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The effect of priming on fraud: Evidence from a natural field experiment*

April 8, 2020

Abstract

We present a natural field experiment designed to examine the extent to which priming can influence the behaviour of sellers in a real world market for credence goods. We employed 40 testers to take 600 taxi journeys in and around Vienna, Austria. Using a between–subject design we vary the script spoken by testers, with each script designed to prime either honest behaviour, dishonest behaviour, or the existence of a market competitor. In contrast to our hypotheses, we find that priming honesty increases taxi fares by 5% in comparison to a baseline, increasing the frequency of overcharging by 15% and the amount overcharged by around 44%. The dishonesty prime has no impact. The market competitor prime increases both overcharging and overtreatment by amounts that are individually indistinguishable from zero, but jointly raise fares by 5%. All of the treatments are found to have no significant effect on journey length (overtreatment).

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1 Introduction

Markets for credence goods are characterised by informational asymmetries between consumers and sellers. For example, a doctor is more informed than the patient about the quality of care the patient needs in order to maximise their health outcomes, a car mechanic is employed by an uninformed motorist in order to determine if their car needs a new engine, and taxi drivers know the quickest and most cost efficient routes for their passengers (Darby & Karni, 1973). The problem arising in each of these examples is that the informational asymmetry puts the seller at a strategic advantage because the consumer is unable to observe the quality of the good they have received *ex post*. This creates a strong material incentive for the seller to behave dishonestly, but profitably, at the expense of the consumer (Dulleck & Kerschbamer, 2006).

The most well studied inefficiencies that arise in markets for credence goods are *overtreatment* and *overcharging* (Darby & Karni, 1973; Dulleck & Kerschbamer, 2006). The first, *overtreatment*, involves the seller providing a higher quality of work than is necessary in order to maximise their own profits. For example, car mechanics can replace an engine when only a tune up is required, or taxi drivers can take passengers on extended detours in order to increase a fare. The second, *overcharging*, involves sellers charging customers for a higher quality than is actually provided, or for a service that has not been supplied. For example, hospitals can charge patients for medicines they have not received, or taxi drivers can add unjustifiable surcharges to the meter when they are not necessary. As Dulleck & Kerschbamer (2006) highlight, although overtreatment reduces consumer welfare to the benefit of the seller, overcharging represents a direct transfer of utility from consumers to sellers.

Different market structures encourage different types of inefficiency, and the majority of previous empirical work has focused on testing the theoretical predictions of Dulleck & Kerschbamer (2006). For example, Balafoutas et al. (2013) use a field experiment to explicitly test the role of informational asymmetries, and find that the extent of overtreatment escalates as the informational disparity increases. Schneider (2012) conducted a field experiment to examine the extent of overtreatment in the market for car repairs, as well as the role played by reputation. Interestingly, Schneider finds that both overtreatment and *undertreatment* are widespread, but finds limited evidence that reputational concerns are important, possibly because of customers inability to assess service quality. Others have examined potential behavioural explanations for the deviations from the theoretical predictions, such as the importance of heterogeneity in social preferences (Kerschbamer et al., 2017), and the phenomenon of 'second degree' moral hazard (Balafoutas et al., 2015). The study of behavioural explanations and solutions to market inefficiencies has grown prominent, as in many markets it may be impossible to achieve the structure required to rule out various types of fraud, or such institutional changes may be costly or difficult to implement.[1]

The purpose of this paper is to gain further insight into how fraudulent behaviour can be reduced by exploring a less costly behavioural approach. We focus on priming, a common technique used in psychology whereby the researcher introduces a stimuli (a "prime") in

[1]See Kerschbamer & Sutter (2017) for a recent review of lab and field experiments in credence goods markets.

order to activate social knowledge structures that can impact people's behaviour outside of their awareness and control (Bargh, 2006). Hertel & Fiedler (1998) define priming as the "procedural feature that some previously activated information impacts on the processing of subsequent information". Previous work on priming in economics has been conducted in the laboratory, examining the effect of primes designed to promote cooperation (Drouvelis et al., 2015; Chen et al., 2014), competitiveness in women (Balafoutas et al., 2018), and even risk preferences (Erb et al., 2002), trust (Burnham et al., 2000), reciprocity and altruism (Cappelen et al., 2011; McKay et al., 2010).[2] Although previous work has used field experiments to examine the importance of priming for tax compliance (Kettle et al., 2017), our study distinguishes itself from others by examining how priming affects behaviour in a market setting, in a context devoid of experimenter scrutiny, and potential experimenter demand effects (Zizzo, 2010).

We conduct a natural field experiment (Harrison & List, 2004) to examine the fraudulent behaviour of taxi drivers in Vienna, Austria. We employed 40 testers to take a total of 600 individual taxi journeys. Following the methodology of Balafoutas et al. (2013), testers took journeys in groups of four, with each tester in a group catching a taxi from the same location and going to the same destination within (approximately) a one minute interval of each other. They each carried a GPS trip logger, and documented detailed information about the journey and charges associated with the taxi fare. This enables us to observe precisely how the driver defrauds the passenger: comparing GPS tracker data allows us to identify unnecessary detours, and therefore the level of overtreatment between treatments, whereas additional charges added to the taxi meter let us examine the extent and intensity of overcharging. For every journey, the tester first signalled to the driver that they were foreign and that they did not know the way to their destination, ensuring that the ride constitutes a credence good (Darby & Karni, 1973; Balafoutas et al., 2013). Testers then spoke a simple script designed to prime the driver into behaving more honestly or dishonestly. In doing so, we examine the effect of priming on fraudulent behaviour when the informational advantage of the seller over the consumer is largest.

