Product–Consumer Substitution and Safety Regulation: Theory and Evidence from Simulation

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Abstract

We develop a novel theory of safety regulation that incorporates both moral hazard and adverse selection. We test our theory using unique data from more than 2 million observations obtained from iRacing, an online racing simulation. Our theory provides new explanations of phenomena studied in the literature. We offer novel policy implications; in particular, we introduce the concept of two-dimensional regulation.

Keywords: safety regulation; adverse selection; moral hazard

JEL classification: K2, L5, D8

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1 Introduction

Risky activities are activities that might yield bad outcomes in terms of health, environment, finance, or other aspects of our lives. Examples of such activities abound. Driving can cause a fatality; investing in financial markets can lead to bankruptcy; practicing sports can end up with devastating injuries or death. Safety regulation aims at making risky activities less dangerous; that is, minimizing the probability of bad outcome.

We develop a novel theory of safety regulation with not only moral hazard (as in the standard theory) but also adverse selection. We support our theory with empirical analysis using over 2 million observations generated by iRacing, an online racing simulator. Our theory sheds a new light on the economics of safety regulation, as well as, offers new and important policy implications.

We divide safety regulation policies into two types. Product regulation determines the level of product safety; that is, what is being consumed. With everything else remaining constant, safer products reduce the likelihood of bad outcome. Consumer regulation is about establishing specific consumer skills; that is, who can consume. Ceteris paribus, higher skills make a risky activities less dangerous.

For instance, in the case of road safety, regulation is about reducing the probability of a fatal accident (bad outcome). Product regulation increases product safety by making cars safer (e.g., seat belts, driving aids, technological limits on the maximum speed a car can reach) or improving the road infrastructure (e.g., fewer potholes, impact-reducing barriers along the road). Consumer regulation screens out people with low driving capabilities and experience. This can be achieved by designing more difficult driving tests and requiring that the test be repeated every few years, or making sure that the potential drivers have the capability to provide first aid to crash victims.

The main concerns of the safety regulation literature are (a) whether higher product safety or consumer skills decreases the probability of bad outcome, and (b) how people react to regulation. When regulation yields the intended result—the probability of bad outcome decreases—then we say that we observe the regular effect. However, when that probability increases, then we observe the Peltzman effect.

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1“The Peltzman effect” is a term we borrow from the literature on road safety. This effect was first studied by Peltzman (1975) who found that the product regulation introduced in the United States in the mid-1960s (e.g., installation of seat belts for driver and all passengers)“had no effect on the highway death toll. There is
According to the standard theory of safety regulation, increasing product safety or consumer skills affects the probability of bad outcome via two channels. First, there is a direct gain which we call the **gain from regulation**. An example of such a direct gain is a 12% reduction in road fatality due to installed air bags.²

Second, there is a problem of moral hazard: regulation induces consumers to adjust their effort (i.e., private safety precautions). In the context of road safety, effort captures how much attention people pay while driving. The **adjustment behavior** can be either **positive** (when consumers increase their effort) or **negative** (when effort decreases).

In short, the standard theory of safety regulation can be depicted in the following way.

\[
\text{change in the probability of bad outcome} = \text{gain from regulation} + \text{moral hazard}
\]

The standard theory of regulation dictates that the only force behind the Peltzman effect is moral hazard: product regulation makes people feel too safe and consumer regulation makes people feel overly confident about their skills inducing a decline in effort large enough that the moral hazard effect is bigger, in absolute terms, than the direct gain from regulation. We call this special case of negative adjustment behavior the **standard offsetting behavior**. It is “standard” since this is the offsetting behavior as defined by the standard theory.

In our paper, we propose a novel theory of safety regulation with not only moral hazard but also adverse selection. We empirically support our theory using data from iRacing ([http://www.iracing.com/](http://www.iracing.com/)), an online car racing simulator. iRacing has been designed to replicate in the virtual world the three main components of physical racing—tracks, cars, and driver behavior—as realistically as possible. The only difference between the iRacing simulations and real world racing is that, in iRacing, nobody gets hurt or dies due to a crash. In addition, given what and how data is collected by iRacing, the simulator is an outstanding environment in which we can test our theory.

The richness, uniqueness, and quality of our data allow us to establish several empirical findings that have previously been unavailable. There are several features of our data we need to discuss. First, we observe separate and objective measures of product safety, consumer skills, and environment (controls). Second, our data consists of several regulation regimes which permits us to go beyond the standard pre-and-post regulation analysis. As far as we know, only Cohen and Einav (2003) and Sobel and Nesbit (2007) use data with multiple regulation regimes.

Third, with over 2 million observations, our data is large enough to avoid any small-sample issues. Fourth, our data is simulation-based and automatically collected which avoids the usual problem of misreporting or missing data. Finally, we are unaffected by one of the concerns in the regulation literature: the gap between what the law imposes and what is being enforced. It takes time before the law is fully enforced and this lack of immediate and full-enforcement might distort the empirical results. For example, Cohen and Einav (2003) recognize this problem in the case of the mandatory seat-belts. In iRacing, this problem is nonexistent.

Our theory of safety regulation starts with recognizing and empirically confirming that there is an important substitution effect between product safety and consumer skills. In order to explain and motivate both this effect and our theory, consider product regulation in the context of road safety: cars become safer or easier to maneuver. This improvement in product safety implies that the low-skill drivers (who previously opted to not drive) can finally afford (in terms of cost of effort) to become actual drivers. In consequence, an increase in product safety is associated with a decrease in consumer skills. This negative correlation between product safety and consumer skills is an example of adverse selection. We call this externality the product-consumer substitution.

Since consumers skills decrease as a consequence of increasing product safety, the impact of product regulation on effort is more complex than suggested by the standard theory. Now, moral hazard affects effort via two channel. The primary channel is the one that the standard theory posits: higher product safety implies adjustment behavior. However, effort changes because of the associated decrease in consumer skills as well. For instance, upon realizing that unskilled people are using roads, drivers might decide to pay more attention in order to mitigate the decrease in driving skills. This is a novel and secondary moral hazard. Since, a priori, neither the size not the sign of the secondary moral hazard is known, this implies that the standard theory not only incorrectly estimates the size of change in effort but also can predict the incorrect direction of that
change.

With adverse selection, we find that product regulation and consumer regulation have opposite impacts on effort. This phenomenon is undetected by the standard theory but has important policy implications for regulators whose goal is to not only decrease the probability of bad outcome but also increase consumer effort. If increasing effort is part of regulator’s objective function, then choosing between product regulation and consumer regulation is a crucial task.

Adverse selection affects not only effort but also the result of regulation (Peltzman effect vs regular effect). With the product-consumer substitution, beside the two forces we know from the standard theory, there are two additional effects influencing the change in safety measure. First, there is the loss from regulation which unambiguously increases the probability of bad outcome. This effect captures the effort-unrelated depreciation in the safety of the environment. In the case of road safety, product regulation (i.e., safer cars) lowers, via the product-consumer substitution, driving skills of the representative driver. Consequently, with everything else constant, the roads become more dangerous. The magnitude of this effect depends on the size of the product-consumer substitution and the importance of skills in reduction of the probability of bad outcome.

Second, there is also an effort-related effect. This is due to the fact that moral hazard changes effort via two channels. In the case of road safety, when product regulation lowers representative driving skills due to cars being safer, then drivers adjust their behavior. We call this new effect the secondary moral hazard and, accordingly, the moral hazard that we know from the standard theory is called the primary moral hazard. A priori, neither the magnitude nor the sign of secondary moral hazard is known.

\[
\text{change in the probability of bad outcome} = \text{gain from regulation} + \text{primary moral hazard} + \text{loss from regulation} + \text{secondary moral hazard}
\]

As the above equation indicates, if the standard theory predicts the regular effect, then the outcome might be less enthusiastic than expected or, even worse, we might observe the Peltzman effect. The opposite is also possible: the analysis based on the standard theory expects that the regulation will yield the Peltzman effect while, actually, the outcome is the desired regular effect. Hence, our theory explains the discrepancies between what the regulators (who rely on the standard theory) expect and what they, actually, observe as well as indicates that the policy recommendation based
on the standard theory might be incorrect.

The first two terms in the above equation—gain from regulation and primary moral hazard—depict the change in the probability of bad outcome as implied by the standard theory. Whenever the sum of these two terms is positive (i.e., probability of bad outcome increases), then we say that we observe the standard offsetting behavior. We show, theoretically and empirically, that, as opposed to what the standard theory indicates, the standard offsetting behavior does not preclude the regular effect.

Our theory also provides an alternative explanation of the Peltzman effect: the standard offsetting behavior need not be the main driving force behind the Peltzman effect. We support this claim with an empirical exercise in which we find the Peltzman effect with negligible standard offsetting behavior.

When adverse selection is a significant problem, then our policy suggestion is a combined product-consumer regulation. This regulation aims at, simultaneously, increasing product safety (consumer skills) and not decreasing consumer skills (product safety). We provide empirical support of such a policy.

To sum, the standard theory of safety regulation disregards the problem of adverse selection which makes it a one-dimensional theory because of focusing on either product safety or consumer skills; not both at the same time. Our approach is two-dimensional since we analyze how regulation simultaneously affects product safety and consumer skills. Incorporating adverse selection into the theory of safety regulation not only enriches our understanding of safety regulation but also leads to novel and important implications for policymakers. In fact, relying on the one-dimensional theory might lead to wrong policies.

