Proprietary Tracking Data, Moral Hazard, and Competition: An Application to Telematics in Auto Insurance[1]

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Abstract:

Declining costs of monitoring hold the promise of eliminating market failures due to moral hazard. However, when adverse selection problems also exist and data are proprietary, incumbents may have incentives to monitor consumers only temporarily to segment safer drivers and generate switching costs in the form of costly effort needed to reveal an agent's type to a competitor. It follows that the relationship between market concentration and rent extraction is theoretically ambiguous. We empirically investigate these issues in auto insurance, focusing on programs offering discounts to consumers observed driving safely. Exploiting the staggered entry of telematics monitoring programs across states influenced by regulations, we employ a difference-in-difference approach to estimate the effect of proprietary monitoring on incumbent profits, with and without competition. We find competition erodes supernormal profits. Lastly, we find that monitoring programs reduce fatal accidents, but only temporarily.

[1] We are grateful to Aaron Brandenburg at the National Association of Insurance Commissioners for providing state-level insurer revenue and cost data, as well as representatives at Progressive, AllState and The Hartford for generously providing data on industry profits and program entry dates.

1. Introduction

Information asymmetries have long generated market failures in insurance and employment markets, among others. Recently, however, rapid declines in costs of collecting data via networked devices (Internet of Things) have increasingly allowed principals to monitor agents inexpensively. Improvements in monitoring and data disclosures are confirmed to alleviate moral hazard problems in prominent contexts (Jin and Leslie; 2003, Jin and Lee, 2014; Luca, 2016), but of course, moral hazard problems are addressed only while agents are monitored. Yet, we posit that incumbent firms under threat of competition may elect to collect consumer data only for short intervals to generate switching costs for the consumers, to lessen competitive pressures and to extract supernormal rents (Klemperer, 1987, 1995). If switching to a competing firm lacking the incumbent's proprietary data, consumers would once again be required to exert costly effort to demonstrate their type to the new firm.

Traditionally, antitrust authorities have been concerned primarily with the relationship between market concentration and prices.[2] But competition may not suffice to lower prices and profits below collusive levels if firms have access to data only for their own customers, giving firms an excessive competitive advantage for existing customers. Competition may even prevent efficient monitoring regimes regardless of the cost of monitoring.[4] Given these possible inefficiencies, it might be prudent for antitrust authorities to consider whether collected data are proprietary in their analyses, even in markets with many competing firms.

We investigate these issues in this paper. We first introduce a simple theoretical model to determine when proprietary data collection prevents competition from reducing the incumbent's rents, and when competition precludes efficient monitoring. We then explore the empirical relationship between proprietary data collection, competition, and incumbent rents, concentrating on auto insurance, an industry comprising roughly 1% of US GDP. We focus on the introduction of telematics devices, which are installed in an insured's car and collect proprietary data on risky behaviors such as hard braking, speeding, and late-night driving, allowing firms to offer tailored discounts to safe drivers. Such programs are generally referred to as usage-based insurance (henceforth UBI). They differ from traditional forms of targeted pricing (Dubé and Misra, 2017; Rossi et al., 1995, 1996; Shiller, 2016; Waldfogel, 2015) because they exploit heterogeneous moral hazard to soften

[2] In addition to monitoring market concentration, regulators penalize deceptive practices and may prohibit price discrimination for sales between one company and another. See https://www.ftc.gov/tips-advice/competition-guidance/guide-antitrust-laws/antitrust-laws

[4] Similarly, competition may result in less than efficient levels of disclosures (Jin and Lee, 2005).

competition. Lastly, we empirically test for this ability to reduce moral hazard by exploring whether UBI programs had a measurable impact on rates of serious accidents by monitoring enrollees.[5]

The theoretical model formalizes the aforementioned intuition. While a monopolist offers permanent monitoring when it is efficient to do so, an incumbent may inefficiently choose to monitor only for short periods when the effort cost of safer driving is moderately high. Monitoring allows firms to identify low-cost consumers who select into the monitoring program on (heterogeneous) moral hazard, similar to Einav et al. (2013). But by monitoring for short periods only, as the first UBI provider in most states did, the incumbent firm generates switching costs which may allow rent extraction even when faced with intense competition in later periods. Moreover, if effort costs of safer driving are sufficiently high, competition may not suffice to lower the incumbent's rents below monopoly levels. It is therefore an empirical question whether competition erodes the incumbent's market power when firms collect proprietary consumer data.

In the empirical component, we employ data on UBI entry dates and insurer profits by state and year, and we exploit variation in the timing of UBI entry across states and insurers to test the predictions from the model. A difference-in-differences estimation confirms that the first firm to offer UBI in a state increases profits, whereas later entrants do not significantly gain from introducing UBI. Our paper's findings thus differ from existing papers' theoretical predictions that pricing based on captured consumer data (e.g. purchase histories) should not raise profits (Acquisti and Varian, 2005; Fudenberg and Villas-Boas, 2007), even for an incumbent. This discrepancy can be attributed to proprietary data collection on an incumbent's own consumers in markets with moral hazard.

Moreover, we find that four or five firms in a market are sufficient to eliminate supernormal rents, slightly more than the prevailing wisdom of only three or four firms for traditional markets (Bresnahan and Reiss, 1991). We provide evidence for the exogeneity of UBI entry, and additional analyses and robustness checks support our main results. We further find that profits increase mainly by decreasing the loss ratio, as the first firms to introduce UBI decrease their costs per customer significantly, suggesting that such programs either attract low-cost consumers (good drivers) due to adverse selection, or that current customers become better (lower-cost) drivers, alleviating the moral hazard problem.

Finally, we test these mechanisms further. If monitoring alleviates moral hazard, and if enough drivers are monitored, the rate of accidents may decrease. We examine this possibility by looking at

[5] Parry et al. (2005) analyzes the impact of mileage based insurance on another externality, pollution.

car accidents and fatalities in each state and year, using the Fatality Analysis Reporting System (FARS). We find evidence suggesting that drivers become safer: the number of fatalities per registered vehicle decreases significantly as more firms offer UBI programs. This is especially true in the first few years in which a firm offers UBI in a state, suggesting the benefits from temporary monitoring programs are short lived.

The remainder of the paper is organized as follows. Section 2 provides an overview of the auto insurance industry and the emergence of usage-based insurance programs since 2008. We introduce a theoretical model in Section 3. Section 4 describes the data. Section 5 explores the empirical relationships between UBI entry, a firm's rents, and competition. In Section 6, we investigate whether UBI programs impacted accident rates. Lastly, we conclude and discuss policy implications in Section 7.

2. Background

2.1 Data Use in Auto Insurance Markets

Auto insurance is a somewhat unusual and data intensive industry. Like in other industries, firms compete on price. But, because the expected insurance losses vary across consumers, insurers try to tailor prices to reflect predicted accident risk. In the 1990s, insurers expanded beyond using demographics and driving records to set prices, incorporating consumer characteristics such as education levels, GPAs, and credit scores (Scism, 2016). This allowed a firm to better predict individual risk. But competing firms could reverse engineer competitors' risk models and apply them to switching customers because the variables used to set prices typically must be reported in publicly available filings to the state, and those data were available for purchase.[6] In addition, information on these consumer characteristics was easily verifiable. Thus, incumbents were neither at an inherent nor permanent advantage.

