Welfare Implications of Proprietary Data Collection: An Application to Telematics in Auto Insurance

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WELFARE IMPLICATIONS OF PROPRIETARY DATA COLLECTION: AN APPLICATION TO TELEMATICS IN AUTO INSURANCE*

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Abstract:

Concerns about anti-competitive effects of proprietary data collection have motivated recent European data portability laws. We investigate such concerns and search for evidence of direct benefits of data collection in the context of Pay How You Drive (PHYD) auto insurance, which offers tailored discounts to drivers monitored by telematics devices. We exploit the staggered entry of PHYD insurance across states and insurers in a difference-in-differences framework, and we replicate the main findings using state insurance regulations as instruments for entry timing. We find a meaningful impact of PHYD programs on fatal accidents, but we find no evidence of antitrust concerns.

Keywords: Proprietary data, data portability, oligopoly, economic competition, asymmetric information (JEL: D43, D82, L13, L40)

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1. Introduction

Data collected by monitoring consumer behavior has some positive welfare implications and some negative ones. Monitoring data may alleviate information asymmetries and associated inefficiencies. However, if the data are truly proprietary, data owners may have a lasting competitive advantage that leads to inefficiencies due to acquired market power.

Officials and lawmakers in the United States and Europe are actively exploring and implementing related policy interventions, although they disagree on optimal policy.[1] Europe's new data portability rules, implemented by its 2018 General Data Protection Regulation (GDPR), allow monitored parties to port their data to competing firms. This should reduce current providers' competitive advantages, if they exist; but compliance costs are substantial and may disincentivize potentially welfare-improving data collection efforts.[2] The United States lacks similar portability rules. Empirical evidence on the impacts of proprietary data collection is sparse due to data limitations. In this paper, we exploit data from a regulated industry to investigate the effects of proprietary data collection on competition and information asymmetries.

We focus on a salient example of consumer monitoring: Pay How You Drive (PHYD) auto insurance. PHYD programs employ telematics devices that, when installed in an insured's car, collect proprietary data on risky behaviors such as hard braking, speeding, and late-night driving. Tailored discounts are then offered to safe drivers.[3] Similar monitoring programs appear in health insurance and property insurance markets, as well as non-insurance contexts.[4]

Our analysis is motivated by intuition from a simple theoretical model. A key insight from the model is that data collected in the past may be useful for segmenting inherently good from inherently bad drivers, but past data are of no use for mitigating the moral hazard problem. If adverse selection is relatively important, then current providers have data to segment consumers,

[1] See, for example, https://tinyurl.com/ya3tc5cw.

[2] Studies estimate compliance costs are about $8 billion just for Fortune 500 companies, and $150 billion for U.S. companies overall. Fines for non-compliance can be €20 million or 4% of global revenues, whichever is larger. Many U.S. companies have ceased operations in the European Union instead of complying.
See https://tinyurl.com/y96ld756 and https://tinyurl.com/ycz2zadq.

[3] PHYD insurance differs from traditional forms of targeted pricing (Dubé and Misra, 2017; Montes, Sand-Zantman, and Valletti, 2017; Rossi, McCulloch, and Allenby, 1995; Shiller, 2016; Waldfogel, 2015) that condition prices only on perceived willingness to pay.

[4] See, for example, http://www.getroost.com/partners, and https://tinyurl.com/yaaxmjbr.

but entrants would have to collect such data from scratch. If collecting data is costly to those monitoring or being monitored, current providers may be able to maintain a competitive advantage after competitors introduce similar programs.[5] Whether PHYD insurance programs increase industry profits, and whether consumers benefit from them, depends on the size of the first-mover advantage and is thus an empirical question.

In our empirical analyses, we exploit variation in the entry timing of PHYD insurance across states and insurers. Using a difference-in-differences estimation strategy, we relate firm profits to PHYD program introduction, and we relate vehicles in fatal accidents to the number of PHYD programs introduced in a state. As an additional causality check, we instrument for PHYD entry with regulations that prohibit or delay PHYD introduction.

Our estimates show that the first firm to offer PHYD insurance in a state increases profits, whereas later entrants do not significantly gain from introducing PHYD insurance. We also find that the presence of four or five firms in a market significantly reduces the first provider's supernormal rents, but time alone does not erode profits. Instrumental variable methods deliver qualitatively consistent results. Our estimates are consistent with the prevailing wisdom that three or four firms are sufficient to restore competition (Bresnahan and Reiss, 1991), suggesting previously gathered data do not provide a lasting competitive advantage in this context.

We then examine whether PHYD programs impact driving behavior, using vehicles in fatal accidents as a measure. We find evidence suggesting that drivers become safer: the number of vehicles in fatal accidents per registered vehicle decreases significantly—by 1.6% for each additional firm offering PHYD insurance programs—implying enrollees reduce their fatal accident risk by about 50%. This result, while large, is consistent with anecdotal reports and other research on driving behavior and incentives (Faccio and McConnell, 2017; Schneider, 2010; Weisburd, 2015). Our findings extend a large literature that has focused on the impacts of monitoring firms, rather than monitoring consumers (Dranove and Jin, 2010).

Yet the benefits from monitoring may be short-lived because the first PHYD insurers in a state typically monitored driving habits for only short periods (and offered prolonged discounts based

[5] See Klemperer (1987, 1995) for an overview of switching costs.

on observed behavior). Consistent with this contention, we find the reduction in accident risk is strongest in the first few years PHYD is offered, suggesting that monitoring programs incentivize costly effort, rather than developing lasting safe-driving habits. Because accidents often involve more than one party, and neither drivers nor their insurers fully internalize other parties' costs, monitoring may be underprovided. Our overall findings are antithetical to the public perception that monitoring is excessive. Instead, at least in the context of auto insurance, there might not be enough data collection, implying optimal policies should encourage monitoring, not discourage it.

2. Background

2.1 Data Use in Auto Insurance Markets

Although insurers have long set prices based on a large set of consumer traits, they have historically used publicly available data to do so. This changed with the inception of Pay How You Drive (PHYD) insurance. In the early 2000s, Progressive began experimenting with telematics devices that directly monitor risky driving behavior—such as speeding, hard braking, quick accelerations, and night driving—when plugged into the insured's car. By 2008, the costs of mobile data transmission had become low enough for Progressive to launch its PHYD program (Karapiperis et al., 2015; Scism, 2016). Enrollees were monitored for periods as short as 30 days, and drivers received permanent discounts based on their monitored driving behavior. Because competitors could not access these data, consumers who chose to switch insurance providers were monitored once again to demonstrate safe driving.

Progressive's PHYD program spread quickly. It initially launched in 6 states in 2008. By 2012, Progressive had expanded its program to 43 states.