Our theory is relevant not only in the context of regulations concerned with road safety or racing but also safety regulation for which moral hazard and adverse selection are pertinent issues. Of course, it is impossible to list all regulations affected by moral hazard, not to mention provide a comprehensive review of the various literatures. Some examples include, but are far from being limited to, regulation of recreational and professional sports (e.g., McCarthy and Talley (1999), Sobel and Nesbit (2007), Pope and Tollison (2010), Chong and Restrepo (2014)), consumer products (e.g., Viscusi (1996), Viscusi et al. (2005)), crime prevention, and financial institutions and

3While Becker (1968) assumes that private crime-preventing expenditures decrease when public expenditures
markets (e.g., Grossman (1992), Gorton and Huang (2004), Dam and Koetter (2012), Farhi et al. (2012), and Allen et al. (2015)).

In Section 2, we discuss in detail what iRacing is and present the data we use in our empirical part. Section 3 presents our theory using a simple mathematical model and includes empirical results supporting our theory. We end with conclusions and policy implications in Section 4.

2 Data from iRacing

iRacing is an online racing simulator developed by iRacing.com Motorsport Simulations. We use data from all races that took place from January 1st to December 31st, 2015. Our observations are at the individual level. That is, for each race we observe the statistics generated by each driver. For example, if there are twenty drivers in a given race, then we obtain twenty observations. Since this is the first time that the data from iRacing is used in an academic paper, we believe that it is necessary to provide a detailed explanation of the simulator.

iRacing generates revenue from subscriptions. The monthly fee is around $12, and the annual fee is around $110. There are no computer-simulated racers; all drivers are humans. Because of its competitive nature, iRacing is an example of an e-sport. In our data, there are over 40,000 racers from more than 100 countries.

Races take place in real time and, at any given moment, each driver can participate only in one race. Like in non-virtual racing, each race begins with a qualification that determines racer’s initial position. Prior to the race, drivers have the possibility to train on the track used in the race. Races take as much time as they do in real life; that is, if a race consists of 100 laps each of 2 miles length, then the racers need to drive for 200 miles. While the miles are virtual, the time it takes to travel them is not. Hence, if an average speed is 100mph, then the racers would spend two hours in the simulator. Consequently, some races can take hours just same as real-life races do. (There are even 24-hour races.) In addition, and as opposed to typical video games, the first-person point of view is the only available view for the racer in the simulator. As in a real race, each driver in

\footnote{In fact, we can find the problem of bailouts and moral hazard discussed in work as old as Bagehot (1873).}
iRacing has a view only from the seating position inside the car.⁵

There are three elements of the racing simulator that are important from our (research) perspective: tracks, cars, and drivers’ behavior. When it comes to the tracks and cars, the objective is to have them designed as virtual replicas of the real-life tracks and cars. That is, the virtual cars are to behave on virtual tracks in the same way their real-life counterparts behave on physical tracks. As we argue below, this objective has been accomplished. While re-creating tracks and cars in a virtual world is an amazing achievement by itself, there still is a question whether iRacing members behave as if in the real-life race. After all, no matter how realistic the simulator is, there is always a risk that players drive recklessly on purpose or crash for fun. Fortunately, there are several strong incentives against such behavior. Consequently, the behavior of iRacing drivers mimics that of real-life drivers. Below, we discuss how iRacing designs their tracks and cars, and motivates its members against undesired behavior.

Tracks. There are over 70 real racetracks from around the world that have been re-created in iRacing. The company uses proprietary technology to design the tracks.

_The goal of the iRacing.com experience is simple: to make each lap driven in simulation as valid as a lap driven on the real-world race circuit._

_To achieve this exceptionally high level of realism, iRacing.com uses its pioneering, proprietary application of three-dimensional laser-scanning technology to create two key features._

_The first is a series of highly detailed sight-pictures. These images, like frames in a movie filmed from an in-car camera, are driver’s-eye views that allow iRacing.com drivers to see specific points of a lap: braking points, turn-in points, or the apex of a corner, for example._

_iRacing.com's sight-pictures are the most accurate and complete ever offered in a racing simulation. You see exactly where you are on the racetrack at any given millisecond, receiving the instantaneous, granular visual input racers require to refine their performance lap after lap._

⁵If the reader is interested in learning more about iRacing, we suggest to watch live streaming of races at http://www.iracing.com/live/, or watch YouTube iRacing-dedicated channels like True Racer (https://www.youtube.com/user/TrueRacerAcademy/) or Empty Box (https://www.youtube.com/user/TacticalCardboard/).
In addition to its sight-picture visuals, iRacing.com replicates the precise physical features of each track’s racing surface. Our laser-scanning technology produces a mathematically ‘bump map’ of the track’s camber, cracks, undulations and patches - recording every millimeter of the surface. A series of “point clouds” capture the three-dimensional profile of the track surface and adjacent curbing.

Combine this mathematically-precise surface mapping with iRacing.com’s hyper-accurate sight-pictures and proprietary mapping software and you have a powerful tool that allows even drivers at the highest levels of professional motorsport to use virtual seat time to hone their skills and improve their real-world performance.6

Cars. There are over 50 cars available in iRacing ranging from easy-to-drive (Pontiac Solstice) to very challenging (Lotus 49). The company focuses on making car behavior realistic. This means that the virtual cars have the same specifications (e.g., weight and horse power) as the real cars, and replications of those specifications is relevant; i.e., the cars behave in the same way that real-life cars behave.

Most arcade or online racing games, in addition to the handful of standalone software packages categorized as racing simulations, have progressed to the point where race cars look real enough; but the question then becomes, do they offer the experience of actual racing when the driver gets behind the wheel? Realistic driving dynamics begin with accurate data. That is why iRacing.com works closely with major auto manufacturers and race car constructors to gather exact masses and dimensions for real vehicle components, whether directly from CAD data, via three-dimensional laser scanning, or even by physically disassembling a particular vehicle in order to weigh and measure individual components.

A real race car is not just a collection of high-performance parts any more than an intense racing simulation experience is derived from a collection of data points. Both elements are highly active and incredibly dynamic. Buoyed by iRacing.com’s proprietary physics engine and tire modeling systems, these individual components combine and morph to create something that is no longer a mere virtual representation of a stock

car, a formula car or sports car, but instead, feels as real as the experience possibly can without burning actual race fuel.

A critical difference between past products and the hyper-accuracy achieved by iRacing.com is the level of the sophistication within its physics engine.

A physics engine is a complex system of high-speed mathematical functions that replicate and deliver dynamic forces using data-driven calculations, thereby leading to a series of instantaneous dynamic actions and reactions. Consequently, iRacing’s virtual world leverages the same physical dynamics and that drivers experience in the real world.

With more than twenty successful racing simulation releases to its credit, iRacing’s Dave Kaemmer and his team are among the world’s leading experts in the mapping of multi-body systems, and the direct calculation of forces and consequent dynamic effects on motion. Kaemmer’s relentless search for accuracy has led to the creation of iRacing’s proprietary tire model that replicates tire forces over a wide range of speeds and loads, adding an important dimension to the accuracy and realization of the iRacing experience.\(^7\)

Here is what some professional racers have to say about the design of tracks and cars in iRacing.\(^8\)

iRacing is the most modern racing simulation ever created. Every inch of every track is modeled perfectly. I’ve used iRacing to learn new courses. Dale Earnhardt, Jr.

I use iRacing a lot before I go to every race to try and get a feel for the racetrack. It’s so realistic. Joey Logano

Today, more than ever, it’s important to be competitive right out of the box. iRacing.com gives me that edge by being able to prepare before I arrive at the track. The cars and tracks are amazingly accurate! Brad Keselowski

iRacing is a great tool at the disposal of every race car driver. Whether it’s a road course, short track, or a superspeedway, nothing beats the iRacing’s accuracy. Ryan Preece

\(^7\)Source: [http://www.iracing.com/car-technology/](http://www.iracing.com/car-technology/); retrieved on August 5, 2016. On that website, there also is a video explaining in detail the design of virtual cars.

Whether racing just for fun or doing serious preparation, iRacing is always in my favorites folder. The detail in the cars and tracks is very impressive. Nick Tandy

iRacing has been a huge part of my preparation as a racing driver. The car and track model accuracy is unprecedented, and the intensity of the online racing is great training. Richie Stanaway

When it comes to choosing a car, the drivers have little flexibility once they pick the race. For about 90% of our data, only one specific car is available. In the remaining races, there are multiple cars available. However, these cars do not significantly differ in terms of their performance measure. Consequently, it is safe to say that in a given race everyone drives the same car.

There are two car-related variables which are of our interest: weight and horse power. In the racing world, a car’s **Weight to Horse Power Ratio** is one of the fundamental metrics in assessing how controllable a car is in a racing environment. The lower this ratio is, the faster the car accelerates and the higher its final speed is. In our paper, the Weight to Horsepower Ratio serves as a measure of product safety regulation.

In the context of our paper, the Weight to Horse Power Ratio is an output (in terms of product safety) of the product regulation. As mentioned in the Introduction, we do not have to worry about the problem of enforcement as the type of car racers use is determined by the computer. That is, it is impossible to ignore the regulation: if a race is for the car Holden Commodore VF V8, then all racers will drive that specific car.

**Drivers and racing.** People who use iRacing range from racing aficionados to professional racing drivers who use the simulator for training purposes.