Using a 4×1 between–subject design, the experiment exogenously varies the script spoken by the testers. In a *Baseline* treatment, the testers only signalled they were a foreigner and did not prime the driver. This serves as a control to which we can compare the other treatments. Using an *Honesty* treatment, testers inform the driver that they have heard about a study in which 80% of taxi drivers were found to behave honestly. In a *Dishonesty* treatment, testers provide drivers with the exact same information as the *Honesty* treatment, but instead emphasise that 20% of drivers were found to behave dishonestly. These treatments are similar in spirit to the literature examining valence framing effects (Levin et al., 1998), where information cast in a different light can have vastly different consequences for behaviour, and how the re-description of a problem cast in positive or negative light influences information processing (Ward et al., 1997; Liberman et al., 2004). Finally, motivated by the prediction of Dulleck & Kerschbamer (2006) that competitive conditions will increase overcharging, we implement an *Uber* treatment, where testers mentioned that a competitor's price for the same journey (an Über taxi), 'seemed cheap'.

[2] We refer to Cohn & Maréchal (2016) for a review of priming in experimental economics.

We report a number of observations. First, we find that taxi fares are around five percent higher when the driver receives the *Honesty* prime in comparison to the *Baseline*. Our analysis reveals that the fare increases in the *Honesty* treatment are a consequence of drivers increasing the amount and frequency of fraudulent overcharging, rather than being due to increases in overtreatment, with drivers being around fifteen percentage points more likely to unjustifiably overcharge a passenger when the *Honesty* prime is spoken. Overcharging in the *Honesty* treatment is found to be 44% higher than the *Baseline*. Despite the *Dishonesty* treatment conveying the exact same information to drivers as the *Honesty* treatment, it is found to have no discernible effect on the drivers' behaviour. We explain these findings as potentially being a consequence of the primes altering the drivers' belief about the probability they will be caught defrauding the passenger.

Second, we find no significant treatment effects on the amount of overtreatment, with the primes having no effect on journey lengths. Importantly, this does not imply that the drivers are not overtreating our testers, but instead that overtreatment is constant between treatments. As the informational asymmetry between the passengers and drivers is high, we expect overtreatment to be prevalent, as in Balafoutas et al. (2013). This observation, taken together with our first observation, is similar to the findings of Balafoutas et al. (2015). They report evidence of increased overcharging by drivers in Athens, but no effect on overtreatment, when a passenger informs the driver they are claiming the fare from their employer.

Third, we find that priming drivers with *Uber* also produces fares that are 5% higher than the *Baseline*. In contrast to the *Honesty* treatment, we find no significant effect of the prime on either overtreatment or overcharging. The fare increases associated with this treatment are attributed to a combined effect of both overtreatment and overcharging, effects that, individually, we cannot distinguish from zero.

This study makes a number of contributions. First, we contribute to the priming literature by providing evidence that priming taxi drivers with honesty increases the likelihood and intensity of fraudulent behaviour. This is done in a natural market setting devoid of intrusive experimenter scrutiny. Second, we contribute to the credence good literature by examining the prediction that increases in competition will increase overcharging. Finally, we contribute to the literature that uses field experiments to examine the predictions of theoretical models of human behaviour absent experimenter scrutiny.

The remainder of this paper is organized as follows. Section 3.2 describes the market place we study. Section 3 outlines our experimental design, motivates our treatments and outlines our hypotheses. Section 4 presents our results. In Section 5 we discuss our results, and Section 6 concludes.

2 The market

Vienna has about 4,500 officially licensed taxis.[3] There are thousands of passenger rides each week, hundreds of licensed taxi stands, and drivers can actively ply for hire by 'cruising' the streets or waiting at taxi stands. The market is highly regulated, and is comparable to

[3] See https://wien.orf.at/v2/news/stories/2921228/ (accessed 26.08.2019.) for more details.

taxi markets in other major cities such as London, New York and Athens.

As in other cities, regulation in Vienna means that taxis must use a tariff system that determines the price of a journey (the fare): for each journey, drivers charge passengers a fixed fee plus a distance and time dependent variable fee. The taxi meter is displayed prominently so the passenger can observe the price of the journey. Additionally, drivers can add extra charges conditional on the number of passengers, if the taxi was pre–ordered, if the journey destination is the airport, and any other special services.

Each extra charge can be added to the meter incredibly easily, either when the taxi has stopped, whilst the meter is still running, or both, and is done by pressing a small button on the front of the taxi meter. This button is typically located near to buttons that stop the journey, or change the variable fee. It is important to understand that for a driver to add any of additional charges to the fare, he must first consult with the passenger *by law*. Any charges that are added to the fare without the passenger's consent, or any wrongful manipulation of the variable fee is a form of overcharging and is illegal.[4]

3 Experimental design and procedure

The experiment was designed to examine the effect of priming on the extent to which drivers' fraudulently charge consumers in a real world market for credence goods. We use a field experiment to observe their behaviour in a natural interaction without intrusive experimenter scrutiny. The subjects, the taxi drivers, were unaware that our study was taking place.

3.1 Testers

To conduct the experiment we employed 'testers', or undercover confederates. The testers were hired through the subject pool at the Vienna Center for Experimental Economics, Austria. An advert was emailed to potential testers and stated that individuals were needed to assist researchers who were conducting a field experiment, the rate of pay was €10 per hour, and that this was a one time opportunity for employment. All testers were interviewed individually to guarantee sufficient English skills, were male, aged in their early to mid twenties, and wore casual clothing. Each tester was required to attend an hour long briefing and training session. The session gave testers the opportunity to practice the procedure, scripts and ask any questions. They received strict instructions about what they should say, being told to follow the scripts as closely as possible and not attempt to influence the driver in anyway. We selected only males in order to avoid any potential gender effects that might interact with our main treatment variables, as found by Castillo et al. (2013); Grosskopf & Pearce (2017); Balafoutas et al. (2015).

[4]The full tariff system, and a list of extra charges that could be added, are given in Appendix B, Table A4.

