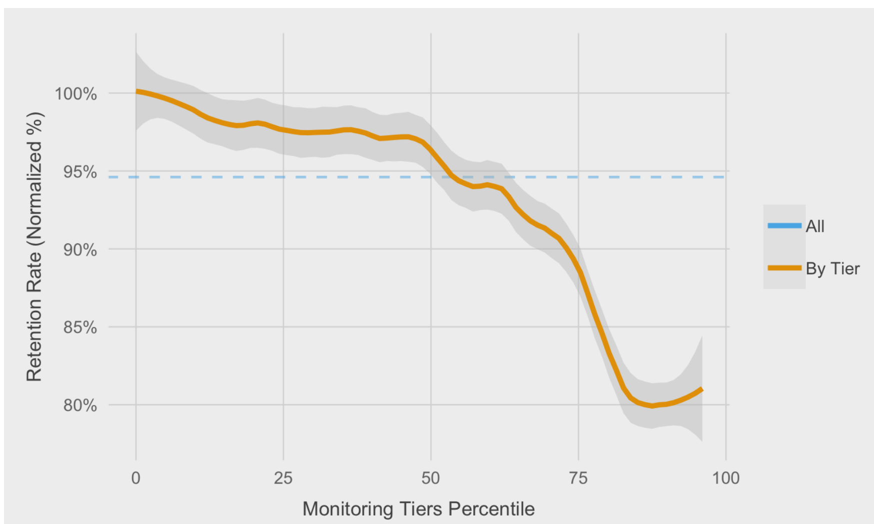

Figure B.4: Indexed Retention Rate

Notes: figure B.3 plots the Firm's pricing schedule for giving monitoring discount. On the horizontal axis, we plot the percentile of monitoring tier, which is monitoring score divided by that expected by the Firm given observables. 74% of people received a discount. The vertical axis is scaled by a factor between 0.5 and 1.5. This is to protect the Firm's identity while demonstrating the scale and shape of the pricing algorithm. The firm went through two pricing schedules. This graph plots the second pricing schedule. The first one is similar, except that no surcharge was given.
figure B.4 uses the same horizontal axis, and non-parametrically plots the retention rate for the semester immediately after drivers finish monitoring (and thus when they first got monitoring discounts). Bandwidth is set as 5, and all numbers are benchmarked/normalized against the mean retention rate of the lowest 5 monitoring tiers. For 93% of monitored drivers, this is the first renewal period.

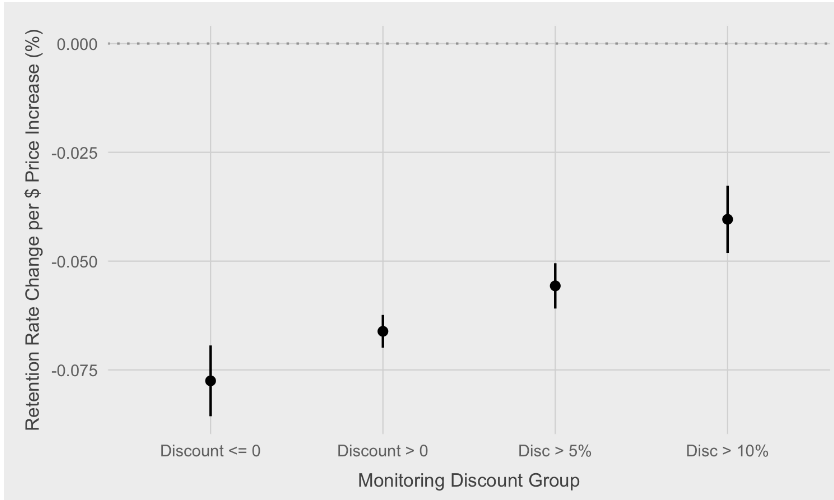

Figure B.5: Comparison of subsequent claim cost across monitoring groups

Notes: This figure plots the estimate of θ from equation (17) in various subsamples. These subsamples are represented on the horizontal axis. Notice that although we segment the data using discount percentage, we use the actual discount amount in the regression to measure demand elasticity. The results are scaled to percentage point terms. Therefore, -0.05 means that the slope of retention demand is such that a one dollar increase in price would lead to a 0.05 percentage point drop in retention rate.

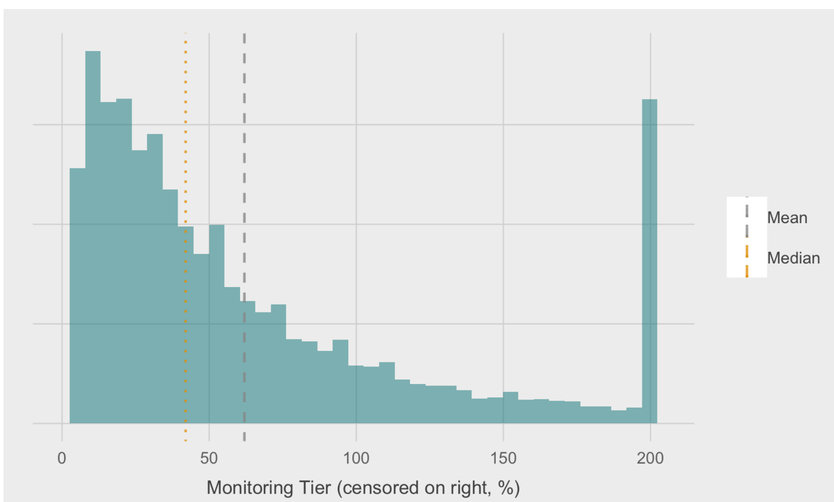

Figure B.6: Distribution of monitoring tier

Notes: This figure plots the empirical density of monitoring tier for all monitored drivers who finished monitoring. It is calculated as the quotient of realized monitoring score over ex-ante expected monitoring score. For monitored driver i, the expected score is derived based on the average driver in i's observable (x_i) group. It does not take into account the fact that i has selected into monitoring. The graph has a long right tail and is truncated at 200%.

C Additional Robustness Checks [For Online Publication]

Table C.1: **ESTIMATES FROM MORAL HAZARD REGRESSION**

	dependent variable: claim count (C)					
explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.046^{***}	0.003	0.004	0.046^{***}	0.003	0.004
	(0.000)	(0.005)	(0.005)	(0.000)	(0.005)	(0.005)
post monitoring indicator	-0.001^{**}	-0.003^{***}	-0.003^{***}	-0.001^{**}	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
monitoring start indicator (m_{start})	-0.009^{***}	-0.008^{***}	-0.008^{***}	0.025^{***}	0.020^{***}	0.020^{***}
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
monitoring intensity (M)				-0.050^{***}	-0.042^{***}	-0.042^{***}
				(0.004)	(0.004)	(0.004)
interaction ($\mathbf{1}_{post} \times m$)	0.006^{***}	0.006^{***}	0.006^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
interaction ($\mathbf{1}_{post} \times M$)				0.028^{***}	0.029^{***}	0.029^{***}
				(0.005)	(0.005)	(0.005)
observables controls (x)	N	Y	Y	N	Y	Y
coverage fixed effects	N	N	Y	N	N	Y
implied risk reduction of a full period of monitoring (%)	28.0	29.4	29.5	27.5	29.4	29.6
pre- / post-periods for "first difference"	0 / 1-2					
treatment / control groups "second difference"	all starters / unmonitored					
number of drivers in balanced panel	812,924					

Notes: This table reports results of equation (2), but instead look at all monitored drivers regardless of whether they finish or not. Again, the estimate on the interaction term ($\mathbf{1}_{post} \times m_{start}$ or z) measures the treatment effect of monitoring ending on claim count. We first balance our panel data to include all drivers who stay till the end of the third semester ($t = 3$). This gives us two renewal semesters ($t \in \{1,2\}$) after the monitoring semester ($t = 0$). We control for a full set of observables, including driver and vehicle characteristics and tiers (past records of violations or claims). It also includes third-order polynomials of calendar year and month. Continuous observable characteristics are normalized. We report estimates with and without these controls.

Pre-Period and Learning Our data does not include consumers' claim record before they come to the firm. The use of past claims are heavily regulated in most states. To the extent that such records are used in firm pricing, we effectively accounts for their role with our risk class measure. However, since monitoring happens in the first period, we do not observe pre-trends of claims across monitoring groups. This does not influence our moral hazard effect, but pre-trends are necessary to distinguish learning versus selection effects. In other words, although we have found that monitored consumers to be safer than unmonitored ones after the monitoring period, it is unclear whether this is due to monitoring changing consumers' persistent risk type (learning) or due to monitoring attracts persistently safer consumers (selection). To tease these out, we use speeding violation records, for which we have aggregated records for each consumer when she or he first starts at the firm. We replicate the analysis in 3, replacing the outcome variable from claims to the number of speeding violations reported. The results are presented below.

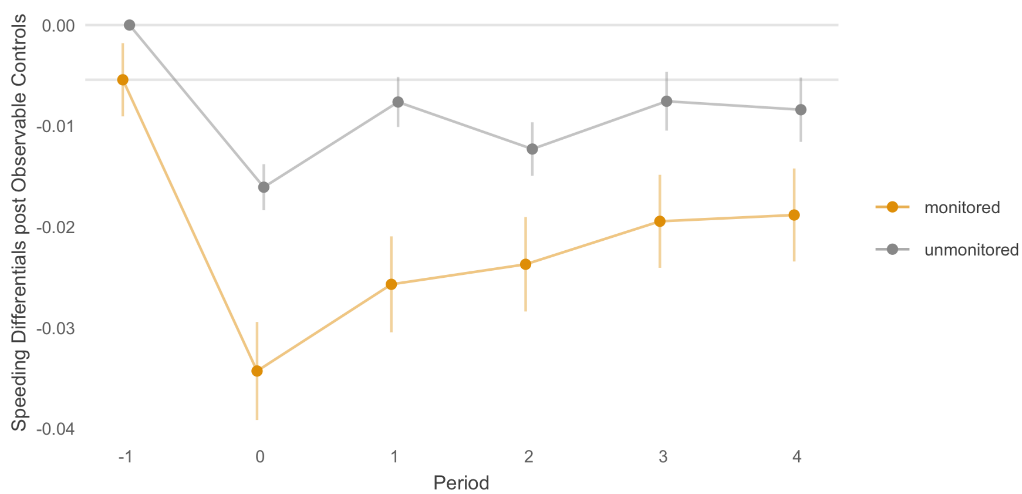

Figure C.1: Speeding Violation Progression across Monitoring Groups

Notes: This graph reports the fixed effect estimates of eq. (3), replacing the outcome variables to the number of speeding violation. The grey line plots ω_t while the orange line plots $\omega_t + \theta_t$, both against insurance periods t. The error-bars report 95% confidence interval.