Progressive held several key patents that initially prevented other firms from launching similar programs, including a business-methods patent on PHYD insurance programs (Greenberg, 2008). However, Progressive's patents were weakened by the Leahy-Smith America Invents Act (AIA) introduced in early 2011. Referred to as the "most significant overhaul of the American patent system in decades" by Brookings, the AIA replaced the existing patent re-examination procedure with a new procedure that shortened review lengths and increased the rate of successful challenges to patent validity from 31% to 70% (Cohen, 2014; Shepherd, 2016).[6] The new re-examination procedure was used to overturn Progressive's main patents protecting its PHYD programs.[7]

Encouraged by the prospect of the AIA, a handful of other insurers introduced PHYD programs. AllState introduced its PHYD program in Illinois in December 2010, in Arizona and Ohio in 2011, and in 44 additional states by 2014. State Farm introduced its PHYD program in 2011, expanding to 45 states by 2014. The Hartford and Liberty Mutual introduced their programs in 2012.[8] Figure I illustrates the programs' rapid expansion patterns, and Table I shows aggregated entry order statistics. Progressive was the first to enter 41 states, State Farm was the first to enter four states, and Allstate was the first to enter one state. The distribution of the second entrants' identities is much less skewed. Table A1 provides an overview of entry timing by each firm in each state.

Available statistics suggest that PHYD enrollment is non-negligible. A pair of 2014 surveys each found that about 9% of adult drivers in eligible states were enrolled in PHYD programs.[9]

2.2 Existing Evidence of the Impacts of Pay-How-You-Drive Insurance

Data collected by PHYD programs have proven useful for predicting accident risk. For example, Progressive has found that a driver who brakes hard more than 8 times in 500 miles, defined as decelerating at least 8 mph in one second, is 73% more likely to be involved in an accident (Scism, 2016). Using monitored driving behavior data, Ayuso, Guillén, and Pérez-Marín (2014) confirm that other monitored driving behaviors correlate with accident risk as well, and the results in Parry (2005) suggest that observed reductions in risk may be partially due to the role of monitoring in solving the moral hazard problem.

Because the algorithm and data collected from PHYD telematics devices are proprietary, the data may give a consumer's current provider a competitive advantage. The current provider can offer

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[6] See https://tinyurl.com/yc3b5dmy.
[7] See https://tinyurl.com/y7eboewt.
[8] Some other insurers (e.g. GMAC/National General, MetroMile, and Travelers) offer prices based only on (approximate) mileage driven but do not factor in behaviors like speeding, hard braking, and so forth. eSurance and SafeCo have also launched PHYD insurance programs. They are subsidiaries of AllState and Liberty Mutual, respectively.
[9] See https://tinyurl.com/y7s7l3an, and https://tinyurl.com/y96s8bfm.

its low-risk drivers prices that are lower than can be reasonably offered by competitors that lack the current provider's data to segment good from bad drivers. Progressive's CEO, Glenn Redwick, concurred, stating, "You have a rate that truly reflects your driving behavior… No one else can know that in the marketplace on a new quote."[10] He further noted that retention was 40% higher than typical for those receiving a substantial discount.

In many cases, the discounted prices in Progressive's PHYD program far exceed actuarially fair rates. Figure II confirms this contention, using national data for Progressive's SnapShot program, reported in a 2014 rate filing in Alaska.[11] Progressive's PHYD score ranges (their measure of relative risk for participants) are shown on the x-axis, from safe drivers to high-risk drivers. The circles in the figure denote loss ratios for each group, defined as $\frac{claims}{earned\ premiums}$. The black-bordered rectangles represent a histogram of earned premiums. Note that drivers receiving the largest discounts also yield the highest margins. The loss ratio for the lowest risk group—with scores between 0 and 9—is only 30.7%, less than half of the industry average of 63.6%.[12] Moreover, the average loss ratio in Progressive's PHYD program is 56.9%, still well below the industry average.[13] Although these simple statistics are suggestive, a more detailed analysis is needed to establish a causal connection and investigate welfare impacts of such proprietary data collection.

3. Model

Suppose there are two types of drivers: good and bad, denoted G and B, respectively. A driver of type i costs the insurer A_i in accident costs each period, where $A_G < A_B$. For simplicity, we assume that good drivers can reduce accident costs from A_G to zero at cost of effort r, while effort costs

[10] See https://tinyurl.com/ydfcybxf.
[11] See Alaska Serff tracking number SERF PRGS-129620997 at https://filingaccess.serff.com/sfa/home/AK.
[12] The industry loss ratio in 2008 was 63.6. See Section 4 for sources of data on industry averages.
[13] Progressive promised not to raise enrollees' rates beyond non-monitored rates for a long time, explaining why drivers identified as risky demonstrated loss ratios exceeding industry averages.

for bad types (r_B) are prohibitively large.[14] Hence, we allow for both adverse selection and heterogeneous moral hazard.

Without loss of generality, we assume that monitoring is costless for the firm.[15] Further, good drivers must exert effort r to drive safely to reveal their type.[16] Firms can use previously gathered information to set prices, and prices may change each period. We further assume a perfectly competitive market for insurance products that do not employ monitoring. The price of standard insurance is $\bar{A} = E[A_i]$, the expected accident cost.[17] Finally, consumers and firms share a common discount rate δ.

We let consumer utility be a linear function of the explicit price and effort costs. Utility-maximizing consumers minimize the total price, including effort costs, assuming insurance is mandatory. The price of each option in period t, including effort costs, is:

$$C_t = \begin{cases} \bar{A} & \textit{if never monitored;} \\ P_t + r & \textit{if currently monitored;} \\ P_t & \textit{if previously monitored.} \end{cases}$$

3.1 PHYD Monopoly: A Single Pay How You Drive Insurance Provider

If unmonitored, all drivers pay $C_t = \bar{A}$. Hence, the highest static incentive-compatible price for a monitoring program is $P_t = \bar{A} - r$. Static profits from each good driver equal:

$$\pi_{t=1}^{M} = \bar{A} - r, \tag{1}$$

where M indicates that the firm is a monopolist and t denotes the time since PHYD introduction.

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[14] In unreported calculations, we verify our main results hold when the cost of reducing the accident cost to some safer level is larger for bad drivers. Supporting this assumption, previous studies find moral hazard costs are heterogeneous (Einav et al., 2013) and positively correlated with an underlying tendency to drive recklessly (Zuckerman and Kuhlman, 2000).

[15] The costs of monitoring can either be borne by drivers or firms, or both. If allowing explicit monitoring cost m, the main results are identical, except r is replaced in with $r + m$.

[16] It is analogous to assume that bad-type drivers would pool with good-type drivers by reducing their accident risk to A_G, if a partial discount were offered.

[17] Eventually, if good-type drivers migrate to a PHYD insurance program, a separating equilibrium ensues. Only bad-type drivers choose standard insurance, and the price of regular insurance will become A_B.

When no longer monitored, consumers exert zero effort, and the highest static incentive-compatible price is $\bar{A}$. Static per-period profit from each good driver, including accident cost A_G, equals:

$$\pi_{t>1}^{M,T} = \bar{A} - A_G, \tag{2}$$

where T indicates temporary (one-period) monitoring.

Profits from continual monitoring are higher than one-period monitoring if and only if $r < A_G$.[18]

3.2 The Incumbent's Problem under Competition

Suppose the incumbent provider subsequently faces competition from (many) new entrants. All firms are identical except for information asymmetries; entrants must monitor to infer driver types.

Entering firms set per-period prices equal to cost, 0 when monitoring, and A_G after they cease monitoring. If switching, a good driver's total long-run discounted prices, including effort costs, are $\frac{r}{1-\delta}$ under permanent monitoring, and $r + \frac{\delta A_G}{1-\delta}$ if monitoring ceases after one period. Surviving competitors offer the monitoring option with the lower total cost, which is permanent monitoring if and only if $r \leq A_G$.

