

Driving Tests and Road Safety: the Case of Mexico City*

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Abstract

The purpose of a driving test is to prevent unskilled people from using cars, which supposedly increases road safety. We find that the obligatory driving tests do not increase road safety. Our empirical analysis relies on the data from Mexico City where the obligatory driving test has been abolished in January 2004. Our theoretical analysis builds on the Reverse Peltzman Effect: drivers become more careful and exert more effort on the roads if they know that the driving environment becomes less safe, due to the presence of incompetent drivers.

Keywords: regulation; driving test; road safety; Reverse Peltzman Effect

JEL classification: L510; K000

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1 Introduction

According to the *World Report on Road Traffic Injury Prevention*, prepared by the World Health Organization, road crashes were responsible for 1.2 million deaths in 2002 and were the eleventh-leading cause of death worldwide (and the first non-illness cause of death). Among children (5-14 years old) and young people (15-29 years old), they are the second-leading cause of death.

Since roads and driving are possible sources of great danger, it is only natural to impose some form of regulation on roads, driving, and who can and cannot drive a car. For economists, it is important to study the effectiveness of such regulation. A seminal example of such a study, Peltzman (1975) focuses on the impact on road safety of regulations, introduced in the United States in the mid-1960s which forced car manufacturers to make changes in car design (e.g., installation of seat belts for driver and all passengers). He found that “safety regulation has had no effect on the highway death toll.” This phenomenon can be explained by the *Peltzman Effect*: If a new regulation imposes restrictions on people’s behavior, then people find ways to follow the new law but also change their behavior in such a way that the net effect of the regulation is null. In the case of Peltzman’s study, having safer cars prompted people to drive more recklessly, and, consequently, car accidents increased. Such behavior is driven by the tradeoff between the demand for safety and the demand for driving intensity (i.e., more speed, recklessness, and driving thrills).¹

The driving test is also a key part of road safety regulations. Obtaining a driver’s license requires more than just showing up at the relevant office and completing paperwork. There are theoretical and practical exams and sometimes even a medical test. We focus on the effect of the driving test (i.e, “the road test”) during which a candidate for a driver’s license demonstrates driving skills and knowledge of traffic rules. As noted by Bertrand et al. (2007) who analyze how corruption affects the provision of driver’s licenses in Delhi, India, “the very rationale for regulation” is “keeping bad drivers from getting licenses.” By doing so,

¹The debate that followed Peltzman’s paper is too extensive to fully discuss here; instead, see Blomquist (1988) for the literature survey. Many researchers attempted to replicate Peltzman’s result using both U.S. and non-U.S. data. For instance, Lindgren and Stuart (1980) analyzed Swedish data for the period 1947–1973 and did not find the presence of the Peltzman Effect. However, it should be noted that Sweden introduced not only safety regulation, but also speed limits, which effectively removed the option of drivers becoming more reckless. Conybeare (1980) used Australian data for the period 1949–1977 and discovered the existence of the Peltzman Effect. As for the U.S. studies, Peterson et al. (1995) confirmed the offsetting behavior hypothesis, while Crandall and Graham (1984) and, more recently, Cohen and Einav (2003) rejected that hypothesis.

the test should increase safety on the roads, as the average quality of drivers is kept at a required level. In this paper, we investigate whether the test actually affects road safety.

In January 2004, Mexico City, the biggest city in Mexico, removed the requirement to pass the driving test. Now, anyone who resides in Mexico City and pays the administrative fee is able to obtain a driver's license. Studying monthly data from January 2000 to December 2013 gives us an opportunity to conduct a natural experiment and verify the effectiveness of a driving test. We use the number of fatal crashes as measures of road safety.

In our empirical analysis, we believe that the most interesting and important finding is precisely what we did not find. We expected that the lack of driving tests should negatively affect road safety. However, the data does not confirm this hypothesis. In fact, if there is any relationship between removing regulation and road safety, it is a positive one.