Two main differences emerge compared with the claims regression. First, the moral hazard effect takes longer to manifest. In the monitored group and after the monitoring period, speeding records seem to converge back to a long-run persistent level more slowly. This could indicate that there is temporary learning that dissipates after one more period. However, official speeding records are noisy and prone to delays induced by lawsuits and administrative errors. We therefore consider our claims records to be far more precise in measuring the moral hazard effect. Second, in the pre-period (period -1), the gap between the monitored and the unmonitored groups seem narrower than their long-run average. This indicates that there could be a learning effect in addition to advantageous selection into monitoring. However, this difference is not statistically significant at the 5% level.

D Estimation Details [For Online Publication]

Intercept and slope parameters We parameterize heterogeneous latent parameters linearly. Broadly consistent with actual firm pricing rules, x_{it}^R and x_i^s only include a polynomial and the log of risk class, which represents firm's risk assessment without monitoring information.

Nest structure Incorporating additional alternative-level random effects can further enrich our model. In our primary specification, we add a random coefficient, ζ, on all choices within $f^\star$. This allows us to capture correlations between choices within the firm. Here, we assume ζ is an independently normally distributed with mean zero and standard deviation σ_ζ (Train 2009). This allows us to escape the Independence of Irrelevant Alternatives property of a simple logit model. The model can therefore achieve better fit on attrition rate differences across consumers facing different contract spaces across states or when mandatory minimum changes.

Taylor approximation approach for nonlinear utility Next, following the literature on auto insurance choices (Cohen and Einav 2007; Barseghyan, Molinari, O'Donoghue, and Teitelbaum 2013), we start with an approximation approach to model the utility function . Assuming that third- or higher-order derivatives are negligible, the utility function can be expressed by a second-order Taylor approximation of the utility function around income w. Normalizing by marginal utility evaluated at w, we get the following expression, in which γ is the absolute-risk-aversion term:

$$v_{idt}(\lambda,\zeta) = \mathbb{E}\left[h_{idt}|\lambda,\zeta\right] - \frac{\gamma}{2}\mathbb{E}\left[h_{idt}^2|\lambda,\zeta\right] \tag{18}$$

This further simplifies product differentiation into consumption bundles with different mean and variance profiles. It also allows us to interpret v in monetary values, as the second term of Equation 18 is exactly the risk premium, while the first is expected consumption. We are currently running robustness checks for alternative utility assumptions such as CARA and CRRA, as well as to allow for richer heterogeneity in risk preference.

Estimation Our model includes random coefficients that enter utility nonlinearly. Private risk, in particular interacts with various observed monitoring and coverage characteristics (renewal price, out-of-pocket expenditure), as well as unobserved demand parameters (risk aversion and monitoring cost). Therefore, we use a simulated maximum likelihood approach (Train 2002; Handel 2013). In particular, the mix logit structure implies that the choice probability is numerically integrated as follows:

$$\begin{aligned} \Pr(d_{it}|\lambda) &= \Pr(\varepsilon_{idt} - \varepsilon_{id't} > [v_{idt}(\lambda) - v_{id't}(\lambda)] \ \forall d' \neq d \\ &= \frac{\exp[v_{idt}(\lambda)/\sigma]}{\sum_{d'} \exp[v_{id't}(\lambda)/\sigma]} \qquad (19) \\ \Pr(d_{it}) &= \int \Pr(d_{it}|\lambda) f_{\lambda}(\lambda) d\lambda \qquad (20) \end{aligned}$$

In general, for each parameter proposal Θ_d, we simulate 50 independent draws of private risk (ε_{λ}) and the zero-mean firm dummy (ζ).[60] Then, we compute the likelihood for observed choices, claim count and severity, monitoring score, and renewal price change. These are averaged over to get the simulated log likelihood. The estimator $\theta^{\star}$ maximizes the log likelihood. Notice that the Taylor approximation allows us to derive closed-form solutions for the first two moments of out-of-pocket expenditures and renewal prices.[61] We therefore do not simulate claim losses or monitoring scores within each draw of random coefficients.

As discussed above, our cost model is easier to estimate but requires a large amount of data to estimate precisely. Our demand model faces the opposite challenge, being computationally demanding but also making use of rich variations in choice environment and outcome. Therefore, we adopt a two-step estimation procedure. First, risk and monitoring score parameters ($\theta_{\lambda}, \sigma_{\lambda}, \theta_s, \sigma_s$) are estimated in the full dataset (except the loss severity parameter, per the discussion above). We then feed the estimates into the demand models as truth.[62] We lose precision by doing so, but both models are identified standalone.

Our model includes unobserved state variables (random coefficients) that enter utility nonlinearly. Therefore, we use a random coefficient simulated maximum likelihood approach (Train 2009; Handel 2013) to estimate the model.

[60] We test the effect of increasing the number of draws in estimation on a 10,000 sub-sample. The effect of going from 50 to 200 draws is minimal.

[61] Further, we restrict α_{ℓ} to be larger than 2 so that the mean and variance of the distribution are both finite, as both moments enter consumers' utility. The mean of the Pareto distribution is thus no more than $2\ell_0$. Therefore, to fit the average cost to the firm well, we set $\ell_0 = 3000$, roughly half the empirical mean of the claim distribution. This parameter is selected in cross-validation, om which we compare model performance in a hold-out dataset by directly calculating the likelihood. In a robustness check, we are also fitting a Gamma model for calculating the firm's cost only.

[62] Standard errors for the demand estimates are current not adjusted for two-step estimation. In a robustness check, we are correcting those standard errors and implementing a joint estimation.

For each parameter proposal θ, we simulate the model 50 times using Halton draws and compute the likelihood for all observations in the data. We then average over these to get the "simulated log likelihood", denoted as $\hat{\mathscr{L}}_{sim}(\theta)$. The estimator $\theta^{\star}$ maximizes the log likelihood. Simulated maximum likelihood suffer from simulation bias

Likelihood Function The log likelihood are sample analogs of four types of data likelihoods (denoted as $\mathscr{L}$) - claims, monitoring score, choices (of firm, coverage and monitoring participation), as well as renewal price. Utilities are history-dependent in our model. Therefore, we need to simulate choice sequence for each driver i. For notational simplicity, we suppress firm-dummy random effect ζ as in our baseline specification. The log likelihood function can then be expressed as follows.

$$\mathscr{L}_i \equiv \sum_{t \leq T_i} \int_{\lambda} \mathscr{L}(\underbrace{R_{it}, s_i, C_{it}, d_{it} | \lambda, \psi, x_{it}, \mathbf{p}_{it}, D_{it}, d_{i,t-1}; \Theta}_{(A)\text{:obs. stoc outcome}}) \cdot \underbrace{g_{\lambda}(\lambda | x_{it}; \theta_{\lambda}, \sigma_{\lambda})}_{(B)\text{:latent var.}} d\lambda$$

The simulation procedure allows us to numerically integrate over λ given parameter proposals θ_{λ} and σ_{λ}. We follow the timing of the model to decompose the likelihood component A as follows.

$$\begin{aligned}
(A) = & \ln \Pr(d_{it} | \lambda, \mathbf{x}_{it}, \mathbf{p}_{it}, D_{it}, d_{i,t-1}; a, \psi_0, \psi_1, \theta_{\eta}, \theta_{\xi}, \alpha, \theta_{\beta}) + \\
& + \ln \Pr(C_{it} | \lambda, \mathbf{x}_{it}) + \ln g(\ell_{it} | d_{it}, \mathbf{x}_{it}; \alpha, \theta_{\beta}) \\
& + \ln g_s(s_i | \lambda, \mathbf{x}_{it}; \theta_s, \sigma_s) + \ln g_R(R_{idt} | C_{it}, s_i, \lambda, \mathbf{x}_{it}, \mathbf{p}_{it}; \theta_{\mathbf{R}}, \theta_{\mathbf{R},\mathbf{m}}, \sigma_R)
\end{aligned}$$

Each component of (A) is modeled in the main text and given distributional assumptions.

Choice probability Our choice probability requires integration over all possible C, ℓ, R_0 and s. In our model, we assume away uncertainty in s, and our Poisson-Gamma model gives analytical solutions for expectation over C and ℓ.

For simplicity, in people's expectation, we only consider the possibility of one claim occurrence per term (Cohen and Einav 2007; Barseghyan et al. 2013). We can then capitalize on the attractive analytical property of gamma distributions and avoid numerical integration over C, ℓ, R_0 and s.

E Simulation Analysis of the Informativeness of Monitoring Signal [For Online Publication]

We can conduct a simple simulation exercise to quantify the spread of private risk and monitoring's effectiveness. To do so, we first simulate a large risk pool by taking the mean of all observable characteristics and simulating each driver's private risk. Figure E.1 plots the density of simulated true risk.[63] Next, Figure E.2 plots the Firm's prior mean for all drivers in the risk pool. The firm has a flat prior for all drivers in the first period, which is far from the perfect belief (represented by the dotted and zoomed in 45-degree line). In Figure E.3, we calculate the evolution of firm belief (posterior mean) in subsequent periods as the Firm observes potential claim realization. The firm's belief evolves towards the truth as claim is a direct measure of risk. However, the sparsity of claims, especially among safe drivers, dramatically slows down the Firm's belief updating.

Monitoring score provides an immediate signal for driver risk after the first period. In Figure E.4, we plot, in orange, how the Firm's belief updates after observing a one-time monitoring score. It is clear that monitoring is far more informative than observing a period of potential claim realization (dark grey line). Monitoring is especially useful in distinguishing the large mass of safe drivers, in which claims are even rarer. To quantify this measure, we can calculate the absolute deviation of firm belief from the true risk in our simulated risk pool. Overall, observing the monitoring score gets the Firm 12.3% closer to the perfect belief (45-degree line).

[63] Our figures use private risk spread among new drivers for illustrative clarity.