The first provider's profits are eliminated if $r \leq A_G$, that is, if effort costs of safer driving are weakly less than the reduction in accident costs. In that case, both the first provider and entrants use continual monitoring to mitigate the moral hazard problem. Consumers thus incur effort costs regardless of whether they switch; switching costs are zero and the market is competitive.

When $r > A_G$, effort costs exceed the reduction in accident costs, and firms prefer temporary monitoring to segment drivers. The current provider—which has already segmented drivers—may maintain a competitive advantage. If switching, good drivers incur a discounted total price (including effort costs) of $r + \frac{\delta A_G}{1-\delta}$. Remaining with the current provider is incentive-compatible if the future discounted price $\left(\frac{P_t^I}{1-\delta}\right)$ is less, that is, if $P_t^I \leq (1-\delta)\, r + \delta A_G$, where P_t^I is the first

[18] If $r > \bar{A}$, the firm may still make positive long-run profits by ceasing monitoring, despite incurring negative profits in the first period.

provider's (incumbent's) price. The first provider's price must also be weakly less than the price of standard insurance, $\bar{A}$. Thus, in subsequent periods, the incumbent provider's per-period profit from each good driver is:

$$\pi_{t>1}^{I,T} = \min(\bar{A}\,, (1-\delta)\, r + \delta A_G) - A_G = \min\big(\bar{A} - A_G\,, (1-\delta)(r - A_G)\big). \qquad (3)$$

<u>Result</u>: *When continual monitoring is optimal, the first provider's profits following entry are zero. When continual monitoring is not optimal, the first provider's profits may lie anywhere between zero and the monopoly profits, depending on the monitoring cost r.*

The result follows from Equation 3. It implies that the incumbent provider's per-period profits under competition in periods $t > 1$ are at most zero when $r \leq A_G$. In this case, all providers monitor permanently, making previously gathered data irrelevant or redundant. But when $r \geq A_G$, firms monitor for a single period to segment consumers, and the incumbent provider's profits under competition increase with r. Profits are bounded above by $\bar{A} - A_G$, i.e. monopoly profits.

3.3 Discussion

Figure III illustrates the relationship between monitoring costs and the profits of the first provider of PHYD insurance, both with and without competition. A monopolist profits by monitoring. With competition, the impact of monitoring is more nuanced. If moral hazard problems are substantial ($r \leq A_G$), then firms monitor continually, regardless of market structure and order of entry, and prior information has no value. In that case, there is no first-mover advantage, and competition drives the first provider's profits to zero. By contrast, if the effort costs of monitoring are sufficiently high ($r > A_G$), then firms monitor temporarily to segment consumers. In that case, the first provider, which already has data to segment consumers, has a lasting advantage over potential entrants, and competition does not drive the first provider's profits to zero. The extent to which competition lowers profits depends on monitoring costs.

Progressive, the first firm to introduce PHYD insurance in most states, monitors drivers only for short periods of time. The extent to which competition from PHYD competitors lowers the incumbent provider's profits (if at all) is therefore an empirical question.

4. Data

The data used in this paper combine three categories of information: (i) PHYD insurance entry dates; (ii) revenue and loss data by firm, state, and year; and (iii) the number of vehicles involved in fatal accidents by state and year. The PHYD insurance entry dates were obtained from representatives of the insurance companies (Progressive, AllState, and The Hartford) and from news articles and historic versions of company websites archived on the Wayback Machine (State Farm and Liberty Mutual). Entry patterns are reported in Section 2 and Table A1 in the Appendix. The remaining datasets are described next.

4.1 Revenues and Profits

The National Association of Insurance Commissioners (NAIC) provided insurance premiums, losses, and containment costs for auto insurance (NAIC codes 19.1, 19.2 and 21.1), by firm, state, and year, from 2008 to 2014. Insurance premiums include payments from consumers less commissions paid to insurance brokers. We subsequently refer to these as *revenues*. An insurance company's variable costs consist of incurred losses (paid claims) and containment costs (investigation and litigation expenses). We construct firm-state-year level variable profits π_{jst} from all types of auto insurance, as earned premiums (revenues) minus the sum of claim payments and containment costs.

Summary statistics for the 25 largest insurers (by 2008 revenue)—the firms used in our analyses—are reported in the top panel of Table II.[19] On average, these insurers earned $157 million in revenue per state for an average profit of $54 million, although there is large variation across firms as well as states. The companies offering PHYD insurance programs were among the largest insurers before the introduction of their PHYD programs, occupying four of the top six spots in terms of revenue in 2008. The fifth PHYD provider, The Hartford, was the eleventh largest company that year. Overall, the PHYD insurers accounted for 42.8% of total revenue and 41.7% of total profit in 2008 across the United States.

[19] The nature of the industry requires that we make some minor adjustments to the data. We describe these in Appendix Section A.1.

4.2 Accidents

We obtain state-year level information on vehicles involved in fatal accidents and the number of registered vehicles from the Fatality Analysis Reporting System (FARS), from 1994 to 2014. The bottom panel of Table II reports summary statistics. On average, 0.21 cars per thousand registered vehicles were involved in fatal accidents annually between 1994 and 2014, with a strong downward trend. While close to 0.25 per 1000 vehicles were involved in fatal accidents in the 1990s, this number has shrunk to about 0.17 in the 2010s.

5. Empirical Impact on Profits

In this section, we estimate the impact of PHYD insurance introduction on profits, with and without the impact of competition from other PHYD firms, using profit and entry data for the top 25 insurers, from 2008 to 2014. An obvious concern is that PHYD introduction could coincide with positive (or negative) state-level profit shocks. We use two separate strategies to address this concern. First, we use a difference-in-differences estimation strategy, exploiting the staggered entry of PHYD insurance across both states and insurers. Second, we use measures of regulatory burden from state insurance regulators to construct instruments for PHYD entry. Both strategies yield similar results.

5.1 Difference-in-Differences

5.1.1 Specification

PHYD insurance introduction varies across both firms and states. We exploit this fact in a difference-in-differences analysis. Formally, we estimate different specifications of the following general form:

$$\pi_{jst} = \beta_0 + \beta_1 PHYD_{jst} + \beta_2 \times PHYD_{jst} \times Comp_{st} + \mu_{jt} + \nu_{js} + \eta_{st} + \epsilon_{jst}, \tag{4}$$

where π_{jst} is firm j's profit in state s and year t, $PHYD_{jst}$ is an indicator that equals one if firm j has introduced PHYD insurance in that state, and $Comp_{st}$ indicates the number of competing firms that have PHYD insurance programs in the state. The remaining controls, μ_{jt}, ν_{js}, and η_{st}, are firm-year, firm-state, and state-year pair fixed effects, respectively.

Note that our state-firm-year panel allows a more robust set of controls than is typical in difference-in-differences specifications. Like standard difference-in-differences specifications, we use state-year fixed effects to control for changes in profits over time unrelated to the treatment, for example, due to inclement weather and changes in market concentration. We also use firm-state fixed effects to account for level differences across firms and states. Additionally, we include firm-year fixed effects to control for divergence between treated and untreated firms that would have occurred even in the absence of PHYD insurance programs. To address potential bias arising from serial correlation, we cluster standard errors at the state level (Bertrand, Duflo, and Mullainathan; 2004).