Drivers are divided into groups based on their **License**. There are seven licenses.
Table 1: Licenses

<table>
<thead>
<tr>
<th>name</th>
<th>numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rookie</td>
<td>1</td>
</tr>
<tr>
<td>class D</td>
<td>2</td>
</tr>
<tr>
<td>class C</td>
<td>3</td>
</tr>
<tr>
<td>class B</td>
<td>4</td>
</tr>
<tr>
<td>class A</td>
<td>5</td>
</tr>
<tr>
<td>class Pro</td>
<td>6</td>
</tr>
<tr>
<td>class Pro World Class</td>
<td>7</td>
</tr>
</tbody>
</table>

New members start with the license Rookie and can be promoted depending on their performance. The drivers license captures the individual’s racing capabilities: this is our measure of consumer skills. From our data, we eliminated all races in which there was at least one Rookie driver. We do this because we are not sure how serious Rookie drivers are about iRacing. The Rookie racers can just test the simulator (as we did) to see if they enjoy the experience; hence, their behavior need not represent the racer’s behavior. This concern is not relevant for higher licenses for the reasons we explain below.

Races are divided into official and unofficial. Unofficial races have no impact on an iRacing member’s career and need not motivate the drivers to behave as if they would in a physical race. Hence, we focus only on official races which replicate the real-life racing behavior. From the schedule of races available online, drivers choose those in which they want to participate in. From January to December 2015, there were over 150,000 official races, or, more than 400 races per day in our cleaned data set. However, not all races are accessible to everyone. Drivers have a limited number of available races they can choose from depending on their license. Each race has a Minimum License requirement.

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9It can be argued that in a race, as in regular driving, individual skills need not be sufficient statistic to capture consumer skills. For example, an excellent racer can achieve an unsatisfactory result not because of his or her fault but because of the low skills of other drivers. Hence, one could think that the proper measure of consumer skills includes also the average license. We conducted the robustness analysis with the pair of two variables—individual license and average license—as the alternative measure of consumer skills. It turns out that all our qualitative results are unaffected by modifying the definition of consumer skills. The results are available from the authors upon request.
We think of the variable Minimum License as a tool of consumer regulation and the variable License as the outcome of regulation. Higher Minimum License is equivalent with more restrictive consumer regulation. Since we care more about the regulation outcome—that is, how product safety or consumer skills change—than a specific policy tool itself, we focus our attention on variable License.

Of course, as we mentioned in the Introduction, in the simulated environment there is no problem with incomplete enforcement of new regulation. If a race requires at least License B, then nobody with License C, D, or Rookie is able to participate in the race.

As opposed to the regular video games in which reckless driving and crashing on purpose are part of the fun, iRacing created strong incentives against such behaviors. In particular, during each race, drivers accumulate **Incident Points** for their involvement in on-track incidents.

- One point for wheels off the racing surface.
- Two points for loss of control.
- Two points for contact with other objects.
- Four points for heavy contact with another driver.

Too many incident points results in an immediate race disqualification. In each race, there is a maximum number of incident points that a driver can accumulate. Reaching that limit results in a race disqualification.\(^{10}\)

The consequences of accumulating incident points across races are more severe. In iRacing, as already mentioned, drivers are ranked into seven licenses. Being promoted to a higher license is a driver’s objective because such a promotion not only fulfills personal ambition and increases driver’s reputation but also allows access to more challenging cars and races with better-skilled drivers. In addition, in the Pro and Pro World class licenses, drivers have an opportunity to participate in NASCAR-sanctioned races with monetary prizes of up to $10,500 for the winner (see [http://www.iracing.com/nascar-iracing-com-series/](http://www.iracing.com/nascar-iracing-com-series/) and [http://www.nascar.com/en_us/iracing.html](http://www.nascar.com/en_us/iracing.html)). Thus, reaching these license levels has strong economic incentives. In

\(^{10}\)We keep only those races in which the maximum number of incident points allowed in a race for a driver before being disqualified equals seventeen. About 94% of the official races allow for exactly this maximum.
order to be promoted to a higher license, a racer has to not only win races but also maintain a
certain level of safe racing. It is possible that someone wins many races but because of reckless
behavior does not receive a promotion. In fact, too many cumulative incident points can result in
a demotion to a lower license.

Incident points generate the main incentive for iRacing member to behave as the racers do in
physical races. In order to be able to use iRacing, “the member will require a controller to enjoy
the full range of experiences afforded by iRacing’s racing simulator. A host of steering wheel/pedal
combos, gamepads, joysticks, mouse-based control systems, and any version of the Microsoft Win-
dows operating system, supporting touch screen driving are compatible with iRacing.com” (source:
http://www.iracing.com/membership/system-requirements/). It is not possible to drive in
iRacing using a keyboard. This significantly differentiates iRacing from typical video games. Ac-
cording to the company that owns and manages iRacing, more than 95% of racers use a wheel and
pedal set. The authors of this paper tried driving in iRacing using a mouse but failed miserably
(which is obviously due to lack of not only proper equipment but also skills). Since members of
iRacing are required to purchase additional equipment, we believe that this works as a pre-selection
mechanism that screens out those whose main objective is to crash on purpose. Finally, and again
as opposed to video games, members of iRacing must race using their real names. The lack of
anonymity also helps to curb irresponsible behavior.

Incident points are equivalent of accident rate in regular driving; more incident points implies less
safety. Hence, we consider incident points as a measure of safety. For each racer, we know how
many points he or she accumulated in a given race. Since races differ in the length of the track
and racers do not always complete the whole race, we define **Incidents Point per Mile** as the
number of incident points per mile driven. This is our dependent variable and our safety measure.

Each race is defined by an already mentioned minimum license requirement as well as type of track
and type of car used in the race. There are four track- and race-related variables that serve as
our controls. First, **Traffic Density** is the average number of drivers per lap in a race. During a
race, some drivers might drop out of the race or be disqualified. Imagine that a race consists of 50
laps, $LR = 50$, with 20 drivers starting the race, $N = 20$. Then, assume that driver $i$ completed
40 of the 50 laps in the race, $LC_i = 40$. We define traffic density as the sum of all completed laps
by all drivers in a race divided the number of laps in that race $\sum_{i=1}^{N} \frac{LC_i}{LR}$. This measure takes into
account the fact that two races that started with the same number of drivers and have the same number of total laps do not present the same traffic density if the quantity of existing drivers per lap during the race differs. Second, **Laps in the Race** is the number of laps in a given race. Third, **Oval** is a binary variable that is one if the track is oval and zero otherwise. Fourth, **Night** is also a binary variable which is one if the race conditions are night conditions and zero otherwise.

We summarize our variables in the table below.

<table>
<thead>
<tr>
<th>variable</th>
<th>purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incident Points per Mile</td>
<td>safety measure</td>
</tr>
<tr>
<td>License</td>
<td>consumer skills</td>
</tr>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>product safety</td>
</tr>
<tr>
<td>Traffic Density</td>
<td>control</td>
</tr>
<tr>
<td>Laps in the Race</td>
<td>control</td>
</tr>
<tr>
<td>Oval</td>
<td>control</td>
</tr>
<tr>
<td>Night</td>
<td>control</td>
</tr>
</tbody>
</table>

Table 2: Variables

The cleaned data used in our studies consists of 2,274,192 observations and includes 41,010 different individuals from 106 countries who, between January and December 2015, participated in 150,598 races. We focus on how product safety measured by the Weight to Horse Power Ratio and consumer skills measured by License affect safety in the racing environment measured by Incidents per Mile.
<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td>Incidents per Mile</td>
<td>0.21</td>
<td>0.48</td>
<td>0.00</td>
<td>48.00</td>
</tr>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>7.78</td>
<td>4.11</td>
<td>1.77</td>
<td>17.89</td>
</tr>
<tr>
<td>License</td>
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<td>1.12</td>
<td>2</td>
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<tr>
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<tr>
<td>Oval</td>
<td>0.49</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Night</td>
<td>0.20</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3: Summary Statistics

Below, we graphically depict the distribution of average Incidents per Mile with respect to Weight to Horse Power Ratio (product safety) and License (consumer skills).

Figure 1: Average Incident Points per Mile for each value of Weight to Horse Power Ratio.
3 Theory and Empirical Results

We begin our analysis with a theory of safety regulation that is standard in the literature. We call the standard theory a one-dimensional theory since it looks at safety regulation from only one dimension, product safety or consumer skills, but not both at the same time. This theory starts with Peltzman (1975) who, like us, also supports his arguments with a mathematical model. From the modelling perspective, the closest to our approach is Viscusi (2007); however, our mathematical model is more general and we provide several new insights.

Next, we introduce a new phenomenon, the product-consumer substitution. We expand the standard theory by adding this phenomenon and obtaining a two-dimensional theory. We support our novel theory with an empirical analysis and stress the novel policy implications.

3.1 One-dimensional theory

Consider an activity that yields either bad outcome (utility zero) or good outcome (utility one). Let \( \alpha \) denote the product safety; higher \( \alpha \) means higher safety. Let \( \beta \) denote the consumer
skills of the representative consumer; higher $\beta$ means higher skills. We think of $\alpha$ as capturing the safety of representative product; i.e., product chosen by the representative consumer.

Product regulation means that the regulator chooses higher $\alpha$ (product becomes safer or easier to use). Consumer regulation is about increasing the value of $\beta$ (consumers become more capable and experienced).

