Contagious Dishonesty: Corruption Scandals and Supermarket Theft

BSE Working Paper 1267
July 2021 (Revised: April 2022)

Giorgio Gulino, Federico Masera

Contagious Dishonesty:
Corruption Scandals and Supermarket Theft*

Giorgio Gulino
UPF and Barcelona GSE

Federico Masera
University of New South Wales

April 9, 2022

Abstract

Is dishonest behavior contagious? We answer this question by studying whether corruption scandals affect the propensity of supermarket customers to steal while using a self-service checkout system. Crucially, this system allows shoppers to engage in dishonest behavior by under-reporting the value of their shopping cart. Exploiting data from random audits on shoppers, we show that the probability of stealing increases by 16% after a local corruption scandal breaks. This effect is not driven by any change in material incentives. Suggestive evidence shows that it is driven by a reduction in the self-imposed cost of stealing triggered by emotions.

JEL Classification: D73, K42, Z1, A13

Keywords: Corruption, Crime, Consumer behavior, Norms

*We are grateful to Ernesto Dal Bó, Paolo Buonanno, Matteo Cervellati, Federico Curci, Gianmarco Daniele, Jennifer Doleac, Ruben Durante, Fred Finan, Gabriele Gratton, Pauline Grosjean, Sergei Guriev, Marco Le Moglie, Giovanni Mastrobuoni, Ricardo Perez-Truglia, Maria Petrova, Salvatore Piccolo, Paolo Pinotti, Steven Raphael, Michele Rosenberg, Paolo Vanin, Juan Vargas and Guo Xu, as well as seminar participants at the University of Antwerp, University of Bergen, University of Bergamo, University of Bologna, University of Barcelona, CUNEF Universidad, Monash University, Pompeu Fabra University, Tor Vergata University of Rome and the XIII Ridge Forum Workshop on the Economics of Crime and ASREC24h conference. Giorgio Gulino acknowledges financial support from the Spanish Ministry of Economy and Competitiveness, through the Severo Ochoa Programme for Centres of Excellence in R&D [CEX2019-000915-S]. Giorgio Gulino acknowledges financial support from the European Union's Horizon 2020 research and innovation program [Grant 759885]. This project received ethics approval from UNSW (HC210155).

1 Introduction

Corruption, the abuse of public power for private gains, is a pervasive problem that affects many countries worldwide.[1] Due to the scale of the phenomenon, the United Nations recognizes corruption as one of the greatest impediments to achieving the Sustainable Development Goals.[2] Policymakers and scholars are concerned that the detrimental effects of corruption may include broad societal harm that extends beyond its already massive direct economic cost.

This hypothesis is bolstered by empirical evidence suggesting that corruption in an individual's country of origin may affect their antisocial behavior in the lab (Barr and Serra, 2010; Gächter and Schulz, 2016; Fell, König, Jung, Sorg, and Ziegler, 2019) or in the real world (Fisman and Miguel, 2007), as well as their reported levels of trust (Chang and Chu, 2006), attitudes towards cheating (Magnus, Polterovich, Danilov, and Savvateev, 2002; Ajzenman, 2021), and perceived legitimacy of formal institutions (Anderson and Tverdova, 2003; Seligson, 2002; Solé-Ollé and Sorribas-Navarro, 2018).[3] However, whether corruption actually compromises individual honesty and the channels through which this may occur remain open questions (Muthukrishna, Francois, Pourahmadi, and Henrich, 2017).

In this paper, we empirically show that exposure to news about corruption makes individuals behave dishonestly. To do so, we study the effect of local corruption scandals on customer behavior in supermarkets, in a context where there are no obvious material cost of misbehaving. We exploit a unique individual-level dataset on customers using the *salvatempo* ("time-saver") system, a type of self-service checkout option available in a leading Italian supermarket chain. The time-saver system allows customers to scan their own products while shopping (see Figure A3). At the end of their shopping trip, they hand over the list of products scanned and pay for the total value of the items on it. Crucially, the system provides shoppers with the opportunity to engage in dishonest behavior by scanning items with a lower value than those actually in their shopping cart.

Our database consists of one year of random audits performed on shoppers in Modena and Ferrara, two Italian provinces in the region of Emilia-Romagna.[4] For each of the 280,000 audits,

[1] A well-established economic literature shows that corruption has a strong negative effect on public performance (Mauro (1998); Svensson (2005); Del Monte and Papagni (2001); Olken and Pande (2012) and Ferraz, Finan, and Moreira (2012)), private investment (Svensson (2003)) and economic development (Mauro (1995)).

[2] Declaration of United Nations Secretary-General António Guterres on Anti-Corruption Day, December 9, 2018.

[3] Additionally, corruption exhibits high geographical concentration. For example, corruption is highly correlated between neighboring cities in Spain (Lopez-Valcarcel, Jiménez, and Perdiguero, 2017), neighboring states in the US (Goel and Nelson, 2007) and neighboring countries across the world (Becker, Egger, and Seidel, 2009).

[4] See Figures A1 and A2. The two provinces are at the top of the Italian (and European) ranking in terms of per-capita income, as well as for several measures of social capital, and low levels of crime and corruption. Modena ranked 4^{th} and Ferrara ranked 53^{rd} in added value per capita in 2016 across the 110 Italian provinces

we have information on the value of the items that customers had in the shopping cart and the value of the scanned items. A customer is said to under-report if the value of items they scanned is lower than the value of items in their shopping cart.

To assemble information on local corruption scandals, we look at the online archives of the two main local newspapers in these provinces, *Gazzetta di Modena* and *Nuova Ferrara*. We use the content of the articles in these newspapers to code corruption scandals involving the public administration at the municipality level.[5] To identify whether a shopper was exposed to a corruption scandal, we use the customer's city of residence and the day of the shopping trip, which we match to the location of the corruption scandal and the day on which the scandal was made public.

In a generalized differences-in-differences setting, we show that on the days following the news of a corruption scandal, customers living in the municipality of the scandal are 2.3 percentage points more likely to under-report than shoppers living in the other municipalities. Given that, on average, 14% of shoppers under-report, this implies a 16% increase in the probability of under-reporting. The effect begins on the day after the corruption scandal is made public and is particularly large during the first four days after a scandal breaks. Smaller effects on the probability of under-reporting can even be detected 20 days after the corruption scandal was first announced.

We show that these effects are not driven by a change in the type of customers who use the time-saver technology, but rather reflect a shift in customer behavior. We also precisely estimate that corruption scandals have no effect on the probability of over-reporting (i.e., when the value of the scanned items is higher than the value of the actual shopping cart). These results indicate that the observed effect is due to an increased probability of stealing and not to selection or an increased probability of making mistakes while using the time-saver technology. Finally, to confirm that the observed effects on stealing are driven by exposure to news about corruption, we show that the effects are larger for more important and visible corruption stories and on days when corruption-related news stories are not competing with other newsworthy local events such as football games.[6]

We highlight two keys aspects of our main results. First, the percentage increase in the probability of under-reporting is most likely a lower bound of the increase in the probability

(See ISTAT). Moreover, Modena ranked 2^{nd} and Ferrara ranked 17^{th} in the number of blood bags donated per capita in 1995, which is a widely used proxy for social capital (see (Guiso, Sapienza, and Zingales, 2004) for more details).

[5]Some local corruption scandals involve politicians from more than one city. In total, we have 26 city-days with a corruption scandal.

[6]This methodology is similar to (Eisensee and Strömberg, 2007; Durante and Zhuravskaya, 2018; Djourelova and Durante, 2019) that exploit the fact that when news-pressure is high because of some important event other news stories are less visible.

of stealing, since not all under-reporting instances should be interpreted as attempts to steal. Making the simplifying assumption that over- and under-reporting mistakes are equally likely, the average probability of stealing is 7.7%. As long as scandals have no effect on the probability of making mistakes, our estimate imply that corruption scandals increase the probability of stealing from a supermarket by 30%. Second, even though the estimated effects are transitory and relate to small thefts from a supermarket, the overall effect of dishonest behavior could be quite large due to the constant media attention and the high frequency of local and national corruption scandals.[7]

We investigate possible channels and mechanisms that could lead to an increase in stealing after exposure to a corruption scandal. The effect of scandals on stealing behavior may be driven by classical material considerations. Following Becker (1968), we might expect that stealing should increase if the price of the good increases, the probability of being caught declines, or the fine received when caught stealing decreases. Our empirical analysis allows us to exclude these three mechanisms. We control for changes in price, which are common to all customers, including calendar day fixed effects. Auditing is random, and therefore the probability of being detected by an audit stays constant across the treated and control groups.[8] Finally, under-reporting is not punished by any fine or other legal costs.

We subsequently turn to two other potential channels that go beyond these direct material considerations. What may change after a corruption scandal is the salience of social norms concerning stealing at the supermarket. These social norms matter because they determine the beliefs that an individual has about the costs that others may impose if they are caught stealing at the supermarket. If an individual believes that stealing at the supermarket is frowned upon by others, this may dissuade them from stealing to avoid social punishment. In the context we study, the scope for social punishment is limited because the only other person aware of the norm violation is the cashier. Another option, even if against the supermarket's protocols, is that other customers could observe the result of the audit. If corruption scandals affect stealing behavior by changing the social costs associated with the latter, we expect the effect to differ with the likelihood that the cashier or other customers can socially punish the misbehaving customer. We test for this possibility by investigating whether the effects are larger in small shops or rural shops, shops close to where a customer lives, or at times when the store is particularly busy. We do not find heterogeneous effects along any of these dimensions. This

[7] Rizzica and Tonello (2018) note that the homepages of 30 national Italian newspapers, "over 64 days between 11 January and 22 March 2014, on average, ... recorded about 12 corruption news items per day, with a peak of 39 corruption news items on one day and a low of just one corruption news item, i.e., there was not a single day with no corruption news."

[8] Shoppers could still wrongly infer that the probability of an audit has increased, which would lead to a decrease in under-reporting. We discard this hypothesis since we find the opposite effect.

provides suggestive evidence that the effect is not driven by a reduction of the social costs associated with dishonest behavior.

Individuals may follow rules of behavior that prescribe truthfully reporting the value of their purchases. If a shopper violates or is caught violating this self-imposed norm, they may experience a utility loss, for example, due to guilt or a loss of self-worth. Exposure to a corruption scandal may modify these internal rules of behavior in two ways. On the one hand, a corruption scandal might change an individual's perception of how widespread dishonest behavior is. Findings from the literature (e.g., Bicchieri and Xiao (2009); Dimant (2019)) indicate that this can affect the cost associated with breaking such self-imposed moral norms. Beliefs about the share of dishonest individuals within one's in-group have been shown to be particularly important when determining moral behavioral norms (e.g., Bicchieri, Dimant, Gächter, and Nosenzo (2020)).[9] On the other hand, exposure to a corruption scandal may generate an emotional response that lowers one's ability to self-control and momentarily changes a customer's ability to follow their own internal rules of behavior. Taxpayers should be particularly sensitive to these emotional triggers since their taxes are used to pay the corrupt public officials. As an exploration of this mechanism we use information on customer age and employment status, to identify those who are likely to be taxpayers. We then test whether the effects are heterogeneous along this dimension and find that taxpayers are the only ones that react to a corruption scandal. [10] It is essential to underline that this only provides suggestive evidence of a potential mechanism because taxpayers are different along many dimensions from other clients.

Finally, to further examine how emotions might trigger stealing behavior, we study the effect of football results (e.g., Card and Dahl (2011); Munyo and Rossi (2013); Depetris-Chauvin, Durante, and Campante (2020)). We restrict the analysis to municipalities with a football team in the two highest leagues (*Serie A* and *Serie B*) during the period of analysis, and explore whether the outcome of the game affects the behavior of supermarket clients. Losing a game has a strong positive effect on under-reporting but no effect on over-reporting, once again suggesting that we have correctly identified stealing behavior.[11] These results reinforce the evidence that emotional triggers can cause an increase in stealing behavior at the supermarket. However, the features of the effect are different from those related to corruption scandals in two

[9]Although identifying the reference group for a given individual is extremely challenging, we exploit customers' gender and that of the public officials involved in the scandal. Gender is easily observable and is often an important characteristic that individuals use to determine their reference group. We study whether individuals react more strongly when faced with corruption scandals by public officials of the same gender. Although these findings are suggestive due to a series of caveats discussed further on in the paper, we do not find heterogeneous effects along this dimension.

[10]In Section 4 we discuss in greater detail the literature that describes how social norms, moral norms, and emotional triggers are determined and may affect dishonest behavior.

[11]We also show that winning a game has no effect on stealing behavior.

dimensions. First, the effect of losing a football game is extremely short, beginning immediately after the game ends and lasting less than 24 hours, and second, it is not concentrated in any sub-group of the customer population.

Our research contributes to several strands of literature. First, it builds on a body of work that addresses the effect of rule violations in people's social environment (e.g., corruption, tax evasion, or political fraud) on antisocial behavior (e.g., Gächter and Schulz (2016); Fisman and Miguel (2007)). In a study closer to our own, Ajzenman (2021) shows that revelations of corruption by local public officials increase secondary students' tendency to cheat on cognitive tests even a few months after the news is revealed. Instead, our paper provides robust causal evidence that news about corruption scandals affects stealing from supermarkets immediately after a news breaks, even in a context where there are no obvious material costs of misbehaving. Moreover, we show that taxpayers are the ones that initially react the most to news about corruption. The effect is not due to changes in material incentives to misbehave or changes in social norms but by an emotional response to corruption.

Building on studies that show how bad actions destroy moral capital and lock in further wrongdoing (e.g., Dal Bó and Terviö (2013)), our results may help explain how cultural traits and social norms can shift due to shorter-run factors (e.g, Winkler (2021)). In line with Cervellati and Vanin (2013), we provide evidence that these short-term factors can inhibit individuals' ability to comply with internal behavioral norms.

More broadly, our paper also relates to previous work on the impact of public figures in the setting of social norms (Acemoglu and Jackson, 2015; Hermalin, 1998), political preferences (Dippel and Heblich, 2021), unethical conduct (d'Adda, Darai, Pavanini, and Weber, 2017; Garz and Pagels, 2018; Cagé, Dagorret, Grosjean, and Jha, 2020; Grosjean, Masera, and Yousaf, 2020), and short-run beliefs and behavior (Bassi and Rasul, 2017; Stroebel and van Benthem, 2012). Our results suggest that leaders might affect citizens propensity to behave dishonestly by changing their self-imposed moral costs of stealing.

Finally, our paper also relates to the literature on the role of morals (non-monetary incentives) in explaining cheating, cooperation, tax compliance and dishonest behavior in general. Due to the unique challenges of causally identifying the effect of non-material incentives, a recent but growing literature studies the effect of moral suasion on individual behavior, primarily by means of lab and field experiments that focus on individuals' subsequent tax compliance.[12] While some of these experiments find a positive effect of tax morale messages on tax compliance (Hallsworth, List, Metcalfe, and Vlaev, 2017; Perez-Truglia and Troiano, 2018), others

[12] See Luttmer and Singhal (2014) for a literature review on "Tax Morale" and Slemrod (2019) on tax compliance and enforcement.

consistently observe that invoking social norms fails to reduce tax evasion (Fellner, Sausgruber, and Traxler, 2013; Bérgolo, Ceni, Cruces, Giaccobasso, and Perez-Truglia, 2017; Bergolo, Leites, Perez-Truglia, and Strehl, 2020; De Neve, Imbert, Spinnewijn, Tsankova, and Luts, 2019). Various reasons could explain such mixed findings: moral incentives may play a marginal role in changing dishonest behavior or the messages transmitted during lab and field experiments may be not strong enough to affect human behavior. Our paper, exploiting a natural experiment in a controlled environment, qualifies these findings by showing that when the moral message sent is strong enough, through the power of example, it has a sizeable effect on self-imposed moral costs and, consequently, on the probability that a customer behaves dishonestly.

The remainder of the paper is organized as follows. Section 2 introduces the time-saver technology and describes the selection of news stories. Section 3 discusses the results on the relationship between scandals and stealing behavior. Sections 4 and 5 present evidence on the mechanism and discuss our conceptual framework. Finally, Section 6 concludes.

2 Background and Data

2.1 Individual-Level Data on Shoppers' Behavior

We use data from the supermarket *Coop Alleanza 3.0* (Coop) located in the Italian provinces of Modena and Ferrara in the region of Emilia-Romagna (See Figures A1 and A2 in the Appendix). Coop is one of the largest supermarket chains in Italy, accounting for 14.5% of the national market share and about 35% of the market share in Emilia-Romagna.[13]

We exploit a panel of audit-level data on shoppers' behavior when using the *time-saver technology*. The system allows shoppers to self-scan their products while shopping so that there is no need to scan them at the end of the shopping trip. Only registered members of the supermarket can access the time-saver technology.[14] Once the customer enters the store, they can decide to take a barcode scanner (see Figure Figure A3 in Appendix) and start scanning. At the end of the shopping trip, the customer places the barcode scanner in a checkout stand and pays for the value of the items they scanned. In other words, time-saver technology allows customers to self-declare the value of their purchases.[15] The supermarket audits at random

[13] Data is from the year 2016. More information is available from Coop at the following link. In Table A27, we compare the overall population to the population of customers in our database. Women, employed individuals, and the active population tend to be over-represented in the audited population.

[14] Membership costs €25 and does not need to be renewed once obtained. It provides access to a series of services that are not solely related to supermarket purchases. Members can access offers and promotions, use meal vouchers, pay bills, and receive discounts for theaters, cinemas, gyms, courses, exhibitions and other opportunities related to culture, sport, and leisure.

[15] The system is designed to allow customers to save time during the checkout process. It also dramatically

a fixed share of clients and checks if their self-declaration matches the actual contents of the shopping chart.[16]

During the audit, the customer must take all the products out of the bags and a cashier scans them again one by one. Supermarkets record both the products that the customer had in the shopping cart and the ones they scanned using the barcode scanner. There are two exceptions to the perfect randomization of audits just described: i) if the customer has under-reported beyond a certain threshold in the past, the probability of being audited increases;[17] ii) security agents can ask for an audit if they suspect that the shopper is trying to pay less than the actual value of their shopping cart. However, this is an extremely rare event. In our analysis, we can control for such changes in auditing behavior.[18]

Discrepancies between the scanned items and the actual shopping cart may be caused by two types of behavior. First, individuals may commit an honest mistake when using the time-saver technology. For example, a customer may forget to scan an item or scan the same product twice. Second, individuals may willingly under-report by not scanning certain items or scanning items of a lower value than what they actually purchased. It is important to note that under-reporting can be caused by both mistakes and stealing behavior, while it is safe to assume that over-reporting is due solely to errors.