We normalize profits because there are substantial level differences in profits across insurers and states, and we expect PHYD to have a proportional impact. Specifically, our transformed dependent variable is $\pi_{jst} = \frac{\pi^*_{jst}}{\bar{R}_{js}}$, where π^*_{jst} is firm j's untransformed profit in state s and year t, and $\bar{R}_{js}$ is firm j's average revenue in state s across all observed years. This normalization allows for negative profits that are expected in insurance markets, where costs are potentially large and inherently random; 1.5% of the observations in our estimation sample exhibit negative profits. The average normalized profit is 0.35, with a standard deviation of 0.18.

5.1.2 Results

Table III shows the estimated effect of introducing PHYD insurance on a firm's normalized profits, distinguishing between different PHYD insurance entry positions and the number of PHYD insurance competitors. In column (1), we report estimates of the effect of PHYD insurance, independent of how many firms already offer PHYD insurance. The results suggest that firms do not consistently profit from introducing PHYD insurance programs. Estimating separate effects by order of entry in column (2) reveals that the first firm to introduce PHYD insurance in a state increases its profits significantly, whereas later entrants do not.

We next explore the impact of time and competition on the profits of the first firm to introduce PHYD insurance in a state. Column (3) flexibly controls for competition by including an indicator variable for each number of entrants. The negative coefficient on an indicator for three or four firms competing with the incumbent PHYD insurance provider is significant at the 10% level, and the point estimate is of similar magnitude to the coefficient on the indicator for the incumbent's PHYD entry. At the mean normalized profit of 0.322 among incumbent PHYD insurers, the point estimates in column (3) suggest that the first firm introducing a PHYD insurance program in a state initially increases profits by 14%, but the profit gain is reduced to less than 1% after three or four competing PHYD providers have entered. Column (4) adds a control for time since the first provider entered. The coefficient on time since incumbent entry is positive but insignificant, and the coefficient on competition by three or four firms remains negative and significant at the 5% level. These results indicate that competition from three or four firms significantly lowers profits and may be sufficient to erode the first provider's supernormal profits, whereas time alone does not erode profits.

These results are robust to many specifications. One might be concerned that our results are driven by spillover effects across firms in the same state, by positive profit shocks to specific firms, or by the functional form of the dependent variable. We provide additional robustness checks to address these concerns in Appendix Section A.2.

5.1.3 Identification

Our difference-in-differences specification alleviates the most obvious endogeneity concerns. First, one might think that firms could introduce PHYD in states anticipated to be more (or less) profitable in general, regardless of whether PHYD insurance is introduced. State-year fixed effects, which are identified by the profitability of firms with no (current) PHYD insurance programs in the state, control for such differences. Second, "treated" firms (i.e., those that introduced PHYD insurance programs) might have systematically different time trends than "non-treated" firms. Variation in when and if treated firms entered each state allows us to include firm-year fixed effects to control for such firm-specific trends.

Endogeneity is therefore only a concern if the introduction of PHYD insurance coincides with strong positive profit shocks that apply only to PHYD firms and only in states they introduced PHYD programs. We believe this is unlikely for three reasons: First, if endogenous entry explained the higher profits, then we would expect this to apply to subsequent entrants as well. But Table III shows only the first firm to enter profits significantly. Second, endogenous entry cannot explain why competition, but not elapsed time, reduces the first provider's profits as Table III shows. Third, PHYD insurance programs were planned and rolled out very quickly, as Figure I shows, implying that firms were focused on rapid expansion. In line with this contention, results in Appendix Section A.3 show that there was no observable increase in interest, as measured by web searches, for an insurer around the time PHYD programs were introduced in a state. In sum, obvious identification concerns are inconsistent with our results when taken in their entirety.

Another concern is that the impact of competition could be biased. If competitors entered states concurrent with positive transient shocks to the profitability of PHYD insurance programs, the positive shock would presumably apply to the first provider's profits as well, somewhat offsetting the decline in the first provider's profits from increased competition. Hence, endogeneity could bias against finding that competition lowers profits. But we found competition does lower profits substantially, alleviating concerns.

5.2 Instrumental Variables

Our difference-in-differences results are not consistent with concerns that PHYD introduction could be timed to coincide with positive or negative profit shocks, and strategic entry timing is unlikely given rapid entry. Hence, our difference-in-differences analyses do not seem threatened by causality concerns. Yet, to provide an additional check, we also employ an instrumental variables strategy.

5.2.1 Instruments and Specification

Cross-state variations in insurance regulations comprise compelling instruments. We consider two types: (i) whether insurers need explicit prior approval before changing prices, and (ii) whether PHYD insurance was legal before 2008.

In prior approval states, insurers must request and justify price changes before implementing them. For novel rate types, several rounds of submissions and responses to objections may be needed. For example, in August 2010, Progressive submitted a request to introduce PHYD insurance prices in Pennsylvania. In October, Progressive responded to regulators' questions. In December, Pennsylvania regulators approved Progressive's PHYD program, allowing the rates to take effect

March 18, 2011.[20] On March 27, 2011, Progressive began offering PHYD insurance. Hence, seven months elapsed between Progressive's request to introduce new prices and its implementation. In states not requiring prior approval, Progressive could have implemented the new pricing schema immediately.

Initial legality of PHYD insurance is our second instrument type. States have various pricing regulations. In states where PHYD insurance was initially illegal, insurers would need to wait, and potentially lobby, for law changes allowing PHYD insurance. Hence, we would expect PHYD insurance to be introduced later in such states.

We have explicit measures of these law types. Hunter (2008) lists the 15 states requiring prior approval at the time. Guensler et al. (2003) surveyed state insurance regulators in 2003, asking whether PHYD insurance was allowable. Twenty-seven responded yes.

Both regulation measures strongly impact entry timing of PHYD programs. To demonstrate this, we regress the year of a firm's PHYD entry in each state on these variables and firm-fixed effects, for the five PHYD firms. Because PHYD insurance was still not offered in all state-firm pairs in the last year observed (2014), we use a censored regression model. Clustering standard errors by state, the results are:

$$\underset{}{Year\ Introduced_{js}} = \underset{(0.30)}{0.52 * Prior\ Approval_s} - \underset{(0.23)}{0.80 * PHYD\ Allowed_{s,2003}} + \alpha_j + \epsilon_{js},$$

where j denotes firm and s denotes state. The prior approval indicator is significant at the 10% level, and the PHYD allowable indicator is significant at the 1% level. Point estimates imply that on average PHYD insurance is introduced 0.52 years later in prior approval states, and 0.80 years earlier in states where PHYD insurance was legal in 2003. Given that each insurer rolled its PHYD program to the majority of states within three years (see Figure I), the effects of the laws are large.

These law indicators provide a promising set of instruments, but we cannot use them directly because they do not vary across time or firms. To operationalize them as instruments, we interact each law indicator with both firm (j) and year (t) fixed effects, generating two sets of triple

[20] https://filingaccess.serff.com/sfa/home/PA. Company code: 11851. Serff tracking number: PRGS-126795175

interaction fixed effects ($\lambda_{j,t,prior\ approval}$ and $\phi_{j,t,PHYD\ allowed}$). These variables determine the likelihood of a specific firm introducing PHYD insurance in a state with a given legal structure in a given year, and hence the likelihood of each firm being the first to do so.