While the Peltzman Effect is a theoretical argument against imposing new regulation, the *Reverse Peltzman Effect* explains why it may be optimal to abolish existing regulation. The Reverse Peltzman Effect occurs when regulation is removed and people adjust their behavior in order to compensate for the lack of regulation. Although our data set is not rich enough to determine why the lack or removal of a driving test does not lower road safety, we believe that the absence of a driving test, which increases the proportion of unskilled drivers, motivates all drivers to become more careful and exert more effort while driving. The net result—measured in rates of fatalities and fatal accidents—is that there is no safety improvement associated with the imposition of driving tests.

Although similar to Peltzman's, in that this study also addresses the problem of imposing safety regulation, there are two significant differences between his paper and ours. In Peltzman (1975), safety regulation meant obligatory changes in automobile design, while in our case, safety regulation is the policy of separating bad drivers from good drivers. The difference is not trivial and is related to two distinct objectives of safety regulation. First, regulation aims to lower the probability of having a car accident. Assuming that higher average driving skills lower the accident rate, this objective is achieved by prohibiting bad drivers from using the roads. Our paper addresses the problems with reaching the first goal. However, it is not possible to eradicate all traffic accidents; hence, the second objective of regulation is to minimize the social costs resulting from accidents. By forcing car producers to make their products safer, regulator aims to lower the probability of death or severe health and property damage, if an accident does occur. Peltzman (1975) and the literature that follows him address the problems with reaching the second goal. The other difference between our and Peltzman's paper is that he analyzes the effect of introducing safety reg-

ulation, while we focus on the consequences of abolishing such regulation. In general, the effects of these two changes need not be the same.

In Section 2, we present and discuss our empirical analysis. In Section 3, we propose a model that uses the Reverse Peltzman Effect to explain why the roads can be as safe, or even safer, without mandated driving tests.

2 Empirical Analysis

Mexico City, with a population exceeding 8 million (around 8% of the whole Mexican population), has had no driving test since January 2004. This allows us to test whether or not there was a structural break after this date. The time span we used is from January 1998 until December 2013 ($T=192$). This means that our data comprise 72 months with required driving tests and 120 without.

Our goal is to determine whether or not a mandatory driving test results in fewer fatalities per registered vehicles. The natural measure of safety on the roads is the number of accidents. Motor vehicle crashes are divided into three categories: (a) fatal, (b) injury only, and (c) property damage only. We focus on fatal crashes since an accident that results in a death is very unlikely to be reported incorrectly or to go unreported. Hence, it is safe to presume that the available data are accurate and complete.

Our dependent variable for this study is fatal crashes per 10,000 vehicles. We use the data provided by Instituto Nacional de Estadística y Geografía (INEGI). This institute provides numbers of fatal accidents on monthly basis and number of vehicles (cars, trucks, buses, and motorcycles) on annual basis. Since we only have data for the yearly number of registered vehicles, we will assume that the number of vehicles is the same for every month within a year.² We tested for unit root and found the data to be stationary.

First, we divided the data into two sets—one ranging from January 1998 to December 2003, and the other from January 2004 to December 2013. Then we conducted a test of difference in means. Table 1 gives the characteristics of both samples.

[Table 1 about here.]

The t-statistic for a test of difference in means, with difference variance for each sample,

²If we assume that the number of vehicles changes every month, then we obtain qualitatively the same results using several different ways to estimate those monthly changes.

equals 4.94 (p-value less than 0.0001). This suggests that the mean of fatal crashes per 10,000 vehicles was different in the two sub-periods. However, the mean of the period in which there was no driving test is significantly smaller than that for the period in which there was a test. Although surprising, this result is consistent with our model, presented in Section 3, that indicates that people might overcompensate for the larger proportion of unskilled drivers on the road by increasing their own effort while driving.

We also need to conduct a time series analysis to determine whether or not there was a structural break in the data when the driving test was removed in Mexico City. Our first estimation uses an AR(1) process,

$$y_t = \underset{(0.00)}{0.04} + \underset{(0.00)}{0.41}y_{t-1} + \epsilon_t, \quad (1)$$

where y_t is the number of fatal crashes at time t , and the values in parentheses are the p-values of the estimated coefficients. The R^2 of the above regression is 0.17.