When cashiers detect any discrepancies, they are trained to avoid any form of shaming. First, they are not to verbally report small mistakes. These are simply recorded in the receipt given to the customer. Second, cashiers are instructed to verbally signal mistakes above a certain threshold in such a way that other consumers are unlikely to overhear. As mentioned, the time-saver technology is a service offered by the supermarket to increase customers and reduce the size of the labour force. The company tries to prevent the possibility of clients feeling offended when audited, since ultimately they want to increase the number of customers using this technology, which reduces personnel costs.[19]

Our database comprises one year of random audits, about 260,000 records.[20] The first

reduces queues, enabling the company to hire fewer employees and cashiers.

[16]One customer per N shoppers is audited at each check-out stand. For security reasons, *Coop Alleanza 3.0* does not allow us to disclose the exact number of N.

[17]The supermarket does not allow us to reveal the threshold above which the probability of being audited increases. However, we know that if the client does not make any mistakes during a subsequent audit, the probability of being audited goes back to normal. Furthermore, the fraction of these customers is small: the share of customers who under-report more than €10 (€5) is 0.01% (2.5%).

[18]We spoke with several Coop managers and they assured us that they train their agents to minimize such discretionary audits. In any case, our identification strategy takes this possibility into account.

[19]The company is aware that this policy will result in some customers under-reporting, and hence a certain degree of lost revenue. It states, however, that the higher number of customers and the reduction of personnel costs more than compensate for the loss.

[20]For the purpose of this analysis. we only use audits of residents of the provinces in the study area (Modena and Ferrara). The database also contains customers who shop in these supermarkets but are not formal residents (e.g., university students and commuters). However, as Table A25 in the Appendix shows, these represent a

audit of the database was recorded on November 23^{rd}, 2016 at 7:57:51, while the last one is timestamped November 19^{th}, 2017 at 20:28:59. The sample includes about 103,000 clients, each of whom was audited 2.5 times on average, or once every 4.5 months. Each record also includes the customer membership card number, which allows us to follow their behavior across days and audits. The membership number also allows us to access some of their personal information such as age, sex, postal code of residence and employment status (see Table A24 for summary statistics). In addition, we know the day, time and location of the supermarket visit. Figure A2 shows that the 35 supermarkets in the sample are mainly clustered around the provincial capitals and other large municipalities, while clients come from all 78 municipalities of the two provinces. We see in Table A24 that 14% of records show some level of under-reporting, while 6% of cases exhibit over-reporting.

One important feature of this dataset is that we are able to observe individuals that under-reported and those who could have under-reported but decided not to. This differs strikingly from much data on antisocial behavior and crime. Most such datasets only allow observations of when individuals perform a criminal act and are caught. This unique feature allows us to overcome two common issues that are encountered while studying the determinants of criminal behavior. First, we are able to measure the change in the likelihood of committing a crime when faced with the possibility of doing so. Usually, crime data cannot be used in this manner because any change in the amount of crime observed cannot be clearly traced back to either an increased likelihood of committing a crime or an increase in opportunities to commit a crime. Second, we can measure whether our results are driven by a change in the selection of individuals. With common crime data, any change in the number of crimes observed could be driven by changes in the likelihood of committing a crime or by the composition of individuals faced with the opportunity to commit a crime.

2.2 Daily Local Corruption Scandals

In order to study the role of corruption scandals on stealing behavior in supermarkets, we assemble information from two local newspapers, *Gazzetta di Modena* and *Nuova Ferrara*, the provinces' two main local newspapers. They both belong to the same editorial group and have an online archive from which published articles are available. In order to select newspaper articles from the period of interest, we download all the articles containing the words "corruzione" (corruption), "concussione" (extortion by a public official), and "abuso d'uffcio" (abuse of power by a public official)—this step of the process delivers around 200 newspaper articles. First, we discard all cases of corruption that did not involve a public official or a worker

small fraction of the total sample.

in the public sector of the two provinces. These articles are mainly national-level corruption scandals, cases from other regions, conferences on the topic or book presentations. Among the 52 news articles left, we identify 20 local corruption scandals during the period covered by the audit dataset. Since some corruption scandals involve officials from multiple municipalities, we have a total of 26 city-days with a corruption scandal. This category includes articles that provide new and negative information about a corrupt public official. These news articles are reminiscent of when the scandal breaks out or when they reach an essential step in the court process, for example, arrests, suspensions from public office, or heavy sentences. We selected news about corruption that provide new and negative information for two main reasons. (i) According to a simple model of Bayesian updating, new and negative information about the level of corruption should affect customer beliefs more than neutral information about corruption. (ii) News that provides new and negative information is more read and talked about, as shown by the evidence presented in the following sections.

Table A1 in the Appendix shows the headlines of the articles covering a scandal (in Italian), the affected municipalities, and the day on which the articles were published.[21] Figure A4 shows the distribution of news over the period of interest, while Figure A5 that of scandals across municipalities. We see that scandals are evenly distributed during the period that courts work at full capacity. Note that, although there are scandals in both provinces, municipalities in the province of Modena are more prone to scandals than those in the province of Ferrara: nine municipalities in Modena and three municipalities in Ferrara have at least one corruption scandal during the year. This is consistent with the fact that Modena has a population that is twice as large as the population of Ferrara.[22]

We classify the news about local corruption that is not a scandal in two different categories. Neutral news (28 articles). This category generally includes journalistic comments on the trial, procedural steps, or statements by lawyers; none of them provides new information. Positive news (4 articles). This category concerns cases of total acquittal or dismissal. In the following sections, we also study the effect of these other news categories, showing that none of them affects customers' under-reporting behavior and does not generate any interest.

[21]Full articles are accessible through the links provided in Table A1 and searching for the news headline in the archive.

[22]The population of the province of Modena was 701,642 in 2016, while the population of Ferrara was 351,436. *Source*: Italian National Institute of Statistics (ISTAT).

3 Baseline Results

To study the effect of corruption scandals on shoppers' behavior, we first define $T_{c,t}^{a}$ as a dummy equal to 1 if, in municipality c and on day t, the distance in time to the closest corruption scandal is a days. Similarly, we define $T_{c,t}^{>a}$ (and $T_{c,t}^{<a}$) as a dummy equal to 1 if, on day t, the distance to the closest corruption scandal is more (or less) than a days. We measure the distance to a corruption scandal such that it is positive if day t is after the corruption scandal and negative if it is before the corruption scandal. These dummies are always equal to zero in municipalities with no corruption scandals in our sample period.

We then estimate the following event study:

$$Y_{i,c,t} = \alpha_{PRE} T_{c,t}^{<-7} + \sum_{\tau \neq -1} \alpha_{\tau} T_{c,t}^{\tau} + \alpha_{POST} T_{c,t}^{>7} + \delta_c + \mu_t + \epsilon_{i,c,t} \tag{1}$$

where $Y_{i,c,t}$ is a dummy taking a value of 1 if customer i, resident in municipality c and audited on day t, is found to under-report and 0 otherwise. The baseline specification also includes municipality δ_c and day μ_t fixed effects. The municipality fixed effects absorb any systematic difference in under-reporting across municipalities due to time-invariant characteristics, including local characteristics of the population, which may influence the likelihood of under-reporting. Calendar day fixed effects account for common trends of under-reporting in all municipalities in any given day, such as national or regional corruption scandals that may affect all customers' likelihood of under-reporting. Since this is a fully saturated event study, where the excluded dummy variable is $T_{c,t}^{-1}$, we interpret α_{τ} (for positive τ) as the change in the probability of under-reporting τ days after the corruption scandal with respect to the day just before it broke in the city where it occurred.

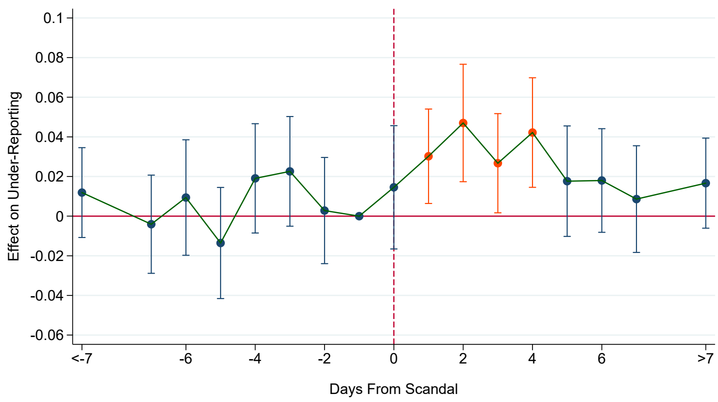
To interpret these estimates as the causal effect of corruption scandals, we follow a potential outcomes framework. The identification strategy is based on the assumption that, absent the corruption scandal, we should not observe any differential changes in under-reporting behavior between the day just before and the days after a corruption scandal in the municipality that had the corruption scandal relative to other municipalities.

We believe that this assumption is valid in our setting for two main reasons. First, given the quasi-random nature of the audits, the behavior we observe is representative of under-reporting behavior of the whole population of customers. Second, because we control for municipality and day fixed effects, we only exploit the randomness of the exact date when a particular corruption scandal is made public. As corruption scandals are made public after a court decision or a police operation, there is no reason to believe that the exact date of such events happen just before an unusual increase in the probability of under-reporting of the clients living in the municipality of the scandal. In Section 3.3, we provide evidence in favor of this assumption. As for standard errors, though we provide results under different clustering approaches, in our benchmark specifications we cluster by municipality $\times$ day.[23]

3.1 Event Study

Figure 1 shows the effect of corruption scandal on the probability a customer under-reports, as estimated using equation (1). Our baseline model uses a window of seven days before and after the news is published.

Figure 1: Corruption scandals and under-reporting



The graph reports coefficient estimates of the effect of corruption scandal on the probability a customer underreports purchases, using Equation (1) with a window of seven days before and after the news is published. Complete data descriptions and sources are reported in Table A28 in the Appendix, and summary statistics are presented in Table A24.

The results indicate that customers audited in the city in which a scandal occurs are more likely to under-report in the days after the scandal breaks. The effect starts the day after the scandal is made public and lasts for four days. This event study also allows us to provide evidence to support the identification strategy by demonstrating that there were no differential trends in under-reporting across municipalities in the days before the scandal broke. The effect starts the day after the corruption scandal is made public, and under-reporting behavior then returns to its pre-scandal levels after a few days. All this evidence is in line with the assumption that, absent the corruption scandal, all cities would have similar trends in under-reporting behavior.[24]

[23]In line with recent literature, we decided to cluster standard errors at the treatment level (municipality-day level). However, in the appendix, we show that the main results of the paper do not depend on this choice.

[24]Figure A6 replicates Figure 1, including also client FE as control. We want to underline that these daily estimates were already extremely demanding specifications even without the inclusion of client FE. Nevertheless, from a qualitative point of view, Figure A6 still shows that there is an effect of corruption scandals on the client's

3.2 Corruption Scandals and Under-reporting

In the previous event study, we observed that most of the effect is concentrated in the first four days after a corruption scandal. Therefore, for our baseline difference-in-difference specification, we consider the corruption scandal treatment as encompassing these four days. Specifically, we do this by estimating the following equation.

$$Y_{i,c,t} = \delta_c + \mu_t + \beta_0 T^0_{c,t} + \beta \sum_{\tau=[1,2,3,4]} T^{\tau}_{c,t} + \gamma \boldsymbol{X_{i,c,t}} + \epsilon_{i,c,t} \tag{2}$$

Where $\sum_{\tau=[1,2,3,4]} T^{\tau}_{c,t}$ is now a dummy variable that takes a value of 1 if day t is within the first four days after a corruption scandal is made public in municipality c. In our baseline specification, we control separately for the day when the corruption scandal happened ($T^0_{c,t}$), since it is unclear whether the effects of the corruption scandal are felt on the day the scandal breaks.

Table 1: Corruption scandals and under-reporting

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	0.0224***	0.0234***	0.0234***	0.0177***	0.0229**
	(0.0046)	(0.0047)	(0.0047)	(0.0066)	(0.0092)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.01	0.01	0.35	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table 1 shows the estimate of our baseline model. In the first column, we only control for municipality and day fixed effects. In addition to the municipality δ_c and day μ_t fixed effects already controlled for in the event study, we also explore whether the effect is robust to the

probability of under-reporting the first days following the scandal.

inclusion of other observable characteristics $\boldsymbol{X_{i,c,t}}$. In the second column, we include store fixed effects to control for store-specific characteristics that may determine the likelihood of under-reporting. This fixed effect is different from the municipality fixed effects since shoppers from different municipalities may visit the same store and some municipalities have more than one store. We also control for time-of-day fixed effects to account for average differences in the probability of under-reporting during the day. In column 3, we control for a series of observable customer characteristics. Column 4 contains the most exhaustive regression, in which we include customer fixed effects to control for any time-invariant customer-specific characteristics.[25] It is important to note that when we include customer-specific regressors, we control for the possibility that the observed changes in under-reporting behavior are due to the selection of customers who decide to shop after a corruption scandal. Estimates of this type of regression can therefore be interpreted as being solely driven by changes in behavior once at the store. Finally, in column 5, we control for Shop FE $\times$ Day FE, a specification meant to control for possible auditor/guard effects. We can add this fixed effect because individuals from many municipalities visit most of our shops. Therefore, by controlling for Shop FE $\times$ Day FE, we exploit differences between individuals coming from treated and control municipalities that go on the same day to the same shop. In other words, we compare differently treated clients who face the same auditor (cashier) and guards, and therefore these results can not be contaminated by changes in auditors' behavior due to the corruption scandal. As expected, the estimated coefficient is very similar to the baseline estimate.

In all specifications, news of a corruption scandal in a municipality increases the probability that a shopper from that municipality under-reports their purchases. The point estimate slightly decreases, although it remains highly significant, when we include customer fixed effects in the controls. As column 4 of Table 1 uses data on shoppers that we observe at least twice in our sample year, the number of observations used to estimate the coefficients is different.[26] To make the magnitude of the coefficients comparable across columns, we keep the number of observations constant in Table A2 in the Appendix, with some columns losing about 50,000 observations. However, Table A2 shows that the results are not affected in any way by the sample restriction. The magnitude of the estimated coefficient is economically meaningful, since it represents a 16% increase in the probability of under-reporting at its mean value in our sample. Given that a fraction of under-reporting represents honest mistakes, our estimate is a lower bound of the true effect of corruption scandals on stealing behavior. The unconditional

[25] As noted previously, each record includes the customer's membership card number, which allows us to follow customer behavior across audits.

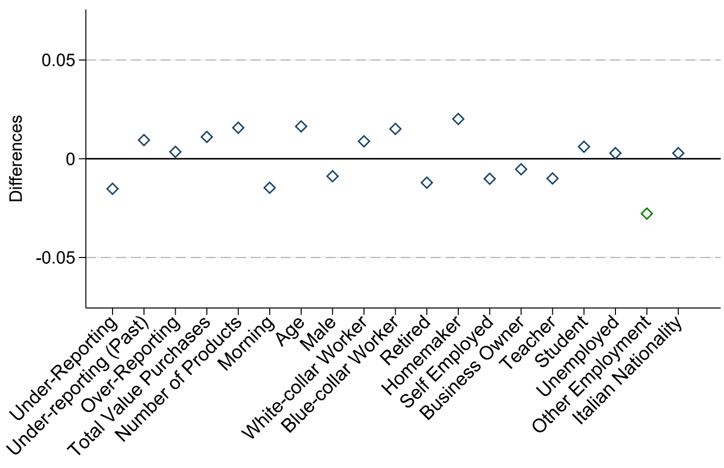
[26] Some records in our database are missing information on customers' personal characteristics, which is why columns 3 and 5 also have slightly fewer observations.

probability of under-reporting is 14%, while the probability of over-reporting is 6.3%. Making the simplifying assumption that honest mistakes account for an equivalent amount of under-reporting (6.3%), the unconditional probability of stealing should be 7.7%, meaning that news of a corruption scandal increases stealing behavior by 30% of its baseline rate.

3.3 Robustness and Inference

Our identification strategy is based on the assumption that no difference in under-reporting behavior should be observed between treated and control customers in the absence of a corruption scandal. In this section, we provide evidence to corroborate this assumption by showing that the timing of the local corruption scandal can be deemed to be as good as random. Additionally, to further demonstrate that we are indeed measuring a change in under-reporting behavior, we show that the effect is robust to alternative specifications of the outcome of interest. We also engage with recent econometric literature on the potential perils of using the two-way fixed effects strategy to estimate a staggered difference-in-differences and follow the diagnostics recommended by De Chaisemartin and d'Haultfoeuille (2020) and the estimation procedure proposed by Sun and Abraham (2020).

Figure 2: Balance in covariates and outcomes prior to treatment



Dots depict the normalized mean difference between several observable characteristics between customers that will and will not be treated by a corruption scandal in the four days beforethe scandal takes place. Diamonds denote the coefficient estimates of regressions that also condition on municipality and day fixed effects. Green coefficients are significantly different from zero at the 10% level. Horizontal dashed lines indicate the threshold of 0.05 standard deviations. Complete data descriptions and data sources are presented in Table A28 in the Appendix. All conditional estimates are reported in Tables A8 in the Appendix.

Balance test. The main threat to our identification strategy is the existence of any differential change in unobservables between the days just before and after a corruption scandal in the municipality in which it occurred relative to other municipalities. As is usual for this type of analysis, we compare several observable characteristics of customers that will be affected ("treated") by a scandal and those that will not in the four days before a corruption scandal takes place.[27] We regress each variable on a dummy that takes a value of one if the municipality will be exposed to a scandal and zero otherwise, including municipality and day fixed effects. Results are reported in Table A8 in the Appendix, while standardized coefficients are reported in Figure 2. Samples are largely balanced between treated and control customers and almost all variables show standardized differences well below the conservative threshold of 0.2 standard deviations, as suggested by Imbens and Rubin (2015).