Although profit trends could differ between states with different regulations, our specification with state-year pair fixed effects utilizes profit changes among non-treated firms (i.e., non-PHYD firms) to account for such trends. Hence, the exclusion restriction is only violated if PHYD firms had abnormal profit shocks to their non-PHYD insurance offerings early on in states with PHYD-friendly regulations, and later in states with less PHYD-friendly regulations. Such patterns are unlikely.

5.2.2 Results

Table IV replicates columns (2)–(4) of Table III, instrumenting for entry order. The coefficients are significant and qualitatively similar to the baseline estimates: the first firm to introduce its PHYD program in a state increases its profits, but competition from other PHYD programs erodes these profits. The coefficients are larger in magnitude, possibly suggesting firms introduced PHYD insurance in states in which they were anticipating negative profit shocks. However, the coefficients on the first firm to enter from the instrumental variable regressions are not significantly different from the baseline estimates. We continue with the baseline difference-in-differences estimation to be conservative.

5.3 Mechanism behind Profit Increases

In this subsection, we explore whether the initial advantage of the first PHYD provider is driven by additional demand (holding markups relatively constant) or by increases in efficiency (holding revenues relatively constant). We examine this by measuring the impact of introducing PHYD insurance on two variables: (i) revenues, again normalized by the firm's mean revenue in the same state over the seven observed years; and (ii) the fraction of earned premiums (revenues) used to pay claims and associated litigation costs.

The results are shown in Table V. Column (1) shows a statistically insignificant impact of PHYD insurance entry on normalized revenue for the first firm to enter. Column (2) presents the results from an analogous regression with the ratio of costs to revenues as the dependent variable. The coefficient on PHYD insurance entry by the first firm is negative and significant at the 10% level, implying PHYD insurance entry, at least by the first firm, lowers costs per dollar of earned premiums. Said another way, PHYD programs increase markups. Specifically, the point estimates imply costs per dollar of revenue fall 6% relative to the median cost ratio of 0.63, even though reported cost ratios include costs from all programs offered by the insurer, including non-PHYD programs. This suggests incumbent PHYD providers were able to segment lower-risk drivers and charge them rates above the actuarially fair rate.

6. Consumer Behavior and Broader Implications

In our previous analyses, we showed that proprietary data collection does not raise antitrust concerns in auto-insurance markets. This suggests the most obvious concern related to proprietary data collection is not realized. But we have yet to establish whether there are any benefits to monitoring data.

Monitoring programs may have direct welfare benefits if they alleviate moral hazard problems by monitoring and incentivizing safer driving. Because drivers do not internalize the costs their dangerous driving may impose on bystanders and bystanders' insurers, explicit rewards for safer driving through PHYD insurance programs may also address an externalities problem.

To investigate whether PHYD insurance programs reduce accidents, we employ information on traffic safety from the Fatality Analysis Reporting System (FARS), which reports the annual number of vehicles involved in fatal accidents by accident location and vehicle registration location (state). Fatal accidents provide an auspicious context because many of the monitored driving behaviors—such as driving in excess of 80 mph, hard breaking, and mileage (which is heavily influenced by driving on interstate highways)—relate to chances of being in the most serious kinds of accidents.

We first estimate the impact of PHYD insurance on vehicles in fatal accidents in a fixed-effects panel estimation with measures of the state-level penetration of PHYD insurance as the independent variable of interest. Formally, we estimate

$$\ln(Vehicles\ in\ Fatal\ Accidents)_{st} = \beta_0 + \beta_1 PHYD_{st} + \beta_2 \ln(Vehicles)_{st} + \mu_s + \eta_t + \epsilon_{st}, \tag{5}$$

where s denotes registration state (including DC), and t denotes the year (from 1994 to 2014). μ_s and η_t are state- and year-fixed effects, respectively, and $PHYD_{st}$ is a measure of PHYD insurance penetration in state s and year t. $\ln(Vehicles)_{st}$, a control variable, accounts for changes in the log number of registered vehicles in a state over time. We first regress the log of vehicles in fatal accidents on the cumulative number of firms that have introduced PHYD insurance programs in state s. We then explore whether safer driving is short-lived, given that drivers are only monitored for short periods of time in some PHYD insurance programs, and might eventually resume unsafe driving.

Table VI shows the coefficients of interest from these regressions. The results in column (1) imply that one more firm offering PHYD insurance would decrease the number of vehicles involved in fatal accidents by approximately 1.6%. Multiplying the percent impact of a PHYD provider on fatal accidents (1.6%) by the average number of PHYD programs per state in 2014 (2.88) implies PHYD programs reduced vehicles in fatal accidents by 4.61% in the average state. Because 9% of drivers were enrolled in PHYD programs by then, a back-of-the-envelope calculation suggests enrolled drivers reduced accident risk by $\frac{4.61}{9} = 0.51\%$. This finding, while strong, is in line with existing evidence. A case study finds a trucking company reduced accidents by 68% by monitoring its drivers using telematics devices.[21] Similarly, Weisburd (2015) finds drivers are involved in 25% fewer accidents when expected financial costs in the event of an accident are $235 higher.

Column (2) of Table VI suggests that the benefits are, to some extent, short-lived. PHYD insurance programs reduce accidents most in the first few years after being introduced, whereas coefficients for more than three years since entry are small and statistically insignificant. Hence, monitoring programs appear to incentivize costly effort during the monitoring period, rather than developing safer driving habits through practice and instruction.

[21] See https://tinyurl.com/y82mwsmh.

One might be concerned that contemporaneous changes at the state level may coincide with the introduction of PHYD insurance. To address this concern, we divide vehicles in fatal accidents by both the accident location and the state where the involved vehicle was registered.[22] This allows us to control for state-level accident risk. Intuitively, any state-level road-safety measures that coincide with PHYD insurance entry should only reduce in-state accidents. For example, suppose Alabama improves visibility on highways by adding lights around the time PHYD insurance programs are introduced in the state. Better lighting might explain reduced accidents in Alabama, but it should not explain reduced accidents involving vehicles registered in Alabama that occur out of state. PHYD insurance availability, however, depends not on where a vehicle is located at a given moment, but rather on where it is registered. Hence, if the number of accidents involving cars registered in Alabama but occurring in Texas falls after PHYD insurance programs are introduced in Alabama, then we can attribute the reduced risk to PHYD insurance.

Following this reasoning, we regress the log number of vehicles in fatal accidents in state l that were registered in state s on PHYD insurance entry in registry state s:

$$\ln(Vehicles\ in\ Fatal\ Accidents + 1)_{lst} = \beta_0 + \beta_1 PHYD_{st} + \beta_2 \ln(Vehicles)_{st} + \kappa_{ls} + \gamma_{lt} + \epsilon_{lst},$$

where l denotes the accident location, s denotes the vehicle's registration location, and t denotes the year. κ_{sl} and γ_{lt} are fixed effects added to control for registry-accident location pairs and accident state-year pairs. By including controls for accident frequencies in each state γ_{lt}, we explicitly control for state-specific developments in safety that may coincide with PHYD insurance introductions.