We focus on what regulation achieves rather than specific regulatory tools. That is, in the case of product (consumer) regulation, we are not interested in how to increase product safety (consumer skills); rather, we are interested in the consequences of establishing a specific value of product safety (consumer skills) that the regulator targets.

We assume that whatever regulation plans to achieve, in terms of changing the product safety or consumer skills, is going to be implemented. That is, there is no issue of incomplete or delayed enforcement. Disregarding this issue is in accordance with the main research questions we ask in this paper as well as with our data in which we have complete and immediate enforcement.

Upon observing the level of regulation, an agent (he) decides whether or not to consume the regulated product. An agent who opts for consumption becomes a consumer and chooses effort $a$ where higher $a$ means more effort. As it is standard in economics, we separate effort and skills. A low-skilled consumer can compensate his low $\beta$ by exerting more effort, and a high-skilled consumer can shirk his effort because of his high $\beta$. The cost of effort is $c(a)$ and the agent is an expected-utility maximizer. If he decides not to consume, then he gains the reservation value that is strictly between zero and one.

If an agent decides to use the product, then he receives utility zero with probability $\lambda$ and utility one with probability $1 - \lambda$. **Probability of bad outcome** $\lambda$ is our safety measure. There are three factors which affect the probability of bad outcome: product safety $\alpha$, consumer skills $\beta$, and consumer effort $a$.

Our assumptions imposed on $c(a)$ and $\lambda(\alpha, \beta, a)$ are standard and straightforward. In particular, $c(a)$ is twice-continuously differentiable, strictly increasing ($c' > 0$), and convex ($c'' \geq 0$). We also assume that product safety, consumer skills, and effort are beneficial. That is, each of these three variables decreases the probability of bad outcome; $\lambda_a = \frac{\partial \lambda}{\partial a} < 0$, $\lambda_\alpha = \frac{\partial \lambda}{\partial \alpha} < 0$, and $\lambda_\beta = \frac{\partial \lambda}{\partial \beta} < 0$. Finally, we assume that $\lambda$ is a strictly convex function of $a$; i.e., $\lambda_a = \frac{\partial^2 \lambda}{\partial a^2} > 0$. This last assumption
is natural, especially if we analyze the probability of good outcome. In the framework of safety regulation, \(1 - \lambda\) is the revenue function from consumer effort \(a\). As it is typical in economics, assuming that the revenue function is increasing and concave (in effort) implies that \(\lambda\) must be decreasing and convex in \(a\).

The consumer chooses \(a\) in order to maximize his expected utility, \(U(\alpha, \beta, a) = 1 - \lambda(\alpha, \beta, a) - c(a)\). We focus on the unique interior solution of the optimization problem denoted by \(a^*\).\(^{11}\)

Let \(\lambda^*\) denote the probability of bad outcome computed at optimal effort, \(\lambda^* := \lambda(\alpha, \beta, a^*)\). From both empirical and theoretical perspectives, we are interested in how \(a^*\) and \(\lambda^*\) react to changes in regulation; these are the two fundamental problems addressed in the literature.

1. How does safety regulation change effort \(a^*\)?

2. How does safety regulation change the probability of bad outcome \(\lambda^*\)?

Since the analysis of product regulation is the same as the analysis of consumer regulation, we discuss in detail only the former. Hence, suppose that the regulatory authorities increase product safety. In the standard theory, changes in product safety have no impact on consumer skills. \(\text{i.e.},\) when \(\alpha\) increases, then \(\beta\) stays the same. Later, we will relax this assumption.

The optimal consumer effort \(a^*\) is a function of product safety and consumer skills; \(\text{i.e.},\) \(a^* := a^*(\alpha, \beta)\). We determine how a change in product safety \(\alpha\) affects the optimal effort.

\[
\frac{da^*}{d\alpha} = -\frac{\lambda^*}{\lambda^*_{\alpha\alpha} + c''(a^*)} \quad (1)
\]

With regulation, there is going to be the **adjustment behavior**: consumer changes his effort because of regulation. If effort increases, then we have the positive adjustment behavior and if effort decreases, then we talk about the negative adjustment behavior.\(^{12}\)

While controversial for some authors, we believe that the negative adjustment behavior is not surprising. In fact, it is a rather expected behavior. After all, product safety or consumer skills

\(^{11}\)We can either assume that the interior solution exists or impose the following standard assumption which guarantee that the interior solution exists: \(\lim_{a\to0} \frac{\partial U}{\partial a} > 0\) and \(\lim_{a\to\infty} \frac{\partial U}{\partial a} < 0\).

\(^{12}\)Without additional assumption, it is not possible to determine whether effort increases or decreases. Observe, however, that \(\lambda^*_{\alpha\alpha} + c''(a^*) > 0\). Consequently, the sign of \(\frac{da^*}{d\alpha}\) is the opposite of the sign of \(\lambda^*_{\alpha\alpha}\). Note that \(\lambda^*_{\alpha}\) is the marginal gain from effort. Hence, whether we observe the positive or negative adjustment behavior depends on how product safety affects that marginal gain.
substitute consumer effort. Consider the following thought experiment. We take two different cars and analyze road safety. The first car is a modern typical vehicle that satisfies all regulatory standards. The second car is a fully autonomous car from the future. In the language of our model, $\alpha$ is higher for the second car. Driving the future car is not really driving as we know today. The driver’s role ends at providing directions to the vehicle. Then, he can relax, eat, read, or even sleep. His “driving” effort does not differ much from the effort the passengers of public transportation exert today. This zero effort is optimal because there is no reason for him to pay attention since his effort has no impact on whether or not there is a bad outcome. Hence, it is rather expected that higher $\alpha$ reduces effort.

Next, we analyze the impact of changing product safety on the probability of bad outcome computed at optimal effort.

$$\frac{d\lambda^*}{d\alpha} = \lambda^*_\alpha + \lambda^*_a \frac{da^*}{d\alpha}$$

We say that safety regulation results in the regular effect if we observe a decrease in the probability of bad outcome. Otherwise, regulation yields the Peltzman effect.

In equation (2), we observe two elements. First, $\lambda^*_\alpha$ is the gain from regulation. This is an unambiguous decrease in the probability of bad outcome. It is a direct impact of regulation that assumes no change in behavior. We can measure the size of the gain from regulation using lab tests or simulations.

Second, there also is an indirect impact of regulation $\lambda^*_a \frac{da^*}{d\alpha}$ that affects the probability of bad outcome via the adjustment behavior. Hence, this second effect is about moral hazard. For the reason that will be clear shortly, we call $\lambda^*_a \frac{da^*}{d\alpha}$ the primary moral hazard effect or, in short, the primary moral hazard.

Since $\lambda^*_a$ is negative, whenever effort increases (decreases), the probability of bad outcome decreases (increases). Consequently, the primary moral hazard can have an undesired impact on the probability of bad outcome. In fact, if effort is an important force in the reduction of the probability of bad outcome or the negative adjustment behavior is large enough, then we observe the Peltzman effect. We call this special case of negative adjustment behavior the standard offsetting
behavior. ¹³

3.2 Regular effect or Peltzman effect: empirical analysis

In our data, we analyze whether product regulation and consumer regulation result in the Peltzman or regular effect. First, we focus on product regulation. As mentioned in Section 2, our dependent variable is the number of Incident Points per Mile a driver accumulates in a race. Product safety, which is the outcome of regulation policy, is captured by the variable Weight to Horse Power Ratio. Our control variables are License (consumer skills) as well as Traffic Density, Laps in the Race, Oval, and Night. If the coefficient of Weight to Horse Power Ratio is negative (positive) and significant, we deduce that product regulation results with the regular effect (Peltzman effect).

Second, we analyze consumer regulation. Incident Points per Mile is again our dependent variable. Now, it is License that is the result of regulation and is the variable we look at. If the coefficient of License is negative (positive) and significant, then we observe the regular effect (Peltzman effect). We control for product safety (Weight to Horse Power Ratio) and Traffic Density, Laps in the Race, Oval, and Night.

Since the coefficients of Weight to Horse Power Ratio and License are negative and significant, we deduce that both product regulation and consumer regulation yield the regular effect.

¹³In order to have the Peltzman effect, we need the following inequality to hold: $\lambda_a^*\lambda_{aa}^* + \lambda_a^*\epsilon'' > \lambda_a^*\lambda_{aa}^*$. This inequality captures mathematically the concept of the standard offsetting behavior.
### Table 4: Testing for the Peltzman effect

<table>
<thead>
<tr>
<th>Model 1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>$-0.0002^{***}$</td>
</tr>
<tr>
<td>License</td>
<td>$-0.0671^{***}$</td>
</tr>
<tr>
<td>Traffic Density</td>
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</tr>
<tr>
<td>Laps in the Race</td>
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</tr>
<tr>
<td>Oval</td>
<td>$-0.0534^{***}$</td>
</tr>
<tr>
<td>Night</td>
<td>$0.0083^{***}$</td>
</tr>
<tr>
<td>N</td>
<td>2,274,192</td>
</tr>
<tr>
<td>Adj $R^2$</td>
<td>0.0378</td>
</tr>
</tbody>
</table>

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

#### 3.3 Product-consumer substitution

In Model 1 (Table 4) we are able to control for all relevant variables; when we consider product regulation we control for consumer skill (License) while when we analyze consumer regulation we control for product safety (Weight to Horse Power Ratio). However, in the literature, it is rather common that we are unable to control for either product safety or consumer skills. Thus, it is only natural to ask whether the omitted variables bias is a significant problem. We answer this question in the next exercise discovering a new and important phenomenon that is a fundamental element of our novel theory.