Alternative samples and outcomes. To demonstrate the robustness of our results, we first replicate the estimates of Equation (2) with different sub-samples of the database. In column 2 of Table A9 in the Appendix, we restrict the sample to include only cities that experienced at least one scandal during the study period. These cities are likely to be systematically different from the others, though the results are robust to excluding never-treated municipalities. In column 3, we restrict the sample to audits in which some level of under-reporting or over-reporting occurs. Finally, in column 4 we drop instances of over-reporting as these are very likely to be mistakes by the customer. All the results presented in the Table A9 confirm the positive and significant effect of the scandal on under-reporting behavior. Among customers who over-report, the effect of a scandal is a 6% increase in under-reporting, a figure that climbs to 16% among customers that do not typically make mistakes.

These results are also confirmed when using several alternative measures of under-reporting. Table A10 shows the estimate of our baseline model using the following dependent variables: the number of objects bought but not declared by the customer, the total value of products bought but not declared and the value of undeclared items as a share of the total value of purchases. The effect is positive and statistically significant for all the alternative measures of under-reporting.

Clusters and bootstrapping. In order to verify the robustness of our findings, we replicate all the results with standard errors clustered at different levels. In Tables 1 and 5, we report standard errors clustered at the municipality-day level, while in Tables A4 and A5 in the Appendix, we show that results are qualitatively unaffected under six different clustering scenarios: robust standard error, municipal, municipal-month, shop, shop-day and shop-month. Likewise, in the Appendix, we show that the results are unaffected when we bootstrap standard

[27] These observable characteristics include: under-reporting, "already caught stealing in the past" [labelled Under-reporting (Past)], over-reporting, total value of purchases, number of products, whether the audit was done in the morning (before 12 pm) or in the evening (after 6 pm), age and sex of the customer, whether the customer is a white-collar worker, blue-collar worker, homemaker, business owner, teacher, student, retired, self-employed or unemployed, and whether or not they are Italian.

errors at the municipality and shop levels (Tables A6 and A7).

Diff-in-diff diagnostics and alternative estimation methods. Recent econometric literature has highlighted the potential issues of the two-way fixed estimator employed in this paper. One concern is that the estimated coefficient is a weighted average of each treatment (corruption scandal) where the weights may be negative. We follow the diagnostics recommended by De Chaisemartin and d'Haultfoeuille (2020) and show that none of the weights are negative. In Figure A8, we display the distribution of these weights. Following Sun and Abraham (2020), we estimate each corruption scandal-specific treatment effect. The distribution of these effects is shown in Figure A7. The average of 0.0248 is, if anything, slightly larger than the baseline coefficient estimated in Table 1.

Already caught stealing in the past. Given that the customers' probability of being audited increases if they have a history of under-reporting, Table A12 replicates Table 1, including among the controls a dummy variable equal to 1 if the customer was already found to be under-reporting the previous time and zero otherwise. The specifications include only clients who have been audited at least twice during the period of analysis. Moreover, the sample size gets even smaller since, in this way, all the first observations of each client are lost. Table A12 shows that, despite controlling for this additional control, the effect is still positive and significant in all specifications of the table. Furthermore, Table A13 shows that the difference in magnitude between Table A12 and the main effect of Table 1 is due to the smaller sample size and not to the inclusion of this further control.

3.4 Validation and Additional Results

Are customers aware of corruption scandals? For corruption scandals to have an effect on customer behavior, news of them must reach shoppers. This may happen directly, through the media, or indirectly through their peers. Rizzica and Tonello (2018) show that Italians are aware of news about corruption and that media reports on corruption change their perception about how widespread it is. These effects are short-lived, lasting at most ten days after exposure to a news story about corruption.

To corroborate whether people are aware of corruption scandals in our context, we examine Google Trends search activity in Emilia-Romagna (Stephens-Davidowitz and Varian, 2014). First, we test whether searches for the word "corruption" are higher after local corruption scandals. We then study whether keywords associated with specific corruption scandals increase after a corruption scandal is made public.

A spike in Google searches for the word "corruption" or the name of corrupt officials after a scandal would indicate that internet users are aware of these scandals and are interested enough to search for further information. However, as stressed by Rotesi (2019), Google Trends data is not based on a full sample of past searches, but are rather based on a Google sub-sample that changes every 24 hours.[28] This may be an issue when focusing on particular local corruption scandal news with a low amount of search activity. In these cases, the results of the queries can display drastically different patterns across days. This is not an issue when searching for the word "corruption" since this keyword always receives substantial interest every day. For our study period, Google Trends provides the data at the weekly level as an index that takes a value of 100 in the week with the highest search activity and 0 in the week with the lowest search activity.

In Table A14 in the Appendix, we first show that the share of customers that reside in a city that had a corruption scandal in the prior four days (share of treated individuals) is positively correlated with the number of searches for the word "corruption." An increase in 10 percentage points (p.p.) of the share of treated individuals is associated with an increase in the Google search index of 14.1 p.p.

There are a few caveats about this specification. (i) Google Trends time-series are not provided at the municipal level. We use data at the regional level and therefore each observation in our sample has the same Google Trends score on the same day. Because of this, we need to drop day fixed effects. (ii) Our audit and corruption scandals data comprises only 2 provinces of Emilia-Romagna that add up to just over 1 million inhabitants. Emilia-Romagna has over 4 milion people. (iii) Google Trends provides their index for the period of our study only at the weekly level.

To overcome caveat (i) and be able to control for day fixed effects we compare the Google Trends index in Emilia-Romagna for the word corruption to other indexes. a) We compare it to the same index for other regions in Italy. b) We compare it to the Google trends index in Emilia-Romagna for other common topics. These are the Google Trends in Emilia-Romagna for football, restaurants, movies, online shopping, job opportunities and travel. c) We compare it to the Google trends index in Emilia-Romagna for other crime-related words. These are the Google Trends in Emilia-Romagna for robberies, homicides, shootings, burglaries and rape. d) We compare it to the Google Trends index for the region of Emilia-Romagna for corruption in the subsequent and the previous 2 years with respect to the year of our analysis. The idea behind these comparisons is that the Google index for the word corruption in Emilia-Romagna should increase more than these alternative indexes the days after the scandals we study in our

[28]For further details, see: link.

paper.

To test this we effectively conduct a Difference-in-Differences estimation where we compare the changes after a scandal in the Google trends index for the word corruption in Emilia-Romagna in the year of our analysis (treated index) to the alternative indexes (control indexes). To do that we estimate the following equation:

$$Y_{i,c,g,t} = \alpha_g + \delta_c + \mu_t + \beta_0 T^0_{c,t} + \beta \sum_{\tau=[1,2,3,4]} [T^{\tau}_{c,t} \times \mathbb{1}(g=0)] + \epsilon_{i,g,c,t} \tag{3}$$

The only difference from our baseline equation is that now there is an extra dimension g that captures all the possible Google Trends indexes. g=0 for the treated index and g=1,...,G for all the alternative indexes. The number of alternative indexes G depends on the specification. To run this regression we duplicated the original dataset G times. $Y_{i,c,g,t}$ is the Google Trend value for index g on day t. It is important to highlight again that the index does not vary at the municipal level c and is a weekly index.

Table 2: Google trends about the word "corruption" vs. other control terms

	Google Trends Corruption			
	(1)	(2)	(3)	(4)
Post Scandal × Treated index	5.2137**	13.1429***	14.4469***	8.6577**
	(1.9285)	(2.7200)	(3.0434)	(2.8756)
Municipality FE	√	√	√	√
Calendar Day FE	√	√	√	√
Index FE	√	√	√	√
Control index	Other Regions	Other Topics	Other Crime Topics	Other Years
Observations	3,388,502	1,824,578	1,563,924	1,303,270
R-Square	0.34	0.62	0.53	0.29

OLS estimates. Observations are at the Google index/Day level. The *dependent variable* is the Google trends index score. In all columns the *Treated index* is the Google Trends index for the word corruption during the year of our study in Emilia-Romagna. In Column (1) the control indexes are the Google Trends index for the word corruption during the year of our study in other Italian regions. In Column (2) the control indexes are the Google Trends index for the topics "football", "restaurants", "movies", "online shopping", "job opportunities" and "travel" during the year of our study in Emilia-Romagna. In Column (3) the control indexes are the Google Trends index for robberies, homicides, shootings, burglaries and rape during the year of our study in Emilia-Romagna. In Column (4) the control indexes are Google Trends indexes for the word corruption in Emilia-Romagna in the two years prior and the two years after the time period of our study. *Post Scandal* is the share of people that had a corruption scandal in their municipality in the last four days. Regressions are weighted by the number of people we observe in our dataset. Robust standard errors clustered at the Google Trends index level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

The results of Table 2 show that, compared to the control indexes, the treated index increase more after a scandal. The result in column (1) assures us that we are capturing changes in Google searches for the word corruption that is specific to Emilia-Romagna instead of a more general shift in interest about corruption happening all over Italy. Results in columns (2) and (3) instead assure us that we are capturing changes in Google searches specifically about corruption instead of a more general change in the number of Google searches for other topics. Finally, column (4) assures us that we are capturing changes in Google searches about corruption in Emilia-Romagna specific to the year of our study instead seasonality in the Google searches for the word corruption that happens every year.[29]

We follow the diagnostic procedure recommended by De Chaisemartin and d'Haultfoeuille (2020) also for this additional model. In Figure A9, we display the distribution of these weights. The vast majority of these weights are positive, and the sum of the positive weight is more than 1,000 times larger than the sum of the negative weights. This means that issues with negative weights in this two-way fixed effects estimation are unlikely to affect the results.

We also follow Sun and Abraham (2020) and estimate the effect of each corruption scandal separately. In Table A11, we calculate the average of these treatment effects and compare it to the naive two-way effects estimate. We do this for each different way of choosing the control indexes. The results show that, if anything, the Sun and Abraham (2020) estimated effects tend to be larger than the ones estimated with the classical two-way effects. These differences are insignificant as shown by the p-values displayed in the last row.

Finally, In Figure A10, we also provide suggestive evidence that when a scandal breaks, the name of the public official involved in the scandal or the nickname given to the scandal are searched for on Google.

Scandal vs other news In this paragraph we provide evidence on how different type of news affects under-reporting behavior at the supermarket. Table A16 shows the effect of the different categories of news articles on the customer probability of under-reporting. In columns (1), we show the effect of all the 52 news articles that involve a public official or a worker in the public sector of the two provinces. The coefficient is positive and statistically significant at 5%, and the magnitude of the estimated parameter is smaller than the effects observed in the main analysis. In columns (2) to (4) of Table A16, we show the effect of the three different news categories described above, separately. Except for the category "Scandals" in column (2), the coefficients of the other categories are close to zero and never statistically significant. Finally, column (5) shows the effect of all the different categories in the same regression, confirming the results of the previous columns: the only news category that affects the customer likelihood of

[29] A similar analysis can be done with a simpler Difference-in-Differences estimation where we collapse the dataset at the Google index/Day level and test whether changes in the treated index are larger in the days when there is a higher percentage of people treated by a scandal. The results of this analysis are displayed in Appendix in Table A15

under-reporting is the one that provides new and negative information to the reader (scandals).

Two main mechanisms can explain the results of Table A16. First, some news may not affect the individual perception of how widespread dishonest behavior is. According to a simple model of Bayesian updating, new and negative information such as the one present in the scandals category should increase the beliefs about the overall level of dishonesty in society. News in the neutral category should not have much effect, while positive news should, if anything, decrease the beliefs about the overall level of dishonesty in society.

Additionally, news articles not directly linked to essential steps of the court process may have less visibility or generate less general interest than other types of news. Similarly, people may only be interested in negative news; instead, positive news may not generate interest, and word-of-mouth spread. As a result, most people are not even exposed to these news and therefore do not change their stealing behavior at the supermarket.

To empirically test the presence of this apparent difference in interest generated by scandals with respect to other types of news about corruption, we exploit again the analysis of Google trends. Table A17 shows how only corruption scandals generate interest among the population. Other categories of news about corruption that, for example, exculpate a politician from a corruption allegation (positive news) or just about a procedural aspect of a corruption trial or a further investigation of an already well-established scandal (neutral news) do not produce any effects on Google search activity. While corruption scandals differ from positive and neutral news along many dimensions these results suggest that one of the reasons why corruption scandals are the only type of news that affects behavior at the supermarket is that they are the only ones that spark enough interest.

Intensity of the treatment. Consistent with the fact that customers are more likely to engage in under-reporting at supermarkets after being exposed to corruption scandals, we expect to see larger effects after more prominent corruption scandals. That is, such scandals are likely to have an impact on a greater number of customers. Since we do not know how many people are exposed to each news item, we use the length of the news article and its position in the newspaper as a proxy. The idea behind this approach is that articles that are longer and more prominently located in the newspaper are more likely to be read. Additionally, the position and length of the article may signal the importance of the corruption scandal. In columns (1) to (3) of Table 3, we show that the effect is stronger for articles that are longer (measured both in terms of the number of words and the natural logarithm of the number of words) and for articles that are published in the first pages of the newspaper.[30]

[30]The variable first pages is a dummy equal to one if the newspaper article is published in the top quartile of the page distribution of the local newspaper (i.e., within the first seven pages) and zero otherwise.

The Google trends index can also be used to show that the scandals that produce the most interest are also the ones that produce the largest effects in under-reporting at the supermarket. To do so, we estimate a regression similar to the one shown in equation 3, but we estimate the effect on the treated index (compared to the control indexes) of each scandal separately. When then use, these estimated effects to check whether scandals that produce the largest increases in the treated index also generate the largest effects in under-reporting at the supermarket.[31] Results, presented in Table 3 column (4) and (5), show that scandals that produced a higher increase in the treated index also produced a larger increase in the share of people under-reporting in the following 4 days after the scandal. Compared to the average scandal, a scandal with a standard deviation above the mean increase in the treated index has an effect on under-reporting that is 50% larger when compared to the average effect.

Table 3: Intensity of the treatment

	Under-Reporting						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Scandal	-0.001	-0.066	0.018***	0.022***	0.025***	0.018***	0.019***
	(0.011)	(0.049)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Post Scandal × Var. H	0.005**	0.015*	0.019**	0.012***	0.016***	-0.028**	-0.024*
	(0.002)	(0.008)	(0.009)	(0.004)	(0.005)	(0.012)	(0.013)
Municipality FE	√	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√	√	√
Var. H	Article N. of Words	Article Ln(N. of Words)	1(First Pages of Newspaper)	Google Trends Norm Coeff.	Google Trends ln(Norm Coeff.)	1(Match-Day)	1(Match-Day or Day After)
Mean Dependent							
Observations	260,192	260,192	260,192	260,192	260,192	125,583	125,583
R-Square	0.01	0.01	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited on a given day. The *dependent variable* is a dummy taking a value of 1 if the customer is found to underreport at least one product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal has been made public in the customer's municipality of residence and zero otherwise. In column (6) and (7) the specification includes also the un-interacted term. Complete data descriptions and data sources are presented in Table A28 in the Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Since the length and position of an article, or the effects on google trend indexes, may be correlated with several characteristics of the corruption scandal itself, we build a measure of news pressure in the spirit of Eisensee and Strömberg (2007) and Durante and Zhuravskaya (2018) based on the dates of professional football games. Our assumption in doing so is that people are less likely to be aware of a corruption-related news story on days when the local football team is playing a game. This measure of news pressure uses a sub-sample of residents who live in a city with a local football team that plays in the highest two divisions of the Italian

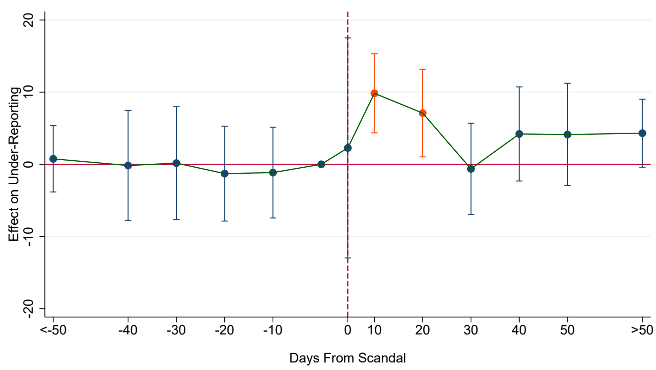
[31] We estimate coefficients using all the four control Google Indexes, and for each scandal, we use the average. The results do not change if we use the coefficients of the four different estimates separately, as they are highly correlated.

football league. If the team of a customer's city of residence is playing a game that day, that customer is arguably more likely to be unaware of the corruption scandal. We also produce a similar measure where the effect includes the day after a game. As shown in columns (4) and (5) of Table 3, customers do not react to news about a corruption scandal on days that football matches occur.

Neighboring municipalities. In this section, we test whether corruption scandals have spillover effects on neighboring municipalities. In other words, we study whether the news about a scandal involving a public official from a specific municipality affects under-reporting by supermarket customers living in the neighboring municipalities. First, we define neighboring municipalities as all municipalities that share a border with the treated municipality and then create a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal is made public in the customer's neighboring municipality and zero otherwise. Results are shown in Table A20. All coefficients are close to zero and about ten times smaller than the main effect on customers from the treated municipality, confirming the absence of any spillover effect on the probability that a customer from a neighboring municipality will be more likely to steal after the scandal.

This result could have two possible explanations. The spread of local news may be extremely local, although newspapers are distributed throughout the entire province. Alternatively, since Italy is a federal state and a large share of local taxes are financed by taxes collected locally, the scandal might only generate an emotional reaction among customers who feel that they are directly financially affected by the scandal.

Figure 3: Persistence of the effect of a corruption scandal



(a) After the Scandal

The graph reports coefficient estimates of the effect of a corruption scandal on the probability that a customer underreports purchases, in the spirit of Equation (1) using a window of fifty days before and after the news is published (each bin represents the effect over a ten-day period). Complete data descriptions and data sources are reported in Table A28 in the Appendix and summary statistics are presented in Table A24.