In order to check for the existence of a structural break, we used the estimator proposed in Bai (1994) and Chong (2001). This estimator is shown to consistently estimate the point at which a structural break occurs in a linear process. The estimator is defined as

$$\hat{\tau}_T = \underset{\tau \in (0,1)}{\operatorname{argmin}} \operatorname{RSS}_T(\tau), \quad (2)$$

where $\operatorname{RSS}_T(\tau) = \operatorname{SSE}_{t=1:[\tau T]} + \operatorname{SSE}_{t=[\tau T]+1:T}$, $[x]$ is the integer part of x , and $\operatorname{SSE}_{t=1:x}$ is the sum of the squared errors obtained from the OLS estimation of the AR(1) process between period 1 and x .

According to the SST, there might be a structural break in the AR(1) process in November 2007, almost four years after the driving test requirement was removed. There is a good reason why we might be observing the delayed response on drivers: initially, the mass of new “bad” drivers need not be large enough to force a change in overall behavior. After some years of having new drivers without test, it will be more evident the effect of the new policy. Figure 1 shows the point estimates of SST.³

[Figure 1 about here.]

³Note that there is a spike in the figure at the beginning of the sample period. This is because the number of fatal accidents in June 1999 is 68 while the average number of fatal accidents and standard deviation for the entire sample are 23.9 and 7.3 respectively. All results presented in this paper remain qualitatively the same and quantitatively almost identical for different treatments of this possible outlier, like winsorizing or trimming.

For testing whether or not the estimated break point is significant, we ran the regression $y_t = c + \rho_0 y_{t-1} + \alpha_1 d_t + \alpha_2 y_{t-1} d_{t-1} + \epsilon_t$, where d_t is a dummy variable that equals 1 if t is smaller than November 2007 and 0 otherwise. If a structural change exists, then the F test of $\alpha_1 = \alpha_2 = 0$ should be rejected. This test has an $F(2,187)$ distribution. The value of the F-statistic is 13.86 and its p-value is less than 0.0001. Hence, the hypothesis of no structural change can be rejected. The coefficient multiplying d_t (α_1) is positive but not significant (p-value=0.17).⁴

As expected, our results suggest that removing the driving test changed drivers' behavior. However, we find no evidence that this change caused an increase in the number of fatal accidents. In fact, if any effect occurred, then, in terms of road safety, it was a beneficial one.

The next section provides the theoretical results that support our empirical findings.

3 Theoretical Analysis

The population of agents (drivers) who use the common system of roads is divided into two groups, according to their ability to drive a car which can be either High or Low. The proportion of High skill drivers in the population is π . We presume that π is commonly known to all agents.

The government decides whether or not to establish an obligatory driving test and, if the test is imposed, determines how restrictive it should be. This policy allows the government to manipulate the value of π between zero and one.

When drivers encounter each other on the road, such a meeting may end in an accident. Let λ denote the probability of avoiding an accident, conditional on the fact that two drivers meet. We identify λ with the agent's revenue. Agent's costs are derived from effort, denoted by e with restriction $e \in [0, 1]$. Effort (i.e., the amount of effort devoted to paying attention while driving) is the only decision that an agent makes. We are interested in the impact of π on the optimal choice of effort. We presume that λ is a linear and increasing function of effort, while cost is a quadratic and increasing function of effort. Later, we discuss how driving skills affect λ .

⁴We run a Q-test on the residuals of the previous AR(1) regressions and find evidence of a third lag in the autorregressive proces. We repeated the exercise adding y_{t-3} to the analysis and find qualitatively the same results.

In our model, we focus only on one agent, Ann, and her choice of effort. Since Ann knows her own driving skill type, we do not need to specify whether Ann’s driving skills are Low or High. Our model does not allow for interaction among the drivers, so Ann does not take into account the fact that the effort of other drivers also affects her probability of avoiding an accident. It is possible to extend our model to a game-theoretic framework. However, adding more players who make decisions about their efforts brings no additional insight but only complicates the mathematical aspects of the model.