We extend Table 4 with two additional models. In Model 2, we analyze product regulation but do not control for consumer skills; i.e., License is omitted. In Model 3, we evaluate consumer regulation without controlling for product safety; i.e., Weight to Horse Power Ratio is omitted.
In Model 1, we detect the Peltzman effect because the coefficient of Weight to Horse Power Ratio is positive and significant which means that when cars become safer/less difficult to drive, then we expect drivers to accumulate more incident points per mile. Recall that in Model 1, where we add License, we observe the regular effect. Hence, the Peltzman effect observed in Model 2 disappears as long as we control for consumer skills. The fact that the magnitude of the bias changes not only quantitative but also qualitative results (from the Peltzman effect to the regular effect) is remarkable and serves as a warning that the omitted variables bias is a significant problem for the empirical literature on safety regulation.

The omitted variables bias is less important when it comes to consumer regulation. In Model 3, we omit product safety and find that consumer regulation results in the regular effect; that is, the coefficient of License is negative and significant. In Model 1, where we add Weight to Horse Power Ration, we also detect the regular effect.

When comparing Model 2 to Model 1, we note that the coefficient of Weight to Horse Power Ratio increases. Comparing Model 3 to Model 1 shows that the coefficient of License increases as well. In both cases, we observe an upward bias. This bias is due to the negative correlation between Weight to Horse Power Ratio and License which is $-0.43$ ($p$-value $< 0.001$) and the fact

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>$-0.0002^{***}$</td>
<td>$0.0068^{***}$</td>
<td></td>
</tr>
<tr>
<td>License</td>
<td>$-0.0671^{***}$</td>
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</tr>
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<td>Traffic Density</td>
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<td>Laps in the Race</td>
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</tr>
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<td>$-0.0529^{***}$</td>
</tr>
<tr>
<td>Night</td>
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<td>$0.0216^{***}$</td>
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<td>N</td>
<td>2,274,192</td>
<td>2,274,192</td>
<td>2,274,192</td>
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<tr>
<td>Adj $R^2$</td>
<td>0.0378</td>
<td>0.0189</td>
<td>0.0378</td>
</tr>
</tbody>
</table>

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 5: The importance of omitted variables bias
that the coefficients of License and Weight to Horse Power Ratio are both negative. This negative correlation is the novel and relevant phenomenon we mentioned at the beginning of this section.\footnote{Note that the coefficients of License in Model 1 and Model 3 are not too different. This is because the coefficient of Weight to Horse Power Ratio is quite small compared to that of License, thus it is expected the impact of the omitted variable bias to be quite small in the consumer regulation’s regression.}

The negative correlation between product safety and consumer skills, which we call the \textbf{product-consumer substitution}, is an example of adverse selection. Prior to regulation, there are agents who opt for the reservation value; their consumer skills are too low and they prefer not to consume the product at all. When the product becomes easier or safer to use, some of these non-consumers—those with consumer skills high enough—now become consumers. This implies that the structure of consumers changes; in particular, the skills of representative consumer decrease. This phenomenon is a self-selection mechanism: when it gets more difficult (easier), then those with lower skills exit (enter). Since changes in product safety affect consumer skills, it is also true that changes in consumer skills have impact on product safety. That is, implementing consumer regulation (increasing skills of representative consumer) results in lower product safety.

The problem of adverse selection is relevant not only for racing but also other regulated activities. Consider the case of regulation in the financial markets. For example, van Rooij et al. (2011) find that people with lower levels of financial literacy are less likely to participate in consumption of complex financial instruments like stock market. According to Lusardi and Mitchell (2014, p. 6), financial literacy captures “peoples’ ability to process economic information and make informed decisions about financial planning, wealth accumulation, debt, and pensions.” In the language of our theory, financial literacy is consumer skills. Complexity of financial instruments measures how difficult it is for an investor to understand and evaluate them (e.g., bonds are simpler than options); that is, complexity is a dimension of product safety. Hence, the negative correlation between financial literacy and participation in financial markets is an example of the product-consumer substitution. Additionally, Moore (2003), Campbell (2006), and Lusardi and Tufano (2015) show that people with less financial literacy are more prone to commit mistakes in their investment decisions. Hence, the product-consumer substitution could lead to the Peltzman effect if regulators lower barriers to entry financial markets without increasing financial literacy.

From the mathematical point of view, the product-consumer substitution means that $\beta$ (consumer skills) is a function of $\alpha$ (product safety) such that the derivative $\frac{d\beta}{d\alpha}$ is negative. We assume that
\( \beta(\alpha) \) is a \( C^1 \) function (continuous, differentiable, and with continuous derivative). Since \( \beta(\alpha) \) is injective, \( \alpha \) can be expressed as a \( C^1 \) function of \( \beta \) with \( \frac{d\alpha}{d\beta} < 0 \).

In the one-dimensional theory, we assume the zero product-consumer substitution. Next, we add adverse selection to the theory of safety regulation.

### 3.4 Two-dimensional theory

While the product-consumer substitution is an interesting phenomenon, the important question is whether this phenomenon really matters in terms of our understanding of safety regulation and policy implications. The answer is positive. In our analysis, we still focus on product regulation, but now we enrich our theory and incorporate the fact that consumer skills decrease when the product safety increases, \( \frac{d\beta}{d\alpha} < 0 \). Our results regarding policy implications, especially those differentiating our approach from the standard theory, are highlighted in text.

The optimization program of our representative agent remains the same; however, instead of fixed \( \beta \), we have a function \( \beta(\alpha) \). This implies that the probability of bad outcome is \( \lambda(\alpha, \beta(\alpha), a) \). Whenever it does not cause a confusion, we simplify the notation and write \( \beta \) instead of \( \beta(\alpha) \) but we keep in mind that this \( \beta \) is a function of \( \alpha \).

As in the one-dimensional theory, we start with the analysis of how an increase in product safety affects the optimal level of effort, \( a^*(\alpha, \beta(\alpha)) \).

\[
\frac{da^*}{d\alpha} = \frac{\partial a^*}{\partial \alpha} + \frac{\partial a^*}{\partial \beta} \frac{d\beta}{d\alpha} \tag{3}
\]

The adjustment behavior consists of two elements. First, there is the **product-driven adjustment behavior** \( \frac{da^*}{d\alpha} \) which we already know from the one-dimensional theory (see equation (1)). Upon observing an increase in product safety, the consumer changes his effort. This is a direct impact of increasing product safety on effort.

The second element of adjustment behavior is the novelty due to the product-consumer substitution. Derivative \( \frac{\partial a^*}{\partial \beta} \) is the **consumer-driven adjustment behavior** and captures the change in effort due to the modification in consumer skills. This is an indirect impact of increasing product safety on effort. The term \( \frac{\partial a^*}{\partial \beta} \frac{d\beta}{d\alpha} \) measures the impact of adverse selection on behavior.
In order to explain what the consumer-driven adjustment behavior is in the context of product regulation, consider the case of road safety. Suppose that the regulator makes cars safer. The direct effect is an increase in $\alpha$ while the indirect effect is a decrease in $\beta$. However, the story does not end here. Drivers know that the pool of consumers has changed because less qualified people have became drivers. Consequently, it is necessary to adapt to the new environment. For instance, as a precautionary measure, drivers may pay more attention as it is not wise to rely on other drivers to maintain a desired safety level. This change in effort, driven by a decrease in driving skills of the representative driver, is precisely the consumer-driven adjustment behavior.

Equation (3) indicates that the adjustment behavior is more complex than what the standard theory posits in equation (1). A priori, neither the sign nor the size of the consumer-driven adjustment behavior is clear.\textsuperscript{15} Hence, we obtain the following result.

**Result 1.** One-dimensional theory incorrectly predicts the change in effort due to regulation. In fact, it is possible that effort increases (decreases) while the one-dimensional theory predicts a decrease (increase) in effort.

To elaborate on Result 1, consider a laboratory test measuring how car safety affects effort. A driver is asked to test-drive cars with different safety/difficulty levels while the experimenter measures a variety of proxies for effort like heart rate, pulse, sweat, etc. Suppose that the observed effort decreases when cars become safer/easier to drive. In the framework of the one-dimensional theory, we conclude that increasing product safety results with the negative adjustment behavior (equation (1)). If effort is a variable that is being used to determine whether or not to introduce regulation, then the regulator might decide against the regulation to avoid the Peltzman effect.

However, in the language of our theory, the experiment determines only that the product-driven adjustment behavior $\frac{\partial a^*}{\partial x}$ is negative. There still is the consumer-driven adjustment behavior $\frac{\partial a^*}{\partial \beta}$ which has not been measured in the experiment. If consumer-driven adjustment behavior is also negative, then either the decrease in effort is smaller than measured in the experiment or, more importantly, the total change in effort is positive. Consequently, with this additional information, the regulator might opt for introducing the regulation.