This may have changed with the inception of usage-based insurance. In the early 2000s, Progressive began experimenting with telematics devices, which, when plugged into the insured's car, can directly monitor risky driving behavior, such as speeding, hard braking, quick accelerations, and night driving. Initially, the telematics devices were cumbersome and mobile networks were too

[6] Rate filings are available for some states at: http://www.serff.com/. Other states provide rate filings upon request.

expensive to transmit the requisite data on a wide scale (Scism, 2016). As data transmission became less expensive, telematics devices were increasingly used to collect data, and discounts were consequently awarded for safe driving.[7] Incumbents typically monitored consumers for only relatively short amounts of time, about 30 days, whereas later entrants opted for longer monitoring periods.[8]

Progressive launched their full-fledged UBI program, called SnapShot, in 6 states in 2008, including Alabama, Kentucky, Louisiana, Maryland, Missouri, and New Jersey. Although Progressive expanded the program quickly, to 43 states by 2012, they might have expanded even faster in the absence of state regulations. States differ in the extent to which insurance prices are regulated. Hunter (2008) found, for example, that 15 states required that insurers obtain explicit approval from state regulators before introducing new prices. Furthermore, Guensler et al. (2004) surveyed state regulators, asking them whether UBI was allowable. Of the 43 representatives who responded, only 27 states reported that UBI programs were allowable.

A handful of other insurers followed suit after Progressive's launch of SnapShot, with AllState introducing its program, DriveWise, in Illinois in 2010, in Arizona and Ohio in 2011, and in 44 additional states by 2014. State Farm was not far behind, introducing its InDrive program in 2011, and expanding to 45 states by 2014. Finally, The Hartford and Liberty Mutual introduced their programs in 2012, with The Hartford offering its UBI program (TrueLane) in 40 states by 2014, and Liberty Mutual offering its program (RightTrack) in 29 states by 2014.[9] Figure 1 shows the expansion of the five firms' UBI programs across all U.S. states.

While Progressive was the first insurer to introduce its UBI program in most states, there still was some variation in which firm entered each state first, and more variation in which firm entered second. Progressive was the first to enter 41 states, State Farm was the first to enter four states, and

[7] Consumers can receive the full discounts from the UBI program after policy renewal, approximately 6 months, at Progressive, State Farm, and The Hartford. Liberty mutual offers full discounts after 90 days. AllState offers rewards for safe driving, which apply immediately. See the FAQ for each UBI program. Accessed Dec 27, 2016.

[8] Progressive, the first to introduce UBI in most states, used monitoring data for a 30 days period, and applied discounts in the future as long as nothing else changed. State Farm used permanent monitoring in for cars with embedded telematics devices (e.g. OnStar, SYNC). Allstate constantly monitored all enrolled consumers. See Karapiperis et al. (2015). The Hartford and Liberty Mutual use 180 day and 90 day monitoring periods, respectively. http://hartfordauto.thehartford.com/landingpages/TrueLane/faqs.shtml. https://www.libertymutual.com/righttrack/righttrack-faq/righttrack-faq-review.

[9] Some other insurers offer prices based on (approximate) mileage driven. For example, GMAC/National General, MetroMile, and Travelers have launched mileage-based insurance products, but do not factor in behaviors like speeding, hard braking, etc. Moreover, eSurance and SafeCo have also launched UBI programs. They are subsidiaries of AllState and Liberty Mutual, respectively.

AllState entered one state first. The distribution of the second entrant's identities is much less skewed. Table 1 shows the order of UBI entry for each firm in each state that it entered.

Aggregate statistics about the take-up of UBI among consumers are difficult to find, but available statistics suggest that usage-based insurance has grown in popularity, and comprises a non-negligible part of the market. A 2014 survey suggested as many as 9% of adult drivers in eligible states were enrolled in usage-based insurance programs, and UBI is expected to grow.[10] One study predicts nearly 100 million drivers in Europe and the U.S. will be enrolled in UBI programs by 2020.[11]

2.2 Simple Indications of UBI Success

UBI data have proven quite useful at 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 et al. (2014) confirm that other monitored driving behaviors correlate with accident risk as well, and the results of Parry (2005) suggest the reduced risk may be partially due to the role of monitoring in solving the moral hazard problem.

Because the algorithm and data collected from UBI devices are proprietary, the data may give a consumer's incumbent provider a competitive advantage.[12] The incumbent provider can offer its low-risk drivers prices that are lower than can be reasonably offered by their competitors, who lack the incumbent provider's data to segment good from bad drivers beyond what can be inferred from publicly available data. 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."[13] In the same interview, he further noted that retention was higher for Snapshot consumers overall, and 40% higher "for those that get a substantial discount."

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[10] See https://www.msn.com/en-us/money/autoinsurance/5-pay-as-you-drive-car-insurance-myths/ar-BB7QEZ7

[11] https://www.forbes.com/sites/sarwantsingh/2017/02/24/the-future-of-car-insurance-digital-predictive-and-usage-based/#578a40ad52fb

[12] Progressive is not required to disclose UBI data to competitors. In fact, Progressive's privacy policy has explicitly prohibited sale of these data to 3rd parties. See Scism (2016). In addition, while Progressive was required to submit its UBI rating algorithm to regulators, it was never publicly revealed to anyone but the regulators, implying competitors could not directly copy it. See https://www.wsj.com/articles/SB10001424052748704433904576212731238464702.

[13] http://news.onlineautoinsurance.com/consumer/progressive-talks-future-with-snapshot-car-insurance-program-910470

In many cases, discounted prices still far exceed actuarially fair rates, allowing the firm employing UBI to profit handsomely. Figure 2 confirms this, using national data for its SnapShot program, reported in a 2014 rate filing in Alaska.[14] Progressive's UBI 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 $loss\ ratio = \frac{payouts\ to\ beneficiaries}{earned\ premiums}$. The figure shows that those drivers who receive the largest discounts also yield the highest margins for Progressive. The loss ratio for the lowest risk group – with UBI scores between 0 and 9 – is only 30.7%, less than half of the industry average of 66%.[15] Non-UBI firms may not be able to offer such low rates to safe drivers, because they lack data on driving habits needed to identify low-risk consumers to offer discounts.

The black-bordered rectangles in Figure 2 represent a histogram of earned premiums. They show that the low-risk groups comprise the majority of the premiums Progressive earns under the program, suggesting that most drivers fall into these low-risk groups. Accordingly, the firm's loss ratio under the UBI program, 56.9%, is well below both Progressive's overall auto-insurance loss ratio (64.2%) and the industry average (66%) in 2014.[16] This suggests that the UBI program could allow the insurer to increase its margins on average, although a more detailed analysis is needed to establish a causal connection.

3. Model

Suppose there are two types of drivers: good drivers, and bad drivers, denoted G and B, respectively. A driver of type i imposes a per-period expected accident cost to the insurer of A_i, where $A_G \leq A_B$. Good drivers can reduce their expected accident cost from A_G to zero at cost of effort to the consumer equal to r.[17] Monitoring a consumer is costly, imposing a per-period cost of m on the firm. If the firm monitors and discovers zero accident risk, it can infer the driver was a type G driver.

[14] See Alaska Serff tracking number SERF PRGS-129620997. https://filingaccess.serff.com/sfa/search/filingSummary.xhtml?filingId=129620997#

[15] For a long time, Progressive promised not to raise enrollees rates beyond non-monitored rates, explaining why drivers identified as risky demonstrated loss ratios exceeding industry averages.

[16] For sources of data on industry averages, see the data section.

[17] In practice, accident risks of careful drivers are above zero, even for good drivers. Normalizing these costs to zero simplifies exposition, without loss of generality. Bad drivers may also reduce accident risk through costly effort. For exposition, we assume it is prohibitively costly for them to do so.