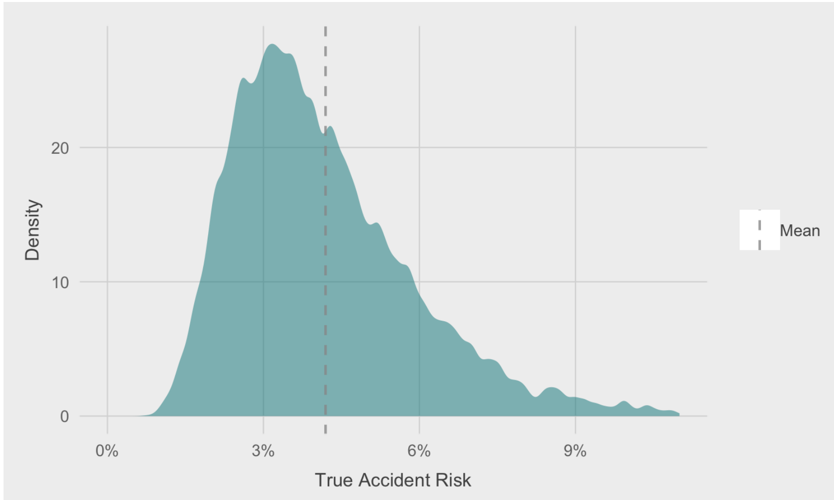

Figure E.1: A simulated mean risk pool given our cost estimate

Notes: This figure plots the distribution of a simulated mean risk pool given our cost estimates.

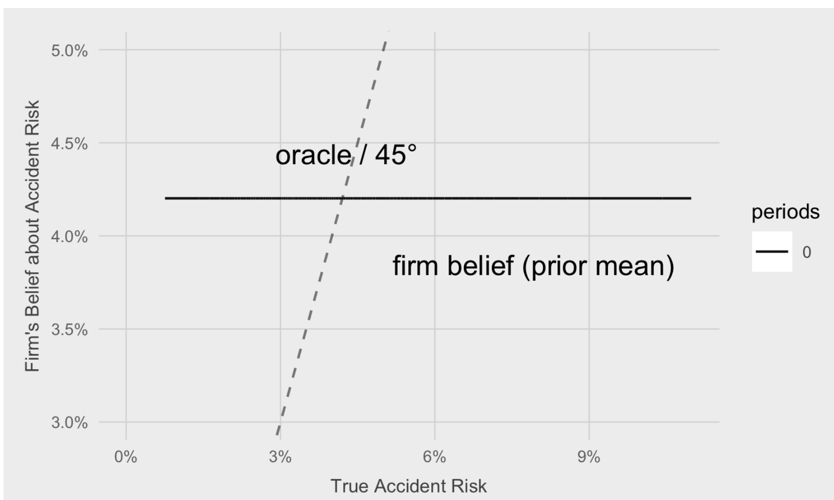

Figure E.2: Firm's prior on simulated risk pool

Notes: This figure plots firm's belief (prior mean / risk rating) for drivers in our simulated pool. In the first period, they are by definition pooled together. Therefore, firm has a flat prior for all drivers in the pool. The dotted line is the 45 degree line, which represents perfect belief.

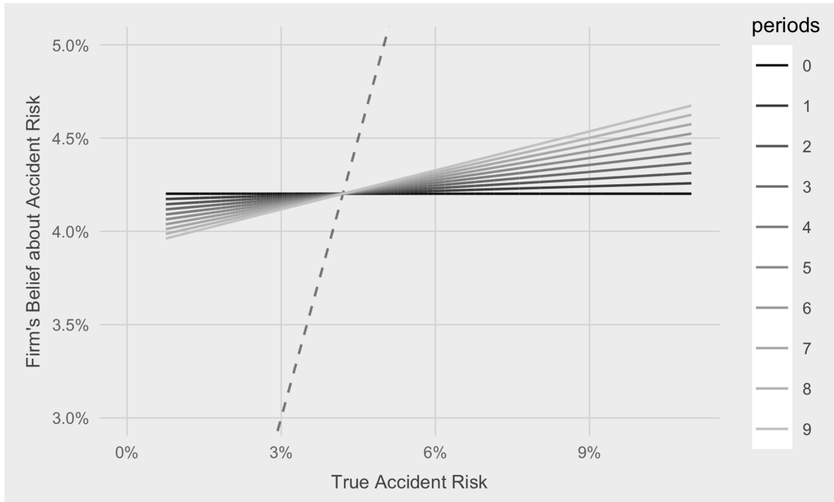

Figure E.3: Firm's posterior updating based on claims

Notes: This figure plots the evolution of firm belief (posterior mean) for drivers in our simulated pool based on liability claims alone. To make the updating analytically feasible, we first fit a gamma distribution on our risk pool by matching the mean and variance. Since gamma distribution is a conjugate prior for poisson updating, we are able to analytically derive the posterior mean.

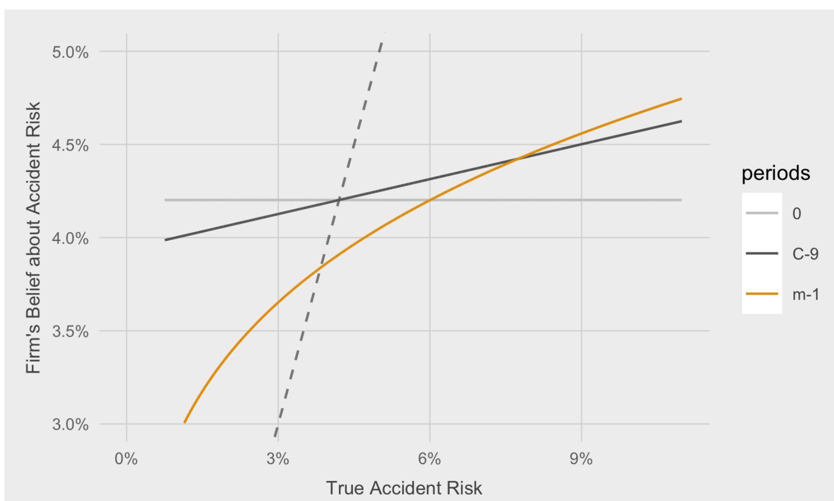

Figure E.4: Firm's posterior updating based on monitoring vs. claims

Notes: This figure plots the evolution of firm belief (posterior mean) for drivers in our simulated pool based on claims versus monitoring. Since lognormal distribution is a conjugate prior for lognormal updating, we are able to analytically derive the posterior mean.

F Counterfactual Simulation Methodology [For Online Publication]

Consistent with our demand model, we take a one-year horizon. The following procedure is used to calculate ex-ante and expected realized (ex-post) quantities.

1. For each driver i, simulate random coefficients (private risk and firm dummy) $L \in \mathbb{N}^+$ times.

2. For each draw $l \in \{1,...,L\}$, calculate ex-ante utility directly and the corresponding certainty equivalent.[64] First-period choice probabilities are also calculated, which gives us the monitoring share. Expected cost of the first semester can be calculated directly. But we also need to form an expectation of the second-period cost (and prices) in order to calculate total surplus (and profit):

3. Simulate $K \in \mathbb{N}^+$ draws of first-period claim occurrence and monitoring score based on private risk.[65] Each draw pins down the renewal price change that driver i would face in the second period. All other prices remain constant. For each first-period choice d, we can then calculate the second period choice probability and the corresponding expected cost.

Sample enumeration Since we observe new customers' origins, as well as the competitive prices they face when coming to the Firm, we can use our model to enumerate a full sample of potential new customers (Train 2009). To do so, we first calculate the probability of each new customer arriving at the Firm. We then follow the same procedure as outlined above, but weight each driver by the inverse of the calculated probability. The simulation is carried out assuming that monitoring is available for all new customers.[66] Overall, our simulated dataset is expanded by a factor of 4.03, which gives us a market share (among the top six firms for which we have data) close to the reality in the states we study.[67] This also allows us to derive a realistic proxy for competitor profit under a symmetric cost assumption; that is, the distribution of risk that we estimate in our dataset is valid when extrapolated to the simulated market.

[64] Due to our Taylor approximation, this should be the negative root of the polynomial.

[65] For simplicity, we assume that R_0 is deterministic conditional on C and s. In reality, the spread of baseline R_0 without claims and monitoring may have subtle nonlinear effects on consumer choice, which we assume away.

[66] Part of the estimation data is pre-monitoring introduction. We use the average opt-in discount for these drivers.

[67] We winzorize the re-weighting scaling factor to be between 1 and 20 to deal with outliers.

In order to enumerate the market, we need to extrapolate the estimated attrition elasticity the Firm faces to understand how the Firm competes with other firms in the first period. To do so, we make a *no-brand-differentiation assumption*: liability insurance contracts offered by different firms only differ financially. This means that our firm-switching inertia estimate consists only of search and switching costs that are state-dependent (on consumers' preexisting firm choice) and that consumers have no unobserved preference for our firm, which is not state-dependent. In the context of our counterfactual simulations, this assumption essentially maintains that the price elasticity the Firm's competitors face when the Firm tries to poach customers away from them (in the first period) is the same as the price elasticity the Firm faces when trying to retain existing customers.

This assumption follows naturally from our data limitation: we do not observe comprehensive micro-level choice or quantity data for the Firm's competitors. But it is also supported by empirical evidence. Honka (2012) uses a survey dataset that includes individual consumer choices across auto insurers. She is then able to tease out switching cost from firm-specific preferences. She finds that the mean firm preferences are not significantly different from 0 for all companies.[68]

[68] Her estimate of search and switching cost is lower than our estimate. However, for the Firm from which our administrative dataset comes from, the reported attrition rate in her dataset is more than three times as large as what we observe. Her estimate is therefore likely biased downwards.

G Counterfactual Demand Models [For Online Publication]

In this section, we show simulation results of removing key components of the demand model, as an illustration of their relative importance in determining monitoring share and the Firm's profitability.