When it comes to changes in effort, there is an important relation between product regulation and

\begin{footnote}{\textsuperscript{15}In Appendix A, we analyze from the theoretical perspective the relation between product-driven and consumer-driven adjustment behaviors.}

26
consumer regulation. Recall that the impact of an increase in product safety on effort is captured in equation (3) and note that an increase in consumer skills affects effort in the following way:

\[
\frac{da^*}{d\beta} = \frac{\partial a^*}{\partial \beta} + \frac{\partial a^*}{\partial \alpha} \frac{d\alpha}{d\beta}.
\]

Suppose that \( \frac{da^*}{d\alpha} > 0 \); i.e., \( \frac{\partial a^*}{\partial \alpha} + \frac{\partial a^*}{\partial \beta} \frac{d\beta}{d\alpha} > 0 \). If we multiply both sides of this inequality by \( \frac{d\alpha}{d\beta} \), then we observe that \( \frac{\partial a^*}{\partial \beta} + \frac{\partial a^*}{\partial \alpha} \frac{d\alpha}{d\beta} < 0 \); i.e., \( \frac{da^*}{d\beta} < 0 \). In other words, effort increases due to product regulation if and only if effort decreases due to consumer regulation. This has important policy implication: if the regulator aims at not only lowering the probability of bad outcome but also increasing effort, then the choice between product regulation and consumer regulation is an important task.

**Result 2.** Product regulation results in an increase in effort if and only if consumer regulation yields a decrease in effort.

Next, we turn to the analysis of how product regulation affects the safety measure in the presence of the product-consumer substitution.

\[
\frac{d\lambda^*}{d\alpha} = \lambda^*_\alpha + \lambda^*_a \frac{\partial a^*}{\partial \alpha} + \lambda^*_\beta \frac{d\beta}{d\alpha} + \lambda^*_a \frac{\partial a^*}{\partial \beta} \frac{d\beta}{d\alpha}.
\]

When the product safety increases, then there is an unambiguous improvement in safety due to the gain from regulation. This effect is either enforced or weaken by the primary moral hazard; i.e., consumer changing his effort due to the product being safer (product-driven adjustment behavior). The first two terms of equation (4) replicate the one-dimensional theory (see equation (2)). However, there are two additional effects due to adverse selection.

First, there is a certain increase in the probability of bad outcome \( \frac{d\beta}{d\alpha} \lambda^*_\beta \). This is a direct impact of adverse selection: consumer skills decrease which makes the environment more dangerous. We call this the **loss from regulation**. How big that effect is depends on the size of the product-consumer substitution and the importance of consumers skills in reduction of the probability of bad outcome.

Second, there is what we call the **secondary moral hazard**. Upon observing the change in consumer skills, the behavior changes; i.e., we experience the consumer-driven adjustment behavior. We call it “secondary” moral hazard since this is the change in effort that is not directly due to
an increase in product safety (which is the primary moral hazard) but rather due to a change in consumer skills caused by the increase in product safety. This secondary moral hazard is a consequence of adverse selection.

Since the sign of the consumer-driven adjustment behavior is unknown, it is impossible to determine whether the secondary moral hazard is positive or negative. However, note that $\frac{d\delta^*}{d\alpha} \lambda_a$ is positive. Hence, if effort increases (decreases) due to lower skills of the representative consumer, then the secondary moral hazard is negative (positive); i.e., the probability of bad outcome decreases (increases).

Without additional assumptions or tests, it is not possible to deduce whether the total impact of adverse selection—as measured by the sum of loss from regulation and secondary moral hazard—has a positive or negative impact on the safety measure. Hence, we obtain the following result which complements Result 1.

**Result 3.** One-dimensional theory incorrectly predicts the change in the probability of bad outcome due to regulation. In fact, it is possible that we observe the Peltzman effect (regular effect) while the one-dimensional theory predicts the regular effect (Peltzman effect).

Result 3 provides a rationalization of the discrepancy between what regulators expect and what they actually achieve. Cohen and Einav (2003) estimate that if 90% of drivers were to wear a seat belt, then about 1,500–3,000 lives would be saved on annual basis. However, they also note that “although this estimate of the effect of increased seat belt usage on saved lives is substantial, it is considerably smaller than the estimate used by the federal government, which is 5,536 saved lives annually.” Our result indicates that even if the regulator takes into account the standard concerns expressed in the literature (i.e., primary moral hazard), then it is still likely that there is a gap between pre-regulation expectation and post-regulation realization due to disregarding the presence of adverse selection.

Our analysis leads to the following observation: change in effort due to higher product safety need not be the only, or even the best, explanation of the observed effect (Peltzman or regular). This observation is important from the policy perspective.

Suppose that we observe the regular effect. The standard theory argues that this is because higher product safety did not have a too negative impact on effort. However, as equation (4) indicates, the
following is also possible. The primary moral hazard is, actually positive and large enough so the sum of the gain from regulation and primary moral hazard is positive. At the same time, the loss from regulation is also positive which enforces the Peltzman effect. Since we observe the regular effect, it must be the secondary moral hazard that is driving the decrease in the probability of bad outcome. This implies that the standard theory would incorrectly explain the observed outcome from regulation which can generate wrong policies in the future.

Next, suppose that we observe the Peltzman effect. The standard theory suggests that the only remedy is to correct the negative product-driven adjustment behavior; i.e., to restrain the primary moral hazard. However, it is possible that the primary moral hazard is actually negative, while it is the secondary moral hazard that is positive. In this case, the Peltzman effect is driven only by adverse selection. In fact, it is also possible that the total effort increases—i.e., \( \frac{\partial a^*}{\partial \alpha} + \frac{\partial a^*}{\partial \beta} \frac{d\beta}{d\alpha} > 0 \)—but we still experience the Peltzman effect. In each case, the standard theory suggests incorrect policies. Rather than designing and implementing tools which curb the (non-existent) negative product-driven adjustment behavior, it is necessary to limit the decrease in consumer skills due to adverse selection.

**Result 4.** *In the case of product regulation (consumer regulation), change in effort due to higher product safety (consumer skills) need not be the only or even the main driving force behind the observed result. The standard theory might generate wrong policies or incorrectly explain the observed result of implemented regulation.*

In order to understand what drives the change in the probability of bad outcome, one could measure the size and sign of each element in equation (4) using laboratory tests and simulations. However, even if we are unable to estimate all the terms in equation (4) because of, for instance, the inability to measure effort, it is still possible to empirically determine the importance of adverse selection as a factor affecting the probability of bad outcome. Such an exercise, which we discuss below, allows the regulator to design an appropriate policy.

### 3.5 Standard offsetting behavior and two-dimensional policy

In order to determine whether adverse selection is an important empirical concern, we need to test whether product regulation results with offsetting behavior when the consumer skills remain
unchanged. When the consumer skills are fixed, then the change in the safety measure becomes $\lambda^*_\alpha + \lambda^*_a \partial a / \partial \alpha$; that is, the change as predicted by the standard theory. When $\lambda^*_\alpha + \lambda^*_a \partial a / \partial \alpha > 0$, then we say that we observe the standard offsetting behavior; this is the offsetting behavior driven only by the increase in product safety.\textsuperscript{16}

**Result 5.** It is necessary to test for the standard offsetting behavior. This test determines whether adverse selection is a relevant problem which, ultimately, helps finding the appropriate policy.

In order to test for the standard offsetting behavior, data has to include a measure of consumer skills. Our data is rich enough allowing us to conduct such a test. We partition the data into groups with identical License value. Because of the number of observations, we focus on four licenses: class D, class C, class B, and class A.\textsuperscript{17} Hence, we have four subsets of data and four regressions: given each subset of data, we regress our dependent variable, Incident Points per Mile, on Weight to Horse Power Ratio and the four controls we previously used (Traffic Density, Laps in the Race, Oval, and Night).

<table>
<thead>
<tr>
<th></th>
<th>class D</th>
<th>class C</th>
<th>class B</th>
<th>class A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight to Horse Power Ratio</td>
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<td>$-0.0004^{**}$</td>
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<tr>
<td>Laps in the Race</td>
<td>$0.0052^{***}$</td>
<td>$0.0029^{***}$</td>
<td>$0.0014^{***}$</td>
<td>$0.0002^{***}$</td>
</tr>
<tr>
<td>Oval</td>
<td>$-0.0497^{***}$</td>
<td>$0.0208^{***}$</td>
<td>$0.0234^{***}$</td>
<td>$0.0238^{***}$</td>
</tr>
<tr>
<td>Night</td>
<td>$-0.0980^{***}$</td>
<td>$-0.0922^{***}$</td>
<td>$-0.0718^{***}$</td>
<td>$-0.0345^{***}$</td>
</tr>
<tr>
<td>N</td>
<td>399,224</td>
<td>443,390</td>
<td>588,855</td>
<td>837,995</td>
</tr>
<tr>
<td>Adj $R^2$</td>
<td>0.015</td>
<td>0.012</td>
<td>0.009</td>
<td>0.005</td>
</tr>
</tbody>
</table>

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 6: Testing for the standard offsetting behavior in product regulation

As Table 6 indicates, for each fixed License (consumer skills), the coefficient of Weight to Horse Power Ratio is negative; that is, we do not detect the standard offsetting behavior.\textsuperscript{18}

\textsuperscript{16}In Appendix B, we discuss the analysis of standard offsetting behavior in the context of consumer regulation.

\textsuperscript{17}Out of 2,274,192 observations, only 4,728 (i.e., 0.2% of the whole data) are with license Pro or Pro World Class. Consequently, these two level of license have negligible impact on our results.