We assume a perfectly competitive market for non-UBI insurance products. Thus, price equals expected cost. If no consumer is monitored, the price of standard insurance is $\bar{A} = E[A_i]$.[18] If a firm offers UBI, it chooses between two monitoring regimes. It may monitor perpetually, or it may monitor for a short period, offering a perpetual discount for safe driving observed while monitored.[19] We assume firms and consumers have a common discount factor $\delta \in (0,1)$. Consumers maximize the present discounted value of their future utility, subject to the constraint that insurance is compulsory. We assume utility is linear in effort costs and prices.[20] If the static price of UBI insurance is P, then the present discounted value of the conditional indirect utility for a type G driver (with cost of effort r) equals:

$$U_G = \begin{cases} -\dfrac{\bar{A}}{1-\delta} & if\ choose\ regular\ insurance \\ \dfrac{-P-r}{1-\delta} & if\ monitored\ perpetually \\ -r-\dfrac{P}{1-\delta} & if\ monitored\ in\ period\ 1\ only \end{cases}$$

We allow for the possibility that a perpetually monitoring UBI insurer may charge a different price than one who monitors only temporarily.[21] Assuming prohibitively large costs of effort, type B drivers always choose regular insurance.

3.1 UBI Monopoly – A Single UBI Provider

Perpetual Monitoring

A Good type driver enrolls in a newly introduced UBI program if the program yields higher discounted utility than standard insurance, i.e. if $\frac{-P-r}{1-\delta} \geq \frac{-\bar{A}}{1-\delta}$, or simplified: $P \leq \bar{A} - r$. Maximum

[18] Eventually, if Good type drivers migrate to a UBI program, leading to a separating equilibrium in which only Bad drivers choose standard insurance, the price of regular insurance will become A_B.
[19] Empirically, early entrants typically offered perpetual discounts for safe driving observed during brief monitoring.
[20] Assuming risk aversion is not necessary to yield our findings, so we assume risk neutral consumers and assume costs equal expected costs for a given consumer, to simplify exposition.
[21] We implicitly assume, without loss of generality, that consumers do not internalize the cost of an accident. We further assume that the consumer's utility is linear in prices, although this assumption is easily relaxed with a re-definition of the variables.

long-run discounted variable profit, incorporating per-period monitoring cost m, equals $\pi_{PM} = \frac{\bar{A}-r-m}{1-\delta}$.[22]

One-Period Monitoring

A type G consumer chooses UBI if doing so yields higher discounted utility than standard insurance. When the UBI firm monitors in period 1 only, this condition can be rearranged to yield $\frac{P}{1-\delta} \leq \frac{\bar{A}}{1-\delta} - r$. A monopolist's maximum long-term variable profit then equals these discounted long-term revenues less the costs of monitoring (m) and the costs of accidents after the monitoring period $\left(\frac{\delta A_G}{1-\delta}\right)$. Hence, $\pi_T = \left(\frac{\bar{A}}{1-\delta} - r\right) - \left(m + \frac{\delta A_G}{1-\delta}\right)$.

<u>Observation 1)</u> *A monopolist offers perpetual monitoring if and only if monitoring is socially efficient.*

By charging different prices to different consumer types, the monopolist is able to extract the surplus created by a UBI program, and therefore prefers a monitoring schedule which maximizes joint surplus, i.e. efficient monitoring. In the context of this model, perpetual monitoring is efficient when the marginal accident cost from unsafe driving exceeds monitoring and effort costs: $A_G \geq r + m$. One can confirm that a monopolist's profit under perpetual monitoring (π_{PM}) exceeds profits from temporary monitoring (π_T) under the same condition.

When instead $A_G \leq r + m$, the monopolist prefers temporary monitoring to segment consumers, even though monitoring – even for short periods – is inefficient from a social planner's perspective.[23]

3.2 The Incumbent's Problem under Competition

We now examine the incumbent firm's incentives and profits – under perpetual monitoring and under one-period monitoring – when the incumbent faces competition from (many) identical new entrants.

Incumbent Offers Perpetual Monitoring

<u>Observation 2)</u> *If the incumbent chooses perpetual monitoring, entry eliminates future profits.*

[22] Since Bad type drivers always choose regular insurance by assumption, these drivers yield zero expected profit for the (perfectly competitive market) firm.
[23] Of course, if the costs of effort and monitoring are so large that π_T becomes negative, the firm cannot gain from offering UBI and may not offer it at all.

If the incumbent offers perpetual monitoring, existing consumers incur the cost of monitoring whether or not they switch to a competing firm. Therefore, the emergence of a perfectly competitive market drives profits to zero, even for the incumbent. The incumbent's long-run profits thus equal the monopoly profits while monitoring during the first period only, before competitors entered: $\pi_{PC} = \bar{A} - r - m$.

Incumbent Offers One-period Monitoring

After the monitoring period, a consumer will remain with the incumbent if her future discounted utility $\left(\frac{-P}{1-\delta}\right)$ is higher than her utility if switching. Following the assumptions of perfect competition among new entrants, entering firms set discounted long-run prices at minimum average cost: $\frac{m}{1-\delta}$ for permanently monitoring competitors, and $m + \frac{\delta A_G}{1-\delta}$ for temporarily monitoring firms. Correspondingly, a consumer's discounted utility from switching is $\frac{-r-m}{1-\delta}$ if competitors monitor permanently, and $-r - m - \frac{\delta A_G}{1-\delta}$ if competitors monitor for just one period. Thus, the incumbent retains consumers if charging a price P such that:

$$\frac{-P}{1-\delta} \geq \max\left(\frac{-r-m}{1-\delta}\ , -r - m - \frac{\delta A_G}{1-\delta}\ , -\frac{\bar{A}}{1-\delta} + r\right), \tag{1}$$

where the last argument is the consumer's IR constraint, which ensures that good drivers are attracted to the UBI program in the first place. Long-run profits of an incumbent using temporary monitoring equal long-run discounted revenues $\frac{P}{1-\delta}$, minus up-front monitoring costs m and discounted accident claims $\frac{\delta A_G}{1-\delta}$.

<u>*Observation 3)*</u> *Entrants use perpetual monitoring if and only if constant monitoring is efficient*

Entrants, which by assumption operate in a perfectly competitive market, price at cost, allowing switching consumers to extract all surplus from entrants. However, permanent and temporary monitoring by entrants might generate different amounts of surplus for consumers when each prices at the respective expected cost. A good type's discounted utility from switching to an entrant using permanent and short-term monitoring are $\left(\frac{-r-m}{1-\delta}\right)$ and $\left(-r - m - \frac{\delta A_G}{1-\delta}\right)$, respectively. Thus, permanently monitoring entrants are preferred if $\left(\frac{-r-m}{1-\delta}\right) \geq \left(-r - m - \frac{\delta A_G}{1-\delta}\right)$. This inequality holds if and only if $A_G \geq r + m$, the necessary and sufficient condition for (perpetual) monitoring to be

efficient.[24] Hence, when monitoring is efficient, switchers select permanently monitoring entrants, and only those entrants retain a nontrivial presence in the market.

<u>Observation 4)</u> Under threat of competition, the incumbent may choose temporary monitoring even if perpetual monitoring is efficient.

Suppose permanent monitoring is efficient, i.e. $A_G \geq r + m$. Then, by Observation 3, surviving entrants use permanent monitoring, implying the second constraint of Equation 1 will not bind. Hence, we can focus attention on the first and third constraints.