3.2 Procedure

The experimental procedure closely follows that of Balafoutas et al. (2013) and was conducted over weekdays in May 2018 and February 2019. At the beginning of each first day, 20 testers were randomly assigned into groups of four. Each group was randomly assigned a sequence of ten journeys, with all testers in a group completing the exact same sequence. For each journey in the sequence, all four testers took individual taxis from the same origin to the same destination, with a break of around 60 seconds between their journeys. All journeys began at taxi stands and ended at well known locations in the city.[5] We refer to the four identical journeys taken in quick succession by a group of testers as a *quadruple*. The order in which testers caught taxis was randomised to control for potential order effects, and the small time difference between journeys within a quadruple rules out potential confounds, as the drivers would have faced identical driving conditions.

When taking a journey, every tester carried a GPS satellite logger that recorded the route the driver took, the distance they travelled and the amount of time taken to complete the journey. Testers also carried an experimental booklet, which they completed once the journey had ended. In the booklet, testers had to first record the driver's subjective appearance characteristics, recording age, gender, and ethnicity. Second, the testers were required to record detailed information about the taxi fare, distinguishing between the metered fare, the number of extra charges added by the driver, and the charged variable fare. Extra charges can be observed by watching the driver press buttons on the meter.[6] With the exception of journeys taken to the airport, all of the journeys taken by our testers should have included no extra charges.[7]

Within a quadruple, each tester was randomly assigned to one of four treatments. For all treatments, the testers always entered the taxi at the front of queue, as is the norm in Vienna, and then spoke the following entry script, "I'd like to go to *destination x*. Do you where it is? I am not from Vienna and I do not know the way," where *destination x* is taken from Table A. This was spoken in English in order to signal to the driver that the passenger was a foreigner, and to ensure that all taxi journeys within the experiment would constitute a credence good (Darby & Karni, 1973; Balafoutas et al., 2013). This exact script is taken from Balafoutas et al. (2013), and was chosen because it represents a situation where the informational advantage of the seller is at its highest.

The experimental treatments vary the prime that the testers spoke after the initial entry script. Each prime was spoken in English in order to maintain the signal that the passenger was a foreigner. Once spoken, the testers were instructed to sit in the back of the taxi in silence. Given the entry script, and the results from Balafoutas et al. (2013), any treatment effect of a prime in comparison to the *Baseline* is at a level at which fraud is already likely be reasonably high. We implemented four different treatments, the *Baseline*, *Honesty*, *Dishonesty* and *Uber* treatments. Table 1 summarizes the experimental design, and details each of the primes. The motivation for each treatment is given below. In each

[5]Table A provides the origins and destinations of all the journeys taken.

[6]Although all drivers in Vienna are required by law to provide a printed receipt that distinguishes between the metered fare and any extra charges, many drivers still provide hand written receipts. Others provide printed receipts that do not distinguish between charges.

[7]Drivers are allowed to include an extra charge of €13 for journeys to the airport.

treatment, the statements provided to drivers are truthful.

3.2.1 Baseline treatment

The *Baseline* serves as a control treatment to which we can compare all others. No additional script was spoken in the *Baseline* treatment. As our testers all wore casual clothing, this treatment is a replication of the *Foreigner Low Income* treatment reported in Balafoutas et al. (2013), but conducted in Vienna, Austria rather than in Athens, Greece.

3.2.2 Honesty and Dishonesty treatments

For the *Honesty* and *Dishonesty* treatments, testers spoke the exact same information to the drivers, however accentuate different aspects: the *Honesty* treatment emphasises the positive portion of the information, stating that 80% of drivers were shown to behave honestly, whereas the *Dishonesty* treatment makes the negative salient, i.e., by highlighting that 20% of drivers behaved dishonestly. We take these percentages from Balafoutas et al. (2013), who find in a field experiment that foreign passengers are defrauded in around 20% of the taxi journeys taken in Athens, Greece.

These treatments are motivated by two strands of literature. First, they are conducted in the spirit of the priming literature (Ward et al., 1997; Liberman et al., 2004) and the literature examining valence framing effects Levin et al. (1998), where casting the same information in a different light can produce large behavioural differences. Second, the primes are grounded in the idea that the majority of people view themselves as honest, and behave in line with some ethical code, but may need reminding to apply this code to their decisions (Kettle et al., 2017). We hypothesise that, by making honesty (dishonesty) more salient, the taxi drivers will behave more honestly (dishonestly) in comparison to the *Baseline*, and fraudulently treat customers by smaller (larger) amounts.

3.2.3 Uber treatment

The *Uber* treatment is designed to prime drivers about their competitors and about price competition. However, the treatment is designed such that no actual pricing information is revealed, removing the possibility that the driver might form a reference point or target a particular fare. This treatment is motivated by Dulleck et al. (2011), who show that under certain competitive market conditions we would expect sellers to provide consumers with the appropriate quality of the good, but overcharge them. We hypothesise that priming sellers with competition will increase the extent to which they fraudulently overcharge consumers, relative to that observed in the *Baseline*.

4 Results

In this section, we outline the results from the field experiment. We use a number of common features throughout the analysis. Where non–parametric tests are used, both the p–value and test statistic are presented in parentheses. All tests are two sided unless

Treatment	*Entry Script*	*Prime*
Baseline	✓	No prime spoken.
Honesty	✓	"Did you hear about that study where researchers found that around 80 % of taxi drivers were shown to behave honestly towards passengers, always taking them on the cheapest route? I read about it on the internet."
Dishonesty	✓	"Did you hear about that study where researchers found that around 20 % of taxi drivers were shown to behave dis-honestly towards passengers, taking them on more expensive routes than necessary? I read about it on the internet."
Uber	✓	"I checked the Über price on line and it seemed cheap."