The results, shown in column (3) of Table VI, are consistent: PHYD insurance programs significantly reduce the number of vehicles involved in fatal accidents in the first few years after introduction.[23]

[22] Accidents involving vehicles registered in two (or more) states will appear twice (or more) as separate observations, one for each location of registry.

[23] We yield similar results when omitting cars involved in accidents in their home state.

7. Conclusion

Our paper provides evidence of the impacts of proprietary data collection to help guide data portability and privacy laws. Our theoretical model suggests collecting proprietary data by monitoring one's own consumers might prevent competition from restoring market efficiency if monitoring is costly (and temporary). In that case, data-portability rules in the European Union's general data protection regulations (GDPR) taking effect in 2018 should be adopted by antitrust authorities in other countries.[24] However, evidence suggests the first-mover advantage is small. Empirically, in the context of auto insurance, we find no evidence that current PHYD providers continue to profit following entry by three or four competing PHYD providers (four of five PHYD firms in total). Antitrust concerns are not exacerbated in this context.

The decrease in accident risk (by 50% among monitored drivers) is economically meaningful. Therefore, data collection has tangible benefits, and burdensome regulations that increase monitoring costs might have negative consequences.

[24] See https://www.eugdpr.org/

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Tables and Figures

Table I: Order of PHYD Insurance Entry by Insurer

	Number states insurer was n^{th} to introduce PHYD insurance				
Order of entry	AllState	The Hartford	Liberty Mutual	Progressive	State Farm
1^{st}	1	0	0	41	4
2^{nd}	10	5	1	1	15
3^{rd}	11	7	3	5	17
4^{th}	14	15	8	1	6
5^{th}	2	15	23	0	2

Note: Insurers entering the state in the same year were considered tied and assigned the highest entry order. For example, if AllState and Progressive each entered a state in the same year, and there were no preexisting PHYD insurance firms there, then both would be assigned an entry order of two, the second to arrive.

Table II: Summary Statistics

NAIC (firm/state/year) [n=6072]	Mean	Std. Dev
Revenues (thousands)	157,413	333,406
Costs (thousands)	103,725	226,269
Profits (thousands)	53,688	113,203
FARS (state/year) [n=1071]	Mean	Std. Dev
Vehicles in fatal accidents	980	988
Registered vehicles (thousands)	4,649	5,061

Notes: The District of Columbia (DC) is considered a separate state in our analyses. NAIC data exclude Michigan due to data reporting irregularities noted by the NAIC. See Appendix Section A1. Some insurers operate in a subset of U.S. states.

Table III: Baseline Estimation: PHYD Insurance, Order of Entry, and Profits

	Dependent variable is normalized profit			
	(1)	(2)	(3)	(4)
Entered PHYD	0.0062			
	(0.0083)			
I(Entered PHYD) × Entry order				
1st		0.0380	0.0466	0.0491
		(0.0185)	(0.0192)	(0.0189)
2nd		0.0187		
		(0.0158)		
3rd		-0.0212		
		(0.0135)		
4th or 5th		-0.0093		
		(0.0162)		
I(Entered and 1st) × I(n competitors)				
$n = 1$			-0.0120	-0.0224
			(0.0189)	(0.0198)
$n = 2$			-0.0145	-0.0272
			(0.0229)	(0.0216)
$n = 3$ or 4			-0.0438*	-0.0620
			(0.0223)	(0.0220)
Years since PHYD entry (incumbent)				0.0075
				(0.0075)
Observations	6072	6072	6072	6072

Notes: The table reports coefficients for a difference-in-differences estimation with state-insurer, state-year, and insurer-year pair fixed effects. The dependent variable is profit normalized by the firm's average revenues in that state. Robust standard errors, clustered at the state level, are shown in parentheses.

Table IV: Instrumental Variables: PHYD Insurance, Order of Entry, and Profits

	Dependent variable is normalized profit		
	(1)	(2)	(3)
I(Entered PHYD) × Entry order			
1^{st}	0.114	0.144	0.132
	(0.0764)	(0.0682)	(0.0618)
2^{nd}	-0.0814		
	(0.0586)		
3^{rd}	0.0024		
	(0.0747)		
4^{th} or 5^{th}	-0.0213		
	(0.0278)		
I(Entered and 1^{st}) × I(n competitors)			
$n = 1$		-0.0457	-0.0604
		(0.0305)	(0.0332)
$n = 2$		-0.0481	-0.0675
		(0.0340)	(0.0358)
$n = 3$ or 4		-0.0832**	-0.113
		(0.0365)	(0.0417)
Years since PHYD entry (incumbent)			0.0149
			(0.0083)
Observations	6072	6072	6072

Notes: The table reports coefficients for the second stage in a two-stage least squares estimation with state-insurer, state-year, and insurer-year pair fixed effects. First-stage instruments for entry position are interactions of year indicators, firm indicators, and state-specific indicators for prior approval rules and PHYD legality in 2003. The dependent variable is profit normalized by the firm's average revenues in that state. Robust standard errors, clustered at the state level, are shown in parentheses.

Table V: Impact of PHYD Insurance on Revenues and Costs

	Normalized revenue (1)	Cost ratio (2)
I(Entered and 1st)	0.0315	-0.0349
	(0.0278)	(0.0204)
I(Entered and 1st) $\times$ I(n competitors)		
$n = 1$	-0.0111	-0.0001
	(0.0201)	(0.0253)
$n = 2$	0.0319	0.0474
	(0.0327)	(0.0311)
$n = 3$ or 4	-0.0421	0.0272
	(0.0318)	(0.0290)
Observations	6072	6072

Notes: The table reports coefficients for a difference-in-differences estimation with state-insurer, state-year, and insurer-year pair fixed effects. Robust standard errors, clustered at the state level, are reported in parentheses.

Table VI: PHYD Insurance and Moral Hazard

	Log(vehicles in fatal accidents)		
	(1)	(2)	(3)
# firms with PHYD	-0.0162		
	(0.0084)		
# firms entering			
this year		-0.0125	-0.0061
		(0.0105)	(0.0074)
last year		-0.0210	-0.0116
		(0.0111)	(0.0071)
2 years ago		-0.0157	-0.0225
		(0.0121)	(0.0097)
3 years ago		-0.0067	-0.0059
		(0.0196)	(0.0147)
4 years ago		-0.0098	-0.0087
		(0.0233)	(0.0167)
Log registered vehicles	0.122	0.123	0.0396
	(0.0608)	(0.0611)	(0.0429)
Observations	1071	1071	55692

Notes: The table reports coefficients for difference-in-differences estimations. In columns (1) and (2), the unit of observations is registry state by year. In column (3), observations are further split by accident location (state). The dependent variable is $ln(autos\ in\ fatal\ accidents_{st})$ in columns (1) and (2). In column (3), we use $ln(1 + autos\ in\ fatal\ accidents_{lst})$. In columns (1) and (2), we include registration-state and year fixed effects. In column (3), we include accident-location/year pair, and accident-location/registry-state pair fixed effects. Standard errors, clustered at the state level, are reported in parentheses.