A profit-maximizing incumbent employs temporary monitoring when profits from doing so exceed profits under permanent monitoring, i.e. $\pi_{TC} \geq \pi_{PC} = \bar{A} - r - m$. If the first constraint in Equation 1 binds, $\pi_{TC} = \frac{r+m}{1-\delta} - m - \frac{\delta A_G}{1-\delta}$, and thus $\pi_{TC} \geq \pi_{PC} \Leftrightarrow \ (1-\delta)\,\bar{A} + \delta A_G \leq (2-\delta)r + m$. If the third constraint in Equation 1 binds, $\pi_{TC} = \frac{\bar{A}}{1-\delta} - r - m - \frac{\delta A_G}{1-\delta}$, and hence $\pi_{TC} \geq \pi_{PC} \Leftrightarrow \ A_G \leq \bar{A}$.

Whether the first or third constraint in Equation 1 binds, the incumbent may not use permanent monitoring even if efficient. If the third constraint binds, the incumbent employs temporary monitoring if $A_G \leq \bar{A}$. This condition holds by assumption, and the firm never uses permanent monitoring, even when efficient. If the first constraint in Equation 1 binds, then the incumbent uses temporary monitoring when $(1-\delta)\,\bar{A} + \delta A_G \leq (2-\delta)r + m$. Recall, permanent monitoring is efficient when $A_G \geq r + m$. Both conditions hold, for example, if $\bar{A} = 10, A_G = 8, \delta = 0.5, m = 1$, and $r = 6$. Hence, when the first constraint in Equation 1 binds, the incumbent may inefficiently elect not to monitor permanently.

<u>Observation 5)</u> The incumbent may continue to yield monopoly profits even in the presence of intense competition in later periods.

If the consumer's IR constraint (the third argument in Equation 1) binds, rather than either IC constraint, competition has no impact on the incumbent's profits.

3.3 Example

Consider the case where $\bar{A} = 10, A_G = 8.5, m = 0$, and $\delta = 0.9$. Figure 3 shows the incumbent firm's discounted profits with competition arriving in the second period, when the incumbent offers

[24] Competitors may also inefficiently offer one-period monitoring when $A_G < r + m$ if the gains to the firm from learning the consumer's type outweigh the costs of monitoring.

perpetual monitoring (dotted line) and when it offers one-period monitoring (solid line), both as a function of the cost of safe driving r. For low values of r (to the left of point A) the incumbent firm earns higher profits by monitoring perpetually, thus removing the moral hazard problem. Between points A and B, competitors (efficiently) offer perpetual monitoring, yet the incumbent monitors temporarily to generate a switching cost and increase profits. To the right of point B, competitors offer temporary monitoring, and hence, not monitoring is efficient. The IR constraint binds to the right of point C. The incumbent still has an incentive to offer UBI, and competition does not lower profits below the monopoly level.

3.4 Discussion

Whether monitoring alleviates the moral hazard problem depends at least in part on the effort cost of safer driving r. While decreasing monitoring costs (m) could in most circumstances address the moral hazard problem, our analysis shows that an incumbent collecting proprietary monitoring data may instead elect for temporary monitoring for competitive reasons, leading to inefficient levels of harmful accidents. The monitoring schedules chosen by incumbents suggest this outcome may have occurred. Progressive, the first firm to introduce UBI in most states, offered temporary monitoring. AllState, The Hartford, and State Farm, which in most states entered later, elected for longer-term monitoring, perhaps suggesting that permanent monitoring was efficient.[25] Whether these monitoring schedules led to prolonged profits is an empirical question which we address in the following sections.

4. Data

The data used in this paper combine two categories of information: (i) UBI entry dates, and (ii) state-level, firm-specific revenue and loss data. Progressive and AllState representatives provided exact entry dates of their SnapShot and DriveWise programs, respectively, and The Hartford provided entry years for their TrueLane program. Entry years for State Farm's InDrive program and Liberty Mutual's RightTrack were found from news articles and historic versions of their websites, using the

[25] AllState used permanent monitoring. State Farm used permanent monitoring for cars with pre-installed onboard devices such as OnStar or SYNC [Karapiperis et al., 2015] The Hartford uses a 180-day monitoring period (http://hartfordauto.thehartford.com/landingpages/TrueLane/faqs.shtml). Liberty Mutual used a relatively short monitoring period, 90 days (https://www.libertymutual.com/righttrack/righttrack-faq/righttrack-faq-review).

Wayback Machine. To be consistent across insurers, we collapsed more detailed entry timing data to the yearly level.[26]

The UBI entry dates were merged with data on annual private auto insurance premiums, losses, and containment costs, for each insurer in each state between 2008 and 2014, which was provided by the National Association of Insurance Commissioners (NAIC, lines 19.1, 19.2 and 21.1). We supplement these datasets with information on traffic safety and car accidents from the Fatality Analysis Reporting System (FARS) by the National Highway Traffic Safety Administration, which we describe in more detail in Section 6.

The structure of the auto insurance industry requires that we make a few adjustments to the raw data. First, there have been several mergers in the insurance industry between 2008 and 2014. To address this issue, we restrict our data to the top 25 firms by domestic auto insurance revenues, completing a thorough search for mergers among these.[27] We consider revenues and costs of the final, merged firms in this paper. Second, while earned premiums and losses are reported accurately in most states, Michigan has serious reporting issues arising from anomalies in their laws. This leads to unusually large variation in profits, and inaccurate reporting.[28] We therefore drop all observations pertaining to the state of Michigan.

4.1 Revenues and Profits

Insurance premiums include payments from consumers less commissions paid to insurance brokers. We will subsequently refer to these as revenues, and denote firm j's revenues in year t and state s as R_{jst}. An insurance company's variable costs consist of incurred losses, which are the paid claims and loss reserves of the company, and the containment costs – costs of investigating claims as well as any related litigation expenses. We construct state-level yearly (variable) profits π_{jst} for each firm, as earned premiums (revenues) minus the sum of claim payments and containment costs.[29]

Revenue and profit are log-linearly distributed across firms. In 2008, State Farm and AllState were the largest insurers, with State Farm earning the largest revenue, at $28.6 billion, and AllState earning

[26] Entry patterns are described in detail in Section 2.
[27] Mergers and acquisitions were found using SNL financial data and internet searches.
[28] The loss ratios that Michigan auto insurers report for no-fault coverage differ wildly across insurers. As a result, NAIC is not able to include the profitability of Michigan no-fault insurance in its survey. See http://www.cpan.us/docs/Angoff_Report_Profitability_and_Pricing_in_Michigan_Auto_Insurance_Market.pdf.
[29] Because we lack state-level fixed costs, we exclude them from calculated profits.

the largest operating profit with $7.7 billion. The 25th largest company (Sentry) earns much less than the largest companies, with a revenue of $906 million. On average, the 25 largest firms earned $5.45 billion in revenue and incurred total costs of $3.61 billion in 2008.[30] By 2014, these numbers have increased to $6.25 billion and $4.31 billion, respectively, for an increase in variable profits from $1.85 to $1.95 billion.

Four of the five companies which offered UBI programs were among the largest six insurers before the arrival of these programs, with two of the top five companies – Farmers (third in terms of revenue) and Berkshire Hathaway (Geico, fourth) – not monitoring their consumers on a comparable scale. The Hartford, which does offer a UBI program, is the eleventh largest company in terms of revenue in 2008.