Table 1: Experimental Design Summary

otherwise stated. In total we collected 150 observations per treatment giving us a total of 600 observations.[8]

4.1 Overtreatment

Given our experimental design, our measure of how a prime affects overtreatment is calculated at the quadruple level, and the effects of a prime are always determined relative to our *Baseline* treatment. As the effect of a prime on overtreatment will manifest itself in the distance taken by the driver, through an increase or decrease in unnecessary detours, we examine if the distance travelled when a particular prime is spoken systematically differs to the *Baseline*.

Following Balafoutas et al. (2013), we first normalise the distance observed using prime p in quadruple i, $D_{p,i}$, by dividing it by the distance of the *Baseline* journey from the same quadruple i, $D_{b,i}$. An identical procedure is done for fares. The normalised distance, $N_{p,i}$, for each prime p, for each quadruple i, is therefore calculated as

$$N_{p,i} = \frac{D_{p,i}}{D_{b,i}}. \tag{1}$$

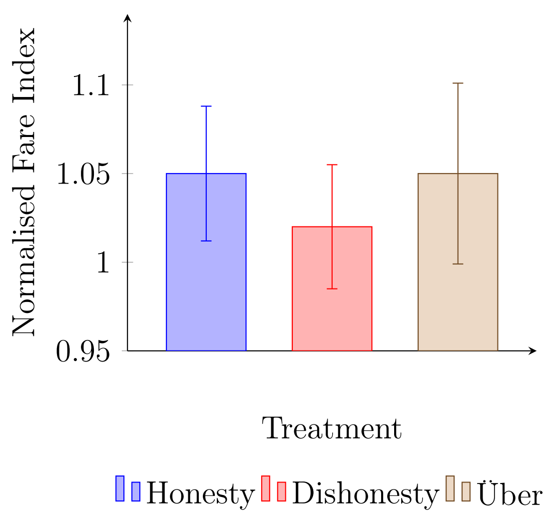
Normalising the outcome variable of interest in this way allows us to consider any treatment effects as a percentage greater than, or smaller than, the *Baseline*. As comparisons are always made to the *Baseline* treatment within a quadruple, we can rule out confounds arising from traffic variations, accidents and other random shocks. Table 2 provides a summary of the fare, normalised fare, distance and normalised distance for each of the treatments. Figure 1 presents the normalised fares graphically.

[8]Due to the unique licence plate being written on the receipt we have been able to check, whether - although very unlikely - we accidentally caught a driver twice. Note that 12 observations in each of the *(Dis)Honesty* treatments and 8 observations in the *Uber* treatment had to be excluded from the analysis for this reason, leaving us with a total of 568 observations. No observations are excluded from the *Baseline*, as the script is very general.

	Baseline	*Honesty*	*Dishonesty*	*Uber*
Fare, €	15.40	15.90	15.47	15.78
	(11.41)	(11.54)	(11.36)	(11.59)
Normalised Fare	1	1.05	1.02	1.05
	(0)	(0.23)	(0.21)	(0.31)
Distance, km	6.37	6.37	6.34	6.54
	(5.86)	(6.03)	(5.95)	(6.09)
Normalised Distance	1	0.99	1.00	1.01
	(0)	(0.23)	(0.22)	(0.22)
Observations:	150	138	138	142

Notes: Normalised fares (distance) are calculated by dividing the paid fare (distance) from each treatment by the fare (distance) from the *Baseline* treatment in each quadruple. Standard deviations in parentheses. Some journeys from the *Honesty*, *Dishonesty* and *Uber* treatments were dropped, due to them being repeated observations of the same driver.

Table 2: Summary Statistics



Note: Error bars indicate 95% confidence intervals.

Figure 1: Normalised Fares

To formally examine if the fares are significantly different to the baseline, we conduct a number of OLS regressions. These are presented in Table 3, models (1)-(5). In each regression, the dependent variable is the normalised fare, and we include dummy variables that take values of 1 (and 0 otherwise) if the observation is from the *Honesty*, *Dishonesty* and *Uber* treatment. The *Baseline* treatment is always taken as the control, and we include a categorical variable to account for any potential order effects. Standard errors in each regression are clustered at the quadruple level. In each subsequent model, the number of explanatory variables is increased in order to examine the robustness of the estimated treatment effects. We include controls for the *Order* in which testers entered the taxis, *Tester* fixed effects, *Day* fixed effects, a set of *Driver* fixed effects and control for the driver using a satellite *Navigation System*. This final control was included as these devices both inform the driver about the shortest route, and display this information clearly to the passenger. These devices may therefore be important for the drivers' decision to overtreat the passenger or not.

Observation 1. *The Honesty and Über treatments increase fares by around 5% relative to the Baseline treatment.*

Support. Table 3, models (1)-(5) show that the coefficient estimate on the *Honesty* treatment dummy is positive and significant at the 5% level ($p \leq 0.02$ in all cases). Its magnitude is also robust to specification changes, with the estimate suggesting fares are between 5-6% larger in the *Honesty* treatment, in comparison to the *Baseline*. Similarly, the coefficient estimate on the *Uber* treatment dummy is estimated to be between 4.6-6% larger than the *Baseline*. The coefficient is found to be significant at the 10% level in models (1)-(3) ($p < 0.1$ in all cases), however, in models (4)-(5) once the full range of controls are included, it is significant at the 5% level ($p \leq 0.031$ in all cases).

Observation 1 outlines that fares are significantly larger in the *Honesty* and *Uber* treatments. However, from this observation alone it is not enough to determine if this is a result of overtreatment, or overcharging, or some combination of the two. To determine if the differences in fares between these two treatments and the *Baseline* are a result of overtreatment, we now examine the distance data collected by the GPS satellite loggers using OLS regressions. These are presented in Table 3, models (6)-(10). We conduct identical regressions to those examined for Observation 1, however now the normalised distance is the dependent variable.