\textsuperscript{18}It is interesting to note that the coefficient on the control variables related to the difficulty of the environment
However, given the richness of our data, we can conduct additional empirical exercises. In particular, we are interested in empirical proofs of the claims we mentioned above: regular effect with a presence of standard offsetting behavior, and Peltzman effect driven by adverse selection. We are able to conduct these exercises because our data consists of several safety regimes.

In our first example, we truncate our data and consider only the observations with Weight to Horse Power Ratio greater than 9.5. This sub-sample consists of around half a million observations. First, we test for the presence of the Peltzman effect in our sub-sample. As in our regression based on the whole data (Table 4), we do not observe the Peltzman effect since the coefficient of Weight to Horse Power Ratio is negative.

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>-0.0013***</td>
</tr>
<tr>
<td>License</td>
<td>-0.0790***</td>
</tr>
<tr>
<td>Traffic Density</td>
<td>-0.0094***</td>
</tr>
<tr>
<td>Laps in the Race</td>
<td>0.0007***</td>
</tr>
<tr>
<td>Oval</td>
<td>0.0842***</td>
</tr>
<tr>
<td>Night</td>
<td>0.0256***</td>
</tr>
<tr>
<td>N</td>
<td>493,454</td>
</tr>
<tr>
<td>Adj $R^2$</td>
<td>0.0327</td>
</tr>
</tbody>
</table>

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 7: Testing for the Peltzman effect (sub-sample)

Next, we test for the standard offsetting behavior; i.e., we replicate Table 6.\(^{19}\)

\(^{19}\)Out of 493,454 observations, only 171 (i.e., 0.3% of the whole data) are with license Pro or Pro World Class. Consequently, these two level of license have negligible impact on our results.
In our sub-sample, although we observe the regular effect, we are unable to reject the hypothesis of the standard offsetting behavior for licenses B and A: in both cases, the coefficient of Weight to Horse Power Ratio is positive. It would seem that when the car difficulty is low enough (i.e., product safety is high), then drivers with high racing skills behave more recklessly when the car difficulty decreases (i.e., when product regulation is implemented). These consumers feel overly confident—after all, the product is safe and their skills are high—which makes them exert less effort while racing.

Our example sheds a new light on our understanding of safety regulation: the regular effect does not preclude the primary moral hazard. This empirically confirms the importance of testing for the standard offsetting behavior (Result 5).

In the next empirical exercise, we look for a sub-sample in which we detect the Peltzman effect. The objective of this example is to conduct a detailed analysis of the origins of the Peltzman effect. We truncate our data and consider only the observations with Weight to Horse Power Ratio smaller than 7, which includes more than half of the data. First, we detect the presence of Peltzman effect in our sub-sample (coefficient of the Weight to Horse Power Ratio is positive).
Weight to Horse Power Ratio 0.0028***
License −0.0629***
Traffic Density −0.0055***
Laps in the Race 0.0010***
Oval −0.0777***
Night 0.0146***

N 1,362,597
Adj $R^2$ 0.0351

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 9: Testing for the Peltzman effect (sub-sample)

Next, we test for the standard offsetting behavior.\textsuperscript{20}

\begin{tabular}{lcccc}
 & class D & class C & class B & class A \\
Weight to Horse Power Ratio & 0.0869*** & −0.0028*** & −0.0028*** & −0.0010** \\
Traffic Density & −0.0106*** & −0.0096*** & −0.0064*** & −0.0037*** \\
Laps in the Race & 0.0104*** & 0.0027*** & 0.0011*** & 0.0001** \\
Oval & −0.2475*** & −0.1351*** & −0.0907*** & −0.0405*** \\
Night & −0.0207*** & 0.0109*** & 0.0204*** & 0.0206*** \\
N & 62,779 & 220,966 & 401,031 & 673,678 \\
Adj $R^2$ & 0.024 & 0.021 & 0.014 & 0.006 \\
\end{tabular}

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 10: Testing for the standard offsetting behavior in product regulation (sub-sample)

In our sub-sample, we detect the standard offsetting behavior only for the lowest license value;\textsuperscript{20} Out of 1,362,597 observations, only 4,143 (i.e., 0.3% of the whole data) are with license Pro or Pro World Class. Consequently, these two level of license have negligible impact on our results.
namely, License D. However, in our sub-sample, there are only 62,779 observations with this specific value of License. In other words, we detect the standard offsetting behavior in only 4.6% of our data. For 95% of observations, we do not detect the standard offsetting behavior.

In our example, the standard explanation of the Peltzman effect is not necessarily a correct explanation of the Peltzman effect reported in Table 9. Rather, the empirical results indicate that this specific Peltzman effect is driven by adverse selection. That is, there either is a large loss from regulation—\(\frac{d\beta}{d\alpha} \lambda^*\) in equation (4)—or we experience a large secondary moral hazard—\(\frac{d\beta}{d\alpha} \lambda^* \frac{d\alpha^*}{d\beta}\) in equation (4). The important conclusion is that the standard offsetting behavior is not a cause of the observed Peltzman effect. Consequently, the regulator who observes the results as presented in Table 9 (product regulation yields the Peltzman effect) but not the detailed analysis in Table 10 (no significant presence of the standard offsetting behavior) might design and implement the wrong policies whose aim is to suppress the Peltzman effect.

Our analysis and empirical examples indicate that if adverse selection is a serious concern, then product regulation must be supported by consumer regulation. The regulator might want to not only curb the decrease in consumer skills but also eliminate that decrease altogether. This requires implementing consumer regulation that introduces a test for the right to be a consumer (e.g., driving test) or educates consumers in order to increase their skills. We call it the **two-dimensional regulation** since, as opposed to standard policies, the objective is to affect both product safety and consumer skills.

Initially, our policy suggestion might seem counter-intuitive. After all, some could argue that one of the reasons of increasing product safety is to make sure that the consumption of that product becomes safer for, especially, consumers with low skills. However, as the product-consumer substitution indicates, higher product safety turns some non-consumers into consumers. Their skills are lower than the lowest consumer skills before regulation. Their low skills need not be compensated by higher product safety. Consequently, their access to consumption should be limited.

**Result 6.** In order to limit the impact of adverse selection, it is necessary to combine product regulation (consumer regulation) with consumer regulation (product regulation).

In our last empirical exercise, we implement the policy recommendation from Result 6 in the case
of Peltzman effect reported in Table 9. In addition to product regulation, we suggest consumer regulation that introduces new restrictions on who can participate in the racing: the minimum license is C. Hence, we replicate the regression from 9 with additional restrictions; we take data restricted to not only Weight to Horse Power Ratio less than 7 but also License at least C.

<table>
<thead>
<tr>
<th></th>
<th>at least C</th>
<th>at least B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight to Horse Power Ratio</td>
<td>−0.0006*</td>
<td>−0.0010***</td>
</tr>
<tr>
<td>License</td>
<td>−0.0505***</td>
<td>−0.0504***</td>
</tr>
<tr>
<td>Traffic Density</td>
<td>−0.0054***</td>
<td>−0.0046***</td>
</tr>
<tr>
<td>Laps in the Race</td>
<td>0.0007***</td>
<td>0.0004***</td>
</tr>
<tr>
<td>Oval</td>
<td>−0.0705***</td>
<td>−0.0581***</td>
</tr>
<tr>
<td>Night</td>
<td>0.0194***</td>
<td>0.0209***</td>
</tr>
<tr>
<td>N</td>
<td>1,299,818</td>
<td>1,078,852</td>
</tr>
<tr>
<td>Adj $R^2$</td>
<td>0.0236</td>
<td>0.0146</td>
</tr>
</tbody>
</table>

*** 1%, ** 5%, * 10%

Significance levels have been calculated using heteroscedastic robust standard errors.

Table 11: Testing for the Peltzman effect (sub-sample)

We observe that the coefficient of Weight to Horse Power Ratio is negative which means that product regulation results in the regular effect. If we limit access to racing to those with the License of at least B, then our policy becomes even more efficient: coefficient of Licence becomes $-0.001$ and is significant at 1%.

4 Conclusions

The standard theory of safety regulation focuses on the role of moral hazard and its negative effect. We propose a novel theory with not only moral hazard but also adverse selection. The fundamental element of our theory is the product-consumer substitution; i.e., the negative correlation between product safety and consumer skills. According to our theory, the primary moral hazard is only a partial, or even irrelevant, force behind the Peltzman effect.
We support our theory with an empirical analysis using more than 2 million observations from iRacing, an online racing simulator. There are three elements of the racing simulator that are important from research perspective: tracks, cars, and drivers' behavior. In iRacing, tracks and cars are designed as virtual replicas of their real life counterparts. The implemented system of incentives implies that the behavior of iRacing drivers replicates the behavior of racers in the real world.

We use Weight to Horse Power Ratio as a measure of product safety; i.e., the direct outcome of product regulation. This ratio is a proxy measure for a car’s controllability: the lower the ratio is the faster the car accelerates and the higher its probable maximum speed. The driver’s License level is our measure of consumer skills. This is the direct outcome of consumer regulation. Drivers are divided into seven groups based on their racing capabilities. To achieve a higher driver license level, it is necessary to both show driving proficiency by finishing races in high positions and maintain a low level of incidents. For each driver and each race, iRacing records the quantity and severity of incidents and captures them in the variable Incident Points. Thus, our safety measure is Incidents Points per Mile.