5. Empirical Strategy and Results

The fact that UBI introduction varies across both insurance companies and states allows us to employ a difference-in-differences analysis in which we compare the change in a firm's yearly state profits after introducing UBI in that state, to changes in yearly state profits of other non-UBI firms in the same state, while also controlling for changes in the same firm's profits in other states in which they had not yet introduced UBI and hence which must be attributed to other firm-level factors. Formally, we estimate different specifications of the following form:

$$\pi_{jst} = \beta_0 + \beta_1 UBI_{jst} + \beta_2 \times UBI_{jst} \times NumComp_{st} + \mu_{jt} + \nu_{js} + \eta_{st} + \epsilon_{jst},$$

where π_{jst} is firm j's profit in state s in year t, UBI_{jst} is an indicator which equals one if the firm has introduced UBI in that state, and $NumComp_{st}$ indicates the number of competing firms which have UBI programs in the state. The remaining controls, μ_{jt}, ν_{js}, and η_{st}, are firm-year, firm-state, and state-year interactions.

Note this setup differs slightly from typical difference-in-differences specifications – our state-firm-year panel allows a more robust set of controls. Like standard difference-in-differences specifications, we use non-treated firms to control for changes in profits in the state over time unrelated to the treatment. Additionally, our specification includes firm-year fixed effects, which use changes in profits in states in which the firm had not introduced UBI to control for divergence

[30] The costs consist of mostly of the incurred losses, with only about 4% of the costs coming from claims investigations and related litigation expenses.

between treated and untreated firms that would have occurred even in the absence of UBI programs. Additionally, factors impacting profitability in a particular state and year, such as unusually inclement weather, are accounted for by η_{st}. After controlling for these differences, the coefficient β_1 should arguably identify the effect that is due to the introduction of UBI by a company in that state, and β_2 the impact of competition from competing UBI firms. We discuss identification further in Section 5.3.

Because we expect the impact of UBI on profits to be proportional to revenues, and because there are substantial level differences in revenues across states and insurers, interpretation of the effect is difficult when using untransformed profits as the outcome measure. The usual solution to this problem is to use the logarithmic transform, and to translate the coefficient into a percentage change as $e^{\beta_1} - 1$. However, the log transform is not applicable in this context because profits are negative in a nontrivial number of instances – about 1.5% of the observations in the estimation sample – due to the inherent randomness of costs in insurance markets. Most negative profits at the state-insurer level were due to losses that were at least 10% larger than in neighboring years. Since the instances of negative profits are not reporting errors, dropping such observations would bias results.

Therefore, instead of using the log transform in our main specification, we account for level differences by normalizing profits by the insurer's average annual revenues in the state during our time period. That is, our dependent variable becomes $\pi_{jst} = \frac{\pi^*_{jst}}{\bar{R}_{js}}$, where π^*_{jst} is the firm's untransformed profit in that state and year, and $\bar{R}_{js}$ is the firm's average revenue in that state across all years.[31] Using our measure, the average normalized profit is 0.35. In robustness checks, we repeat the main estimation results using log profits as the outcome variables, with the caveat that negative profit observations are dropped. We also use the asymptotic sine (asinh) transform, which does not drop negative observations. Our results remain qualitatively unchanged, and quantitatively very similar.

Finally, we expect heteroskedasticity to arise for two reasons. First, the variance in normalized profits in insurance markets depends on the number of people insured. Second, there are adjustments to insurance costs, such as losses and containment costs, which appear to span years, implying errors are not iid. For example, if the insurer recovered some of its costs through a lawsuit, they would correspondingly reduce losses in the year of the court decision, sometimes leading to

[31] We normalize profits by the firm's average revenues, rather than profits, in that state because such average profits could in rare instances be negative, making interpretation of the transformed variable difficult.

negative losses. However, these cross-year adjustments are not easily identified in the available data. To address these issues, we use robust standard errors.[32]

5.1 Baseline Estimation – UBI, Profits, and Competition

Table 2 shows the estimated effect of introducing UBI on a firm's normalized profits, distinguishing between different UBI entry positions, and the number of UBI competitors. In column (1), we report estimates of the effect of UBI independent of how many firms already offer UBI. These results suggest that firms do not consistently profit from introducing UBI programs. Estimating separate effects by order of entry, in column (2), reveals that the first firm which introduces UBI in a state increases its profit significantly, whereas later entrants do not significantly profit. These findings are consistent with the theoretical model presented in Section 3.

We next explore the impact of competition. Column (3) interacts the number of competing UBI firms with the incumbent's UBI entry dummy, using a linear specification. The coefficient on the number of entrants is negative, albeit small and statistically insignificant at the 10% level. Column (4) controls for competition more flexibly by including an indicator variable for each number of entrants. The negative coefficient on an indicator for 3 or 4 firms competing with the incumbent is significant at the 10% level, and of similar magnitude to the coefficient on the indicator for the incumbent's entry. This indicates that 4 or 5 firms in total may be sufficient to erode the incumbent's supernormal profits.

The theory from Section 3 implies that whether any amount of competition will erode an incumbent's profits is an empirical question. We find, in the context of auto insurance, that entry by four or more firms appears sufficient to restore a competitive marketplace, slightly more than the three firms needed in contexts where firms did not collect extensive proprietary monitoring data on their consumers (Bresnahan and Reiss, 1991).

Our results suggest a large increase in profits, which is eventually eroded by competition. At the mean normalized profit level of 0.322, the results in column (4) suggest that introducing a UBI program initially increases profits by 14%, but the profit gain is reduced to less than 1% after four or five firms have entered. Counterfactual simulations, using the model in column (4) of Table 2, yield similar predictions. Specifically, we used the model to simulate profits of the firms which

[32] We do not cluster standard errors because we are less concerned about serial correlation due to the wide nature of our panel.

actually introduced UBI in a state first, under three counterfactual environments; (i) no firm introduced a UBI program, (ii) actual incumbents introduced a UBI program but no competitors did, and (iii) actual incumbents introduced UBI, but immediately faced three or more competitors (four or five UBI firms in total). The predicted average percent increase in profits from introducing a monopoly UBI program equals 16.2% (SE=6.5).[33] However, the predicted average percent increase in profits is only 1.0% (SE=9.6) when immediately facing competition by three or more firms.

5.2 Robustness

Our data structure and the timing of events could give rise to interpretation concerns. For example, Progressive is the first firm to introduce UBI in 41 U.S. states. It is possible that we measure the impact of introducing UBI on Progressive's profits, rather than the impact of introducing UBI on profits for other firms when they are the first firm to enter. Second, it is possible that we are falsely attributing declining profits over time to increasing competition because time since entry and the extent of competition are correlated. Third, our results may be driven by our choice of the functional form of the dependent variable.

We address these concerns in Table 3. In the first column, we interact our first-to-enter indicator with a second indicator that is turned on if the entrant is Progressive, to explore whether the estimated impact is driven mostly by that firm. The main coefficient, UBI entry by the first entrant, remains positive and significant. The negative coefficient on the interaction of UBI entry and the Progressive indicator suggests that Progressive may have yielded a smaller gain in profit from being the first firm to offer UBI in a state. The second column includes an interaction of having been the first to enter and the time since entry. Its coefficient is positive and insignificant, and the coefficient on the number of competitors remains negative and of similar magnitude. It thus appears that competition, rather than elapsed time, explains declining profitability of UBI programs.

Lastly, in columns (3) and (4) of Table 5, we explore alternative transformations of the dependent variable. In column (3) we use the log of firm profits, dropping observations with negative profits. Because dropping observations with negative profits may bias results, we also use the asinh transformation (Burbidge et al., 1988) of profits in column (4). Both transformations yield similar results to the main specification: introducing a UBI program increases profits, at least for the first firm to enter. However, competition is not found to increase profits in the log(profits) specification.

[33] Standard errors calculated using the delta method.

This is not entirely surprising. If competition lowers profits, more instances of negative profits will be expected for UBI firms when facing competition. Using the log transform requires dropping those observations, biasing the coefficient on competition.