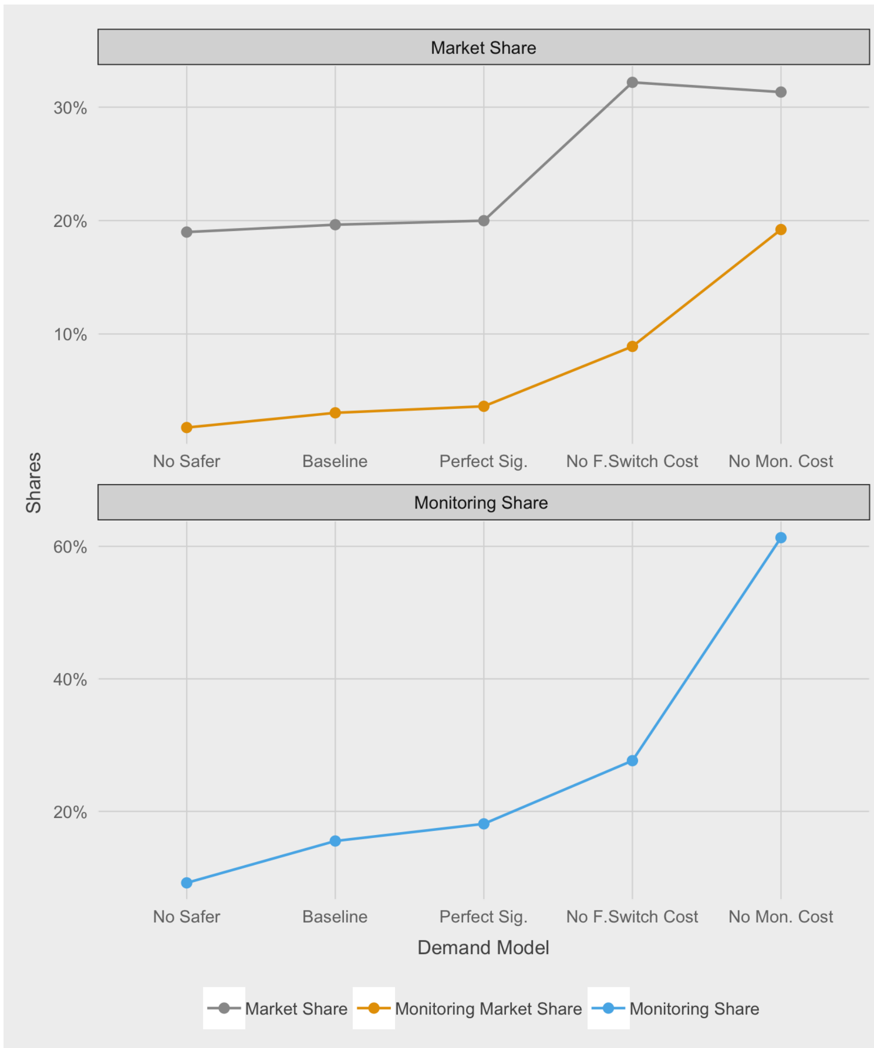

Figure G.5: Demand Share Simulation Across Demand Model Assumptions

Notes: These figures correspond to our analyses in **??**. The top graph plots the counterfactual market share of the Firm, as well as the unconditional share of monitored drivers in the market, when prices are fixed but the demand model changes. The bottom graph plots the conditional monitoring share within the Firm. See main text for definitions of each model - importantly, changes in model features are *not* cumulative from left to right. We also enumerate our sample of new customers to the full market with model-predicted likelihood of each new customer being in our dataset.

Second, the "Perfect Sig." model assumes that the monitoring signal is perfect in consumers'

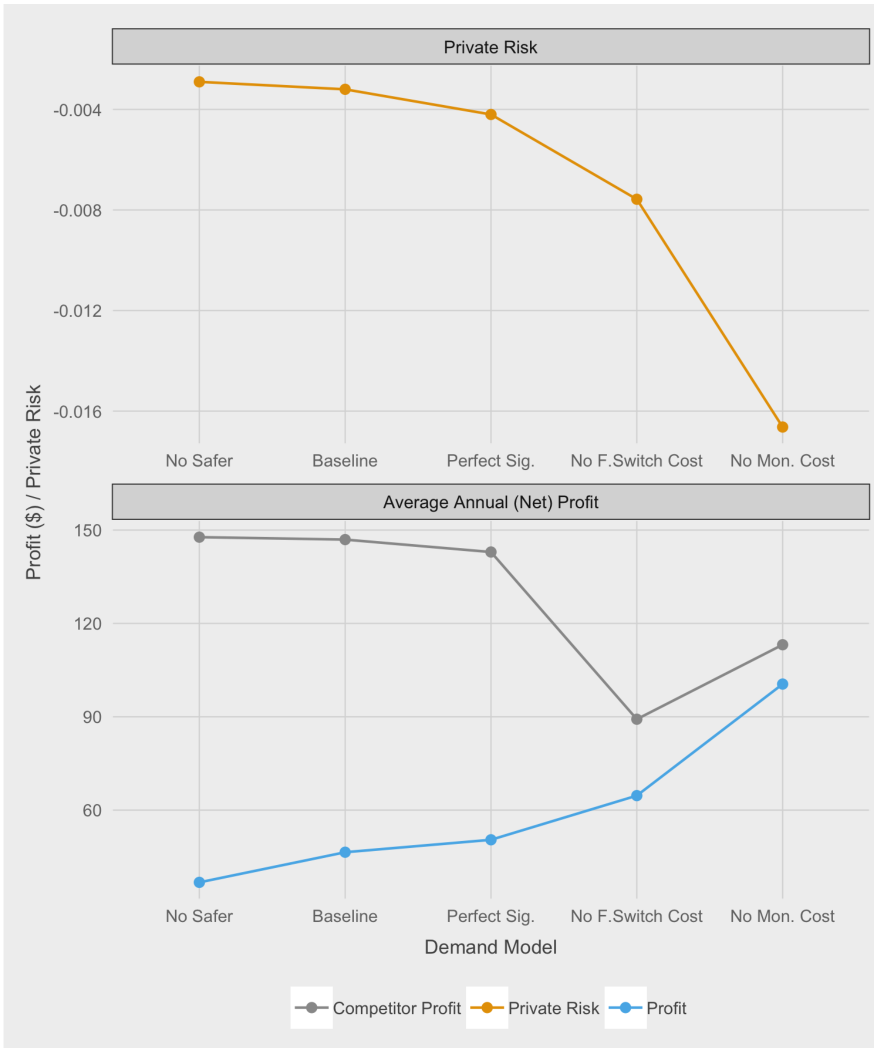

Figure G.6: Simulation - Profit Under Different Demand Model Assumptions

Notes: Corresponding to the figure above, these graphs plot firm profit and competitor profit, holding prices fixed. The top graph plots the expected private risk among the Firm's customers. Notice that private risk has mean zero in the population. It is numerically integrated over in the counterfactual simulations. With each draw, we weight each person's private risk with her probability of arriving at the Firm to get the number shown above. It therefore represents both the monitored and the unmonitored pools of the Firm.

expectation by setting σ_s to zero. The market share, unconditional and conditional monitoring shares increase by 0.4pp, 0.6pp, and 2.6pp, respectively. In reality, our specification is consistent with a dynamic framework in which firm-switching is infinitely costly within a year. This will likely overstate the effect of reclassification risk. Nevertheless, the impact of a perfect signal on demand is small compared to that of other forces.[69]

Demand frictions are the most important deterrent against monitoring participation. The third model removes firm-switching inertia, which dramatically lowers the barrier for drivers with good private risk to participate in monitoring. However, It also clears the way for drivers to explore attractive outside options. We find that the Firm is able to gain market share by 12.6pp, while increasing its monitoring share by 12.1pp so that 5.9% of drivers in the market has monitoring. Lastly, we remove monitoring cost. This generates the biggest impact on monitoring by far. In particular, any driver with good private risk would prefer monitoring with any coverage within the Firm. The monitoring share rises to 61.3%, with 16.2% of the market opting in the Firm's monitoring program.

Firm profit is influenced not only by its market share, but also by risk selection. To directly visualize this, we isolate the risk selection effect from the overall profit impact in Figure G.6. It plots the expected private risk parameter ($\varepsilon_{\lambda,i}$, mean 0) for the Firm's customers, both monitored and unmonitored. This clarifies the changes in the private risk of the marginal customers that come to the Firm as we relax demand factors, which is crucial in understanding competition in selection markets. As the Firm cream-skims better drivers in its monitored pool, the unmonitored pool in and outside of the Firm deteriorates. These pool may therefore eventually unravel as firms adjust prices.

[69] A caveat is that we assume rational expectation in our model. This means that the effect of a systematic over- or under-estimation of the monitoring signal's noise would show up in drivers' monitoring cost instead of be attributed to reclassification risk.

H Regulatory Filing Examples [For Online Publication]