Table 4: Long term effect of a corruption scandal

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal (1-4 Days)	0.0232***	0.0243***	0.0243***	0.0189***	0.0237***
	(0.0046)	(0.0047)	(0.0047)	(0.0067)	(0.0091)
Post Scandal (5-20 Days)	0.0057*	0.0062**	0.0062**	0.0088**	0.0066
	(0.0031)	(0.0031)	(0.0031)	(0.0038)	(0.0055)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.01	0.01	0.35	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited on a given day. The *dependent variable* is a dummy taking a value of 1 if the customer is found to underreport at least one product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal has been made public in the customer's municipality of residence and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in the Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Persistence of the effect. Figure 1 shows that there are no statistically significant effects beyond the first four days after a corruption scandal, though all the estimated effects after the corruption scandal are positive. This indicates that the effects of the corruption scandal may persist even after four days, but these effects are too small to be detected by an event study in which bins have a length of one day. In Figure 3, we test for this possibility by estimating an event study similar to the one shown in Figure 1 but with bins that have a length of 10 days. This might have enough power to detect even small effects on under-reporting. The results show that the effects of a corruption scandal may last over 20 days after the corruption scandal has been made public. As expected, the magnitude of the estimated parameters is almost four times smaller than the effects observed in the first four days. Once again, Figure 3 shows that no pre-treatment trend exists in the days prior to the news being published. In Table 4, we also explore this possibility in a difference-in-difference setting. The effects are detectable even after 20 days, but are substantially lower than the large effects observed in the first four days.

4 Mechanism

In this section, we begin by confirming that the observed changes in the likelihood that a customer underreports are driven by shifts in stealing behavior and not by a change in the selection of customers that go shopping or by a change in the likelihood of making mistakes while using time-saver technology. We then investigate what might generate this change in stealing behavior.

4.1 Mistakes Using Time-Saver Technology

Given that time-saver technology is relatively new for many customers, it is not surprising that some make mistakes. For example, around 6% of audits detect some level of over-reporting, where the value of the scanned items is greater than that is actually in their shopping cart. These instances are clearly due to error, since the customer would end up paying more than is necessary. Even among audits that detect some under-reporting, we suspect that many of these are simply honest customer mistakes.

We must therefore query whether greater under-reporting of supermarket purchases is simply driven by an increase in the amount of mistakes customers make while using the time-saver technology. While it is not clear why customers would make more mistakes after a corruption scandal is made public, we can nonetheless examine this possibility. We do so by estimating whether news about corruption scandals make over-reporting more likely. These, as stated before, are unambiguously mistakes. Results are shown in Table 5. All the coefficients are close to zero and their magnitude is over ten times smaller than that of under-reporting, confirming that there is no change in the probability of making more mistakes in the days following a scandal. Table A3 in the Appendix shows that results are not affected in any way by the sample restriction.

Figure 4 shows the normalized effect of a corruption scandal for different levels of under- and over-reporting. In the figure, each parameter is estimated from a different regression in which we vary the outcome of interest. The first four regressions estimate the effect of corruption scandal news on the probability of under-reporting amounts between €0.00 and €2.50, between €2.50 and €5.00, between €5.00 and €7.50, and more than €7.50. The final four regressions estimate the effect on over-reporting by those same amounts.[32] The results show no effect of corruption scandals on different levels of over-reporting, suggesting that customers do not make

[32] To estimate the effect on under-reporting, we define the outcome as 1 if the under-reporting amount falls into the described bins and 0 if the client did not under-report. Similarly, we define the over-reporting outcome as 1 if the over-reporting amount falls into the described bins and 0 if the client did not over-report.

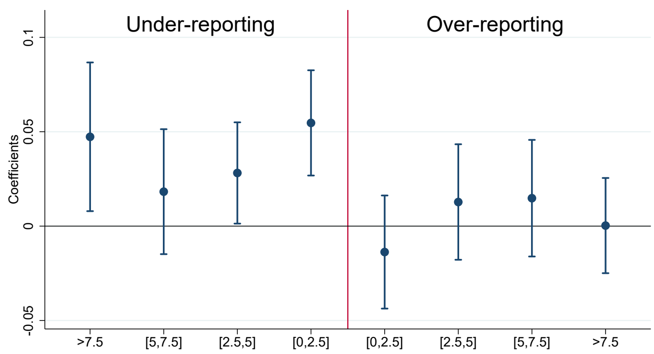
more mistakes after finding out about a scandal. Moreover, the effect of a corruption scandal is evenly distributed across the various levels of under-reporting.

Table 5: Corruption scandals and over-reporting

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	-0.0011	-0.0008	-0.0007	-0.0012	-0.0020
	(0.0037)	(0.0036)	(0.0036)	(0.0046)	(0.0064)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.06	0.06	0.06	0.06	0.06
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.00	0.01	0.31	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited on a given day. The *dependent variable* is a dummy taking a value of 1 if the customer is found to overreport at least one product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal has been made public in the customer's municipality of residence and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in the Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Figure 4: Corruption scandals and the value of goods stolen



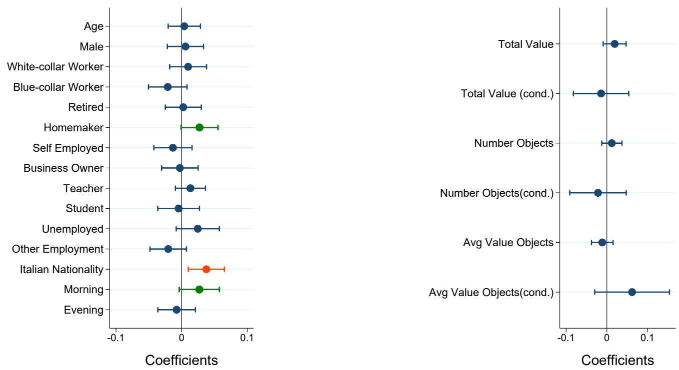
The graph reports coefficient estimates of the effect of corruption scandal on: under-reporting values between 0 and 2.5 euro (included), between 2.5 and 5 euro (included), between 5 and 7.5 (included), and bigger than 7.5 euro (left panel); over-reporting values between 0 and 2.5 euro (included), between 2.5 and 5 euro (included), between 5 and 7.5 (included), and bigger than 7.5 euro (righ panel). Complete data descriptions, data sources are reported in Table A28 in Appendix, and summary statistics are presented in Table A24.

4.2 Selection

Corruption scandals may also increase the probability that a customer under-reports their purchases if the type of customers that goes shopping changes after a corruption scandal breaks. To test this possibility, we investigate whether we are more likely to observe specific types of individuals after a corruption scandal. The results are shown in Figure 5.A (Table A18 in the Appendix), which reports the standardized coefficients of our baseline model where the outcomes of interest are a series of customer characteristics.[33] The graph shows that most of the standardized coefficients are not statistically different from zero, while those that are different from zero do not have an economically meaningful magnitude. For example, the results suggest that the probability that an Italian customer is audited one day after a scandal breaks is 0.01% higher.

In column 8 (Panel B) of Table A18, we collapse the sample at the municipality-day level and test whether the scandal increases the total number of customers that go shopping at the supermarket – we do not observe a rise in this number in the days following such news. We then turn to purchasing behavior, testing whether the scandal has an effect on the total value purchased, the number of products, and the average value of the product purchased. Figure 5.B (Table A19 in the Appendix) shows that here as well, the estimated coefficients of these regressions are never statistically different from zero.

Figure 5: Selection into supermarket and purchasing behavior



(a) Selection effect (b) Purchasing behavior

The graphs report coefficient estimates of the effect of a corruption scandal on different measures of supermarket (graph a) and purchasing behavior (graph b), following Equation (2). All conditional estimates are reported in Tables A18 and A19 in the Appendix. Complete data descriptions and sources are reported in Table [tab: app data] in the Appendix, and summary statistics are presented in Table A24.

Overall, these results imply that the increase in under-reporting behavior after a corruption

[33] These include gender, age and dummies for type of employment, nationality and whether the audit was done in the morning (before 12 pm) or in the evening (after 6 pm).

scandal is not generated by a change in the composition of customers that use time-saver technology due to the scandal. This suggests that individuals do not decide to go to the supermarket and use the time-saver technology as a reaction to being exposed to a corruption scandal. Rather, it would appear that some customers, once at the supermarket, make a spur-of-the-moment decision to steal.

5 Stealing at the Supermarket

Since corruption scandals do not change the decision of individuals to use time-saver technology or their likelihood to commit a mistake when using it, any observed change in under-reporting behavior should be driven by some number of customers deciding to steal. Building on criminal decision models pioneered by Becker (1968), a customer's decision to steal when using time-saver technology should be determined by the trade-off between the expected benefit the shopper receives from the stolen items and the various costs related to their dishonest behavior. In this section, we investigate the factors that might bring about a change in stealing behavior, examine the costs and benefits of such behavior, and discuss which of these elements could be affected by exposure to a corruption scandal.

First, the shopper will consider the probability of getting audited and the material costs they will have to face if caught stealing. This may include monetary fines and even time in jail. Second, shoppers may care about the social costs associated with being caught stealing. For example, customers may worry that family members, friends, or neighbors may find out that they have stolen, and fear being ostracized or punished because of their dishonest behavior. Finally, a customer may simply dislike stealing independently of the potential monetary or social costs. For example, the shopper may experience a utility loss due to guilt, loss of self-worth, or from a violation of an internal norm of conduct.

5.1 Material Incentives

An increase in under-reporting purchases after a scandal is made public could, a priori, be due to a change in any of these factors. One of the strengths of our analysis is that we can safely exclude some of these factors thanks to the specific setting and the frequency of the data. For example, it is safe to assume that any change in under-reporting after a corruption scandal cannot be due to a shift in the direct material benefits from under-reporting because the value of the items in the supermarket is unlikely to change after a scandal. Additionally, given that we focus on one supermarket chain in a small geographical area, any potential change in prices is controlled by day fixed effects.

We can also rule out the possibility that changes in under-reporting behavior are due to shifts in the expected direct material costs because, as described above, most shoppers under-report only a few euros and there are no fines or other legal costs in place to punish such behavior.[34] Furthermore, since auditing is random, the probability of being detected by an audit remains constant after a corruption scandal. The only exception is that guards' behavior may change because of the corruption scandal. We are able to control for this possibility by including supermarket-day fixed effects and comparing only the change in under-reporting behavior of shoppers who go to the same shop on the same day – and are thus likely to be under the scrutiny of the same guards – but who come from different municipalities. As shown in Table 1, the estimated effect does not change when controlling for these fixed effects. It also possible that shoppers, after the news of a corruption scandal, may update upwards their beliefs about how likely it is that corrupt actions will be detected. Because of this, they might even wrongly infer that the probability of an audit has also increased. This would ultimately lead to a decrease in under-reporting. We can discard this hypothesis since we find the opposite effect.

5.2 Social Norms

What may change after a corruption scandal is the salience of social norms concerning stealing at the supermarket. These social norms matter because they determine the beliefs that an individual has about the costs that others may impose if they are caught stealing at the supermarket. If an individual believes that stealing at the supermarket is frowned upon by others, this may dissuade them from stealing to avoid social punishment. Once news emerges of a corruption scandal, the shopper might believe that other people will impose smaller costs on customers who are found under-reporting because dishonest behavior has now become normalized.[35] This may be particularly true in our setting because under-reporting a few euros pales in comparison with the amounts stolen in a corruption scandal. On the other hand, dishonest behavior is made more salient following a corruption scandal, which may reignite anger and increase the public focus towards dishonest behavior, thus raising the expected social punishment.[36] We believe that these mechanisms are unlikely because the auditing process is private,

[34] The share of customers who under-reporting more than 10 euros is 0.01%.

[35] Keizer, Lindenberg, and Steg (2008), in a field experiment, show that observing others violating a certain social norm makes the subject more likely to violate other norms. This could be caused by an observed decrease in the expected social punishment involved in violating norms. Bursztyn, Egorov, and Fiorin (2020) show how Donald Trump's rise in popularity normalized the expression of xenophobic views because the social costs of holding these views decreased. Individuals use information on how popular or frequent a certain action or view is to infer the social cost associated with it.

[36] Gino, Ayal, and Ariely (2009) show that experimentally increasing the salience of cheating decreased anti-social behavior in the lab, possibly as the result of a decrease in the expected social punishment.

meaning that individuals who could socially punishment the shopper are unlikely to be aware of the result of the audit.

Table 6: THE SOCIAL COST OF STEALING

	Dep. Var. UNDER-REPORTING					
	(1)	(2)	(3)	(4)	(5)	(6)
POST SCANDAL	0.020***	0.024***	0.026***	0.031***	0.024***	0.022***
	(0.006)	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)
POST SCANDAL × VAR. H	0.010	-0.001	-0.005	-0.010	-0.002	0.004
	(0.011)	(0.011)	(0.009)	(0.009)	(0.014)	(0.009)
Municipality FE	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√	√
Client Controls	√	√	√	√	√	√
VAR. H	Small Supermarket	Supermarket in Small Municipality	Crowded Hours	Home Supermarket	Previous Audit Close (4 min.)	Next Audit Close (4 min.)
Mean Dependent	0.14	0.14	0.14	0.14	0.14	0.14
Observations	255,749	255,749	255,749	255,749	255,749	255,749
R-Square	0.01	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited on a given day. The *dependent variable* is a dummy taking a value of 1 if the customer is found to underreport at least one product while shopping and 0 otherwise. POST SCANDAL is a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal has been made public in the customer's municipality of residence and zero otherwise. In all columns the specification includes also the un-interacted term. Complete data descriptions and data sources are presented in Table A28 in the Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***..

We nevertheless explore whether changes in social norms might play a role by testing whether the effect of a corruption scandal is larger in situations where people who can socially punish the customer may be aware of the audit result. We believe there are two possible social punishers. First, the cashier, who should be the only person aware of the auditing result, could be in the set of people who can socially punish the customer. Second, other customers in the supermarket if they become aware of the results of the audit could decide to socially punish customers who under-report. We believe that this is unlikely since the result of the audit is supposed to be hidden from other customers. The possibility that the cashier or the other costumers are in the set of people that can socially punish the misbehaving customer is larger in small rural stores, or stores close to the customer's house. Other costumers could more easily see the results of the audit if the shop is particularly busy.[37] Because of this we test whether the effects of a scandal are larger along these dimensions. As shown in Table 6 we do not find any differential

[37] We use the following three variables to proxy for times when the shop is particularly busy: *Crowded Hours* is a dummy that takes a value of 1 if the customer makes the purchase during a moment when the number of customers is above the median, and zero otherwise. *Previous Audit Close* is a dummy that takes a value of 1 if the previous customer audit in the supermarket took place less than 4 minutes ago (top quartile of the times between client audits), and zero otherwise. Finally, *Next Audit Close* is a dummy that takes a value of 1 if the next customer audit in the supermarket takes place within 4 minutes (top quartile of the times between client audits), and zero otherwise.

effects along these dimensions. Even though these dimensions are correlated with many other characteristics of the customers or the scandal we see these results as preliminary evidence that changes in social norms may play only a small role in the observed effects.

5.3 Moral Cost and Internal Rules of Behavior

Shifts in stealing behavior may, alternatively, be caused by a change in moral costs. These costs might be determined by individuals' internal rules of behavior that prescribe the truthful reporting of one's purchases. If a shopper violates or is caught violating this self-imposed norm, they may experience a utility loss, for example, due to guilt or a loss of self-worth.[38] Corruption scandals could change these internal rules of behavior in two ways.

Firstly, individuals may start believing that behaving dishonestly is not such a morally reprehensible action and therefore change their own rules of behavior. This is in line with a large body of evidence that studies the link between descriptive norms (a person's perception of how common a behavior is) and injunctive norms (how a person believes they and others should behave) (Bicchieri and Xiao, 2009).[39]After being exposed to a corruption scandal, shoppers might update their beliefs about how common antisocial behavior is in their community and, as a result, update their internal moral norms. They will therefore judge themselves less harshly when stealing at the supermarket. In this conception, the behavior of people that the customer considers to be part of their in-group is particularly important when updating their moral norms (Bicchieri et al., 2020). While it is unclear how individuals define their in-group, here we focus on gender, in that it is easily observable by customers and therefore a natural in-group marker. Thus, we expect customers to react more strongly to corruption scandals in which the perpetrator is of the same gender.[40] Column 1 of Table 7 shows that the effects are not heterogeneous based on the gender of the public official involved compared to the gender of the costumer.

Secondly, exposure to a corruption scandal may lead to emotional reactions of anger or indignation that could reduce individuals' ability to control themselves and lead to a short-term change in their internal rules of behavior.[41] In line with this, Bazurli and Portos (2019)

[38] In an experiment conducted in a maximum security prison Cohn, Maréchal, and Noll (2015) show that inmates cheat more when researchers endogenously render their criminal identity more salient.

[39] See Moore and Gino (2013) for a literature review.

[40] If multiple public officials are involved in a corruption scandal, we take the gender of the main public official involved as defined by the number of mentions in the newspaper article.