In our benchmark regression including product and consumer regulations we do not detect the Peltzman effect. Next, we analyze the importance of the omitted variable bias and conclude that it is a serious problem for the empirical literature on safety regulation. In particular, when analyzing product regulation but disregarding License (consumer skills) as a covariate we do observe the Peltzman effect; i.e., the coefficient in Weight to Horse Power Ratio becomes positive. This leads us to detect the presence of the product-consumer substitution which, consequently, necessitates a new theory.

Disregarding adverse selection creates incomplete or even incorrect depiction of safety regulation. In particular, assuming that the product-consumer substitution is zero results with the incorrectly estimated changes in consumer effort and probability of bad outcome. In fact, it is possible that while the standard theory predicts an increase (decrease) in effort or the probability of bad outcome, we, actually, observe a decrease (increase).

Adverse selection implies that product regulation and consumer regulation have opposite impacts on effort. This result is important if consumer effort is an objective of policy; for example, the regulator cares not only about the safety measure but also the response of the public.
In order to test whether adverse selection is an important problem, it is necessary to test for the presence of the standard offsetting behavior. We empirically analyze the impact of product regulation for each level of consumer skills separately. When we consider the whole data, we observe the regular effect for each value of License. In other words, we reject the hypothesis of the standard offsetting behavior.

However, we also test for the standard offsetting behavior in sub-samples of our data. In the first example, we detect the regular effect as well as the standard offsetting behavior for two groups of consumers (Licenses B and A). This example shows that we should not disregard the problem of the standard offsetting behavior even if the Peltzman effect is not detected.

In our second example, we detect the Peltzman effect. However, despite what the standard theory suggests, we observe the standard offsetting behavior in only 4.6% of our data. Clearly, the standard explanation of this specific Peltzman effect is not the best. Rather, it is the product-consumer substitution that is the main force behind our result. Our empirical examples indicate that it is important to test for the standard offsetting behavior.

If the outcome of safety regulation is weaken by adverse selection, then it is necessary to design a two-dimensional policy. In the case of product regulation (consumer regulation), the objective is to not only increase product safety (consumer skills) but also control the decline in consumer skills (product safety) by simultaneously imposing consumer regulation (product regulation). We provide an empirical analysis of this combined product-consumer regulation.

Appendix A  Product-driven and consumer-driven adjustment behavior

We discuss the relation between the product-driven adjustment behavior $\frac{\partial a^*}{\partial \alpha}$ and the consumer-driven adjustment behavior $\frac{\partial a^*}{\partial \beta}$ in the context of product regulation. First, we derive both adjustment behaviors.

$$\frac{\partial a^*}{\partial \alpha} = -\frac{\lambda^{*}_{aa}}{\lambda^{*}_{aa} + c''(a^*)}$$
\[
\frac{\partial a^*}{\partial \beta} = -\frac{\lambda^*_{a\beta}}{\lambda^*_a + c''(a^*)}
\]

Since \(\lambda_{aa} + c'' > 0\), the sign of each derivative depends on their numerators. Suppose that \(\lambda^*_{a\alpha} > 0\). In order to guarantee the negative product-driven adjustment behavior, we assume that \(\lambda_{a\alpha} > 0\). That is, the marginal gain from effort \(\lambda_a\) decreases with product safety.

We could argue that whatever we assume about \(\lambda_{aa}\) (positive or negative), then it is only appropriate to assume the same about \(\lambda_{a\beta}\). That is, product safety and consumer skill have the same qualitative impact on the marginal gain from effort. This implies that \(\frac{\partial a^*}{\partial \alpha}\) and \(\frac{\partial a^*}{\partial \beta}\) have the same sign. Since \(\frac{d\beta}{d\alpha}\) is negative, it must be true that product-driven and consumer-driven adjustment behaviors work in opposite way. That is, the product-driven adjustment behavior decreases effort if and only if the consumer-driven adjustment behavior increases effort.

**Appendix B  Standard offsetting behavior in consumer regulation: empirical analysis**

In the case of consumer regulation, the product-consumer substitution means that \(\alpha\) is a function of \(\beta\). The total change in safety measure is

\[
\frac{d\lambda^*}{d\beta} = \lambda^*_\beta + \lambda^*_{a\beta} \frac{\partial a^*}{\partial \beta} + \frac{da^*}{d\beta} \left[ \lambda^*_{a\alpha} + \lambda^*_{a\alpha} \frac{\partial a^*}{\partial \beta} \right].
\]

As with the product regulation, when the regulator wants to implement the consumer regulation, it is necessary to test for the standard offsetting behavior defined as \(\lambda^*_{\beta} + \lambda^*_a \frac{\partial a^*}{\partial \beta} > 0\) (i.e., we keep product safety fixed). This test allows us to determine whether we should be concerned with adverse selection.

In the context of consumer regulation, we empirically test for the presence of the standard offsetting behavior in iRacing data. There are 39 different values of Weight to Horse Power Ratios in our data set; hence, we partition the data into 39 subsets with unique Weight to Horse Power Ratio. In each subset, we regress Incident Points per Mile, on License and our four control variables (Traffic Density, Laps in the Race, Oval, and Night). To save space, for each regression, we only present the results related to the coefficient on License as this is our variable of interest.
<table>
<thead>
<tr>
<th>Weight to Horse Coefficient Standard Power Ratio</th>
<th>N</th>
<th>on License</th>
<th>Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.77</td>
<td>8,177</td>
<td>-0.042***</td>
<td>0.005</td>
<td>0.00</td>
</tr>
<tr>
<td>1.80</td>
<td>1,449</td>
<td>-0.125***</td>
<td>0.047</td>
<td>0.01</td>
</tr>
<tr>
<td>1.95</td>
<td>1,258</td>
<td>-0.073**</td>
<td>0.040</td>
<td>0.07</td>
</tr>
<tr>
<td>2.21</td>
<td>2,699</td>
<td>-0.069***</td>
<td>0.018</td>
<td>0.00</td>
</tr>
<tr>
<td>2.24</td>
<td>150,264</td>
<td>-0.050***</td>
<td>0.002</td>
<td>0.00</td>
</tr>
<tr>
<td>2.67</td>
<td>6,499</td>
<td>-0.106***</td>
<td>0.010</td>
<td>0.00</td>
</tr>
<tr>
<td>3.00</td>
<td>2,546</td>
<td>-0.088***</td>
<td>0.012</td>
<td>0.00</td>
</tr>
<tr>
<td>3.77</td>
<td>35,774</td>
<td>-0.013***</td>
<td>0.003</td>
<td>0.00</td>
</tr>
<tr>
<td>3.79</td>
<td>16,725</td>
<td>-0.061***</td>
<td>0.004</td>
<td>0.00</td>
</tr>
<tr>
<td>3.82</td>
<td>5,801</td>
<td>-0.060***</td>
<td>0.006</td>
<td>0.00</td>
</tr>
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<td>5,892</td>
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<tr>
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<td>-0.074***</td>
<td>0.003</td>
<td>0.00</td>
</tr>
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<td>4.55</td>
<td>19,743</td>
<td>-0.090***</td>
<td>0.004</td>
<td>0.00</td>
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<td>4.86</td>
<td>4,693</td>
<td>-0.060***</td>
<td>0.005</td>
<td>0.00</td>
</tr>
<tr>
<td>4.90</td>
<td>14,178</td>
<td>-0.047***</td>
<td>0.003</td>
<td>0.00</td>
</tr>
<tr>
<td>4.95</td>
<td>28,257</td>
<td>-0.064***</td>
<td>0.004</td>
<td>0.00</td>
</tr>
<tr>
<td>5.08</td>
<td>68,570</td>
<td>-0.062***</td>
<td>0.002</td>
<td>0.00</td>
</tr>
<tr>
<td>5.09</td>
<td>9,987</td>
<td>-0.101***</td>
<td>0.009</td>
<td>0.00</td>
</tr>
<tr>
<td>5.14</td>
<td>65,384</td>
<td>-0.056***</td>
<td>0.003</td>
<td>0.00</td>
</tr>
<tr>
<td>5.31</td>
<td>158,076</td>
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<td>0.002</td>
<td>0.00</td>
</tr>
<tr>
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<td>77,393</td>
<td>-0.053***</td>
<td>0.002</td>
<td>0.00</td>
</tr>
<tr>
<td>5.37</td>
<td>55,274</td>
<td>-0.065***</td>
<td>0.003</td>
<td>0.00</td>
</tr>
<tr>
<td>5.44</td>
<td>329,896</td>
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<td>0.001</td>
<td>0.00</td>
</tr>
<tr>
<td>5.45</td>
<td>4,664</td>
<td>-0.063***</td>
<td>0.006</td>
<td>0.00</td>
</tr>
<tr>
<td>5.52</td>
<td>106,777</td>
<td>-0.029***</td>
<td>0.001</td>
<td>0.00</td>
</tr>
<tr>
<td>5.52</td>
<td>11,968</td>
<td>-0.066***</td>
<td>0.006</td>
<td>0.00</td>
</tr>
<tr>
<td>6.08</td>
<td>62,134</td>
<td>-0.071***</td>
<td>0.002</td>
<td>0.00</td>
</tr>
<tr>
<td>6.96</td>
<td>76,347</td>
<td>-0.103***</td>
<td>0.001</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Table 12: Testing for the standard offsetting behavior in consumer regulation

As Table 12 indicates, for each value of Weight to Horse Power Ratio (product safety), we do not detect the standard offsetting behavior.

References