OHIO
VOLUNTARY PRIVATE PASSENGER AUTO
PREMIUM CALCULATION

ROUND AFTER EACH CALCULATION TO THE NEAREST PENNY

STEP #		AA	BB	CC	DD	HH	DNC*^	HNC*^
1	TERRITORIAL BASE RATE (RP-1BR)							
2	RATE ADJUSTMENT FACTOR (PENNY ROUND)	x 1.598	x 1.594	x 1.410	x 1.121	x 1.111	x 1.121	x 1.111
3	INCREASED LIMIT FACTOR/ADDEND (RP-3A)	x	+	x				
4	POLICY GROUP FACTOR (RP-4A-1 through RP-4A-2)	x	x	x	x	x	x	x
5	RATING TIER FACTOR (RP-5A)	x	x	x	x	x	x	x
6	ALLSTATE® YOUR CHOICE AUTO INSURANCE OPTION PACKAGE FACTOR (RP-15A)	x	x	x	x	x	x	x
7	POLICY CLASS FACTOR (RP-7A-1 through RP-7A-4)	x	x	x	x	x	x	x
8	HOUSEHOLD COMPOSITION FACTOR (RP-8A-1 and RP-8A-2)	x	x	x	x	x	x	x
9	SMART STUDENT DISCOUNT FACTOR (RP 10A and RP-11A)	x	x	x	x	x	x	x
10	DEFENSIVE DRIVER DISCOUNT FACTOR (RP-10A and RP-12A)	x	x	x	x	x	x	x
11	MULTIPLE POLICY DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
12	HOMEOWNER DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
13	THE GOOD HANDS PEOPLE® DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
14	RESPONSIBLE PAYER DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
15	FULLPAY DISCOUNT (RP-15A)	x	x	x	x	x	x	x
16	ALLSTATE EASY PAY PLAN DISCOUNT (RP-15A)	x	x	x	x	x	x	x
17	EARLY SIGNING DISCOUNT (RP-15A)	x	x	x	x	x	x	x
18	ALLSTATE AUTO/LIFE DISCOUNT℠ (RP-15A)	x	x	x	x	x	x	x
19	ALLSTATE eSMART℠ DISCOUNT (RP-15A)	x	x	x	x	x	x	x
20	SAFE DRIVING CLUB (RP-10A and RP-13A through RP-14A)	x	x	x	x	x	x	x
21	PRIOR NON-STANDARD CARRIER SURCHARGE (RP-16A)	x	x	x	x	x	x	x
22	ACCIDENT SURCHARGE FACTOR (RP-17A)	x	x	x	x		x	
23	MAJOR VIOLATION SURCHARGE FACTOR (RP-18A)	x	x		x		x	
24	MINOR VIOLATION SURCHARGE FACTOR (RP-19A)	x	x		x		x	
25	MODEL YEAR FACTOR (RP-20A)				x	x	x	x
26	DEDUCTIBLE BY PGS FACTOR (RP-20A)				x	x	x	x
27	EXPERIENCE GROUP RATING FACTOR (EGR PAGES and RP-21A-24A)	x	x	x	x	x	x	x
28	ALLSTATE DRIVE WISE® ENROLLMENT DISCOUNT (RP-26A)	x	x	x	x	x	x	x
29	ALLSTATE DRIVE WISE® PERFORMANCE RATING (RP-26A)	x	x	x	x	x	x	x
30	ANNUAL VEHICLE MILEAGE FACTOR (RP-16A)	x	x	x	x	x	x	x
31	VEHICLE USAGE FACTOR (RP-16A)	x	x	x	x	x	x	x
32	FARM DISCOUNT FACTOR (RP-16A)	x	x		x		x	
33	ELECTRONIC STABILITY CONTROL DISCOUNT FACTOR (RP-16A)	x	x	x	x		x	
34	PASSIVE RESTRAINT DISCOUNT (RP-16A)			x				
35	ANTILOCK BRAKE DISCOUNT (RP-16A)	x	x		x		x	
36	NEW CAR DISCOUNT FACTOR (RP-16A)	x	x	x	x	x	x	x
37	CERTIFIED RISK SURCHARGE FACTOR (RP-16A)	x	x					
38	CAMPER UNIT ADDITIONAL PREMIUM (RP-25A)				+	+		
39	NEW CAR EXPANDED PROTECTION FACTOR (RP-25A)						x	x
40	RATE TRANSITION FACTOR (Rule 72)	x	x	x	x	x		
41	COMPLEMENTARY GROUP RATING (CGR) FACTOR (RP-9A-1 through RP-9A-13)	x	x	x	x	x	x	x
42	FIXED EXPENSE PREMIUM ^^ (RP-16A)	+						
43	SUB-TOTAL VEHICLE PREMIUM	=	=	=	=	=	=	=

	RENTAL REIMBURSEMENT (UU)	
	RENTAL REIMBURSEMENT BASE RATE (RP-52BR)	
	RENTAL REIMBURSEMENT INCREASED LIMIT FACTOR (RP-3A)	x
44	TOTAL RENTAL REIMBURSEMENT COVERAGE PREMIUM	=

	TOWING & LABOR COSTS (JJ) (RP-25A)	
	SOUND SYSTEMS (ZA) (RP-25A)	+
	TAPE (ZZ) (RP-25A)	+
45	TOTAL MISCELLANEOUS COVERAGES	=

	PER AUTO UM/UIM - PROPERTY DAMAGE COVERAGE (SSP)	
46	UM - PROPERTY DAMAGE PREMIUM RATE (RP-3A)	

	POLICY UM/UIM - BODILY INJURY COVERAGE (SS)	
	TERRITORIAL BASE RATE (RP-1BR)	
	RATE ADJUSTMENT FACTOR (PENNY ROUND)	x 0.872
	INCREASED LIMIT FACTOR/ADDEND (RP-3A)	x
	POLICY GROUP FACTOR (RP-4A-1 through RP-4A-2)	x
	RATING TIER FACTOR (RP-5A)	x
	POLICY CLASS FACTOR (RP-7A-1 through RP-7A-4)	x
	HOUSEHOLD COMPOSITION FACTOR (RP-8A-1 through RP-8A-2)	x
	SMART STUDENT DISCOUNT FACTOR (RP 10A and RP-11A)	x
	DEFENSIVE DRIVER DISCOUNT FACTOR (RP-10A and RP-12A)	x
	HOMEOWNER DISCOUNT FACTOR (RP-15A)	x
	RESPONSIBLE PAYER DISCOUNT FACTOR (RP-15A)	x
	FULLPAY DISCOUNT (RP-15A)	x
	SAFE DRIVING CLUB (RP-10A and RP-13A through RP-14A)	x
	ACCIDENT SURCHARGE FACTOR (RP-17A)	x
	MAJOR VIOLATION SURCHARGE FACTOR (RP-18A)	x
	MINOR VIOLATION SURCHARGE FACTOR (RP-19A)	x
	RATE TRANSITION FACTOR (Rule 72)	x
	COMPLEMENTARY GROUP RATING (CGR) FACTOR (RP-9A-1 through RP-9A-13)	x
47	TOTAL UM/UIM - BODILY INJURY COVERAGE	=

48	**TOTAL SEMI-ANNUAL VEHICLE 1 PREMIUM = 43 + 44 + 45 + 46 +47**	+
49	**TOTAL SEMI-ANNUAL VEHICLE 2 PREMIUM = 43 + 44 + 45 + 46 +47**	+
50	**TOTAL SEMI-ANNUAL VEHICLE 3 PREMIUM = 43 + 44 + 45 + 46 +47**	+
51	**TOTAL SEMI-ANNUAL VEHICLE 4 PREMIUM = 43 + 44 + 45 + 46 +47**	+
52	**TOTAL SEMI-ANNUAL POLICY PREMIUM = 48 + 49 + 50 +51**	=

A ALLSTATE FIRE AND CASUALTY INSURANCE COMPANY 04-

Figure H.1: Pricing Algorithm - Insurer 1 OH

Notes: This page is taken from an insurer's Ohio rate filing, which demonstrates their pricing algorithm.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
NB Effective Date: 9/05/2014

Exhibit: 11

RATE ORDER OF CALCULATION

The first step of the rate calculation formula is to determine the Household Risk Factor. The Household Risk Factor is the average of the Developed Driver Risk Factors for all eligible to be rated drivers up to the number of vehicles (or at least one in the case of a named operator policy). For policies where there are more drivers than vehicles, the Household Risk Factor is the average of the highest ranked drivers, up to the number of vehicles. The rank is determined by the Developed Driver Risk Factor for BI (higher factor = higher rank). The Developed Driver Risk Factor is determined as follows:

Driver Risk Factor Items	**BI**	**PD**	**COMP**	**COLL**	**LOAN**	**MED**	**RENT**	**ROADSIDE**	**UMPD**
Driver Classification Factor									
Years Licensed Factor	x	x	x	x	x	x	x	x	x
Driving Record Points Factor	+	+	+	+	+	+	+	+	+
Violation Leniency Factor [1]	-	-	-	-	-	-	-	-	-
Subtraction of One	-1	-1	-1	-1	-1	-1	-1	-1	-1
(1 - Distant Student Discount)	x	x	x	x	x	x	x	x	x
(1 - Minor Child Discount)	x	x	x	x	x	x	x	x	x
(1 - Good Student Discount)	x	x	x	x	x	x	x	x	x
(1 - Senior Citizen Discount)	x	x	x	x		x			
Household Member Factor	x	x	x	x	x	x	x	x	x
Driver Age Point Factor	x	x	x	x	x	x	x	x	x
Financial Responsibility by Clean Factor	x	x	x	x	x	x	x	x	x
Developed Driver Risk Factor									

The second step of the rate calculation formula uses the Household Risk Factor and follows

	BI	**PD**	**COMP**	**COLL**	**LOAN**	**MED**	**RENT**	**ROADSIDE**	**UMPD**
Household Risk Factor									
Base Rate	x	x	x	x	x	x	x	x	x
Financial Responsibility Factor	x	x	x	x	x	x	x	x	x
Financial Responsibility by Number of Drivers Factor	x	x	x	x	x	x			x
Deductible Savings Bank Factor	x	x	x	x		x			
Occupation/Education Rating Factor	x	x	x	x	x	x			x
Full Coverage Factor	x	x				x			
Household Structure Factor	x	x	x	x	x	x			x
Residency Rewards Factor	x	x	x	x	x	x	x		x
Luxury Vehicle Factor	x	x	x	x	x	x			x
Tier Factor	x	x	x	x	x	x	x	x	x
Policy Term Factor	x	x	x	x	x	x	x	x	x
Vehicle Age Factor [3]	x	x	x	x	x	x	x	x	x
Excess Vehicle Factor	x	x	x	x	x	x			x
Limit Factor	x	x			x	x	x	x	x
Deductible Factor			x	x					
Vehicle Age by Deductible Factor			x	x					
Vehicle Symbol Factor	x	x	x	x	x	x			x
Value Class Factor (for Vehicle symbols 67 & 68)			x	x	x				x
Vehicle Garaging Location Factor	x	x	x	x	x	x	x	x	x
(1 - Homeowner/Mobile Home/Multi-car Discount)	x	x	x	x		x	x	x	x
(1 - Advance Quote [1]/Three-year Safe Driving/Five-year Accident Free Discount)	x	x	x	x		x			x
(1 - Three-year Safe Driving Bonus) [1]	x	x	x	x		x			x
(1 - Agent Discount) [1]	x	x	x	x		x			x
(1 - Electronic Funds Transfer Discount)	x	x	x	x		x			x
(1 - Paid In Full Discount)	x	x	x	x		x			x
(1 - Online Quote Discount) [2]	x	x	x	x		x			x
(1 - Loyal Customer Discount) [2]	x	x	x	x		x			x
(1 - Paperless Discount)	x	x	x	x	x	x	x	x	x
(1 - Continuous Insurance Discount)	x	x	x	x	x	x	x	x	x
(1 - Multi-policy Discount)	x	x	x	x		x	x	x	x
(1 + Business Use Surcharge)	x	x	x	x		x			x
(1 + Financial Responsibility Filing Surcharge)	x	x	x	x		x			x
Bad Debt Factor	x	x	x	x		x			x
Apply Rate Capping Rule P23 [4]	x	x	x	x	x	x	x	x	x
Usage-based Insurance Factor	x	x	x	x	x	x	x	x	x
(1 - E-signature discount) [2]	x	x	x	x	x	x	x	x	x
Round to the Whole Dollar									
Operations Expense [5]	+		+						
Acquisition Expense [2,6]	+		+						
Developed Premium [8]									

[1] Applies to Progressive Specialty Insurance Company (AG) Only

[2] Applies to Progressive Direct Insurance Company Only (DI)

[3] If coverage is BI, PD, UM/UIM, MED, RENT, or ROADSIDE and Vehicle Symbol = 66, then Vehicle Age Factor = 1.0.
If coverage is COMP, COLL, LOAN, or UMPD and Vehicle Symbol = 66, 67, 68, or 69, then Vehicle Age Factor = 1.0.