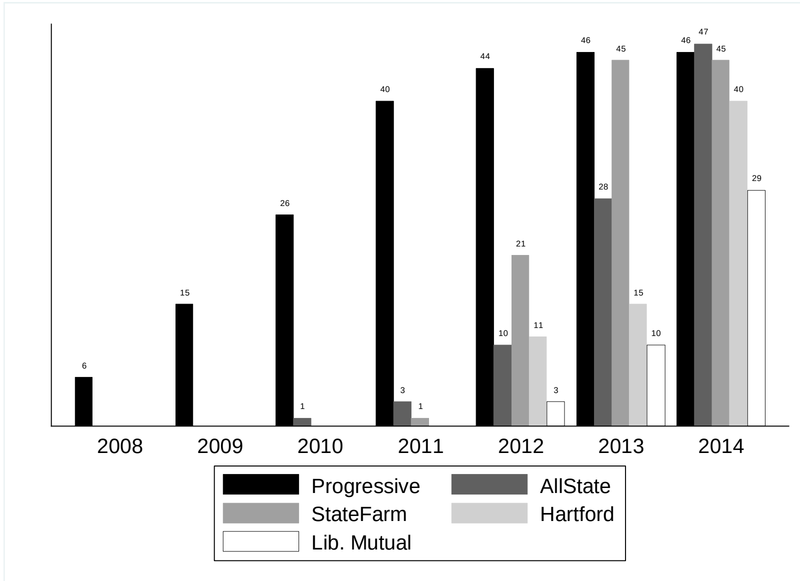

Figure I: PHYD Program Penetration, by Firm and Year

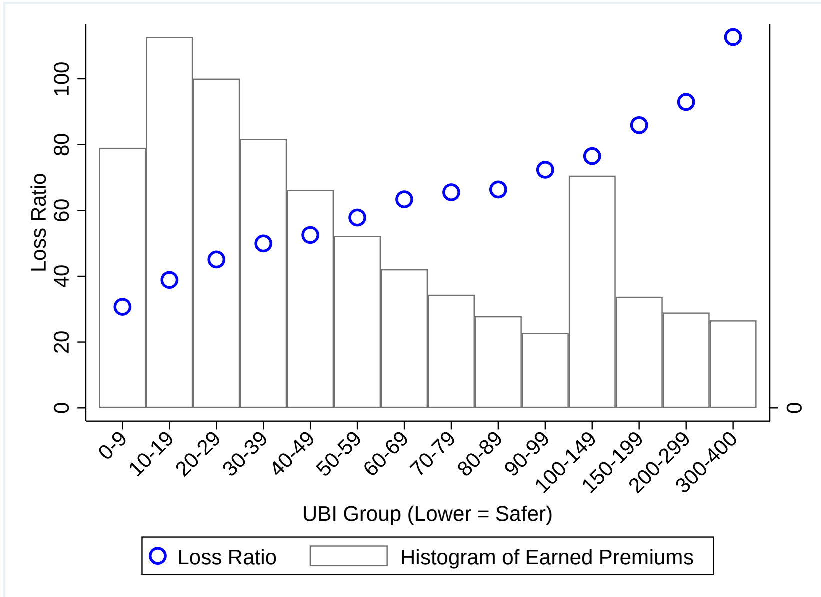

Figure II: Progressive's Loss Ratio and Earned Premiums 2014, by PHYD Group

Notes: Data correspond to Progressive's SnapShot 2.0 PHYD insurance program nationally. Data are from Progressive's initial PHYD rate filing in Alaska in 2014.

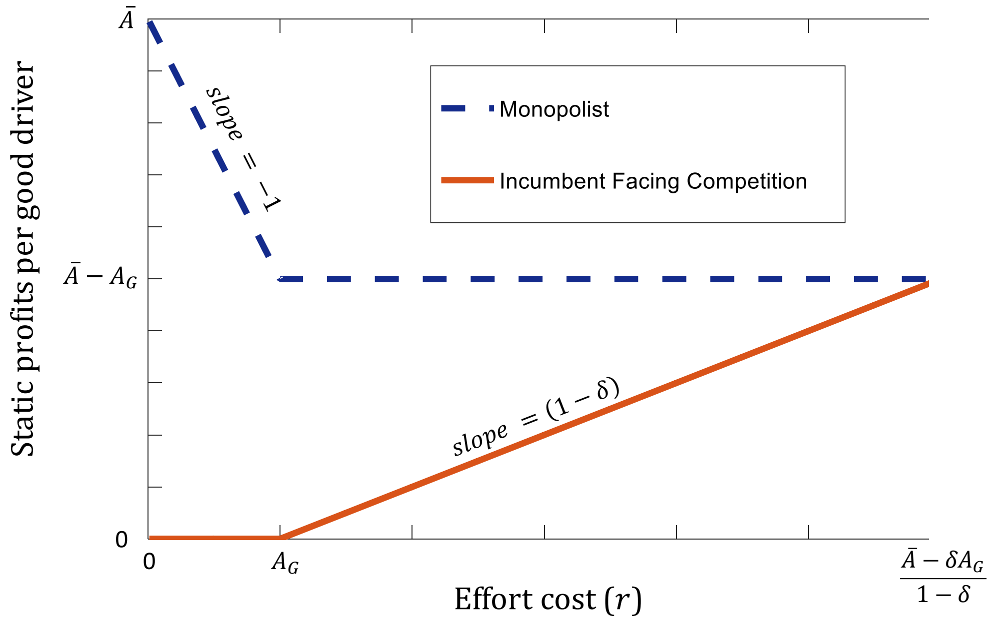

Figure III: First Provider's Profits in Later Periods

Appendix

A.1 Data Construction and Adjustments

The structure and accounting details of the auto insurance industry require that we make a few adjustments to the raw data. First, we complete a thorough search for mergers among the insurance firms between 2008 and 2014. We consider revenues and costs of the final merged firms in the paper, even in periods prior to the merger. Second, although earned premiums and losses are reported accurately in most states, Michigan has serious reporting issues arising from anomalies in their laws that lead to unusually large variation in profits and inaccuracies in reporting.[25] We therefore drop all observations pertaining to the state of Michigan in the profit analyses.

A.2 Robustness of Profit Regressions

Our main difference-in-differences regression results show that the first PHYD provider increases its profits relative to other firms in the state and relative to its own profits in other states. We further examine the robustness of these results in Table A2.

First, we have assumed that the estimated change in profits is driven by the PHYD provider increasing its profits in the state of PHYD introduction. However, it is also possible that PHYD introduction lowers other insurers' profits by recruiting away the lowest-cost consumers. We address this concern by estimating the impact of PHYD entry by firm j in state s on two groups: firm j in state s, and other firms in the same state (which have not yet introduced PHYD). This specification treats firms in states with no current PHYD provider as the control group. We estimate the regression with year-firm and state-firm fixed effects only, so the impact of PHYD on all treatment groups is identified. Column (1) of Table A2 shows a statistically significant positive impact on the first firm to introduce its PHYD program in a state, whereas the impacts on profits for *other* firms in the state are small and statistically insignificant. This is evidence that our main estimation is correctly specified and PHYD introduction primarily impacts one's own profits.

Another potential concern arises from the fact that Progressive is the first firm to introduce PHYD insurance in most states (i.e., 41 states). It is possible that we measure the impact of introducing

[25] The loss ratios that Michigan auto insurers report for no-fault coverage differ wildly across insurers. As a result, the NAIC is not able to include the profitability of Michigan no-fault insurance in its survey. See https://tinyurl.com/y9p6nqcu.