Dependent Variable:	*Normalised Fare (models 1-5)*					*Normalised Distance (models 6-10)*				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Honesty Treatment	0.049**	0.052**	0.051**	0.061**	0.063**	-0.01	-0.009	-0.01	-0.003	-0.003
	(0.02)	(0.022)	(0.022)	(0.025)	(0.025)	(0.019)	(0.02)	(0.02)	(0.023)	(0.023)
Dishonesty Treatment	0.022	0.024	0.024	0.02	0.016	0.001	0.004	0.003	-0.004	-0.008
	(0.018)	(0.019)	(0.018)	(0.021)	(0.022)	(0.018)	(0.019)	(0.018)	(0.02)	(0.02)
Uber Treatment	0.046*	0.046*	0.046*	0.061**	0.064**	0.01	0.012	0.011	0.025	0.026
	(0.026)	(0.027)	(0.027)	(0.028)	(0.029)	(0.018)	(0.018)	(0.018)	(0.019)	(0.02)
Constant	1.007***	-0.108**	-0.009	1.126***	1.081***	1.007***	0.988***	1.001***	0.988***	0.968***
	(0.016)	(0.053)	(0.057)	(0.071)	(0.073)	(0.012)	(0.044)	(0.049)	(0.068)	(0.078)
Observations:	568	568	568	527	511	568	568	568	527	511
Controls										
Order	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tester		✓	✓	✓	✓		✓	✓	✓	✓
Day			✓	✓	✓			✓	✓	✓
Driver				✓	✓				✓	✓
Navigation System					✓					✓

Notes: The Normalised Fare (Distance) is calculated by dividing the fare (distance) from each treatment by the paid fare from the *Baseline* treatment. Robust standard errors in parentheses, clustered by quadruple. The presented explanatory variables are dummy variables that take a value of 1 if the observation is taken from that treatment (and 0 otherwise). ***, ** and * denote significance at the 1%, 5% and 10% level.

Table 3: Treatment Effects on Fares and Distances - OLS Regressions

Observation 2. *There are no treatment effects on journey distances.*

Support. Table 2 outlines how the normalised distances of all the treatments are close to 1. This implies that the distance taken by the driver when treated with any of the three primes is similar to the distance of the journey in the *Baseline*. Table 3 lends formal support to this, with models (6)–(10) estimating the coefficient on all the treatment dummies to be close to zero and insignificant at conventional levels ($p > 0.1$ in all cases, and in all models).

Observation 2 suggests there is no difference in the level of overtreatment between the treatments and the *Baseline*. Importantly, Observation 2 does *not* imply that overtreatment is not observed. On the contrary, as our *Baseline* treatment represents a situation where the informational difference between seller and consumer is at a maximum, overtreatment is potentially prevalent (Balafoutas et al., 2013).[9] As fares are significantly higher in both the *Honesty* and *Uber* treatments in comparison to the *Baseline*, but the level of overtreatment is identical, this suggests that drivers must be overcharging customers by larger amounts, or be overcharging them more frequently, in journeys in which they receive the *Honesty* and *Uber* primes.

4.2 Overcharging

To examine the source of the differences in fares between treatments, we consider the detailed information collected by our testers. As specified in Section 3.2, each tester recorded various methods of overcharging associated with the journey. We obtain the number of *Extra charges* added to the meter observed from button presses, how much *Kept Change* the driver took once the tester had paid, and also *Other Charges*, such as if the driver manipulated the tariff or not. We know these additional charges were added to the fare because of the information recorded on the receipts, and by analysing the data collected from the GPS satellite loggers.[10]

In order to keep the analysis concise, we focus our analysis on the amount of *Total Overcharging* committed by the driver, which is the sum of all three individual measures, as it is this measure that captures the total amount of fraudulent behaviour. Table 4 summarizes the collected information in detail. Figure 2 presents the amount of overcharging observed in each treatment, in Euros, graphically.

To determine the effects of the primes on how much overcharging occurs, we conduct a number of Tobit regressions, with total overcharging as the dependent variable. To determine the impact of the primes on whether drivers overcharged passengers or not, we conduct Probit regressions with a dummy variable that takes a value of 1 if the driver overcharged

[9] It's important to note that, by looking at the logged GPS data, there is limited evidence that the vast majority of drivers took detours. However, some drivers quite clearly do take extended journeys. The raw GPS data is available from the authors upon request.

[10] In some cases, the variable rate charged was recorded on the receipt, and in others it was not. Some testers reported that they were unable to tell if the driver had manipulated the fare, but paid inflated fares despite identical journal distances. For example, some drivers were reported to purposefully obscured button presses or the meter during the journey and then provided a receipt that did not record any charges. Appendix A discusses this in further detail.

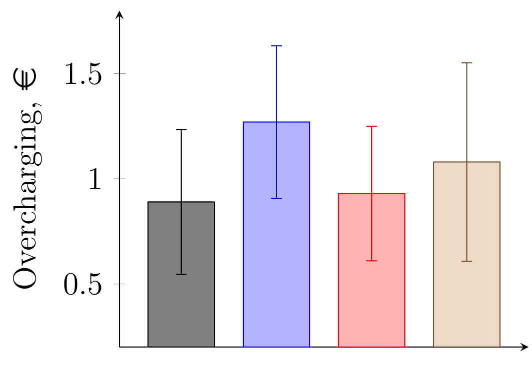


Figure 2: Total Overcharging, €

	Baseline	*Honesty*	*Dishonesty*	*Uber*
Proportion of Journeys with Overcharging	0.43 (0.50)	0.57 (0.50)	0.51 (0.50)	0.46 (0.50)
Total Overcharging, €	0.89 (2.17)	1.27 (2.18)	0.93 (1.92)	1.08 (2.87)
Extra Changes, €	0.18 (0.67)	0.15 (0.75)	0.10 (0.47)	0.14 (0.55)
Kept Change, €	0.12 (0.29)	0.13 (0.26)	0.11 (0.23)	0.18 (0.95)
Other Charges, €	0.59 (2.05)	0.98 (2.05)	0.71 (1.69)	0.76 (2.38)
Observations:	150	138	138	142

Notes: Standard deviations in parentheses.