[4] Policy level rate changes are capped at +/- 10% as described in Rule P23. The Snapshop Usage Based Insurance Program (UBI) is not taken into consideration when applying the Rate Capping Rule

[5] Operations expense is added to BI if BI is selected; if BI is not selected, then Operations Expense is added to COMP.

[6] Acquisition expense is added to BI if BI is selected; if BI is not selected, then Acquisition Expense is added to COMP.

[7] Average factors are determined by taking the average of Location, Symbol, Vehicle Age factors, and Business Use Surchage for each vehicle, respectively

[8] There is a minimum premium of $5 for each coverage selected for each vehicle.

[9] The trailer coverages will receive the factors associated with COMP and COLL, unless otherwise noted.

NOTES
x means factor is to be used multiplicatively
/ means factor is to be used as a divisor
+ means factor is to be added
- means factor or amount is to be subtracted

Figure H.2: Pricing Algorithm - Insurer 2 OH 1/2

Notes: These pages are taken from a an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
NB Effective Date: 9/05/2014

Exhibit: 11

	UM/UIM
Base Rate	
Financial Responsibility Factor	x
Financial Responsibility by Number of Drivers Factor	x
Deductible Savings Bank Factor	x
Occupation/Education Rating Factor	x
Full Coverage Factor	x
Household Structure Factor	x
Residency Rewards Factor	x
Driver Count Factor	x
Luxury Vehicle Factor	x
Tier Factor	x
Policy Term Factor	x
Avg. Vehicle Age Factor [3,7]	x
Excess Vehicle Factor	x
Limit Factor	x
Avg. Vehicle Symbol Factor [7]	x
Avg. Vehicle Garaging Location Factor [7]	x
(1 - Homeowner/Mobile Home/Multi-car Discount)	x
(1 - Advance Quote[1]/Three-year Safe Driving/Five-year Accident Free Discount)	x
(1 - Three-year Safe Driving Bonus) [1]	x
(1 - Agent Discount) [1]	x
(1 - Electronic Funds Transfer Discount)	x
(1 - Paid In Full Discount)	x
(1 - Online Quote Discount) [2]	x
(1 - Loyal Customer Discount) [2]	x
(1 - Paperless Discount)	x
(1 - Continuous Insurance Discount)	x
(1 - Multi-policy Discount)	x
(1 + Avg. Business Use Surcharge [7])	x
(1 + Financial Responsibility Filing Surcharge)	x
Bad Debt Factor	x
Apply Rate Capping Rule P23 [4]	x
(1 - E-signature discount) [2]	x
Round to the Whole Dollar	
Developed Premium [8]	

	ACPE	COMP-TRLR [1,9]	COLL-TRLR [1,9]	CONTENTS [1]	OPERATIONS EXPENSE [5]	ACQUISITION EXPENSE [2,6]
Base Rate				0.015 * Value		
Financial Responsibility Factor		x	x	x		
Deductible Savings Bank Factor		x	x			
Residency Rewards Factor		x	x			
Tier Factor		x	x	x		
Policy Term Factor	x	x	x	x	x	x
Limit Factor	x					
Deductible Factor		x	x			
Vehicle Symbol Factor		x	x			
Value Class Trailer Factor [1]		x	x			
Vehicle Garaging Location Factor	x	x	x			
(1 - Paperless Discount)	x	x	x	x	x	
(1 - Continuous Insurance Discount)		x	x			
(1 - Multi-policy Discount)						x
Operations Expense Factor 1					x	
Operations Expense Factor 2					x	
Operations Expense Factor 3					x	
Acquisition Expense Full Coverage Factor [2]						x
Acquisition Expense Homeowner Factor [2]						x
Acquisition Expense Online Quote Factor [2]						x
Acquisition Expense Prior Insurance Factor [2]						x
Acquisition Expense Vehicle Count Factor [2]						x
Number of Vehicles						/
Apply Rate Capping Rule P23 [4]	x	x	x	x	x	x
Bad Debt Factor		x	x			
Usage-based Insurance Factor	x				x	x
(1 - E-signature discount) [2]	x				x	x
Round to the Whole Dollar						
Developed Premium [8]						

Total Policy Premium = Sum of Developed Premiums

[1] Applies to Progressive Specialty Insurance Company (AG) Only
[2] Applies to Progressive Direct Insurance Company Only (DI)
[3] If coverage is BI, PD, UM/UIM, MED, RENT, or ROADSIDE and Vehicle Symbol = 66, then Vehicle Age Factor = 1.0.
If coverage is COMP, COLL, LOAN, or UMPD and Vehicle Symbol = 66, 67, 68, or 69, then Vehicle Age Factor = 1.0.
[4] Policy level rate changes are capped at +/- 10% as described in Rule P23. The Snapshop Usage Based Insurance Program (UBI) is not taken into consideration when applying the Rate Capping Rule
[5] Operations expense is added to BI if BI is selected; if BI is not selected, then Operations Expense is added to COMP.
[6] Acquisition expense is added to BI if BI is selected; if BI is not selected, then Acquisition Expense is added to COMP.
[7] Average factors are determined by taking the average of Location, Symbol, Vehicle Age factors, and Business Use Surchage for each vehicle, respectively
[8] There is a minimum premium of $5 for each coverage selected for each vehicle.
[9] The trailer coverages will receive the factors associated with COMP and COLL, unless otherwise noted.

NOTES
x means factor is to be used multiplicatively
/ means factor is to be used as a divisor
+ means factor is to be added
- means factor or amount is to be subtracted

Figure H.3: Pricing Algorithm - Insurer 2 OH 2/2

Notes: These pages are taken from an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages   Effective: New Business 10/2/2009 Renewals 10/2/2009   Rate Gen 01
Rate Order of Calculation: Private Passenger

Machine Rated, Exception: Licensed/Registered Dune Buggies rated as PPV are **Manually Rated**

Oper	Step		BI	PD	MED	UM-UND	UMBI	UMPD	COMP	COLL	ERS	RR	MBI
Base Rate													
	Base Rate		X	X	X	X	X	X	X	X	X	X	X
*	Limit Factor		X	X	X	X	X	X			X	X	
*	Deductible Factor								X	X			
*	Term Factor		X	X	X	X	X	X	X	X	X	X	X
*	Upgraded Accident Forgiveness Factor		X	X	X	X	X	X	X	X			
Driver Level Rating Steps- Composite Relativities													
*	Driver Class Factor (Composite Relativity)		X	X	X	X	X	X		X			
	Accident Factor		X	X	X	X	X	X		X			
	* Minor Violation Factor		X	X	X	X	X	X		X			
	* Major Violation Factor		X	X	X	X	X	X		X			
	* Speeding Violation Factor		X	X	X	X	X	X		X			
	* DUI Violation Factor		X	X	X	X	X	X		X			
	* Unverifiable Driving Record Factor		X	X	X	X	X	X		X			
	= Merit Factor		X	X	X	X	X	X		X			
*	Merit Factor (Composite Relativity)		X	X	X	X	X	X		X			
Driver Level Discounts: Composite Relativities													
*	*Good Driver Discount (Composite Relativity)*		X	X	X	X	X	X		X			
*	*Student Away at School Discount (Composite Relativity)*		X	X	X	X	X	X		X			
*	*Driving Experience Discount (Composite Relativity)*		X	X	X	X	X	X		X			
*	*Good Student Discount (Composite Relativity)*		X	X	X	X	X	X		X			
*	*Defensive Driver Discount (Composite Relativity)*		X	X	X	X	X	X		X			
*	*Deployed Driver Discount (Composite Relativity)*		X	X	X	X	X	X		X			
Vehicle Level Rating Steps													
*	Vehicle Type Factor												
*	Annual Mileage/ Vehicle Use Factor		X	X	X	X	X	X	X	X			
*	Vehicle Classification Factor		X	X	X	X	X	X	X	X			
*	Vehicle Cost Factor		X	X	X	X	X	X	X	X			
*	Model Year Factor		X	X	X	X	X	X	X	X			
*	Vehicle Age Factor		X	X	X	X	X	X	X	X	X		
*	MBI Model Year Factor												X
*	MBI Coverage Age												X
Vehicle Level Discounts													
*	*Anti-Theft Discount*								X				
*	*New Vehicle Discount*		X	X	X	X	X	X	X	X			
*	*Extra Vehicle Discount*		X	X	X	X	X	X	X	X			
*	*Anti-Lock Brake Discount*		X	X	X	X	X	X	X	X			
*	*Restraint Discount*				X	X	X						
Policy Level Rating Steps													
*	Household Composite Factor		X	X	X	X	X	X	X	X			
*	Maximum Named Insured Age Factor		X	X	X	X	X	X	X	X			
*	Policy Occurrence Factor		X	X	X	X	X	X	X	X			
*	Risk Tier Factor		X	X	X	X	X	X	X	X	X	X	X
Policy Level Discounts													
*	*Financial Responsibility Discount*		X	X	X	X	X	X	X	X	X	X	X
*	*Seat Belt Discount*				X	X	X						
*	*Multi-Vehicle Discount*		X	X	X	X	X	X	X	X	X	X	X
*	*Continuous Insurance Discount*		X	X	X	X	X	X	X	X			
*	*Military Discount*		X	X	X	X	X	X	X	X			
*	*Multi-Line Discount*		X	X	X	X	X	X	X	X	X	X	X
*	*CDL Discount*												
Policy Level Discounts 2													
*	*Sponsored Marketing Discount*		X	X	X	X	X	X	X	X	X	X	X
*	*Associate Discount*		X	X	X	X	X	X	X	X	X	X	X
*	*E-Banking Discount*		X	X	X	X	X	X	X	X	X	X	X
Expense Constants													
+	Vehicle Expense Load		X	X									
+	Policy Expense Load		X	X									

Figure H.4: Pricing Algorithm - Insurer 3 OH

Notes: These pages are taken from an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

OHIO
VOLUNTARY PRIVATE PASSENGER AUTO
POLICY CLASS FACTOR

POLICY CLASS FACTOR CALCULATION

Complete the steps below for all applicable coverages. Round to 4 decimals after each step.