PHYD insurance on Progressive's profits, and other firms do not profit from introducing PHYD programs. We address this concern in column (2) of Table A2 by estimating the impact of introducing PHYD insurance first separately for Progressive and for other PHYD firms. Both coefficients are positive and statistically significant. This suggests that our results are not driven by just one firm.

In columns (3) and (4), we explore alternative transformations of the dependent variable. Column (3) uses the log of firm profits, dropping observations with negative profits. Because dropping observations with negative profits may bias results, we also use the asymptotic sine transformation (Burbidge, Magee, and Robb, 1988) of profits in column (4). Both transformations yield similar results to the main specification: introducing a PHYD insurance program increases profits, at least for the first firm to enter. Competition is not found to reduce profits in the log(profits) specification, presumably because observations with negative profits are dropped, biasing coefficients on variables that cause lower profits.

A.3 Evidence of Exogeneity

The difference-in-differences specifications rely on the assumption that PHYD entry is exogenous, or at least not driven by expectations of profit changes. We provide evidence in the main text that this assumption is satisfied. As an additional test for potential endogeneity of PHYD entry, we examine monthly, state-specific Google search volume for the phrase "Progressive Car Insurance," using Google Trends data.[26] Our attention is restricted to Progressive, because it entered 41 states first, and firms entering second or later are not found to increase their profits.

We regress search volume on date- and state-fixed effects, and we plot the residuals against the months since Progressive introduced PHYD insurance in the respective states in Figure A1. Note that search volume does not appear to increase leading up to or soon after PHYD insurance introduction, suggesting that PHYD insurance introduction was not timed to coincide with increasing awareness of Progressive's auto insurance products.[27]

[26] The data are normalized so that the highest search volume in any state equals 100.
[27] To be sure, we included each firm's state-specific annual search volume in unreported profit regressions, finding that these additional controls have no meaningful effect on the coefficients of interest.

Table A1: Year of PHYD Entry by State and Firm

State	Progressive	Allstate	State Farm	Liberty Mutual	The Hartford
AK	2015	2014	2013		
AL	2008	2014	2012	2015	2014
AR	2011	2013	2013	2015	2013
AZ	2010	2011	2012	2012	2012
CA					
CO	2009	2012	2012	2013	2014
CT	2009	2013	2013		2012
DC	2011	2014	2013	2014	2015
DE	2012	2014	2013	2014	2014
FL	2011	2012	2013		
GA	2009	2014	2013		
HI	2015	2014	2013		
IA	2010	2014	2012	2014	2014
ID	2011	2013	2012	2013	2012
IL	2012	2010	2011	2013	2014
IN	2015	2013	2012		2015
KS	2009	2014	2012		2014
KY	2008	2013	2013	2014	2014
LA	2008	2013	2013	2014	
MA	2012	2014		2015	
MD	2008	2013		2015	2014
ME	2011	2014	2014	2013	2014
MI	2010	2012	2012		2014
MN	2010	2013	2012	2014	2012
MO	2008	2013	2012	2014	2012
MS	2011	2013	2013	2015	2014
MT	2011	2013	2013		
NC					
ND	2011	2014	2013		2014
NE	2010	2014	2013	2014	2014
NH	2010	2014	2013	2014	2013
NJ	2008	2012	2013	2014	2014
NM	2011	2013	2012	2014	2012
NV	2009	2013	2013	2014	2012
NY	2010	2012		2014	2014
OH	2009	2011	2012	2013	2014
OK	2009	2013	2013	2015	2012
OR	2010	2012	2012	2012	2012
PA	2011	2012	2012	2013	2014
RI	2009	2014		2014	2015
SC	2011	2015	2013	2012	2013
SD	2010	2014	2012		2014
TN	2013	2013	2012	2014	2014
TX	2009	2015	2013	2014	2014
UT	2011	2013	2012	2014	2014
VA	2010	2014	2012	2016	2013
VT	2011	2014	2013	2014	2014
WA	2013	2013	2013		2014
WI	2010	2013	2012	2013	2012
WV	2012	2014	2013	2014	2012
WY	2011	2014	2012		2014

Table A2: Robustness Checks and Alternative Specifications

	Dependent variable is:			
	Normalized profit		Log(profit)	Asinh(profit)
	(1)	(2)	(3)	(4)
I(Entered and 1st)	0.0277		0.0624	0.777
	(0.0158)		(0.0361)	(0.319)
I(Other firm introduced PHYD in state)	-0.0080			
	(0.0117)			
I(Entered and 1st) × I(Progressive)		0.0303		
		(0.0156)		
I(Entered and 1st) × I(not Progressive)		0.101		
		(0.0498)		
I(Entered and 1st) × # competitors	-0.0077	-0.0116	0.0078	-0.323
	(0.0071)	(0.0071)	(0.0129)	(0.233)
Observations	6072	6072	5980	6072

Notes: The table reports coefficients for difference-in-differences estimations with state-insurer, state-year, and year-insurer pair fixed effects in columns (2), (3) and (4). In column 1, state-firm and year-firm fixed effects are included. Robust standard errors, clustered at the state level, are shown in parentheses.

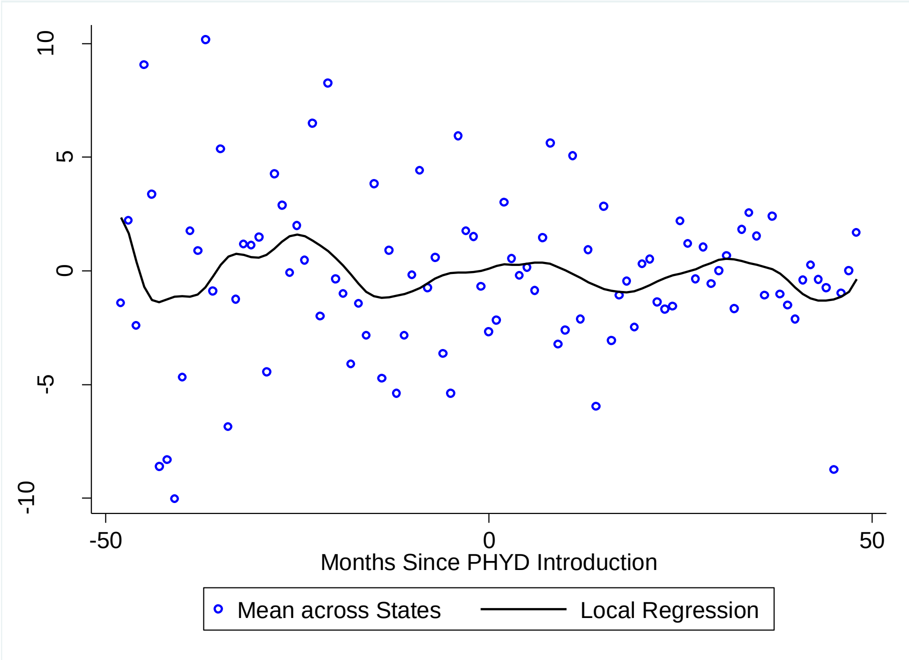

Figure A1: Relative Search Volume around Progressive Insurance's PHYD Introduction