[41] Dal Bó and Terviö (2013) and Cervellati and Vanin (2013), building on the standard economic approach pioneered by Becker (1968), explicitly consider problems of self-control. Cervellati and Vanin (2013) show that in the presence of self-control problems, moral values may increase individual material welfare (and utility) by serving as a self-commitment device. Dal Bó and Terviö (2013) conceptualize an environment in which temptations yield consumption value and resisting temptations yields self-esteem. The authors identify conditions for

describe how corruption can fuel grievances and outrage among the general public.[42] Heller, Shah, Guryan, Ludwig, Mullainathan, and Pollack (2017) and Heilmann and Kahn (2019) show how this self-control issue may lead to an increase in crime and antisocial behavior. In our context, taxpayers may be particularly susceptible to such an emotional trigger because their taxes finance the salary of the corrupt public official(s) as well as the mismanaged public funds. We test this hypothesis by using information on the customer's age and employment status to categorize people into taxpayers and non-taxpayers. As an exploration of this mechanism we use information on customer age and employment status, to identify those who are likely to be taxpayers. We define a customer as a taxpayer if their declared employment status is white collar employee, blue collar employee, self-employed, business owner, or teacher. Non-taxpayers include those who report their employment status to be homemaker, student, unemployed, or retired. All the remaining customers, whose employment status is difficult to classify, are included in a third category. Alternatively, we identify customers as being of working age – and therefore a likely taxpayer – if they are between 25 and 65 years old. We then test whether the effects are heterogenous along these dimensions. [43]

In columns 2 to 4 of Table 7, we can indeed observe that only taxpayers react to corruption scandals. Moreover, the results of columns 5 and 6 of Table A21 in the Appendix show that this effect is primarily concentrated among relatively poorer taxpayers (white and blue collar employees), which is consistent with studies showing that individuals with lower returns to legality should benefit most from self-imposed moral costs in the presence of self-control problems (e.g., Cervellati and Vanin (2013)). It is important to point out that this heterogeneous effect may also be caused by other un-observable characteristics related to customers' age or employment status. One further consideration is the fact that taxpayers may also be more likely to closely follow the news about local politics and corruption scandals. Because of this we take these results only as speculative evidence that emotion may play a role in the observed behavior.

individuals to build an introspective reputation for goodness (moral capital) and for good actions to lead to a stronger disposition to do good.

[42] Howard and Cordes (2010) and Reynolds, Fitzgerald, and Hicks (2018) show, more generally, that individuals exposed to injustice and unfairness experience anger and emotional exhaustion.

[43] We performed several robustness exercises with the thresholds used to define the working age population and the results are robust to different choices. In our sample, about 70% of customers under 25 do not have a job.

Table 7: The moral cost of stealing

	Dep. Var. Under-Reporting			
	(1)	(2)	(3)	(4)
Post Scandal	0.024***	0.034***	0.003	-0.000
	(0.007)	(0.005)	(0.009)	(0.010)
Post Scandal × Var. H	-0.002	-0.040***	0.031***	0.031***
	(0.010)	(0.010)	(0.011)	(0.011)
Total Effect	0.024***	-0.006	0.033***	0.031***
	(0.007)	(0.009)	(0.006)	(0.005)
Municipality FE	√	√	√	√
Calendar Day FE	√	√	√	√
Shop FE	√	√	√	√
Hour of the Day FE	√	√	√	√
Client Controls	√	√	√	√
Var. H	In-Group Gender	Client is not Taxpayer	Client is Taxpayer	Client is Working Age
Mean Dependent	0.14	0.14	0.14	0.14
Observations	255,749	255,749	255,749	255,749
R-Square	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited on a given day. The *dependent variable* is a dummy taking a value of 1 if the customer is found to underreport at least one product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes a value of 1 if a given day falls within the first four days after a corruption scandal has been made public in the customer's municipality of residence and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in the Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

To further explore whether emotional cues may underlie the effect of corruption scandals on stealing from supermarkets, we study other events that could generate anger. We focus in particular on the results of matches played by local football teams. Football is by far the most followed sport in Italy and people tend to be fans of their local football team.

In their study on the impact of NFL games on intra-household violence, Card and Dahl (2011) find that upset losses are associated with a 10% increase in violence toward female partners, while expected defeats have no impact. Similarly, Munyo and Rossi (2013) show that upset losses increase violent property crime whereas unexpected victories strongly reduce such crime. In light of such work, we accordingly assess whether a town's residents change their behavior at the supermarket following a loss by their local team. To do so, we look at residents who live in a town where the local football team plays in the first or second Italian football division (*Serie A* and *Serie B*). We then estimate an event study where an individual is treated if they live in a town where the local football team loses an official football match.

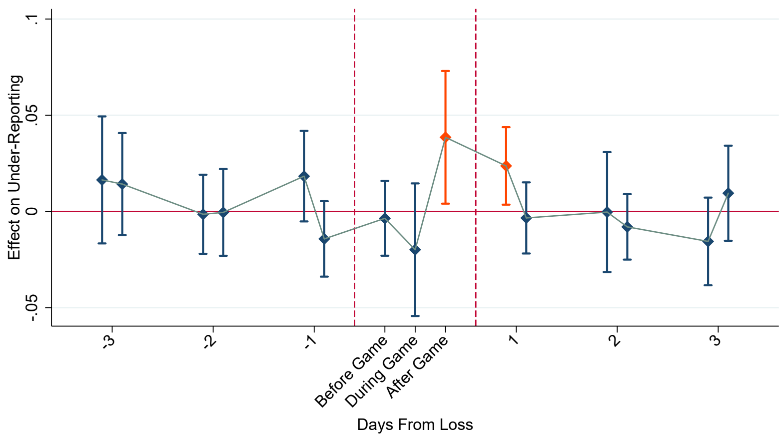
In Figure 6, we show the estimated coefficients of the event study, which focuses on a 3-day period around the match day.[44] In order to capture any within-day variation in the likelihood of under-reporting for the days before and after the match day, we separately estimate a morning (before 2 pm) and afternoon (after 2 pm) effects.[45] For the match day, we estimate three

[44]Since football games are held every week, we exploit a window of three days around the game in order to avoid overlaps between the pre- and post-match day dummies.

[45]We chose this threshold to divide the sample equally between morning and afternoon. In Italy, like other

coefficients: before the match, during the match, and after the match. In this event study, the omitted period is any other day outside this 3-day window around the match day.

Figure 6: Effect of losing a football game on under-reporting



The graph reports coefficient estimates of the effect of losing a football game (conditional on a game being held) on the probability that a customer underreports purchases, following Equation (1) and using a window of three days before and after the day of the game. For each day there are two bins: morning (before 2 pm, inclusive) and afternoon (after 2 pm). On day 0, there are three bins: before, during and after the football game. Complete data descriptions, data sources are reported in Table A28 in the Appendix, and summary statistics are presented in Table A26.

Figure 6 shows that losing a game has a strong positive effect on under-reporting at the supermarket. The effect starts immediately after the game is lost and continues to the morning after the match day. At the same time, Figure A23 shows that losing has no effect on over-reporting, once again suggesting that we are correctly identifying stealing behavior. Furthermore, Figure A11 shows that winning a game has no effect on under-reporting.

These results reinforce the fact that emotional triggers can cause an increase in under-reporting at the supermarket. However, the features of the effect are different than those related to corruption scandals. First, the effect survives for a shorter period, beginning immediately after the game ends and lasting less than 24 hours, while the effect of corruption scandals lasts for at least twenty days. Finally, Tables A22 and A23 in the Appendix show that the effect of losing a game, unlike the effect of a corruption scandal, is not concentrated among taxpayers. This reinforces the idea that the marked effect of corruption scandals on taxpayers is due to the anger caused by the misuse of their taxes and not because taxpayers react more intensely to emotional triggers.

southern European countries, people tend to have dinner very late in the evening (around 8-9pm). Supermarkets close at 9 pm.

6 Conclusions

Not only does corruption generate massive economic costs by wasting public resources, it may also have much broader negative societal effects. These include the erosion of trust in others and the reduction of stigma attached to antisocial behavior. Exploiting unique data on supermarket customers, we present systematic evidence that the dishonest, highly visible behavior of prominent public officials leads to increased dishonest behavior by customers. In particular, we show that the publication of news about local corruption scandals increases the probability that a shopper steals from the supermarket by at least 16% of the baseline value.

This study's unique setting allows us to exclude the possibility of customers' behavior changing due to material incentives for stealing or a change in social norms. Instead, we show that exposure to a corruption scandal lowers the cost associated with breaking a self-imposed moral cost, thus increasing the probability of stealing at the supermarket. In other words, the dishonest behavior of leaders lowers the individual sense of guilt when facing the possibility of stealing at the supermarket.

References

Acemoglu, D., and M. O. Jackson (2015): "History, expectations, and leadership in the evolution of social norms," *The Review of Economic Studies*, 82(2), 423–456.

Ajzenman, N. (2021): "The power of example: corruption spurs corruption," *(forthcoming) American Economic Journal: Applied Economics*.

Anderson, C. J., and Y. V. Tverdova (2003): "Corruption, political allegiances, and attitudes toward government in contemporary democracies," *American Journal of Political Science*, 47(1), 91–109.

Barr, A., and D. Serra (2010): "Corruption and culture: An experimental analysis," *Journal of Public economics*, 94(11-12), 862–869.

Bassi, V., and I. Rasul (2017): "Persuasion: A case study of papal influences on fertility-related beliefs and behavior," *American Economic Journal: Applied Economics*, 9(4), 250–302.

Bazurli, R., and M. Portos (2019): "Crook!: The impact of perceived corruption on non-electoral forms of political behaviour," *International Political Science Review*, p. 0192512119881710.

Becker, G. S. (1968): "Crime and punishment: An economic approach," in *The Economic Dimensions of Crime*, pp. 13–68. Springer.

Becker, S. O., P. H. Egger, and T. Seidel (2009): "Common political culture: evidence on regional corruption contagion," *European Journal of Political Economy*, 25(3), 300–310.

Bergolo, M., M. Leites, R. Perez-Truglia, and M. Strehl (2020): "What Makes a Tax Evader?," *NBER Working Paper*, (w28235).

Bérgolo, M. L., R. Ceni, G. Cruces, M. Giaccobasso, and R. Perez-Truglia (2017): "Tax audits as scarecrows: Evidence from a large-scale field experiment," Discussion paper, National Bureau of Economic Research.

Bicchieri, C., E. Dimant, S. Gächter, and D. Nosenzo (2020): "Social Proximity and the Erosion of Norm Compliance," .

Bicchieri, C., and E. Xiao (2009): "Do the right thing: but only if others do so," *Journal of Behavioral Decision Making*, 22(2), 191–208.

Bursztyn, L., G. Egorov, and S. Fiorin (2020): "From extreme to mainstream: The erosion of social norms," *American Economic Review*, 110(11), 3522–48.

Cagé, J., A. Dagorret, P. Grosjean, and S. Jha (2020): "Heroes and Villains: The Effects of Combat Heroism on Autocratic Values and Nazi Collaboration in France," .

Card, D., and G. B. Dahl (2011): "Family violence and football: The effect of unexpected emotional cues on violent behavior," *The quarterly journal of economics*, 126(1), 103–143.

Cervellati, M., and P. Vanin (2013): ""Thou shalt not covet": Prohibitions, temptation and moral values," *Journal of Public Economics*, 103, 15–28.

Chang, E. C., and Y.-h. Chu (2006): "Corruption and trust: exceptionalism in Asian democracies?," *The Journal of Politics*, 68(2), 259–271.

Cohn, A., M. A. Maréchal, and T. Noll (2015): "Bad boys: How criminal identity salience affects rule violation," *The Review of Economic Studies*, 82(4), 1289–1308.

d'Adda, G., D. Darai, N. Pavanini, and R. A. Weber (2017): "Do leaders affect ethical conduct?," *Journal of the European Economic Association*, 15(6), 1177–1213.

Dal Bó, E., and M. Terviö (2013): "Self-esteem, moral capital, and wrongdoing," *Journal of the European Economic Association*, 11(3), 599–633.

De Chaisemartin, C., and X. d'Haultfoeuille (2020): "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 110(9), 2964–96.

De Neve, J.-E., C. Imbert, J. Spinnewijn, T. Tsankova, and M. Luts (2019): "How to improve tax compliance? Evidence from population-wide experiments in Belgium," *Evidence from Population-Wide Experiments in Belgium (May 05, 2019). Saïd Business School WP*, 7.

Del Monte, A., and E. Papagni (2001): "Public expenditure, corruption, and economic growth: the case of Italy," *European journal of political economy*, 17(1), 1–16.

Depetris-Chauvin, E., R. Durante, and F. Campante (2020): "Building nations through shared experiences: Evidence from African football," *American Economic Review*, 110(5), 1572–1602.

Dimant, E. (2019): "Contagion of pro-and anti-social behavior among peers and the role of social proximity," *Journal of Economic Psychology*, 73, 66–88.

Dippel, C., and S. Heblich (2021): "Leadership in Social Movements: Evidence from the "Forty-Eighters" in the Civil War," *American Economic Review*, 111(2), 472–505.

Djourelova, M., and R. Durante (2019): "Media attention and strategic timing in politics: Evidence from US presidential executive orders," .

Durante, R., and E. Zhuravskaya (2018): "Attack when the world is not watching? US news and the Israeli-Palestinian conflict," *Journal of Political Economy*, 126(3), 1085–1133.

Eisensee, T., and D. Strömberg (2007): "News droughts, news floods, and US disaster relief," *The Quarterly Journal of Economics*, 122(2), 693–728.

Fell, C. B., C. J. König, S. Jung, D. Sorg, and M. Ziegler (2019): "Are country level prevalences of rule violations associated with knowledge overclaiming among students?," *International Journal of Psychology*, 54(1), 17–22.

Fellner, G., R. Sausgruber, and C. Traxler (2013): "Testing enforcement strategies in the field: Threat, moral appeal and social information," *Journal of the European Economic Association*, 11(3), 634–660.

Ferraz, C., F. Finan, and D. B. Moreira (2012): "Corrupting learning: Evidence from missing federal education funds in Brazil," *Journal of Public Economics*, 96(9-10), 712–726.

Fisman, R., and E. Miguel (2007): "Corruption, norms, and legal enforcement: Evidence from diplomatic parking tickets," *Journal of Political Economy*, 115(6), 1020–1048.

Gächter, S., and J. F. Schulz (2016): "Intrinsic honesty and the prevalence of rule violations across societies," *Nature*, 531(7595), 496.

Garz, M., and V. Pagels (2018): "Cautionary tales: Celebrities, the news media, and participation in tax amnesties," *Journal of Economic Behavior & Organization*, 155, 288–300.

Gino, F., S. Ayal, and D. Ariely (2009): "Contagion and differentiation in unethical behavior: The effect of one bad apple on the barrel," *Psychological science*, 20(3), 393–398.

Goel, R. K., and M. A. Nelson (2007): "Are corrupt acts contagious?: Evidence from the United States," *Journal of Policy Modeling*, 29(6), 839–850.

Grosjean, P. A., F. Masera, and H. Yousaf (2020): "Whistle the Racist Dogs: Political Campaigns and Police Stops," *Available at SSRN*.

Guiso, L., P. Sapienza, and L. Zingales (2004): "The role of social capital in financial development," *American economic review*, 94(3), 526–556.

Hallsworth, M., J. A. List, R. D. Metcalfe, and I. Vlaev (2017): "The behavioralist as tax collector: Using natural field experiments to enhance tax compliance," *Journal of public economics*, 148, 14–31.

Heilmann, K., and M. E. Kahn (2019): "The urban crime and heat gradient in high and low poverty areas," Discussion paper, National Bureau of Economic Research.

Heller, S. B., A. K. Shah, J. Guryan, J. Ludwig, S. Mullainathan, and H. A. Pollack (2017): "Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago," *The Quarterly Journal of Economics*, 132(1), 1–54.

Hermalin, B. E. (1998): "Toward an economic theory of leadership: Leading by example," *American Economic Review*, pp. 1188–1206.

Howard, L. W., and C. L. Cordes (2010): "Flight from unfairness: Effects of perceived injustice on emotional exhaustion and employee withdrawal," *Journal of Business and Psychology*, 25(3), 409–428.

Imbens, G. W., and D. B. Rubin (2015): *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Keizer, K., S. Lindenberg, and L. Steg (2008): "The spreading of disorder," *Science*, 322(5908), 1681–1685.

Lopez-Valcarcel, B. G., J. L. Jiménez, and J. Perdiguero (2017): "Danger: local corruption is contagious!," *Journal of Policy Modeling*, 39(5), 790–808.

Luttmer, E. F., and M. Singhal (2014): "Tax morale," *Journal of economic perspectives*, 28(4), 149–68.

Magnus, J. R., V. M. Polterovich, D. L. Danilov, and A. V. Savvateev (2002): "Tolerance of cheating: An analysis across countries," *The Journal of Economic Education*, 33(2), 125–135.

Mauro, P. (1995): "Corruption and growth," *The quarterly journal of economics*, 110(3), 681–712.

——— (1998): "Corruption and the composition of government expenditure," *Journal of Public economics*, 69(2), 263–279.

Moore, C., and F. Gino (2013): "Ethically adrift: How others pull our moral compass from true North, and how we can fix it," *Research in organizational behavior*, 33, 53–77.

Munyo, I., and M. A. Rossi (2013): "Frustration, euphoria, and violent crime," *Journal of Economic Behavior & Organization*, 89, 136–142.

Muthukrishna, M., P. Francois, S. Pourahmadi, and J. Henrich (2017): "Corrupting cooperation and how anti-corruption strategies may backfire," *Nature Human Behaviour*, 1(7), 1–5.

Olken, B. A., and R. Pande (2012): "Corruption in developing countries," *Annu. Rev. Econ.*, 4(1), 479–509.

Perez-Truglia, R., and U. Troiano (2018): "Shaming tax delinquents," *Journal of Public Economics*, 167, 120–137.

Reynolds, P. D., B. A. Fitzgerald, and J. Hicks (2018): "The expendables: A qualitative study of police officers' responses to organizational injustice," *Police Quarterly*, 21(1), 3–29.

Rizzica, L., and M. Tonello (2018): "Persuadable perceptions. The effect of media content on beliefs about corruption," *Economic Policy*.

Rotesi, T. (2019): "Do Social Media Matter? The Impact of Twitter on Political Participation."," Discussion paper, Mimeo.

Seligson, M. A. (2002): "The impact of corruption on regime legitimacy: A comparative study of four Latin American countries," *The journal of Politics*, 64(2), 408–433.

Slemrod, J. (2019): "Tax compliance and enforcement," *Journal of Economic Literature*, 57(4), 904–54.

Solé-Ollé, A., and P. Sorribas-Navarro (2018): "Trust no more? On the lasting effects of corruption scandals," *European Journal of Political Economy*, 55, 185–203.

Stephens-Davidowitz, S., and H. Varian (2014): "A hands-on guide to Google data," *further details on the construction can be found on the Google Trends page*.

Stroebel, J., and A. van Benthem (2012): "The power of the church-the role of roman catholic teaching in the transmission of hiv," *Available at SSRN 2018071*.