Step 1: Based on number of male and female operators on the policy, obtain a value from Value Table 1a and find the corresponding factor from Factor Table 1a.

Step 2: Based on number of single operators, married operators, operators aged <25, and operators aged 25+ on the policy, obtain a value from Value Table 1b and find the corresponding factor from Factor Table 1b.

Step 3: Based on age and gender, obtain a value from Value Table 1c for **each** operator and calculate the geometric average of the corresponding factors from Factor Table 1c to obtain a factor for step 3.

Step 4: Multiply steps 1, 2, and 3 together to obtain the policy class factor to be applied to all vehicles on the policy.

See **RP-6A** for instructions on how to calculate the geometric average.

VALUE TABLE 1a - GENDER

Continuous Prior Insurance	# of Males	# of Females 0	1	2	3+
Yes	0	-	1	2	3
Yes	1	10	11	12	13
Yes	2	20	21	22	23
Yes	3+	30	31	32	33
No	0	-	4	5	6
No	1	14	15	16	17
No	2	24	25	26	27
No	3+	34	35	36	37

VALUE TABLE 1b - MARITAL STATUS AND AGE

Continuous Prior Insurance (Y/N)	# age >= 25	# age < 25	Marital Status: # Married 0 / # Single 1	0 / 2	0 / 3+	1 / 0	1 / 1	1 / 2	1 / 3+	2 / 0	2 / 1	2 / 2	2 / 3+	3+ / 0	3+ / 1	3+ / 2	3+ / 3+
Yes	0	1	1			16											
Yes	0	2		3			18			33							
Yes	0	3+			6			21	25		36	40	45	52	62	70	77
Yes	1	0	2			17											
Yes	1	1		4			19			34							
Yes	1	2			7			22			37			53			
Yes	1	3+			8				26			41	46	54	63	71	78
Yes	2	0		5			20			35							
Yes	2	1			9			23			38			55			
Yes	2	2			10				27			42		56	64		
Yes	2	3+			11				28				47	57	65	72	79
Yes	3+	0			12			24	29		39	43	48	58	66	73	80
Yes	3+	1			13				30			44	49	59	67	74	81
Yes	3+	2			14				31				50	60	68	75	82
Yes	3+	3+			15				32				51	61	69	76	83
No	0	1	84			99											
No	0	2		86			101			116							
No	0	3+			89			104	108		119	123	128	135	145	153	160
No	1	0	85			100											
No	1	1		87			102			117							
No	1	2			90			105			120			136			
No	1	3+			91				109			124	129	137	146	154	161
No	2	0		88			103			118							
No	2	1			92			106			121			138			
No	2	2			93				110			125		139	147		
No	2	3+			94				111				130	140	148	155	162
No	3+	0			95			107	112		122	126	131	141	149	156	163
No	3+	1			96				113			127	132	142	150	157	164
No	3+	2			97				114				133	143	151	158	165
No	3+	3+			98				115				134	144	152	159	166

VALUE TABLE 1c - AGE AND GENDER

Age	Male	Female
16 and Under	1	20
17	2	21
18	3	22
19	4	23
20	5	24
21	6	25
22	7	26
23	8	27
24	9	28
25-29	10	29
30-49	11	30
50-54	12	31
55-59	13	32
60-64	14	33
65-70	15	34
71-75	16	35
76-80	17	36
81-84	18	37
85+	19	38

RP-7A-1 ALLSTATE FIRE AND CASUALTY INSURANCE COMPANY 04-01-2014

Figure H.5: Variable Definition and Interactions

Notes: This is an excerpt from an insurer's rate filing on how observable information is used and interacted.

Driver Class Factors - 2

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages Effective: New Business 06/07/2013 Renewals 07/22/2013 Rate Gen 12
Driver Class Factors

** Risk Group: B = B10, B20, and B30; C = C10, C20, C30; D = D10, D20, D30
** Z in Risk Tier represents all Risk Tiers
** Driver Age 999 = 80 and older
** RV Factor = 1.0

Risk Group	Risk Tier	Rated Vehicle Type	Coverage	Named Insured Indicator	Gender	Marital Status	Driver Age	Factor
B	Z	PP	BI	N	F	S	24	1.1660
B	Z	PP	BI	Y	M	M	24	0.9460
B	Z	PP	BI	N	M	M	24	1.1976
B	Z	PP	BI	Y	M	S	24	0.9361
B	Z	PP	BI	N	M	S	24	1.1387
B	Z	PP	BI	Y	F	M	25	0.7939
B	Z	PP	BI	N	F	M	25	0.8392
B	Z	PP	BI	Y	F	S	25	0.9649
B	Z	PP	BI	N	F	S	25	1.1458
B	Z	PP	BI	Y	M	M	25	0.9460
B	Z	PP	BI	N	M	M	25	1.1633
B	Z	PP	BI	Y	M	S	25	0.9361
B	Z	PP	BI	N	M	S	25	1.1178
B	Z	PP	BI	Y	F	M	26	0.8060
B	Z	PP	BI	N	F	M	26	0.8520
B	Z	PP	BI	Y	F	S	26	0.9649
B	Z	PP	BI	N	F	S	26	1.0819
B	Z	PP	BI	Y	M	M	26	0.9460
B	Z	PP	BI	N	M	M	26	1.1360
B	Z	PP	BI	Y	M	S	26	0.9361
B	Z	PP	BI	N	M	S	26	1.0359
B	Z	PP	BI	Y	F	M	27	0.8060
B	Z	PP	BI	N	F	M	27	0.8520
B	Z	PP	BI	Y	F	S	27	0.9649
B	Z	PP	BI	N	F	S	27	1.0525
B	Z	PP	BI	Y	M	M	27	0.9460
B	Z	PP	BI	N	M	M	27	1.0460
B	Z	PP	BI	Y	M	S	27	0.9361
B	Z	PP	BI	N	M	S	27	1.0251
B	Z	PP	BI	Y	F	M	28	0.8060
B	Z	PP	BI	N	F	M	28	0.8520
B	Z	PP	BI	Y	F	S	28	0.9649
B	Z	PP	BI	N	F	S	28	1.0398
B	Z	PP	BI	Y	M	M	28	0.9460
B	Z	PP	BI	N	M	M	28	1.0260
B	Z	PP	BI	Y	M	S	28	0.9361
B	Z	PP	BI	N	M	S	28	1.0172
B	Z	PP	BI	Y	F	M	29	0.8060
B	Z	PP	BI	N	F	M	29	0.8530
B	Z	PP	BI	Y	F	S	29	0.9649
B	Z	PP	BI	N	F	S	29	1.0118
B	Z	PP	BI	Y	M	M	29	0.9460
B	Z	PP	BI	N	M	M	29	1.0110
B	Z	PP	BI	Y	M	S	29	0.9361
B	Z	PP	BI	N	M	S	29	0.9821
B	Z	PP	BI	Y	F	M	30	0.8060
B	Z	PP	BI	N	F	M	30	0.8440
B	Z	PP	BI	Y	F	S	30	0.9649
B	Z	PP	BI	N	F	S	30	1.0100
B	Z	PP	BI	Y	M	M	30	0.9460
B	Z	PP	BI	N	M	M	30	0.9900
B	Z	PP	BI	Y	M	S	30	0.9361
B	Z	PP	BI	N	M	S	30	0.9800
B	Z	PP	BI	Y	F	M	31	0.8060
B	Z	PP	BI	N	F	M	31	0.8360
B	Z	PP	BI	Y	F	S	31	0.9648
B	Z	PP	BI	N	F	S	31	1.0010
B	Z	PP	BI	Y	M	M	31	0.9415
B	Z	PP	BI	N	M	M	31	0.9760
B	Z	PP	BI	Y	M	S	31	0.9360
B	Z	PP	BI	N	M	S	31	0.9710
B	Z	PP	BI	Y	F	M	32	0.8060
B	Z	PP	BI	N	F	M	32	0.8270
B	Z	PP	BI	Y	F	S	32	0.9648
B	Z	PP	BI	N	F	S	32	0.9900
B	Z	PP	BI	Y	M	M	32	0.9421
B	Z	PP	BI	N	M	M	32	0.9670

Figure H.6: Rating Factors based on Observables

Notes: This is an excerpt from an insurer's rate filing on how observable information is translated into pricing factors.

Progressive Direct Insurance Company
State of Ohio
New Business Effective: January 23, 2015
Renewals Effective: February 20, 2015

D06-Driving Violation Descriptions

The following chart lists the violation codes and their associated descriptions:

Violation Code	Violation Description
AAF	At Fault Accident
AFM	Accident found on MVR only at renewal - Not Chargeable
ANC	Waived Claim – Closed
ANO	Waived Claim – Open
ASW	Accident Surcharge Waived
CML	Commercial Vehicle Violation
CMP	Comprehensive Claim
CMU	Comprehensive Claim Less Than $1000
CRD	Careless or Improper Operation
DEV	Traffic Device/Sign
DR	Drag Racing
DWI	Drive Under Influence
FDL	Foreign Drivers Lic
FEL	Auto Theft/Felony Motor Vehicle
FFR	Failure to File Required Report
FLE	Fleeing from Police
FTC	Following Too Close
FTY	Failure to Yield
HOM	Vehicular Homicide
IP	Improper Passing
IT	Improper Turn
LDL	Operating Without Owner's Consent
LIC	License/Credentials Violation
LTS	Leaving the Scene
MAJ	Other Serious Violation
MMV	Minor Moving Violation
NAF	Not At Fault Accident
NFX	Waived Not At Fault Accident
PUA	Permissive Use At Fault Accident
PUN	Permissive Use Not At Fault Accident
RKD	Reckless Driving
SLV	Serious License Violations
SPD	Speeding
SUS	Driving Under Suspension
TMP	Dispute - At Fault Accident
UDR	Unverifiable Record
WSR	Wrong Way on a One Way Street

Figure H.7: Violation Captured in OH

Notes: This is an excerpt from an insurer's rate filing on the kinds of violations recorded in tier rating in Ohio.