Table 4: Overcharging Summary Statistics

the tester (and 0 otherwise) as the dependent variable. In each of these regressions, we include a dummy variable for each of the primes, and vary the same sets of controls as those described in Section 4.1. The controls are increased in each subsequent regression to examine the robustness of the estimates, and we cluster all observations at the quadruple level.

Table 5 presents all our estimates, with the Tobit regressions presented in models (1)–(5). The average marginal effects from the Probit regressions are presented in models (6)–(10).[11]

[11] Full Probit regression estimates are presented in Appendix D.

Dependent Variable:	*Total Overcharging, models (1)–(5)*					*Overcharged or Not, models (6)–(10)*				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Honesty Treatment	0.372*	0.384*	0.38*	0.493**	0.506**	0.145***	0.148**	0.15***	0.153**	0.142**
	(0.21)	(0.225)	(0.224)	(0.237)	(0.239)	(0.056)	(0.058)	(0.058)	(0.062)	(0.063)
Dishonesty Treatment	0.036	0.035	0.033	-0.071	-0.233	0.067	0.056	0.058	0.043	0.023
	(0.242)	(0.223)	(0.221)	(0.242)	(0.226)	(0.062)	(0.061)	(0.06)	(0.06)	(0.062)
Uber Treatment	0.194	0.188	0.185	0.242	0.238	0.023	0.003	0.004	0.003	-0.003
	(0.308)	(0.293)	(0.289)	(0.28)	(0.278)	(0.063)	(0.062)	(0.062)	(0.062)	(0.064)
Constant	0.872***	0.805	0.868	1.749**	1.737**					
	(0.238)	(0.548)	(0.553)	(0.763)	(0.824)					
Observations:	568	568	568	527	511	568	568	568	527	511
Controls										
Order	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tester		✓	✓	✓	✓		✓	✓	✓	✓
Day			✓	✓	✓			✓	✓	✓
Driver				✓	✓				✓	✓
Navigation System					✓					✓

Notes: Baseline treatment is taken as the baseline. Robust standard errors in parentheses, clustered by quadruple. The number of observations falls as the number of controls are increased due to missing entries. Models (1)–(5) are Tobit regressions censored at 0. The presented explanatory variables are dummy variables that take a value of 1 if the observation is taken from that treatment (and 0 otherwise). Models (6)–(10) are Probit regressions, and the presented coefficients are the estimated average marginal effects of the treatment dummies. Regression coefficients are given in Table A5, Appendix D. In all models the *Baseline* treatment is taken as the baseline. ***, ** and * denote significance at the 1%, 5% and 10% level.

Table 5: Treatment Effects on the Amount and Frequency of Overcharging

Observation 3. *The Honesty treatment increases the amount and frequency of overcharging in comparison to the Baseline treatment.*

Support. Table 5, models (1)-(5) outline how the coefficient on the *Honesty* priming dummy is always positive and significant, becoming significant at the 5% level as the number of controls is increased. The magnitude and sign of the coefficient is robust to specification changes. This suggests the *Honesty* prime significantly increases the amount of overcharging by a driver. Considering the frequency of overcharging, Table 5, models (6)–(10) estimate the marginal effect of the *Honesty* dummy to be positive and significant at the 1% level ($p < 0.01$ in all cases). This suggests that the frequency of overcharging is increased by around 15% in comparison to the *Baseline*. The marginal effects on all other treatment dummies are not significantly different from zero ($p > 0.1$ in all cases).

Our observations highlight how the *Honesty* treatment increases fares relative to the *Baseline* by increasing the extent and intensity of overcharging; total overcharging is increased from around €0.90 to around €1.30, an increase of around 44%. The frequency of overcharging is increased by around 15%. This observation goes against our initial hypothesis that the *Honesty* prime would reduce fraudulent behaviour. It is also interesting to note that the *Dishonesty* treatment has no discernible effect on the behaviour of drivers, despite the exact same information being conveyed to the driver. Further, Observations 2 and 3 highlight how the *Uber* treatment does not produce significantly more overtreatment or overcharging in comparison to the *Baseline*, despite fares being significantly larger.

5 Discussion

Our observations raise a number of questions. First, why do drivers respond to the *Honesty* treatment by behaving less honestly, and why does the *Dishonesty* treatment produce no discernible effect? Second, why do drivers in the *Honesty* treatment use overcharging, rather than overtreatment, in order to defraud passengers? Third, how can we reconcile the observation that *Uber* treatment increases fares, but has had no significant effect on behaviour?

An explanation for the drivers' response to the *Honesty* treatment could be related to their beliefs about the proportion of drivers behaving honestly. As the prime emphasises the proportion of drivers behaving honestly, upon hearing the prime the driver may update his beliefs such that he believes the passenger believes the majority of drivers behave honestly, and that the customer is trusting taxi drivers in general. As the truthful information provided to drivers was taken from a study conducted in Athens, rather than Vienna, it is possible the information altered their beliefs significantly. The driver's belief about the probability that he would be scrutinised by the passenger would then go down, and be smaller than if the *Honesty* prime were not spoken, i.e. would be smaller than beliefs in the *Baseline*. As such, drivers hearing the *Honesty* prime would have a greater incentive to defraud the passenger in comparison to the *Baseline*.