Sun, L., and S. Abraham (2020): "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*.

Svensson, J. (2003): "Who Must Pay Bribes and How Much? Evidence from a Cross Section of Firms," *The Quarterly Journal of Economics*, 118(1), 207–230.

——— (2005): "Eight questions about corruption," *Journal of economic perspectives*, 19(3), 19–42.

Winkler, M. (2021): "Do Disasters Affect the Tightness of Social Norms?," .

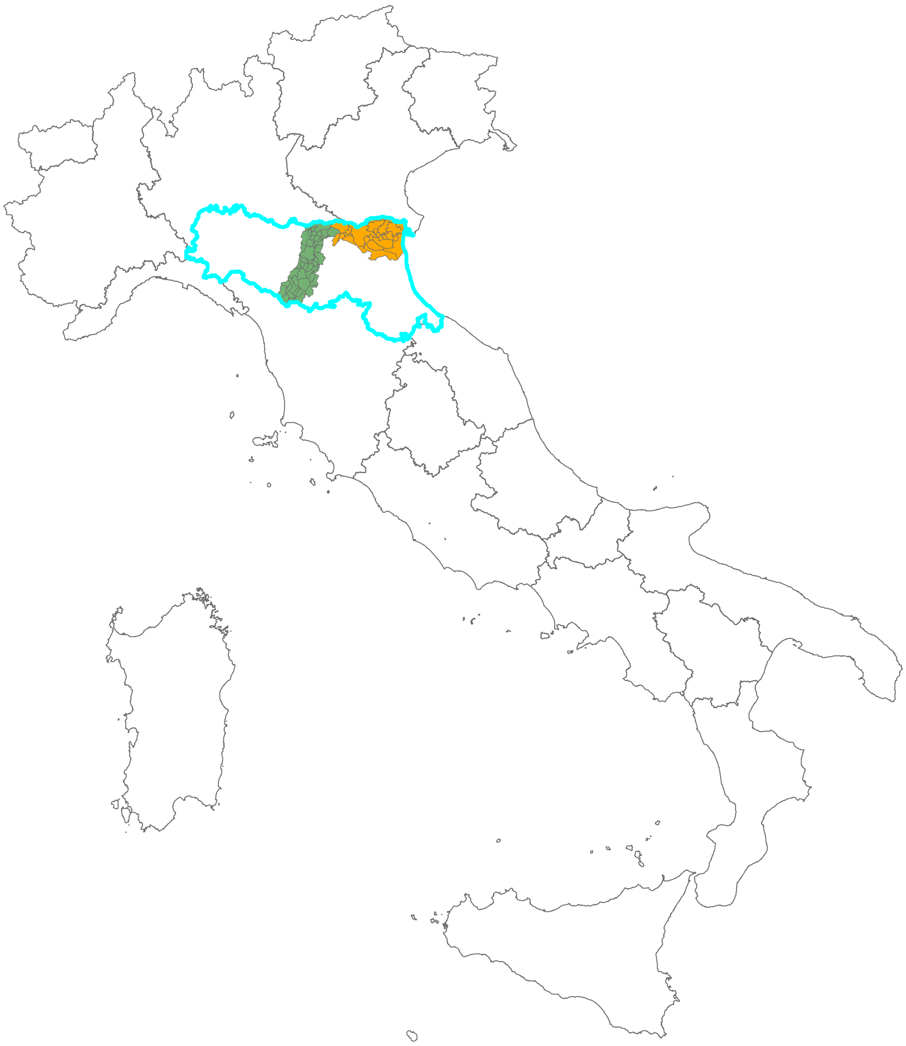
Online Appendix
(NOT FOR PUBLICATION)

Table of Contents (Appendix)

1 Background and Setting

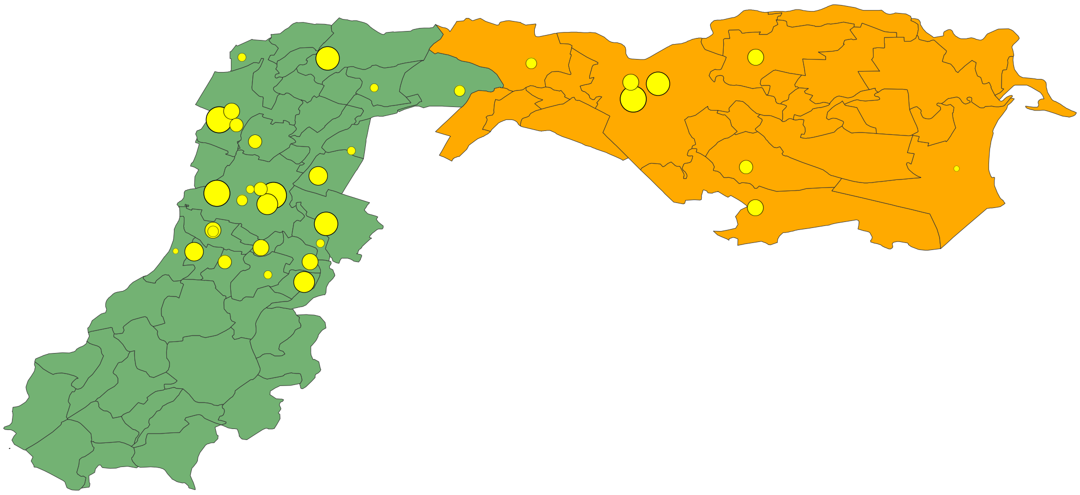
1.1 Customers' Sample

Figure A1: Provinces of Modena and Ferrara



The maps shows the provinces of Modena (in green) and Ferrara (in orange) in the region Emilia-Romagna (light green edges).

Figure A2: Supermarkets *Coop Alleanza 3.0* in Modena and Ferrara



The maps show the municipalities of the provinces of Modena (in green) and Ferrara (in orange). Yellow dots represent the location of supermarkets. The bigger is the dots, the higher is the number of random audits done to shoppers in the supermarket.

1.2 Time-Saver Technology

Figure A3: Time-Saver technology: bar-code scanner

(a) Bar-Code Scanner (b) How to Scan a Product

The figure shows the bar-code scanner that is used by clients that exploit the system called *time-saver technology*.

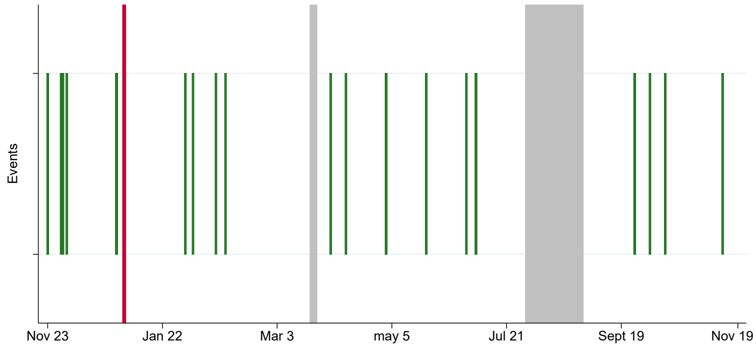
1.3 News Selection and Scandals

Table A1: News Headline (Italian), municipality and day of the treatment

Day	News Headlines	Municipality
23^{th} November 2016	Abuso edilizio: Bonucchi condannato	Sestola & Serramazzoni
30^{th} November 2016	Serra, l'ex sindaco resta sotto processo	Serramazzoni
1^{st} December 2016	I difensori contro l' accusa al processo "pratiche veloci"	Ferrara
3^{rd} December 2016	In appello mini-condanna per la Modena	Modena
29^{th} December 2016	Ambrisi-Bonini, la storia dalle origini fino all'usura	Sassuolo, Fiscaglia & Maranello
3^{rd} February 2017	"Maresciallo, sospensione giusta"	Sassuolo
7^{th} February 2017	"Appalti e mazzette: processate quei 49"	Carpi
19^{th} February 2017	"Patto illecito con i privati per devastare il paesaggio"	Serramazzoni
24^{th} February 2017	Policlinico, dirigente Ccc: "Mai corrotto"	Carpi
20^{th} April 2017	Soldi e regali in cambio di lavori, arrestati	Palagano
28^{th} April 2017	La prescrizione devasta il maxi processo	Serramazzoni
19^{th} May 2017	Corruzione: Rispoli condannato a 5 anni	Carpi & Castelfranco Emilia
9^{th} June 2017	Illeciti sui funerali? "Ora bisogna indagare"	Ferrara
30^{th} June 2017	Soldi sottratti a Terre: il buco è di 64mila euro	Argenta
5^{th} July 2017	"Condannate Baglio e i suoi, Ralenti no"	Serramazzoni
5^{th} July 2017	Caso Niagara, un'altra condanna	Poggio Renatico
26^{th} September 2017	Scandalo concorsi truccati. Indagata la Fregni: interdetta dall'ateneo di Modena	Carpi, Modena & Ferrara
4^{th} October 2017	Caso Cardiologia: oggi attesa la sentenza	Modena
12^{th} October 2017	"Mazzette in Comune" Un post scatena il sindaco	Castelfranco Emilia
11^{th} November 2017	Sei anni a Sangiorgi, stangate le aziende	Modena

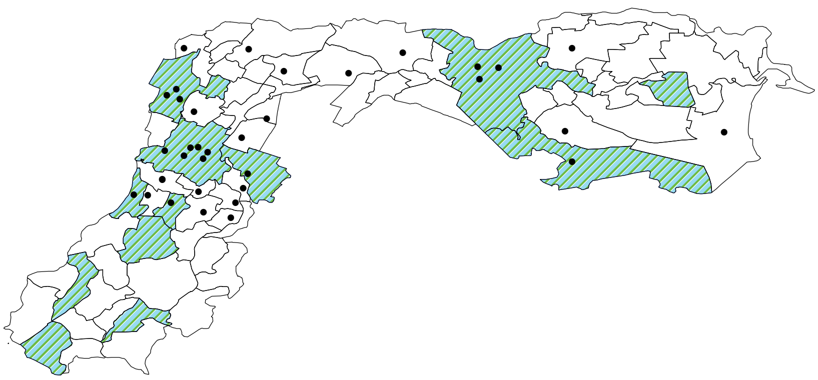
The table shows the municipality and the day in which the scandal is published on the newspaper and the news headline of the article in Italian. *Source*: the news can be found in on-line archives *Gazzetta di Modena* and *Nuova Ferrara* at the following link, respectively: https://ricerca.gelocal.it/ricerca/gazzettadimodena and https://ricerca.gelocal.it/ricerca/lanuovaferrara.

Figure A4: Distribution of corruption scandals over the period



The figure shows the distribution of corruption scandals over the period of interest. The green vertical lines represent the day of the scandals, the red line represents January 1^{st}, 2017, while the gray areas represent easter break and August 2017, respectively.

Figure A5: Distribution of corruption scandals across municipality

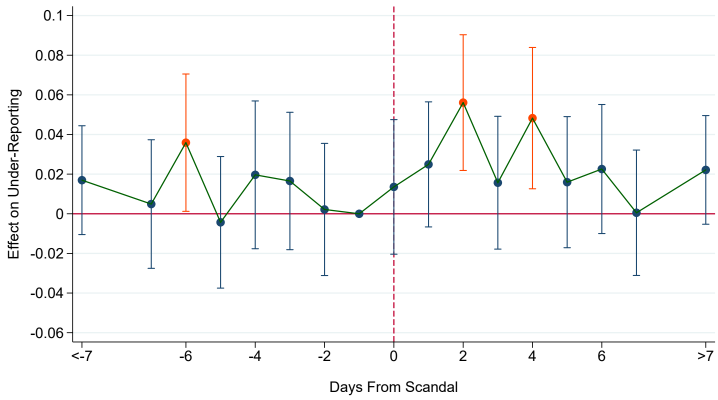


The map shows the distribution of scandals across municipalities. Black dots represent the supermarket, while the light green municipalities are those in which there is at least a corruption event over the period of interest.

2 Baseline Results and Robustness

2.1 Daily Graph with Client FE

Figure A6: Corruption scandals and under-reporting



The graph reports coefficient estimates of the effect of corruption scandal on the probability a customer underreports purchases, using Equation (1) with a window of seven days before and after the news is published. Complete data descriptions and sources are reported in Table A22 in the Appendix, and summary statistics are presented in Table A18.

2.2 Constant Sample

Table A2: Corruption scandals and under-reporting (constant sample)

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	0.0236***	0.0248***	0.0245***	0.0188***	0.0261**
	(0.0051)	(0.0053)	(0.0052)	(0.0066)	(0.0102)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	213,857	213,857	213,857	213,857	213,857
R-Square	0.01	0.01	0.01	0.34	0.06

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A3: Corruption scandals and over-reporting (constant sample)

	Over-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	-0.0036	-0.0032	-0.0028	-0.0009	-0.0044
	(0.0037)	(0.0036)	(0.0037)	(0.0046)	(0.0071)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.06	0.06	0.06	0.06	0.06
Observations	213,857	213,857	213,857	213,857	213,857
R-Square	0.00	0.01	0.01	0.31	0.06

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to over-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

2.3 Alternative Cluster and Bootstrap

Table A4: CORRUPTION SCANDALS AND UNDER-REPORTING (ALTERNATIVE CLUSTER)

	UNDER-REPORTING				
	(1)	(2)	(3)	(4)	(5)
POST SCANDAL					
Cluster:					
Robust Standard Error	0.022***	0.023***	0.023***	0.018**	0.023**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.010)
Muinicipality Level	0.022***	0.023***	0.023***	0.018***	0.023***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)
Muinicipality × Month Level	0.022***	0.023***	0.023***	0.018***	0.023**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Shop Level	0.022***	0.023***	0.023***	0.018**	0.023***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
Shop × Day Level	0.022***	0.023***	0.023***	0.018***	0.023**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.010)
Shop × Month Level	0.022***	0.023***	0.023***	0.018***	0.023***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.01	0.01	0.35	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. POST SCANDAL is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard error in the first row, and then clustered at: municipal, municipal-month, shop, shop-day and shop-month level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A5: Corruption scandals and over-reporting (alternative cluster)

	Over-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal					
Cluster:					
Robust Standard Error	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Muinicipality Level	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.005)	(0.004)	(0.005)	(0.007)	(0.004)
Muinicipality × Month Level	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Shop Level	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
Shop × Day Level	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Shop × Month Level	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.003	0.005	0.006	0.306	0.052

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to over-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard error in the first row, and then clustered at: municipal, municipal-month, shop, shop-day and shop-month level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A6: Corruption scandals and under-reporting (bootstrap)

	Under-reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal					
Bootstrap:					
Municipality Level	0.022**	0.023***	0.023***	0.018**	0.023
	(0.009)	(0.007)	(0.007)	(0.009)	(0.017)
Shop Level	0.022***	0.023***	0.023***	0.018***	0.023***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.01	0.01	0.35	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Bootstrap standard errors clustered at the municipality level and at the shop level in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A7: CORRUPTION SCANDALS AND OVER-REPORTING (BOOTSTRAP)

	OVER-REPORTING				
	(1)	(2)	(3)	(4)	(5)
POST SCANDAL					
Bootstrap:					
MUNICIPALITY LEVEL	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.006)	(0.005)	(0.006)	(0.007)	(0.008)
SHOP LEVEL	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.004)	(0.003)	(0.005)	(0.008)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.06	0.06	0.06	0.06	0.06
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.00	0.00	0.01	0.31	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to over-report at least a product while shopping and 0 otherwise. POST SCANDAL is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Bootstrap standard errors clustered at the municipality level and at the shop level in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

2.4 Balance Rest

Table A8: Balance in covariates and outcomes days before treatment

	Control Group		Treated Group		(1)	(2)	
	mean	SD	mean	SD	diff.	p-value	obs.
Under-Reporting	0.13	0.34	0.14	0.34	-0.01	0.40	40436
Under-Reporting in the Past	0.15	0.36	0.16	0.36	0.00	0.77	8870
Over-Reporting	0.06	0.24	0.06	0.24	0.00	0.81	40436
Total Value Purchases	49.40	46.82	51.77	49.09	0.52	0.53	40436
Number of Products	22.85	20.68	23.59	21.16	0.33	0.36	40436
Morning	0.45	0.50	0.43	0.50	-0.01	0.33	40436
Age	53.64	14.32	54.06	14.58	0.24	0.33	40368
Male	0.40	0.49	0.43	0.49	-0.00	0.58	40436
White-collar Worker	0.31	0.46	0.34	0.48	0.00	0.59	40436
Blue-collar Worker	0.20	0.40	0.18	0.38	0.01	0.36	40436
Retired	0.13	0.34	0.15	0.35	-0.00	0.43	40436
Homemaker	0.08	0.27	0.07	0.25	0.01	0.23	40436
Self Employed	0.05	0.22	0.05	0.22	-0.00	0.48	40436
Business Owner	0.06	0.24	0.05	0.23	-0.00	0.73	40436
Teacher	0.04	0.20	0.05	0.21	-0.00	0.55	40436
Student	0.03	0.17	0.03	0.18	0.00	0.74	40436
Unemployed	0.01	0.11	0.01	0.12	0.00	0.86	40436
Other Employment	0.08	0.27	0.06	0.24	-0.01	0.07	40436
Italian Nationality	0.95	0.21	0.94	0.23	0.00	0.57	40436

Variables description and data sources are reported in Tables A28. For each variable, means and standard deviations in both the control group and the treatment group are reported. Column (1) reports the mean difference bwteen the treatment and the control group; Column (2) reports the p-values of the treatment coefficient of a regression which includes as control municipality and day fixed effect.