The key question is: Does lowering π (i.e., increasing the proportion of Low skill drivers) increase Ann’s probability of not having an accident? We identify the conditions under which the answer is positive. Here our intuition is based on the presumption that a more dangerous driving situation (i.e., lower π) induces drivers to make more effort while driving, thereby decreasing the probability of an accident. With more Low skill drivers on the roads, all agents compensate for the decrease in overall quality of drivers by increasing their effort. It is possible that this increase in effort is so big that the roads actually become safer when the proportion of High skill drivers decreases.

Our agent, Ann, drives her car and encounters another driver on the road. Ann chooses her effort. The probability that she will meet a High skill driver is π . We define λ in the following way.

$$\lambda(e) = \begin{cases} \lambda^H(e) = \alpha_1 + \beta_1 e & \text{if the other driver is High skill} \\ \lambda^L(e) = \alpha_2 + \beta_2 e & \text{if the other driver is Low skill} \\ 1 & \text{if } \alpha_i + \beta_i e > 1, \text{ for } i = 1, 2 \\ 0 & \text{if } \alpha_i + \beta_i e < 0, \text{ for } i = 1, 2 \end{cases} \quad (3)$$

It is natural to presume that, for each level of effort, the probability of avoiding an accident when the other driver is High skill type is at least as high as when the other driver is Low skill type. Since λ^H and λ^L are linear functions of effort, it is enough that $\lambda^H(e) > \lambda^L(e)$ at two points, $e = 1$ and $e = 0$. That is, we need $\alpha_1 + \beta_1 \geq \alpha_2 + \beta_2$ and $\alpha_1 \geq \alpha_2$. This first requirement is captured in Assumption 1.

Assumption 1 $\alpha_1 + \beta_1 \geq \alpha_2 + \beta_2$

The next assumption is formulated in terms of β ’s rather than α ’s unlike the prior analysis.

Assumption 2 $0 \leq \beta_1 < \beta_2$

Although, Assumptions 1 and 2 imply that $\alpha_1 \geq \alpha_2$, it is important to explain why Assumption 2 is not stated directly as $\alpha_1 \geq \alpha_2$. The reason is the significance of coefficients β_1 and β_2 . Assumption 2, the most important requirement in our model, says that effort has a stronger effect on marginal gain when Ann encounters a driver who is a Low skill type, rather than a High skill type. The former situation can be called dangerous, while the latter safe. However, Assumption 2 captures our intuition, dictated by reality, that when a situation is more dangerous, Ann increases her effort in order to avoid an accident, as she cannot count on the other agent. In the safer situation, Ann can rely on the skills of the other driver and be more confident about his responsible behavior. Assumption 2 is also crucial to our model for a technical reason. If effort were marginally more valuable in a safe situation than it is in a dangerous situation, then Ann would not be able to compensate for the lack of other driver's skills by increasing her own effort.

The next assumption imposes a quadratic cost function.

Assumption 3 $c(e) := \frac{1}{2}\mu e^2$ with $\mu > 0$

The final assumption is purely technical in nature. Although it is not necessary for our model, Assumption 4 simplifies the analysis and notation by guaranteeing that optimal effort is a strictly monotonic function of π .

Assumption 4 $\beta_2 \leq \mu$

Ann's effort depends on the probability of the other driver being a High skill type, π . Ann maximizes expected revenue,

$$\max_e \left[\pi \lambda^H(e) + (1 - \pi) \lambda^L(e) - \frac{1}{2} \mu e^2(\pi) \right], \quad (4)$$

which yields the optimal effort level, written as a function of π ,

$$e^*(\pi) = \frac{\pi \beta_1 + (1 - \pi) \beta_2}{\mu}, \quad (5)$$

and the expected probability of success (i.e., not having an accident) computed at the optimal level of effort,

$$E(\lambda(e^*(\pi))) = \pi \alpha_1 + (1 - \pi) \alpha_2 + \frac{(\pi \beta_1 + (1 - \pi) \beta_2)^2}{\mu}. \quad (6)$$

Due to Assumption 2, $e^*(\pi)$ in (5) is a decreasing function of π . That is, the safer the roads become, the lower Ann's effort will be as Ann relies more on the other driver's skills.