5.3 Identification

While our results are robust to a wide set of specifications, one might remain concerned that firms may introduce UBI programs in states where profits were expected to increase even in the absence of a UBI program. This would lead to an overestimate of the impact of UBI introduction on profits, and an underestimate of the impact of competition. However, such concerns do not appear to be driving the results.

Our difference-in-differences specification alleviates the most obvious endogeneity concerns. First, "treated" firms, i.e. those which introduced UBI programs, might have systematically different time trends from "non-treated" firms. Variation in when and if treated firms entered each state allows us to include firm-year fixed effects to control for any such differences, addressing this concern. Second, firms could enter states anticipated to be more profitable in general, whether or not UBI is introduced. State-year fixed effects, which are identified by the profitability of firms with no (current) UBI programs in the state, control for such differences.

Therefore, endogeneity is only a concern if the introduction of UBI coincides with strong positive profit shocks that apply only to the state and UBI firm. We believe this is unlikely, for two reasons. First, if UBI firms endogenously chose to enter states where higher profits were anticipated, we would expect this to apply not only to the first entrant, but also to subsequent entrants. However, as Table 2 shows, only the first to enter profits significantly. Second, UBI programs were planned in advance and rolled out very quickly. For example, between 2008 and 2010, Progressive's annual report stated plans to introduce UBI in the following year in 12-15 states, 15 states, and 15 states, respectively, at least partially depending on regulatory approval.[34]

Perhaps a more important concern, because the theoretical model gives ambiguous predictions about whether competition erodes incumbent profits, is whether the impact of competition is biased. If later entry were endogenous in the sense that entrants elected to enter states where UBI was

[34] http://media.corporate-ir.net/media_files/irol/81/81824/pdf/ar/Progressive2008-FinancialReview.pdf
http://media.corporate-ir.net/media_files/irol/81/81824/pdf/ar/Progressive2009-FinancialReview.pdf
http://media.corporate-ir.net/media_files/irol/81/81824/pdf/ar/Progressive2010-FinancialReview.pdf

increasingly profitable, this might bias against finding an impact of competition on incumbent profits. For example, if competitors entered states concurrent with positive transient shocks to the profitability of UBI programs, the positive shock would presumably apply to the incumbent's profits as well, somewhat offsetting the decline in the incumbent's profits from increased competition. Hence, if we found competition does not lower profits, one might be concerned the result might be attributed to endogeneity concerns. But we did not. We instead find that three or four competitors (four of five UBI firms in total) are sufficient to eliminate nearly all of the incumbent's profits.

Still, we investigate whether endogenous factors impact entry timing using monthly, state-specific Google search volume for "Progressive Car Insurance," using Google Trends data.[35] Our attention is restricted to Progressive, because it entered 41 states first, and entry by subsequent firms is not associated with higher profits. We regress search volume on date and state fixed effects, and we plot the residuals against the months since Progressive introduced UBI in the state in Figure 4. Note that search volume does not visibly increase leading up to or soon after UBI introduction, suggesting that UBI introduction was not timed to coincide with increasing awareness in Progressive's auto insurance products.[36]

If endogeneity doesn't explain entry, what does? To explore entry-timing decisions among the 5 UBI firms, we employ a Cox proportional hazards model, controlling for each firm's yearly tendency to introduce UBI programs, reporting the estimated relative odds of introducing UBI in Table 4. First, we investigate state-level laws. In column (1), we relate entry timing to whether the regulator surveyed by Guensler et al. (2004) believed UBI programs abided by state laws in 2003. In column (2), we relate entry timing to whether insurers needed to obtain prior approval from state insurance regulators before altering their pricing (Hunter, 2008).[37] Proportional hazard ratios are reported in place of coefficients. The impacts are large and consistent with our expectations. Firms are 66% more likely in a given year to introduce UBI programs in states in which regulators believed UBI abided by state laws in 2003, and slower to introduce UBI in states which required prior approval based on a 2008 assessment. Columns (3) and (4) consider the impact of incumbent firms on entry. The likelihood of a firm introducing a UBI program is inversely correlated with the number of existing

[35] We normalized the data so the highest search volume in any state equals 100.
[36] To be sure, we included each firm's state-specific annual search volume in unreported profit regressions, finding that these additional controls have no effect on the coefficients of interest.
[37] States were classified into six categories: (1) states not reviewing rates, (2) states only reviewing rates if increases exceed a specified threshold, (3) states which require rate filings ex-post, (4) states which require the insurer to file before use, (5) states which require prior approval of rates, and (6) state sets allowable rates.

UBI firms in the state, which is consistent with the contention that later entrants profit less from UBI programs, and thus firms were presumably less inclined to enter after another firm had already entered the state.

5.4 Mechanism behind Profit Increases

It seems clear that the first firm to utilize UBI can profit from the additional information about consumers. It is not clear yet whether this advantage 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 UBI on earned premiums and cost measures separately. We specifically consider two variables: (i) revenues, again normalized by the firm's mean revenue in each state over the seven observed years, and (ii) the fraction of earned premiums (revenues) used to pay claims and associated litigation costs.[38]

The results are shown in Table 5. The point estimates have sensible signs. Column (1) reports results from a regression of normalized revenues on UBI entry and the extent of competition faced by the incumbent. The coefficient on UBI entry by the first firm is statistically insignificant, although its positive sign might suggest higher revenues. Column (2) presents the results from an analogous regression with the ratio of costs to revenues as the dependent variable. The coefficient on UBI entry by the first firm is negative and significant at the 10% level, implying UBI entry, as least by the first firm, significantly lowers costs per dollar of earned premiums (revenues), or said another way, increases markups. These results support the evidence presented in Figure 2: UBI insurers are able to identify and target safe drivers quite effectively, or entice existing customers to drive more safely.

6. Moral Hazard and Long-Term Implications

The fact that incumbents continue to earn higher profits years after introducing UBI could signify a switch by the safest drivers to those firms which offer the largest discounts – an example of adverse selection, or selection on moral hazard as in Einav et al. (2013). At the same time, consumers in a UBI program may respond to incentives and drive more safely while monitored than they otherwise would. If consumers are incentivized to drive safely under UBI, this suggests that the impacts of UBI

[38] This ratio is often referred to as the DCC (Defense and Cost Containment) ratio (http://www.naic.org/consumer_glossary.htm)

may extend beyond rent seeking, and yield tangible impacts on societal welfare by reducing accidents.[39] Since drivers do not internalize the costs of dangerous driving on the harm caused to other drivers they might crash into, explicit rewards for safer driving through UBI programs may alleviate a source of market failure.

To investigate whether UBI programs reduce accidents, we employ information on traffic safety from the Fatality Analysis Reporting System (FARS), which reports annual accidents by accident and vehicle registration location (state). On average, 0.21 cars are involved in fatal accidents per thousand registered vehicles annually between 1995 and 2014, although this number has decreased substantially over the last decades, from 0.25 in 1995 to 0.16 in 2014.

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

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

Where s denotes the state in which the car is registered, and t denotes the year. μ_s and η_t are state and year fixed effects, respectively, and UBI_{jt} is a measure of UBI penetration in state s and year t. $\ln(Vehicles)_{st}$, a control variable, indicates the log number of registered vehicles.

We first regress log-accidents on the cumulative number of firms which have introduced UBI 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 UBI programs, and might eventually resume unsafe driving.

Table 6 shows the coefficients of interest from these regressions. The results in column (1) imply that one more firm offering UBI would decrease the number of cars involved in fatal accidents by approximately 1.6%. Column (2) suggests the benefits are to some extent short-lived. UBI programs reduce accidents most in the first three years after being introduced, providing suggestive evidence that UBI addresses the moral hazard problem, but the benefits eventually fade after monitoring ceases or consumers stop being as attentive of their driving habits.