2.5 Alternative Outcome and Samples

Table A9: Corruption scandals and under-reporting (alternative sample)

	Baseline	Ever Scandal	Under Vs. Over	Under Vs. Zero
	(1)	(2)	(3)	(4)
Post Scandal	0.023***	0.018***	0.042***	0.025***
	(0.005)	(0.005)	(0.014)	(0.005)
Municipality FE	√	√	√	√
Calendar Day FE	√	√	√	√
Shop FE	√	√	√	√
Hour of the Day FE	√	√	√	√
Client Controls	√	√	√	√
Mean Dependent	0.14	0.14	0.69	0.15
Observations	255,749	149,664	51,298	240,173
R-Square	0.01	0.01	0.02	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. In column 1 the sample is unrestricted as from Tables 5; in column 2 the sample is restricted cities that have experienced at leas a scandal during the period of analysis; in column 3 the sample is restricted to customer that during the sample period have been observed under-reporting or over-reporting purchases at least once; in column 4 we drop from the sample customer that over-report. The *dependent variable* is a dummy taking value 1 if customer is found to over-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

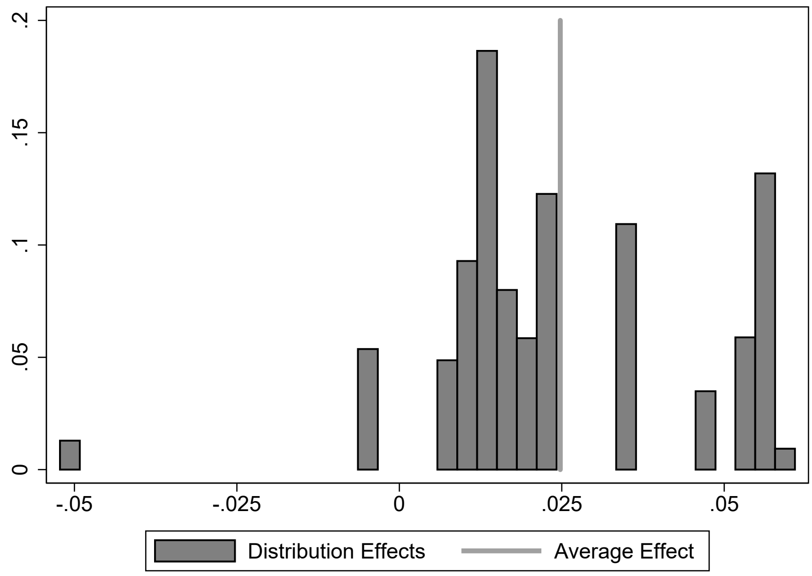
Table A10: Corruption scandals and under-reporting (alternative outcomes)

	Objects Stolen	Value Stolen (ln)	Share Value Stolen
	(1)	(2)	(3)
Post Scandal	0.052**	0.031***	0.180**
	(0.021)	(0.009)	(0.078)
Municipality FE	√	√	√
Calendar Day FE	√	√	√
Shop FE	√	√	√
Hour of the Day FE	√	√	√
Client Controls	√	√	√
Mean Dependent	1.87	3.55	7.10
Observations	256,189	256,189	256,189
R-Square	0.01	0.01	0.00

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* are: the number of object taken but not declared by the customer while using the time-saver technology (column 1); the total value of products taken but not declared by the customer while using the time-saver technology (column 2); the total value of products taken but not declared by the customer over the total value of purchases (column 3). Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

2.6 Distribution Effects - Sun, Abrahams (2020)

Figure A7: Distribution of the Treatment Effects



The graph reports distribution of the effect of each corruption scandal on the likelyhood of undereporting. The vertical line shows the average of these effects.

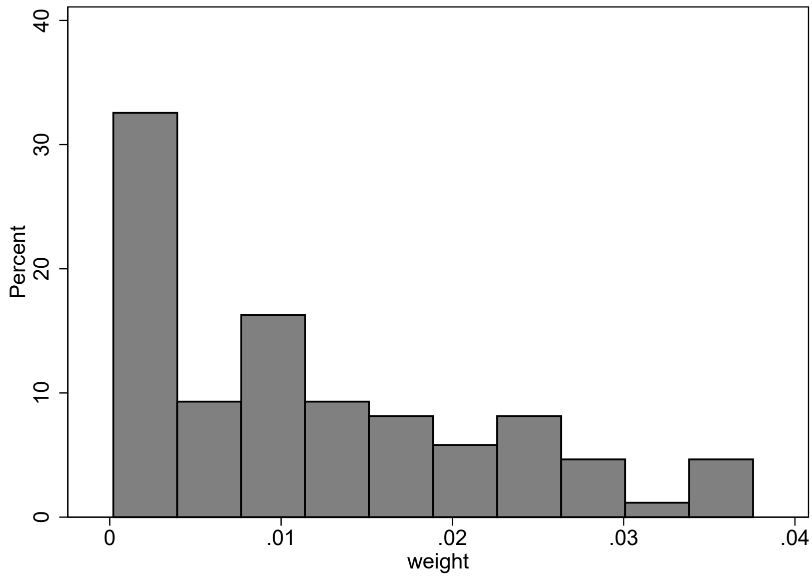
Table A11: Comparing two-way fixed effects estimates with Sun, Abrahams (2020)

	Google Trends Corruption			
	(1) Other Regions	(2) Other Topics	(3) Other Crime Topics	(4) Other Years
Two-Way Fixed Effects	5.2137	13.1429	14.4469	8.6577
Sun, Abrahams (2020)	5.7068	14.5231	10.2997	10.2997
P-value Difference	0.7982	0.6119	0.5680	0.5680

This table report the classical two-way fixed effects estimate in the first row and the average treatment effects estimated following Sun and Abraham (2020) method in the second row. The last row displayes the p-value of test that has a null hypothesis that the two-way fixed effects estimate is equal to the average treatment effects estimated following Sun and Abraham (2020).

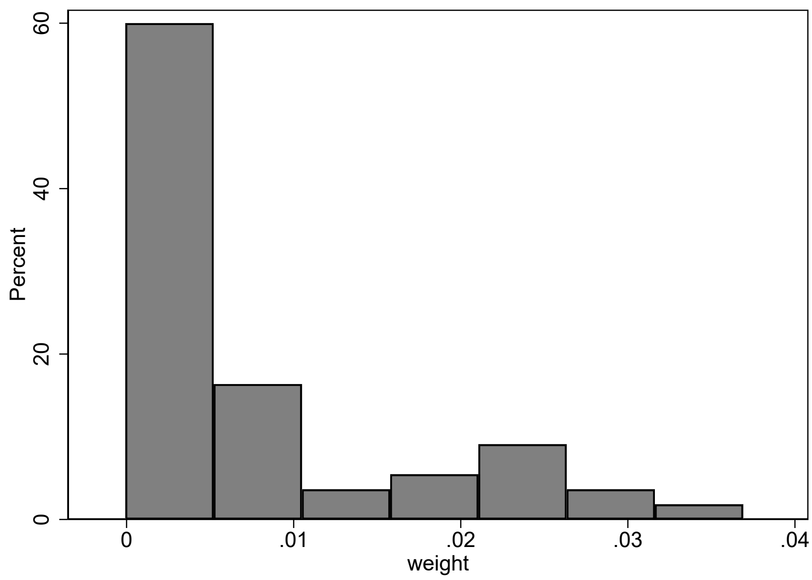
2.7 Distribution Weights - De Chaisemartin, D'Haultfoeuille (2020)

Figure A8: Distribution of the weights of the treatment effect



De Chaisemartin and d'Haultfoeuille (2020) shows that in a two-way fixed effect setting the estimated treatment effect is a weighted average of each treatment effect. The figure reports distribution of these weights.

Figure A9: Distribution of the weights of the Google news effect



De Chaisemartin and d'Haultfoeuille (2020) shows that in a two-way fixed effect setting the estimated treatment effect is a weighted average of each treatment effect. The figure reports distribution of these weights.

2.8 Already Caught Stealing in the Past

Table A12: Controlling for the client past behavior

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	0.0288***	0.0305***	0.0313***	0.0291***	0.0254**
	(0.0064)	(0.0065)	(0.0064)	(0.0085)	(0.0126)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	157,105	157,105	155,119	130,970	154,313
R-Square	0.02	0.02	0.02	0.36	0.09

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A13: Same sample as A12 without the control

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	0.0300***	0.0318***	0.0324***	0.0287***	0.0285**
	(0.0063)	(0.0064)	(0.0063)	(0.0089)	(0.0127)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	157,105	157,105	155,119	130,970	154,313
R-Square	0.01	0.01	0.01	0.33	0.08

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

3 Validation and Additional Results

3.1 Google Trends - Corruption News

Table A14: GOOGLE TRENDS ABOUT THE WORD "CORRUPTION"

Dep. Var. GOOGLE TRENDS ABOUT THE WORD CORRUPTION	
	(1)
POST SCANDAL	14.642***
	(4.120)
Municipality FE	√
Observations	260,651
R-Square	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is the number of searches for the word corruption in the Region Emiglia Romagna. POST SCANDAL is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

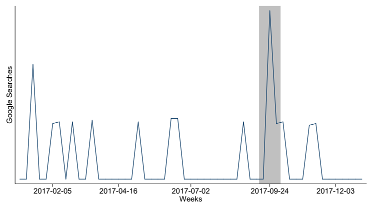
Table A15: GOOGLE TRENDS ABOUT THE WORD "CORRUPTION" VS. OTHER CONTROL TERMS

	GOOGLE TRENDS CORRUPTION			
	(1)	(2)	(3)	(4)
Percentage of Treated × Treated Index	0.2357**	0.6272***	0.7048***	0.1165*
	(0.0800)	(0.0737)	(0.0579)	(0.0630)
Municipality FE	√	√	√	√
Calendar Day FE	√	√	√	√
Search Term FE	√	√	√	√
Control Terms	Other Regions	Other Topics	Other Crime Topics	Other Years
Observations	4,602	2,478	2,124	1,770
R-Square	0.34	0.62	0.54	0.41

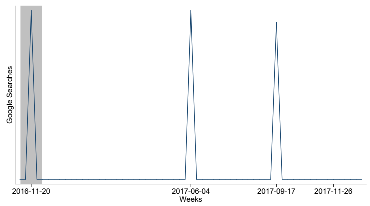
OLS estimates. Observations are at the Google index/Day level. The *dependent variable* is the Google trends index score. In all columns the *Treated index* is the Google Trends index for the word corruption during the year of our study in Emilia-Romagna. In Column (1) the control indexes are the Google Trends index for the word corruption during the year of our study in other Italian regions. In Column (2) the control indexes are the Google Trends index for the topics "football", "restaurants", "movies", "online shopping", "job opportunities" and "travel" during the year of our study in Emilia-Romagna. In Column (3) the control indexes are the Google Trends index for robberies, homicides, shootings, burglaries and rape during the year of our study in Emilia-Romagna. In Column (4) the control indexes are Google Trends indexes for the word corruption in Emilia-Romagna in the two years prior and the two years after the time period of our study. *Post Scandal* is the share of people that had a corruption scandal in their municipality in the last four days. Regressions are weighted by the number of people we observe in our dataset. Robust standard errors clustered at the Google Trends index level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Figure A10 shows the search activity for some scandals. The blue lines show the normalized scores reported by Google Trends while the gray areas identify the week of the scandal. For example, the scandal of Maria Cecilia Fregni (graph (a) of Figure A10) bursts for the first time during the period of analysis. She is an university professor of law, who was involved in a big scandal of "competition rigging" in public universities. Another important case is the so called "Operazione Teseo" (graph (b) in Figure A10) about the ex-mayor of Seramazzoni, municipality in the province of Modena, who was involved in a case of rigged contracts discovered for the first time in 2012, that over the years has had many important developments, involving new administrators and bureaucrats. Indeed, for this keyword the graph shows many peaks both before and after the week identified in the newspapers. Also the scandal about Domenico Guigli, ex-mayor of Palagano, a small municipality in the province of Modena, is a case that broke out in 2003, and had some recent developments. However, for this scandal we do not find any other peak of search activities in the reference period, probably due to the fact that it is an old scandal or that Palagano is a small municipality.

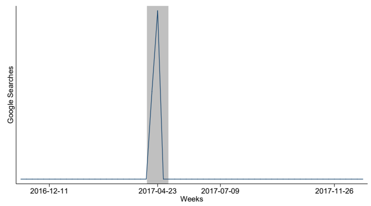
Figure A10: Google trends search activity about scandals



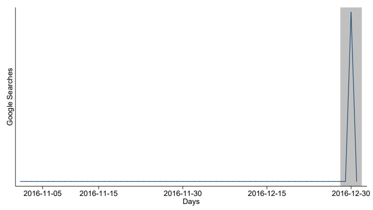
(a) "Maria Cecilia Fregni"



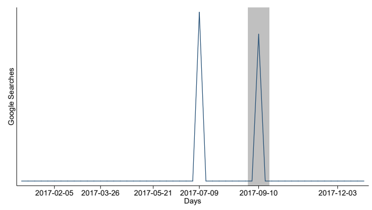
(b) "Operazione Teseo"



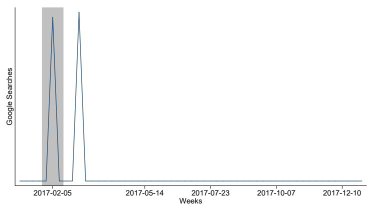
(c) "Domenico Guigli"



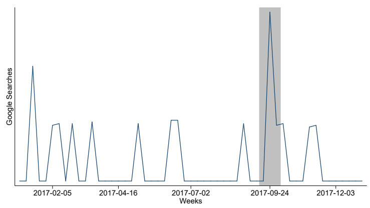
(d) "Adamo Bonini"



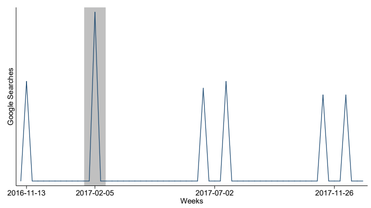
(e) "Rocco Antonio Baglio"



(f) "Stefano Cencetti"



(g) "Francesco Tesauro"



(h) "Camici Sporchi"

The graphs report Google trends search activity about the names of public officials involved into corruption scandals. Table A1, in Appendix, shows the news headline of the articles (in Italian).

3.2 Scandal vs Other News

Table A16: News categories

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Any News	0.0080**				
	(0.0033)				
Post Scandal		0.0234***			0.0254***
		(0.0047)			(0.0050)
Post Positive			0.0030		0.0043
			(0.0064)		(0.0071)
Post Neutral				-0.0009	-0.0023
				(0.0042)	(0.0043)
Municipality FE	√	√	√	√	√
Calendar Day FE	√	√	√	√	√
Shop FE	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√
Client Controls	√	√	√	√	√
Mean Dependent					
Observations	255,749	255,749	255,749	255,749	255,749
R-Square	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Any News is a dummy variable that takes value 1 if a given day is in the first four days after any news with the word corruption is made public in the municipality of the client and zero otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Post Positive is a dummy variable that takes value 1 if a given day is in the first four days after news with positive information is made public in the municipality of the client and zero otherwise. Post Higher Court is a dummy variable that takes value 1 if a given day is in the first four days after news about a higher court decisions is made public in the municipality of the client and zero otherwise. Post Other Neutral is a dummy variable that takes value 1 if a given day is in the first four days after news with neutral information about corruption case is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A17: Google trends about the word "corruption" vs. other control terms

	Google Trends Corruption			
	(1)	(2)	(3)	(4)
Post Positive × Treated Index	-0.9385	1.3823	-0.6217	4.1168
	(2.1456)	(2.0875)	(3.0360)	(2.9122)
Post Neutral × Treated Index	2.7587	1.2451	1.9858	1.1798
	(2.1640)	(0.6826)	(1.3290)	(1.4745)
Post Scandal × Treated Index	6.2253***	14.8748***	16.2852***	9.6653**
	(2.0250)	(2.8854)	(3.3227)	(3.1509)
Municipality FE	√	√	√	√
Calendar Day FE	√	√	√	√
Index FE	√	√	√	√
Control Index	Other Regions	Other Topics	Other Crime Topics	Other Years
Observations	3,388,502	1,824,578	1,563,924	1,303,270
R-Square	0.34	0.62	0.53	0.29

OLS estimates. The *dependent variable* is the Google trends index score. In all columns the *Treated index* is the Google Trends index for the word corruption during the year of our study in Emilia-Romagna. In Column (1) the control indexes are the Google Trends index for the word corruption during the year of our study in other Italian regions. In Column (2) the control indexes are the Google Trends index for the topics "football", "restaurants", "movies", "online shopping", "job opportunities" and "travel" during the year of our study in Emilia-Romagna. In Column (3) the control indexes are the Google Trends index for robberies, homicides, shootings, burglaries and rape during the year of our study in Emilia-Romagna. In Column (4) the control indexes are Google Trends indexes for the word corruption in Emilia-Romagna in the two years prior and the two years after the time period of our study. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Post Positive is a dummy variable that takes value 1 if a given day is in the first four days after news with positive information is made public in the municipality of the client and zero otherwise. Post Neutral is a dummy variable that takes value 1 if a given day is in the first four days after news with neutral information about corruption case is made public in the municipality of the client and zero otherwise. Robust standard errors clustered at the municipality-day and Google Trends index level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

4 Effect on Selection and Purchase Behavior

4.1 Clients Selection into Supermarket

Table A18: Corruption scandals and selection into treatment

	Age	Male	White-C. Worker	Blue-C. Worker	Retired	Homemaker	Self-Employed	B. Owner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Scandal	0.056	0.003	0.005	-0.009	0.001	0.008**	-0.003	-0.001
	(0.179)	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)
Mean Dependent	53.52	0.41	0.32	0.21	0.13	0.08	0.05	0.06
Observations	260,166	260,651	257,416	257,416	257,416	257,416	257,416	257,416
R-Square	0.03	0.02	0.01	0.02	0.02	0.01	0.01	0.00
	Teacher	Student	Unemployed	Other E.	Italian	Morning	Evening	N. Clients
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Scandal	0.003	-0.001	0.003	-0.005	0.009***	0.012*	-0.002	-1.388
	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(2.323)
Municipality FE	√	√	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√	√	√
Mean Dependent	0.04	0.03	0.01	0.08	0.94	0.27	0.04	15.43
Observations	257,416	257,416	257,416	257,416	260,651	260,651	260,651	16,885
R-Square	0.01	0.01	0.00	0.03	0.02	0.04	0.03	0.92