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages Effective: New Business 06/07/2013 Renewals 07/22/2013 Rate Gen 12
Accident Factors

** Risk Group: B = B10, B20, and B30; C = C10, C20, C30; D = D10, D20, D30
** Z in Risk Tier represents all Risk Tiers
** For Coverages BI,PD, COLL, COLL PP, and COLL TL Driver Age 18 = 18 and younger; 999 = 80 and older. All other Coverages Driver Age 18 = 18 and you

Risk Group	Risk Tier	Rated Vehicle Type	Coverage	Driver Age	Number of Chargeable Occurrences	Months Since First Occurrence	Months Since Second Occurrence	Factor
B	Z	PP	BI	31	4	23	35	3.3112
B	Z	PP	BI	31	4	35	35	3.0748
B	Z	PP	BI	31	99	11	11	4.9426
B	Z	PP	BI	31	99	11	23	4.5307
B	Z	PP	BI	31	99	11	35	4.3248
B	Z	PP	BI	31	99	23	23	3.9644
B	Z	PP	BI	31	99	23	35	3.7842
B	Z	PP	BI	31	99	35	35	3.5140
B	Z	PP	BI	32	0	0	0	1.0000
B	Z	PP	BI	32	1	11	0	1.6375
B	Z	PP	BI	32	1	23	0	1.3267
B	Z	PP	BI	32	1	35	0	1.2320
B	Z	PP	BI	32	2	11	11	2.2925
B	Z	PP	BI	32	2	11	23	2.1014
B	Z	PP	BI	32	2	11	35	2.0059
B	Z	PP	BI	32	2	23	23	1.6550
B	Z	PP	BI	32	2	23	35	1.5797
B	Z	PP	BI	32	2	35	35	1.4669
B	Z	PP	BI	32	3	11	11	3.5525
B	Z	PP	BI	32	3	11	23	3.2565
B	Z	PP	BI	32	3	11	35	3.1083
B	Z	PP	BI	32	3	23	23	2.8493
B	Z	PP	BI	32	3	23	35	2.7199
B	Z	PP	BI	32	3	35	35	2.5256
B	Z	PP	BI	32	4	11	11	4.3248
B	Z	PP	BI	32	4	11	23	3.9644
B	Z	PP	BI	32	4	11	35	3.7842
B	Z	PP	BI	32	4	23	23	3.4689
B	Z	PP	BI	32	4	23	35	3.3112
B	Z	PP	BI	32	4	35	35	3.0748
B	Z	PP	BI	32	99	11	11	4.9426
B	Z	PP	BI	32	99	11	23	4.5307
B	Z	PP	BI	32	99	11	35	4.3248
B	Z	PP	BI	32	99	23	23	3.9644
B	Z	PP	BI	32	99	23	35	3.7842
B	Z	PP	BI	32	99	35	35	3.5140
B	Z	PP	BI	33	0	0	0	1.0000
B	Z	PP	BI	33	1	11	0	1.6375
B	Z	PP	BI	33	1	23	0	1.3267
B	Z	PP	BI	33	1	35	0	1.2320
B	Z	PP	BI	33	2	11	11	2.2925
B	Z	PP	BI	33	2	11	23	2.1014
B	Z	PP	BI	33	2	11	35	2.0059
B	Z	PP	BI	33	2	23	23	1.6550
B	Z	PP	BI	33	2	23	35	1.5797
B	Z	PP	BI	33	2	35	35	1.4669
B	Z	PP	BI	33	3	11	11	3.5525
B	Z	PP	BI	33	3	11	23	3.2565
B	Z	PP	BI	33	3	11	35	3.1083
B	Z	PP	BI	33	3	23	23	2.8493
B	Z	PP	BI	33	3	23	35	2.7199
B	Z	PP	BI	33	3	35	35	2.5256
B	Z	PP	BI	33	4	11	11	4.3248
B	Z	PP	BI	33	4	11	23	3.9644
B	Z	PP	BI	33	4	11	35	3.7842

Figure H.8: Tier Factors

Notes: This is an excerpt from an insurer's rate filing on how tier information is rated.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
Effective Date: January 23, 2015

Usage-based Insurance Factor Table - Initial Discount (DI Experience) **Exhibit: 9C**

UBI SCORE	BI/PD	COLL	COMP	LOAN	MED	RENT	ROADSIDE	UMPD	ACPE	OPERATIONS EXPENSE	ACQUISITION EXPENSE
0	0.56	0.56	0.96	0.96	0.56	0.56	0.96	0.56	0.96	1.00	1.00
1	0.61	0.61	0.96	0.96	0.61	0.61	0.96	0.61	0.96	1.00	1.00
2	0.65	0.65	0.97	0.97	0.65	0.65	0.97	0.65	0.97	1.00	1.00
3	0.75	0.74	0.97	0.97	0.75	0.74	0.97	0.75	0.97	1.00	1.00
4	0.79	0.79	0.97	0.97	0.79	0.79	0.97	0.79	0.97	1.00	1.00
5	0.83	0.83	0.97	0.97	0.83	0.83	0.97	0.83	0.97	1.00	1.00
6	0.86	0.87	0.97	0.97	0.86	0.87	0.97	0.86	0.97	1.00	1.00
7	0.89	0.89	0.97	0.97	0.89	0.89	0.97	0.89	0.97	1.00	1.00
8	0.89	0.90	0.97	0.97	0.89	0.90	0.97	0.89	0.97	1.00	1.00
9	0.89	0.91	0.97	0.97	0.89	0.91	0.97	0.89	0.97	1.00	1.00
10	0.90	0.90	0.97	0.97	0.90	0.90	0.97	0.90	0.97	1.00	1.00
11	0.90	0.90	0.97	0.97	0.90	0.90	0.97	0.90	0.97	1.00	1.00
12	0.90	0.90	0.98	0.98	0.90	0.90	0.98	0.90	0.98	1.00	1.00
13	0.91	0.89	0.98	0.98	0.91	0.89	0.98	0.91	0.98	1.00	1.00
14	0.91	0.88	0.98	0.98	0.91	0.88	0.98	0.91	0.98	1.00	1.00
15	0.91	0.90	0.98	0.98	0.91	0.90	0.98	0.91	0.98	1.00	1.00
16	0.92	0.90	0.98	0.98	0.92	0.90	0.98	0.92	0.98	1.00	1.00
17	0.92	0.91	0.98	0.98	0.92	0.91	0.98	0.92	0.98	1.00	1.00
18	0.92	0.91	0.98	0.98	0.92	0.91	0.98	0.92	0.98	1.00	1.00
19	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
20	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
21	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
22	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
23	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
24	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
25	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
26	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
27	0.93	0.93	0.99	0.99	0.93	0.93	0.99	0.93	0.99	1.00	1.00
28	0.93	0.94	0.99	0.99	0.93	0.94	0.99	0.93	0.99	1.00	1.00
29	0.93	0.94	0.99	0.99	0.93	0.94	0.99	0.93	0.99	1.00	1.00
30	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
31	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
32	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
33	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
34	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
35	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
36	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
37	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
38	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
39	0.95	0.96	0.99	0.99	0.95	0.96	0.99	0.95	0.99	1.00	1.00

Note:
-The premium-weighted average factor for the vehicle is calculated and applied to all coverages for the vehicle as indicated in the Rate Order of Calculation. This factor cannot be lower than 0.70 or greater than 1.0.

-If a vehicle does not participate in the Usage-based Insurance program it is assigned a 1.0 factor.

Figure H.9: Violation Captured in OH

Notes: This is an excerpt from an insurer's rate filing on how monitoring pricing is filed.

Progressive Direct Insurance Company (DI) & Progressive Specialty Insurance Company (AG)
Private Passenger Automobile Program
Supporting Exhibits for the State of Ohio
Effective Date: September 5, 2014
Coverage: BI **Exhibit 10Y**

Limit Factor

Experience	Has Prior Insurance	Limit	Incurred Loss Capped	Indicated Factor	Proposed Factor	Current Factor	Percent Change
AG	N	$25,000/$50,000	243,943,611	1.00	1.00	1.00	0.0%
AG	N	$50,000/$100,000	102,950,757	1.16	1.08	1.08	0.0%
AG	N	$100,000 CSL	1,444,950	1.24	1.11	1.11	0.0%
AG	N	$100,000/$300,000	70,326,408	1.54	1.29	1.29	0.0%
AG	N	$300,000 CSL	3,758,408	2.04	1.50	1.50	0.0%
AG	N	$250,000/$500,000	9,874,286	2.15	1.68	1.68	0.0%
AG	N	$500,000 CSL	5,350,267	2.25	1.80	1.80	0.0%
AG	Y	$25,000/$50,000	302,253,249	1.00	1.00	1.00	0.0%
AG	Y	$50,000/$100,000	256,452,902	1.21	1.13	1.12	0.9%
AG	Y	$100,000 CSL	7,102,129	1.26	1.19	1.16	2.6%
AG	Y	$100,000/$300,000	388,729,047	1.53	1.37	1.33	3.0%
AG	Y	$300,000 CSL	25,394,374	1.85	1.45	1.46	-0.7%
AG	Y	$250,000/$500,000	85,216,412	2.10	1.69	1.80	-6.1%
AG	Y	$500,000 CSL	45,591,859	2.15	1.93	1.95	-1.0%
DI	N	$25,000/$50,000	94,310,074	1.00	0.95	0.95	0.0%
DI	N	$50,000/$100,000	71,807,198	1.16	1.00	1.00	0.0%
DI	N	$100,000 CSL	81,354	1.27	1.11	1.11	0.0%
DI	N	$100,000/$300,000	45,810,439	1.54	1.28	1.28	0.0%
DI	N	$300,000 CSL	254,864	1.56	1.41	1.41	0.0%
DI	N	$250,000/$500,000	10,296,001	2.00	1.49	1.49	0.0%
DI	N	$500,000 CSL	440,458	2.16	1.59	1.59	0.0%
DI	Y	$25,000/$50,000	182,880,315	1.00	1.00	1.00	0.0%
DI	Y	$50,000/$100,000	199,882,577	1.15	1.05	1.05	0.0%
DI	Y	$100,000 CSL	1,287,766	1.22	1.17	1.17	0.0%
DI	Y	$100,000/$300,000	286,763,971	1.40	1.33	1.33	0.0%
DI	Y	$300,000 CSL	4,867,338	1.74	1.39	1.39	0.0%
DI	Y	$250,000/$500,000	53,447,656	1.82	1.47	1.47	0.0%
DI	Y	$500,000 CSL	5,998,809	2.13	1.60	1.60	0.0%

Figure H.10: Tier Factors
Notes: This is an excerpt from an insurer's rate filing on how limit choices influence pricing.