In contrast, the *Dishonesty* treatment emphasises the proportion of dishonest drivers. Upon hearing the prime, a driver may form a belief that the passenger believes a large proportion of drivers behave dishonestly, and are therefore *more* likely to inspect his behaviour, that the customer is suspicious of taxi drivers, and if the taxi driver wants to defraud the customer, he has to be more careful. This may then cause the driver to reduce the level of fraud, in comparison to the *Baseline*. However, as the experimental design is such that the informational asymmetry between the passenger and driver is high, drivers may believe there is a minimum level of fraud that they can successfully apply to the fare without being caught. This would then explain why drivers do not reduce the amount of fraud in the *Dishonesty* treatment in comparison to the *Baseline*.

The observation that the *Uber* treatment produces significantly higher fares in comparison to the *Baseline*, but no individual overtreatment and overcharging effects, is likely a consequence of the prime increasing both forms of fraud by small amounts. When considered individually, the increases in both overtreatment and overcharging are not significant, as evidence in the coefficient estimates on the *Uber* treatment dummy in Table 3 models (6)–(10) and Table 5 models (1)–(5). However, when considering the total amount of fraud (the sum of overtreatment and overcharging) by comparing fares, the *Uber* treatment then produces a significant treatment effect in comparison to the *Baseline*. This provides some support for the theoretical prediction regarding increased competition, and increased overcharging, made by Dulleck & Kerschbamer (2006).

6 Conclusion

We present a natural field experiment designed to examine if priming can reduce the fraudulent behaviour of taxi drivers in a real world market for credence goods. Using undercover passengers equipped with GPS satellite loggers, we collected data on 600 individual taxi rides in the Austrian capital of Vienna. Using a 4×1 between–subject design, we exogenously varied the prime spoken to drivers. Building on the novel experimental design of Balafoutas et al. (2013), we minimize potential confounds by taking journeys in *quadruples*, each within 60 seconds of each other. The data gained from the GPS trackers along with the comprehensive data collected by the testers, and from receipts, enables us to distinguish between the two channels of fraud in this market: overtreatment and overcharging.

In contrast to our hypotheses, our main conclusion is that the priming either increased or had no effect on the fraudulent behaviour of taxi drivers. While the *Honesty* and *Uber* treatment are shown to increase total fares by around 5% relative to the *Baseline* treatment, the *Dishonesty* prime does not influence prices. Analyzing the channels through which prices could be inflated, we find no evidence that the primes increase overtreatment relative to the *Baseline*. Instead, we report drivers overcharging in the *Honesty* treatment. The price difference of the *Uber* treatment seems to be driven by a combination of both, overtreatment and overcharging, behaviours which individually are not significantly different from zero. We explain our results as being driven by the updating of the drivers' beliefs in response to the different primes.

We acknowledge that we have focused on a single, one–shot interaction and cannot comment on any long–term impacts that our primes may have on taxi drivers. In particular, we cannot shed light on how the same driver faced with repeated primes might behave, or how the same driver primed with two different primes in sequential journeys might respond. Further, we cannot address how the driver might behave towards subsequent passengers if they too used a prime, or even if they used no prime at all. However, we have shown that using priming as a low cost tool to reduce fraud in markets for credence goods is detrimental for the consumer. Although the informational asymmetry between the expert seller and the customer is kept constant, our primes increases the price charged by the expert. The main implication of this is that a consumer who finds herself to have an informational disadvantage in comparison to a seller should say as little as possible, reducing the possibility of increasing dishonest behaviour further.

In general, and in–line with the suggestions of Levitt & List (2007), further examinations of priming in the field will shed light on both their effectiveness in different contexts and the extent to which the results obtained from the laboratory generalize to other settings. Future investigations of the stability of priming effects across time might prove fruitful. Other interesting avenues for further research could be to focus on primes that have previously been found to effect behaviour in the lab, and if primes can effect other economically relevant behaviours.

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Appendix

A Routes

Route No.	*Origin*	*Destination*	*Uber Price*
1	Main Station	Wiener Staatsoper	7.5
2	Hotel Sacher	Schottentor	10.5
3	Schottentor	Messe Wien	14.5
4	Messe Wien	Vienna Marriott	8
5	Vienna Marriott	Alser Spitz	10.5
6	Alser Spitz	Main Station	9.5
7	Main Station	Sports Center Gudrun	13
8	Sports Center Gudrun	Vienna Westbahnhof	7
9	Vienna Westbahnhof	Vienna Airport Arrival (!)	31
10	Vienna Airport Arrival (!)	Main Station	10
11	Main Station	Zipperstreet Underground Station	14.5
12	Zipperstreet Underground Station	Meidling Station	13.5
13	Meidling Station	U4 Vienna	10
14	U4 Vienna	Hietzing Hospital	18
15	Hietzing Hospital	Kennedy Bridge	11.5
16	Kennedy Bridge	Johann-Nepomuk-Berger-Place	5.5

Table A1: Routes Part 1/3

Route No.	*Origin*	*Destination*	*Uber Price*
17	Johann-Nepomuk-Berger-Place	Nussdorfer Street Station	7
18	Nussdorfer Street Station	Sieveringer Street McDonalds	6
19	Sieveringer Street McDonalds	Alterlaa Bowling Center	28.5
20	Alterlaa Bowling Center	Main Station	17.5
21	Main Station	Vienna Meidling Station	7.5
22	Vienna Meidling Station	Alterlaa Bowling Center	12.5
23	Alterlaa Bowling Center	Vienna Liesing Station	8.5
24	Vienna Liesing Station	Vienna Uno city	30.5
25	Vienna Uno city	Rennbahnweg Station	9
26	Rennbahnweg Station	Messe Wien	12
27	Messe Wien	Schottentor	11.5
28	Schottentor	Ambassador Hotel	9.5
29	Ambassador Hotel	Vienna Marriott	5
30	Vienna Marriott	Main Station	7
31	Main Station	Vienna Airport Arrival (!)	30
32	Vienna Airport Arrival (!)	Vienna Westbahnhof	32

Table A2: Routes Part 2/3

B Vienna taxi tariffs

The Viennese taxi fares are taken from here. In addition to the local authority provides the following additional information about the taxi tariff system, in particular where possible additional surcharges may be added to the fare:

- 1 surcharge if the taxi was ordered via a "taxi-rank-phone" (Standplatztelefon);
- 2 surcharges if the taxi was ordered via call centre (Taxifunkzentrale);
- € 2.00 surcharge for the carriage of 4 or more passengers;
- € 13.00 surcharge if the destination is the airport and the taxi was not pre-ordered;
- further surcharges e.g. for loading the luggage or for going to the station are prohibited.
- The driver has to inform the passenger about any surcharges added.