Our main goal is to compare the probability of not having an accident in two scenarios. In the first scenario, the government introduces the obligatory driving test that guarantees only High skill types are drivers. This scenario generates $\lambda^H(e^*(1)) = \alpha_1 + \frac{\beta_1^2}{\mu}$. In the second scenario, the government allows for $\pi \neq 1$ and attempts to maximize the expected probability of not having an accident, $E(\lambda(e^*(\pi)))$. We are interested in the conditions, determined by the parameters of the model and π , that imply that $\lambda^H(e^*(1)) < E(\lambda(e^*(\pi)))$. We define

$$f(\pi) := E(\lambda(e^*(\pi))) - \lambda^H(e^*(1)), \quad (7)$$

and seek to identify when $f > 0$. Note that f is a quadratic function of π , and since $E(\lambda(e^*(1))) = \lambda^H(e^*(1))$, we know that $\pi = 1$ is one of its roots. The second root, $\hat{\pi}$, is defined as

$$\hat{\pi} = \frac{\beta_2^2 - \beta_1^2 - \mu(\alpha_1 - \alpha_2)}{(\beta_2 - \beta_1)^2}. \quad (8)$$

Given this, it is straightforward to show that f is a convex function. Therefore, we need to consider three cases determined by $\hat{\pi}$, as shown in Figures 2–4.

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

In Case 1 (shown in Figure 2), f is strictly above zero for all $\pi \in [0, 1)$, which implies that the government should not prevent anyone from driving. This case holds when $2\beta_1(\beta_2 - \beta_1) \geq \mu(\alpha_1 - \alpha_2)$. In Case 2 (shown in Figure 3), $f > 0$ for $\pi \in [0, \hat{\pi})$. Case 2 obtains when two conditions, (a) and (b) listed below, hold.

$$(a) \quad 2\beta_1(\beta_2 - \beta_1) < \mu(\alpha_1 - \alpha_2) \quad (9)$$

$$(b) \quad \beta_2^2 - \beta_1^2 > \mu(\alpha_1 - \alpha_2) \quad (10)$$

Case 3 (shown in Figure 4), which is true when $\beta_2^2 - \beta_1^2 \leq \mu(\alpha_1 - \alpha_2)$, implies that f is below zero on the whole interval $[0, 1)$. Therefore, the government should impose rules that allow only High skill types to obtain a driver's license.

Next we identify the two competing forces that determine which of these three cases is true. Since our objective is to analyze the impact of abolishing regulation, it is only natural to focus on the consequences of lowering π .

- (1) **Bad Quality Effect:** When π decreases, the average quality of drivers decreases, the roads become more dangerous. In consequence, f is increasing in π .
- (2) **Reverse Peltzman Effect:** When π decreases, Ann's perception about the driving environment changes. She begins to feel less safe and, driven by fear, increases her effort. As a result, it becomes safer to drive on the roads. In consequence, f is decreasing in π .

In Case 1, the Reverse Peltzman Effect is the dominant force, which implies that for values of π but one, namely $\pi = 1$, it makes sense to abolish the driving test and allow Low skill drivers to use the roads. In Case 2, for values of π above the minimum of f , the Bad Quality Effect is stronger than the Reverse Peltzman Effect. However, when π is smaller than the minimum of f , the average quality of drivers is not as important. What do matter are the perceptions which are a main force behind the Reverse Peltzman Effect. Cases 1 and 2 are valid for our purpose, as they explain why the introduction of or increase in danger improves road safety. In Case 3, however, only the Bad Quality Effect matters. In his case, it is always better to have certainty of safety rather than even a low level of danger—clearly, this goes against our empirical results.