Out of the concern that contemporaneous changes at the state level may coincide with the introduction of UBI, we divide accidents by both the accident location and the state in which the

[39] Mitigating adverse selection may reduce externalities if prices better reflect underlying risks, and high risk consumers, who subsequently face higher insurance prices, drive less.

involved vehicle was registered, controlling for state-level accident risk.[40] Intuitively, any state-level road-safety measures that coincide with UBI entry should only reduce in-state accidents. For example, suppose Alabama improves visibility on highways by adding lights around the time UBI programs are introduced in the state. Better lighting might explain reduced accidents in Alabama, but should not explain reduced accidents involving vehicles registered in Alabama that occur out of state. UBI availability, however, depends not on where a vehicle is located at a given moment, but rather on where it is registered. Hence, if accidents involving cars registered in Alabama but occurring out of state fall after UBI programs are introduced in Alabama, we can attribute the reduced risk to UBI.

We exploit this intuition, regressing the number of vehicles registered in state s involved in fatal accidents in state l on UBI entry in the state where the vehicle is registered, controlling for changes in accident risks in state l:

$$\log(Vehicles\ in\ Fatal\ Accidents)_{slt} = \beta_0 + \beta_1 UBI_{st} + \beta_2 \ln(Vehicles)_{st} + \kappa_{sl} + \gamma_{lt} + \epsilon_{st},$$

where s denotes the vehicle's registration location, l denotes the accident 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 which may coincide with UBI introductions.

The results are shown in column (3) of Table 6. The results are consistent: UBI programs significantly reduce the number of vehicles involved in fatal accidents, but the benefits dissipate a few years after the introduction of UBI programs.[41]

7. Conclusion

In this article, we demonstrate two points that might concern policy makers as monitoring costs fall. First, incumbents might elect to monitor consumers for short periods, after which consumers face switching costs if moving their consumption to a competing firm. While short-term monitoring may increase the incumbent's profits in the face of competition, it may be inefficient, as agents resume shirking after monitoring ceases. In the case of auto insurance, monitoring for only short periods may later lead to unsafe driving and unnecessary accidents. Second, due to the effort cost of

[40] Accidents involving vehicles registered in two (or more) states will appear twice (or more) as separate observations, one for each location of registry.
[41] We yield similar results when omitting cars involved in accidents in their home state.

demonstrating safe habits while monitored again by a competing firm, incumbents may maintain market power with their consumers even after many competing firms enter.

In the empirical sections, we find mixed results in regards to these concerns. We find that competition by three or four entrants (four of five firms in total) seems sufficient to eliminate the incumbent's rents from UBI programs, though we caution that this finding may be industry specific. Second, we find that while UBI programs seem to lead to an economically meaningful reduction in the number of accidents, and that the benefits dissipate over time, which may be due to the choice of the incumbent to use temporary, rather than permanent monitoring.

The presence of competition may, theoretically, fail to reduce incumbent rents, but it may encourage firms to monitor temporarily even when permanent monitoring would address the moral hazard problem. These findings arise because incumbents collect proprietary data on their consumers' behaviors, suggesting that regulators might consider requiring collected data be shared with competitors, to avoid market failures from remaining even as monitoring costs fall. The findings also suggest that in some circumstances mergers which lead to substantial industry concentration might have a negligible impact on consumer welfare if competition leads to inefficient monitoring levels.

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Tables and Figures

Table 1: Order of UBI entry by insurer

	Number States Insurer was n^{th} To Introduce UBI				
Order of Entry	AllState	The Hartford	Liberty Mutual	Progressive	State Farm
1	1	0	0	41	4
2	10	5	1	1	15
3	11	7	3	5	17
4	14	15	8	1	6
5	2	15	23	0	2

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

Table 2: Baseline estimation: UBI, order of entry, and profits

	Dependent Variable is Normalized Profit			
	(1)	(2)	(3)	(4)
Entered UBI	0.00622			
	(0.0086)			
Entry Order				
1st		0.0380**	0.0457**	0.0466**
		(0.0179)	(0.0205)	(0.0186)
2nd		0.0187		
		(0.0165)		
3rd		-0.0211		
		(0.0158)		
4th		-0.00893		
		(0.0158)		
5th		-0.00973		
		(0.0185)		
UBI firms competing with incumbent			-0.00992	
			(0.00755)	
Number competitors				
1				-0.0120
				(0.0228)
2				-0.0145
				(0.0267)
3 or 4				-0.0438*
				(0.0265)
Observations	6072	6072	6072	6072

Notes: The table reports coefficients for a difference-in-differences estimation with state-insurer, state-year, and year-insurer fixed effects. The dependent variable is profit normalized by the firm's average revenues in that state. Robust standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 3: Robustness checks and alternative specifications

	(1)	(2)	(3)	(4)
	Dependent Variable is:			
	Normalized Profit			
			Log(Profit)	Asinh(Profit)
Entered 1st	0.101*	0.0467**	0.0624*	0.777**
	(0.0566)	(0.0205)	(0.0375)	(0.324)
UBI competitors	-0.0116	-0.0130	0.00777	-0.323
	(0.00789)	(0.00817)	(0.0142)	(0.217)
Entered 1st x I(Progressive)	-0.0706			
	(0.0548)			
Years since incumbent entered		0.00469		
		(0.00774)		
Observations	6072	6072	5980	6072

Notes: The table reports coefficients for a difference-in-differences estimation with state-insurer, state-year, and year-insurer fixed effects. The dependent variable is profit normalized by the firm's average revenues in that state. Robust standard errors reported in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 4: Relative Odds of Introducing UBI Programs, 2008-2014

	UBI Entry			
	(1)	(2)	(3)	(4)
State allowed UBI 2003	1.668***	1.657***		
	(0.237)	(0.236)		
Prior Approval Required for Rate Changes	0.733*			
	(0.117)			
Previous UBI entrants			0.664**	
			(0.112)	
1 previous UBI entrant				0.519
				(0.224)
2 previous UBI entrants				0.303**
				(0.165)
3 previous UBI entrants				0.297**
				(0.178)
4 previous UBI entrants				0.111***
				(0.0869)
Observations	1453	1453	1453	1453

Note: The table reports the results of a Cox hazards model predicting firms' introduction of UBI programs in each state. The event variable is an indicator variable noting entry of firm j in year t in state s. Hazard ratios are reported instead of coefficient values. Standard errors in parentheses. Additional controls include firm-year pair indicators (for all models) and state indicators in columns 3 and 4. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Impact of UBI on revenues and costs

	(1) Normalized Revenue	(2) Cost Ratio*
Entered 1st	0.0354	-0.0380*
	(0.0314)	(0.0216)
UBI firms competing with incumbent		
1	-0.0112	0.00131
	(0.0228)	(0.0343)
2	0.0312	0.0370
	(0.0344)	(0.0388)
3	-0.0442	0.0354
	(0.0370)	(0.0374)
Observations	6071	6071

Notes: The table reports coefficients for a difference-in-differences estimation with state-insurer, state-year, and year-insurer fixed effects. The dependent variable in column (1) is log revenue, and the dependent variable in column (2) is the ratio of costs to revenues. A single observation with negative reported revenues was omitted. Robust standard errors in parentheses. *p<0.1, **p<0.05