Charging anything different than mentioned is an administrative offence.

Route No.	*Origin*	*Destination*	*Uber Price*
33	Vienna Westbahnhof	Sports Center Gudrun	11.5
34	Sports Center Gudrun	Main Station	6.5
35	Main Station	Alser Spitz	10.5
36	Alser Spitz	Vienna Marriott	8
37	Vienna Marriott	Messe Wien	10
38	Messe Wien	Schottentor	12
39	Schottentor	Wiener Staatsoper	7.5
40	Hotel Sacher	Main Station	6.5
41	Main Station	Alterlaa Bowling Center	10
42	Alterlaa Bowling Center	Sieveringer Street McDonalds	35.5
43	Sieveringer Street McDonalds	Nussdorfer Street Station	6
44	Nussdorfer Street Station	Johann-Nepomuk-Berger-Place	8
45	Johann-Nepomuk-Berger-Place	Kennedy Bridge	9
46	Kennedy Bridge	Hietzing Hospital	7.5
47	Hietzing Hospital	U4 Vienna	11
48	U4 Vienna	Meidling Station	4
49	Meidling Station	Zipperstreet Underground Station	7.5
50	Zipperstreet Underground Station	Main Station	9

Table A3: Routes Part 3/3

		Daytime	Nighttime/Weekend
Fixed Fee		€ 3.80	€ 4.30
Variable Fee (Mileage Charge, Wait Time Charge)	0-4,000m	€ 0.20 per 140.7m	€ 0.20 per 123.2m
	4,000-9,000m	€ 0.20 per 184.6m	€ 0.20 per 156.8m
	>9,000m	€ 0.20 per 190.6m	€ 0.20 per 169.5m
	Waiting Time	€ 0.20 per 25.9sec.	€ 0.20 per 25.9 sec.
One Surcharge		€ 1.40	€ 1.40

Table A4: Viennese Taxi Fares by Time

C Overcharging Calculation

In a minority of cases where either the helper was not able to tell whether the driver added charges, or the prices varied from the other rides in the *quadruple* despite no charges being recorded as being added, we calculated *Other Charges* by analysing the GPS logger data, alongside the information presented on the receipts from the taxi driver. This is because the driver is likely to have added charges in a manner undetected by the tester. This was done in the following systematic way:

- We compared the prices within every quadruple. If the prices were equal (+/- €0.40) we set our overcharging dummy (OCD, hereafter) to 0; otherwise if prices were different:
  - Is the difference in (i) distance, (ii) time justifying the price difference? (i.e. is there a 300–400metre difference in journey distance?)
    - If yes, $OCD = 0$, as it is overtreatment rather than overcharging.
    - If no, $OCD = 1$, and *Other Charges* equals the difference between the cheapest ride within a quadruple and the ride itself.
  - If the (i) distance, (ii) time from the cheapest ride is n.a., then the (i) distance, (ii) time from the second cheapest has been taken.
  - If multiple rides have the cheapest price, compare with the ride with the shorter distance.
  - If *Kept Change* or *Extra charges* are >0 and $OCD = 0$, then the amount is *Other Charges* and OCD is set to 1.
  - If the ride's destination is the airport, €13.00 are excluded from *Extra Charges* because this is a standard charge.

D Full Probit Regression Estimates

Model:	(6)	(7)	(8)	(9)	(10)
Honesty Treatment	0.368**	0.406**	0.411**	0.441**	0.413**
	(0.143)	(0.16)	(0.161)	(0.179)	(0.183)
Dishonesty Treatment	0.169	0.153	0.157	0.124	0.066
	(0.157)	(0.165)	(0.165)	(0.172)	(0.18)
Uber Treatment	0.059	0.009	0.011	0.008	-0.01
	(0.16)	(0.171)	(0.172)	(0.18)	(0.185)
Observations:	568	568	568	527	511
Controls					
Order	✓	✓	✓	✓	✓
Tester		✓	✓	✓	✓
Day			✓	✓	✓
Driver				✓	✓
Navigation System					✓

Notes: Controls correspond to the controls described in Section 4. Model numbers correspond to the Probit regressions in Table 5.

Table A5: Full Probit regressions for Table 5

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Parampreet Christopher Bindra, Graeme Pearce

The effect of priming on fraud: Evidence from a natural field experiment

Abstract
We present a natural field experiment designed to examine the extent to which priming can influence the behaviour of sellers in a real world market for credence goods. We employed 40 testers to take 600 taxi journeys in and around Vienna, Austria. Using a between-subject design we vary the script spoken by testers, with each script designed to prime either honest behaviour, dishonest behaviour, or the existence of a market competitor. In contrast to our hypotheses, we find that priming honesty increases taxi fares by 5 % in comparison to a baseline, increasing the frequency of overcharging by 15 % and the amount overcharged by around 44 %. The dishonesty prime has no impact. The market competitor prime increases both overcharging and overtreatment by amounts that are individually indistinguishable from zero, but jointly raise fares by 5 %. All of the treatments are found to have no significant effect on journey length (overtreatment).

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