In analyzing f , as defined in (7), we focus on comparing revenues, $E(\lambda(e^*(\pi)))$ and $\lambda(e^*(1))$, and ignore costs. Whether a regulation is imposed or removed, there are costs that society must bear. With new regulation, there are the costs of implementing the regulation. In the case of driving tests, these costs include opening offices, hiring and training specialized personnel, and the time and money spent by people who must take the test. When a regulation is abolished, there also can be social costs. In our particular case, allowing unskilled drivers to use roads means that all drivers must increase their effort while driving. There are two reasons why we have neglected these costs, so far. First, due to the lack of data about both the costs of implementing regulation and drivers' effort, we can only focus on social revenues. This is not a problem specific to our paper, rather it afflicts the whole literature about regulation and road safety. Second, in the particular case of road safety, the social costs seem significantly less important than social revenues. After all, social revenue represents a decrease in the number of people who die in car crashes, while social costs are related to an increase in drivers' effort. It is likely that, from a policymaker's perspective, saving lives is more important than making the driving experience less pleasant.

Nevertheless, next we incorporate social costs into our analysis and compare social profits. In order to capture the fact that social revenue might be relatively more important than costs, instead of the standard formula,

$$Profit = Revenue - Costs,$$

where revenue is measured via λ and costs are due to effort, we use the weighted profit function,

$$Profit = Revenue - \delta * Costs,$$

where δ measures the relative importance of costs versus revenue. For $\delta \in [0, 1]$, costs are less relevant than revenue. We believe that most governments are characterized by small δ .

Again, we need to characterize the conditions under which not having a driving test (thus, allowing Low skill drivers) is better than having one (i.e., only allowing High skill drivers). We compare weighted profits,

$$(E(\lambda(e^*(\pi)) - \delta\mu(e^*(\pi))^2) - (\lambda(e^*(1)) - \delta\mu(e^*(1))^2)), \quad (11)$$

and find that $\pi = 1$ and $\pi = \tilde{\pi}$, where

$$\tilde{\pi} = \frac{(2 - \delta)(\beta_2^2 - \beta_1^2) - 2\mu(\alpha_1 - \alpha_2)}{(\beta_2 - \beta_1)^2}, \quad (12)$$

are two roots of (11). As before, there are three cases determined by $\tilde{\pi}$. We skip their analysis, as it brings nothing interesting to this paper. Instead we focus on δ . In particular, there exists $\check{\delta} = 2 - \frac{(\beta_2 - \beta_1)^2 + 2\mu(\alpha_1 - \alpha_1)}{\beta_2^2 - \beta_1^2}$, such that whenever $\delta \leq \check{\delta}$, then, for each level of π , it is optimal to allow for Low skill drivers on the roads. This is the previously discussed Case 1, in which the Reverse Peltzman Effect is the dominating force. That is, when δ is small enough (i.e., saving lives is more important than increasing drivers' effort) a policymaker should abolish the driving test, regardless of the other parameters.

4 Conclusions

This paper extends the literature stemming from Peltzman (1975), which showed that car safety regulation in the mid-1960s did not increase road safety. One possible explanation for

this phenomenon is the Peltzman Effect, which holds that drivers offset the potential gains from having safer cars by taking more risks while driving. However, instead of analyzing the effectiveness of introducing new car safety measures, we investigate the consequences of removing regulation that requires driver to pass a driving test in order to obtain a licence. Using monthly time series data for Mexico City, where a driving test was abolished in January 2004, we show that road safety actually did not decrease and possibly increased after that regulation was removed. Our results can be explained by the Reverse Peltzman Effect, which posits that removing the obligation to pass a driving test increases the proportion of unskilled drivers, prompting all drivers to pay more attention while driving, which, in turn, compensates for the lack of regulation.