Table 6: UBI and Moral Hazard

	Log(cars in fatal accidents)		
	(1)	(2)	(3)
# firms with UBI	-0.0162*		
	(0.00838)		
# firms entering this year		-0.0125	-0.00607
		(0.0105)	(0.00741)
# firms entering last year		-0.0210*	-0.0116
		(0.0111)	(0.00706)
# firms entering 2 years ago		-0.0157	-0.0225**
		(0.0121)	(0.00968)
# firms entering 3 years ago		-0.00672	-0.00593
		(0.0196)	(0.0147)
# firms entering 4 years ago		-0.00979	-0.00871
		(0.0233)	(0.0167)
Log registered vehicles	0.122**	0.123**	0.0396
	(0.0608)	(0.0611)	(0.0429)
Observations	1071	1071	55692
	0.991	0.991	0.937

Notes: The table reports coefficients for a difference-in-differences estimation with registration-state and year fixed effects in columns 1 and 2. Additional controls include the number of registered vehicles in the vehicle's state of registration. Standard errors, clustered at the state level, in parentheses. *p<0.1, **p<0.05, ***p<0.01

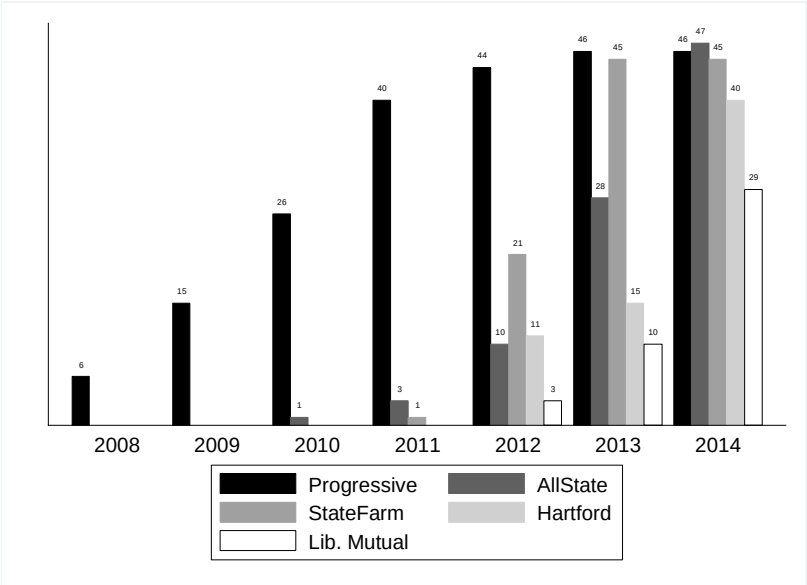
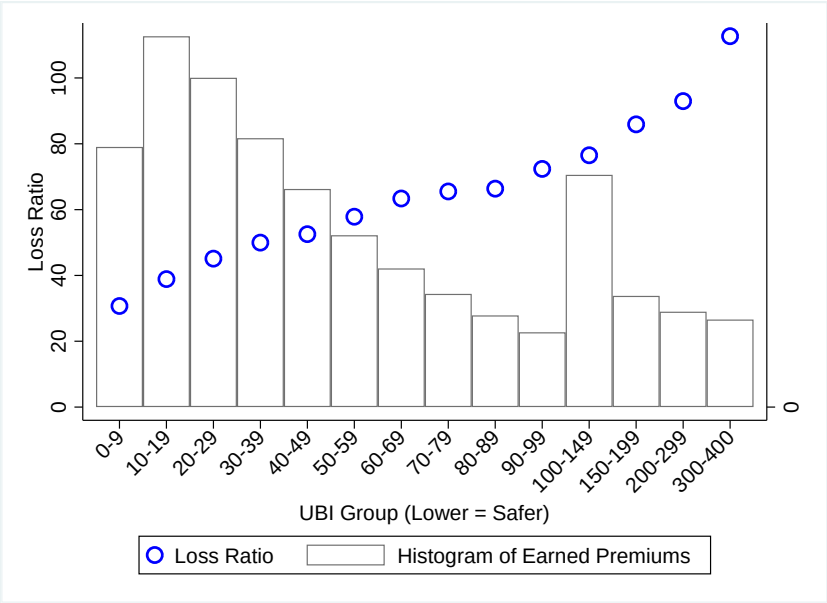


Figure 1: Number of states with UBI programs by insurance company



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

Figure 2: Progressive's loss ratio and earned premiums 2014, by UBI group

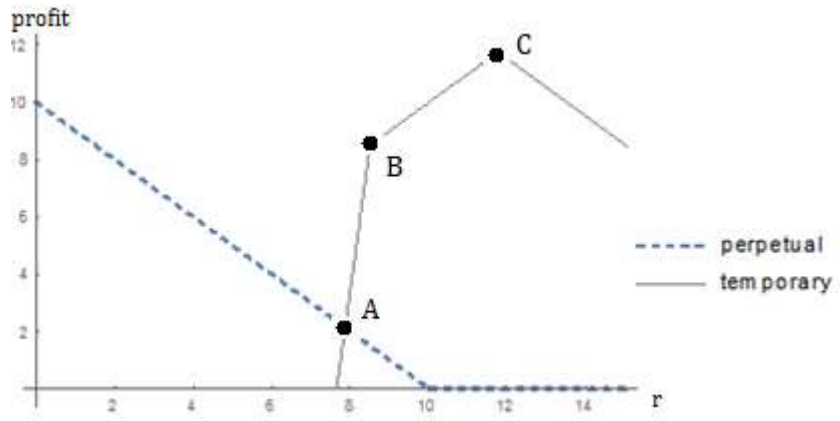


Figure 3: The incumbent's profits under threat of entry with perpetual and temporary monitoring

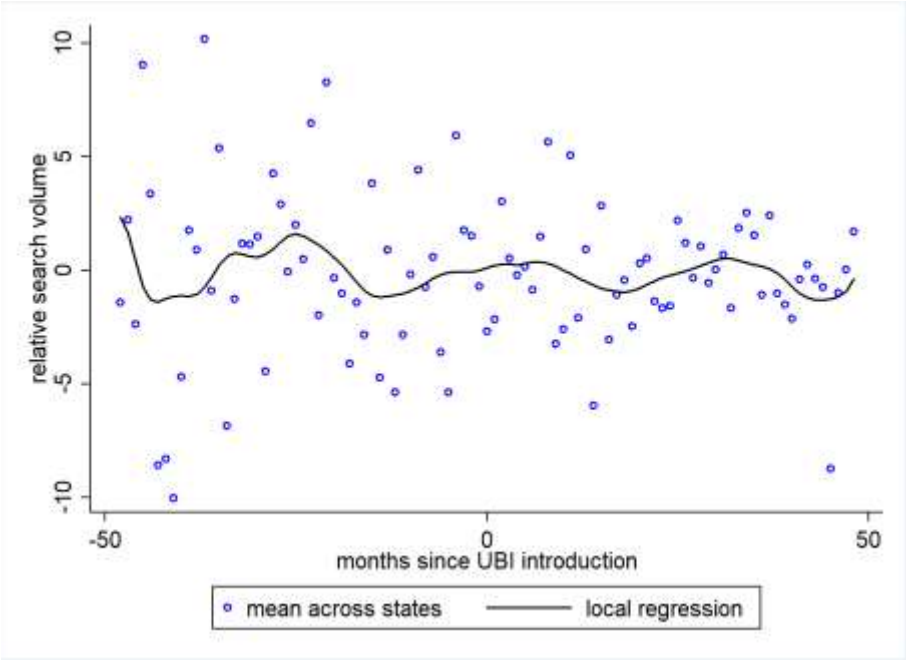


Figure 4: Relative Search Volume Around Progressive's UBI Entry