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. *dependent variable* are: the age of the customer (column 1.a); a dummy taking value 1 if customer is male and 0 otherwise (column 2.a); a dummy taking value 1 if customer is a white collar-employee and 0 otherwise (column 3.a); a dummy taking value 1 if customer is a blue-collar worker and 0 otherwise (column 4.a); a dummy taking value 1 if customer is retired and 0 otherwise (column 5.a); a dummy taking value 1 if customer is a housewife and 0 otherwise (column 6.a); a dummy taking value 1 if customer is self-employed and 0 otherwise (column 7.a); a dummy taking value 1 if customer is a business owner and 0 otherwise (column 8.a); a dummy taking value 1 if customer is a teacher and 0 otherwise (column 1.b); a dummy taking value 1 if customer is a student and 0 otherwise (column 2.b); a dummy taking value 1 if customer is unemployed and 0 otherwise (column 3.a); a dummy taking value 1 if customer employment is not classified under any of the previous category and 0 otherwise (column 4.a); a dummy taking value 1 if customer has Italian nationality and 0 otherwise(column 5.b); a dummy taking value 1 if the audit was done in the morning, before 12am and zero otherwise (column6.b); a dummy taking value 1 if the audit was done in the evening, after 6pm and zero otherwise (column 7.b); the total number of customers that go to the supermarket (column 8.b). Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

4.2 Purchasing Behavior

Table A19: Corruption scandals and purchasing behavior

	Total Value	Total Value	N. Objects	N. Objects	Avg Value Objects	Avg Value Objects
	(1)	(2)	(3)	(4)	(5)	(6)
Post Scandal	0.996	-0.819	0.276	-0.536	-0.041	0.105
	(0.687)	(2.061)	(0.265)	(0.911)	(0.053)	(0.080)
Municipality FE	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√	√
Client Controls	√	√	√	√	√	√
Mean Dependent	51.66	69.80	23.77	32.65	2.62	2.32
Observations	256,201	35,271	256,201	35,271	255,855	35,271
R-Square	0.12	0.15	0.08	0.11	0.02	0.05

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. In column 2, 4 and 6 the sample is restricted to customer that during the sample period have been observed under-reporting purchases at least once. *dependent variable* are: the total value of object purchased (columns 1 & 2); the total number of products purchased (columns 3 & 4); the average value of a products (columns 5 & 6). Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

5 Neighbouring Municipalities

Table A20: Corruption scandals and under-reporting - neighbouring municipalities

	Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Scandal	0.022***	0.024***	0.024***	0.017**	0.027***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.010)
Post Scandal Neighboring M.	0.000	0.002	0.002	-0.001	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Municipality FE	√	√	√	×	√
Calendar Day FE	√	√	√	√	√
Shop FE	×	√	√	√	√
Hour of the Day FE	×	√	√	√	√
Client Controls	×	×	√	×	√
Client FE	×	×	×	√	×
Shop FE × Day FE	×	×	×	×	√
Observations	260,192	260,192	255,749	217,344	255,445
R-Square	0.005	0.008	0.010	0.345	0.055

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Post Scandal Neighboring M. is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the neighboring municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

5.1 Moral Cost of Stealing

Table A21: The moral cost of stealing (sub-groups)

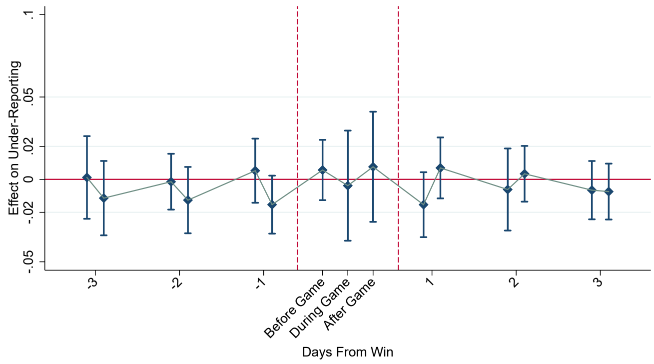
	Dep. Var. Under-Reporting						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Scandal	0.024***	0.027***	0.028***	0.017***	0.020***	0.024***	0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.008)
Post Scandal × Var. H	-0.025	-0.055***	-0.029**	0.018*	0.018	-0.010	0.029***
	(0.021)	(0.020)	(0.013)	(0.010)	(0.015)	(0.022)	(0.011)
Total Effect	-0.001	-0.028	-0.002	0.035***	0.038***	0.014	0.036***
	(0.021)	(0.019)	(0.013)	(0.008)	(0.014)	(0.021)	(0.007)
Municipality FE	√	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√	√	√
Client Controls	√	√	√	√	√	√	√
Var. H	Client is a Student	Client is a Homemaker	Client is Retired	Client is an Employee	Client is a Process Worker	Client is a Rich Taxpayer	Client is a Poor Taxpayer
Mean Dependent	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Observations	255,749	255,749	255,749	255,749	255,749	255,749	255,749
R-Square	0.01	0.01	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Scandal is a dummy variable that takes value 1 if a given day is in the first four days after a corruption scandal is made public in the municipality of the client and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A24. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

6 Football Game and Customers behavior

6.1 Winning a Football Game on Under-reporting

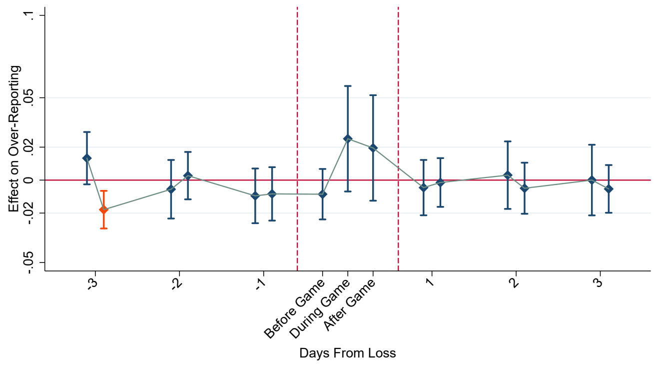
Figure A11: Winning a football game on under-reporting



The graph reports coefficient estimates of the effect of winning a football game (conditional on having a game) on the probability a customer under-report purchases, in the spirit of equation (1), using a window of three days before and after the day of the game. For each day there are two bins: morning (befor 14pm, included) and aftertnoon (after 14pm). As for game day at 0 there are three bins, before, during and after the football game. Complete data descriptions, data sources are reported in Table A28 in Appendix, and summary statistics are presented in Table A26.

6.2 Losing a Football Game on Over-reporting

Figure A12: Losing a football game on over-reporting



The graph reports coefficient estimates of the effect of losing a football game (conditional on having a game) on the probability a customer over-report purchases, in the spirit of equation (1), using a window of three days before and after the day of the game. For each day there are two bins: morning (befor 14pm, included) and aftertnoon (after 14pm). As for game day at 0 there are three bins, before, during and after the football game. Complete data descriptions, data sources are reported in Table A28 in Appendix, and summary statistics are presented in Table A26.

6.3 Heterogeneity of Losing a Football Game on Under-reporting

Table A22: Losing a football game on under-reporting

	Dep. Var. Under-Reporting				
	(1)	(2)	(3)	(4)	(5)
Post Loss	0.028**	0.028	0.025*	0.035*	0.020
	(0.011)	(0.018)	(0.014)	(0.021)	(0.019)
Post Loss × Var. H		0.001	0.013	-0.011	0.012
		(0.024)	(0.031)	(0.027)	(0.027)
Total Effect	0.028**	0.029*	0.038	0.024*	0.033**
	(0.011)	(0.015)	(0.025)	(0.014)	(0.016)
Municipality FE	√	√	√	√	√
Calendar Day FE	√	√	√	√	√
Shop FE	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√
Client Controls	√	√	√	√	√
Var. H		Client is Female	Client is not Taxpayer	Client is Taxpayer	Client is Working Age
Mean Dependent	0.14	0.14	0.14	0.14	0.14
Observations	65,122	65,122	65,122	65,122	65,122
R-Square	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Loss is a dummy variable that takes value 1 if a given hour is in the first twenty four hours after the football team of client municipality lost the game and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A26. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table A23: Losing a football game on under-reporting

	Dep. Var. Under-Reporting						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Loss	0.028**	0.031**	0.022*	0.025*	0.023*	0.035***	0.015
	(0.012)	(0.012)	(0.013)	(0.014)	(0.012)	(0.011)	(0.017)
Post Loss × Var. H	0.027	-0.037	0.038	0.010	0.029	-0.084**	0.025
	(0.078)	(0.042)	(0.039)	(0.024)	(0.034)	(0.036)	(0.024)
Total Effect	0.054	-0.006	0.060*	0.035*	0.053*	-0.049	0.040**
	(0.076)	(0.039)	(0.035)	(0.019)	(0.031)	(0.036)	(0.016)
Municipality FE	√	√	√	√	√	√	√
Calendar Day FE	√	√	√	√	√	√	√
Shop FE	√	√	√	√	√	√	√
Hour of the Day FE	√	√	√	√	√	√	√
Client Controls	√	√	√	√	√	√	√
Var. H	Client is a Student	Client is a Homemaker	Client is Retired	Client is an Employee	Client is a Process Worker	Client is a Rich Taxpayer	Client is a Poor Taxpayer
Mean Dependent	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Observations	65,122	65,122	65,122	65,122	65,122	65,122	65,122
R-Square	0.01	0.01	0.01	0.01	0.01	0.01	0.01

OLS estimates. The unit of observation is the customer, resident in a given municipality and audited a given day. The *dependent variable* is a dummy taking value 1 if customer is found to under-report at least a product while shopping and 0 otherwise. Post Loss is a dummy variable that takes value 1 if a given hour is in the first twenty four hours after the football team of client municipality lost the game and zero otherwise. Complete data descriptions and data sources are presented in Table A28 in Appendix, while summary statistics are presented in Table A26. Robust standard errors clustered at the municipality-day level are in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

7 Variables Description & Summary Statistics

7.1 Summary Statistics

Table A24: Summary statistics

	N	Mean	Std. Dev.	Min.	Max.
Total Obs	260195	.	.	.	.
Clients	103036	2.5	2.5	1	73
Shops	35	7447	7592	698	35866
Municipalities	78	3342	8356	1	59528
Customer Characteristics:					
Age	.	54	14	18	109
Male	.	41	49	0	100
White collar employee	.	32	47	0	100
Blue collar employee	.	21	40	0	100
Retired	.	13	34	0	100
Housewife	.	7.7	27	0	100
Self employed	.	4.9	22	0	100
Business owner	.	6.1	24	0	100
Teacher	.	4.1	20	0	100
Student	.	3	17	0	100
Unemployed	.	1.3	12	0	100
Other employment	.	7.6	26	0	100
Italian nationality	.	94	24	0	100
Province of Birth	116	2247	12340	5	123959
Audits Record:					
Under-Reporting	.	14	35	0	100
Over-reporting	.	6.1	24	0	100
Total Value	.	52	48	0	709
Share of Value of Under-Reported	.	7.1	11	.004	179
Share of Value of Over-Reported	.	6.6	15	.004	200

7.2 Summary Statistics Non-residents

Table A25: Summary statistics for audits done to non-residents

	N	Mean	Std. Dev.	Min.	Max.
Total Obs	21610	.	.	.	.
Clients	11893	1.8	1.6	1	35
Shops	35	619	1136	13	4912
Municipalities	1311	17	89	1	1810
Customer Characteristics:					
Age	.	46	14	18	102
Male	.	49	50	0	100
White collar employee	.	31	46	0	100
Blue collar employee	.	18	39	0	100
Retired	.	5.5	23	0	100
Housewife	.	5.2	22	0	100
Self employed	.	5.2	22	0	100
Business owner	.	6.7	25	0	100
Teacher	.	2.7	16	0	100
Student	.	9.6	29	0	100
Unemployed	.	1.5	12	0	100
Other employment	.	14	35	0	100
Italian nationality	.	93	25	0	100
Province of Birth	114	190	506	1	3346
Audits Record:					
Under-Reporting	.	17	38	0	100
Over-reporting	.	6	24	0	100
Total Value	.	63	57	0	897
Share of Value of Under-Reported	.	6.5	10	.0048	179
Share of Value of Over-Reported	.	7.1	17	.013	175

7.3 Summary Statistics Football Games

Table A26: Summary statistics for audits done to non-residents

	N	Mean	Std. Dev.	Min.	Max.
Total Obs	125583	.	.	.	.
Clients	50343	2.5	2.4	1	63
Shops	35	3595	6293	8	27052
Municipalities	4	31456	22030	6508	59528
Customer Characteristics:					
Age	.	54	15	18	107
Male	.	44	50	0	100
White collar employee	.	34	47	0	100
Blue collar employee	.	17	38	0	100
Retired	.	14	35	0	100
Housewife	.	6.8	25	0	100
Self employed	.	5.9	23	0	100
Business owner	.	5.8	23	0	100
Teacher	.	4.8	21	0	100
Student	.	3.5	18	0	100
Unemployed	.	1.3	11	0	100
Other employment	.	6.3	24	0	100
Italian nationality	.	93	25	0	100
Province of Birth	116	1085	5558	5	54004
Audits Record:					
Under-Reporting	.	14	35	0	100
Over-reporting	.	6.1	24	0	100
Total Value	.	53	49	0	709
Share of Value of Under-Reported	.	7.2	11	.004	166
Share of Value of Over-Reported	.	6.9	16	.0055	200
Games Record:					
Loosing a Game	.	.038	.19	0	1
Winning a Game	.	.024	.15	0	1

7.4 Summary Whole Population

Table A27: Summary statistics (Whole Population)

	Mean Population	**Mean Our Sample**
Province of Modena:		
Age [1]	43.4	52.9
Male [1]	48.9	40.3
Retired Men [2]	21.6	16.0
Retired Women [2]	22.3	11.1
All types of self-employed [3] *	25.8	15.5
All types of employee [3] **	74.2	84.4
Italian nationality [4]	90.3	93.3
Province of Ferrara:		
Age [1]	47.4	55.3
Male [1]	48.1	43.0
Retired Men [2]	26.4	17.1
All types of self-employed [3] *	21.6	16.2
All types of employee [3] **	78.4	83.8
Retired Women [2]	26.1	8.7
Italian nationality [3]	93.6	96.1

Source (1): year 2019
Source (2): year 2019
Source (3): year 2016
Source (4): year 2016
∗ Categories included: Self employed and Business owner
∗∗ Categories included: White collar employee, Blue collar employee, Teacher

7.5 Variables Description and Data sources (1/2)

Table A28: VARIABLES DESCRIPTION AND DATA SOURCES: MAIN VARIABLES

Main treatment:

Post scandal. It is a dummy taking value 1 the four day after is published a news about a scandal involving a public official that works in municipality of the customer and 0 otherwise

Main outcomes:

Under-reporting. It is a dummy taking value 1 if customer is found to under-report at least a product and 0 otherwise.

Over-reporting. It is a dummy taking value 1 if customer is found to over-report at least a product and 0 otherwise.

Alternative outcomes:

Object stolen. Number of object taken but not declared by the customer while using the time-saver technology.

Value stolen (ln). Total value of products taken but not declared by the customer while using the time-saver technology.

Share value stolen. Total value of products taken but not declared by the customer over the total value of purchases.

Customer characteristics:

Age. The age of the customer.

Male. It is a dummy taking value 1 if customer is male and 0 otherwise.

White collar employee. It is a dummy taking value 1 if customer is employee and 0 otherwise.

Blue collar employee. It is a dummy taking value 1 if customer is a process worker and 0 otherwise.

Retired. It is a dummy taking value 1 if customer is retired and 0 otherwise.

Housewife. It is a dummy taking value 1 if customer is a housewife and 0 otherwise.

Self-employed. It is a dummy taking value 1 if customer is self-employed and 0 otherwise.

Business owner. It is a dummy taking value 1 if customer is a business owner and 0 otherwise.

Teacher. It is a dummy taking value 1 if customer is a teacher and 0 otherwise.

Student. It is a dummy taking value 1 if customer is a student and 0 otherwise.

Unemployed. It is a dummy taking value 1 if customer is unemployed and 0 otherwise.

Other employment. It is a dummy taking value 1 if customer employment is not classified under any of the previous category and 0 otherwise.

Italian nationality. It is a dummy taking value 1 if customer has Italian nationality and 0 otherwise.

Province of birth. The province of birth of the customer.

7.6 Variables Description and Data Sources (2/2)

Table A29: VARIABLES DESCRIPTION AND DATA SOURCES: MAIN VARIABLES

Other characteristics:

Morning. It is a dummy taking value 1 if the audit was done in the morning, before 12am and zero otherwise.

Evening. It is a dummy taking value 1 if the audit was done in the evening, after 6pm and zero otherwise.

Number of Clients. The total number of customers that go to the supermarket.

Purchasing behavior:

Total value. The total value of object purchased.

Total number of objects. The total number of products purchased.

Average value objects. The average value of a product.

Interaction terms:

Article number of words. The number of words of the newspaper article which we exploit to identify the case of corruption scandals.

First Pages of Newspaper. It is a dummy variable equal to one if the news is published within the first seven pages and zero otherwise.

Match-Day. It is a dummy variable equal to one if the day in which the news is published has been played a game of the football team of the municipality and zero otherwise.

Match-Day or Day After. It is a dummy variable equal to one if the day, of the four days after, in which the news is published has been played a game of the football team of the municipality and zero otherwise.

Small supermarket. It is a dummy taking values one weather the supermarket has less than the median number of clients within a year and zero otherwise.

Supermarket in Small Municipality. It is a dummy taking values one weather the supermarket of the shopping visit is in a municipality that has less than the 30,000 inhabitants and zero otherwise.

Crowded hours. It is a dummy taking values one weather within the reference hour of the day there are less than the median number of clients within a hour and zero otherwise.

Home supermarket. It is a dummy taking values if the client go shopping in a supermarket located in the municipality of residence and zero otherwise.

In-group gender. It is a dummy taking values if the client and the public official involved in the corruption scandal are of the same gender and zero otherwise.

Client is not Taxpayer. It is a dummy taking values if the client self-report of being housewife, student, unemployed or retired and zero otherwise

Client is Taxpayer. It is a dummy taking values if the client self-report of being white collar employee, blue collar employee, self-employed, business owner, teacher and zero otherwise.

Working Age. It is a dummy taking values if the client of age between 28 and 65 and zero otherwise.