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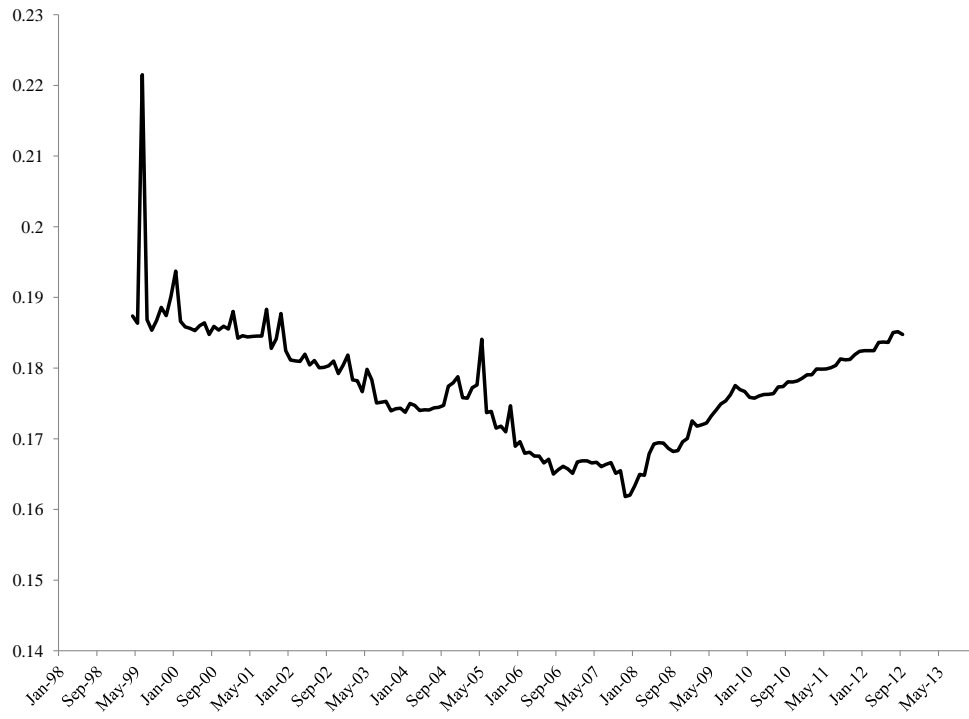


Figure 1

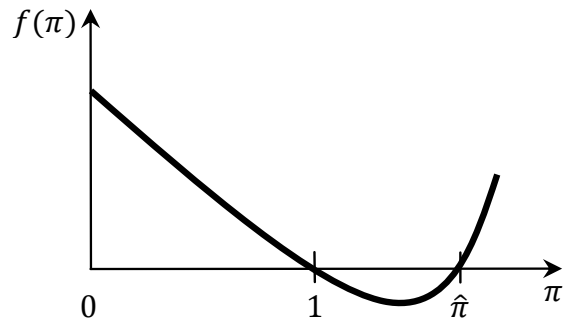


Figure 2: Case 1 ($\hat{\pi} \geq 1$).

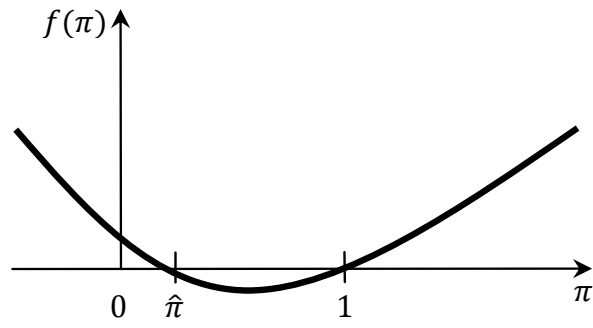


Figure 3: Case 2 ($\hat{\pi} \in (0, 1)$).

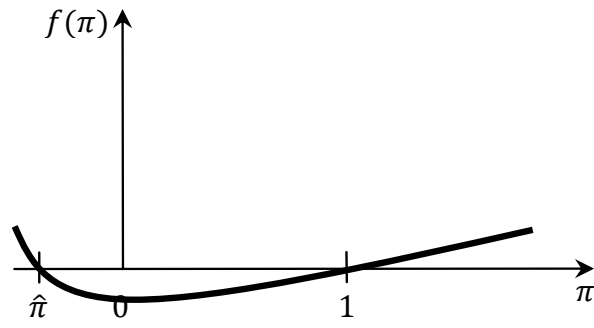


Figure 4: Case 3 ($\hat{\pi} \leq 1$).

Sample	Periods	Mean	Std. Dev.
Jan 1998 - Dec 2004	72	0.10160	0.03985
Jan 2004 - Dec 2013	120	0.07572	0.02534

Table 1