PAGING INSPECTOR SANDS: THE COSTS OF INFORMING THE PUBLIC ABOUT IMPENDING EVENTS*

Sacha Kapoor† Arvind Magesan‡

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Abstract

Most existing empirical studies on the role of information in markets analyze policies that reduce asymmetries in the information possessed by market participants. We instead exploit the introduction of pedestrian countdown signals - timers that indicate when traffic lights will change - to evaluate a policy that increases the information that participants on all sides have about an event that is in their common interest. We find that although countdown signals reduce the number of pedestrians struck by automobiles, they increase the number of collisions between automobiles. We conclude that welfare gains can be attained by creating asymmetries in information.

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†Email: sachakapoor@uchicago.edu, Phone: 773-702-4196, Fax: 773-834-3040, Address: University of Chicago, Becker-Friedman Institute, 1126 East 59th Street, Chicago IL, 60637, USA.

‡Email: anmagesa@ucalgary.ca, Phone: 403-220-5276, Fax: 403-282-5262, Address: University of Calgary, Department of Economics, 2500 University Drive N.W., Calgary AB, T2N 1N4, Canada.

1 Introduction

Few know who Inspector Sands is, and still fewer have met him. This is for good reason. Theater companies in the United Kingdom are believed to use the code name 'Inspector Sands' to alert ushers to pending emergencies, such as bomb threats and fires, without inciting panic among their patrons.[1] In emergency situations, managers of the theater page Inspector Sands to the location of the emergency or ask that he escort people from the premises in a safe and orderly manner.[2] By hiding emergencies from the public eye, ushers can complete their tasks without, at the same time, having to deal with hysterical crowds.[3]

While a policy that hides bomb threats has advantages,[4] there are circumstances where a public announcement of a threat is a more sensible policy. The number of patrons and exits in the theater will determine the policy choice that gets the most patrons out safely before a bomb explodes. When there are as many exits as patrons, the better policy is a public announcement of the threat. Everyone will exit the theater safely. When there is one exit and many patrons, the better policy is to page 'Inspector Sands'. The stampede that a public announcement causes would make it more difficult for patrons to exit the building and, moreover, be a danger in and of itself. Because most emergency situations lie between the two extremes, the challenge for theater companies is to determine the number of patrons per exit that makes one policy better than the other.

The dilemma is one that policymakers often face.[5] With privileged access to information

[1] Apparently, public transit authorities in the United Kingdom still use the code phrase to alert authorities and their staff to presence of threats to public safety. Rumors of its use can be found in the popular press and in second hand accounts. For more details, see http://www.telegraph.co.uk/comment/personal-view/3599228/When-a-voice-calls-Inspector-Sands-terror-is-never-far-away.html.

[2] For example, a manager might announce "Inspector Sands please report to the control room".

[3] People can die when crowds are made aware of life-threatening situations. For example, 168 people died near a Hindu Temple in India because visitors became hysterical after finding out about a bomb threat in the area (http://www.foxnews.com/story/0,2933,431285,00.html).

[4] As reasonable as the policy seems, it is not without controversy. A recent decision by authorities in Bangkok to withhold information about a terrorist threat for fear of inciting panic caused consternation among some members of the media. See http://www.bangkokpost.com/opinion/opinion/275924/keeping-quiet-about-a-threat-is-truly-scary for more details.

[5] The dilemma often arises in settings that are commonly studied by economists. For instance, [Stiglitz,

about impending events, they must decide whether and how they should share the information with the public. On one hand, sharing gives people a better sense of what they can do to avoid harm. On the other, what they end up doing can endanger the lives of others. When many lives are in endangered, the policymaker should either hide the information or disseminate in some other way.[6]

In this paper, we study empirically the effects of providing the public with information that reduces its uncertainty about impending events. Specifically, we draw on a natural experiment that was conducted in a major urban center to study the effect of pedestrian countdown signals - timers that warn road users about when the traffic light will change from green to yellow - on the behavior and safety of road users.[7] We exploit the setting to further consider whether and how policymakers should share information about impending events with the public.

The setting provides a natural laboratory for studying these issues for three main reasons. The first is that road users face the prospect of light changes on a regular basis. In other settings, drawing empirical conclusions about the response to information provision is difficult because events such as bomb threats and fires are so rare. The second is that there is natural variation in what road users know about light changes. Before countdown signals

2002] makes an analogy between announcing a fire in a crowded theater and bank runs. He identifies an IMF announcement that they were closing several banks, without announcing which banks and with limited insurance for depositors, as a cause of the run on banks that led to the 1997-1998 Indonesian banking crisis. While the IMF announcement gave people a chance the withdraw their funds before the closures, it also increased the chance that everyone would try to do so at the same time. Because banks only keep some of their deposits on reserve, some people were left standing in line when the banks ran out of money.

[6]The dilemma is becoming more common as time passes because governments are increasingly adopting systems that help them alert the public to critical situations. This is likely to be the case in the United States, where in 2006 the President issued Executive Order 13047: "It is the policy of the United States to have an effective, reliable, integrated, flexible, and comprehensive system to alert and warn the American people in situations of war, terrorist attack, natural disaster, or other hazards to public safety and well-being (public alert and warning system), taking appropriate account of the functions, capabilities, and needs of the private sector and of all levels of government in our Federal system, and to ensure that under all conditions the President can communicate with the American people."

[7]Although pedestrian countdown signals are intended for pedestrian use, they are visible to all who transit an intersection.

were introduced they were left to guess when the light would change. After the introduction, they knew exactly when it would change. As a result, countdown signals provide road users with a better sense of what needs to be done to avoid getting stuck waiting at an intersection for the next green light. The third is that the policy choice that saves the most lives is unclear. In our setting, information provision can cause more harm than good. The good is that road users can make more informed decisions. The bad is that the decisions they make can come at the expense of others. If road users speed up when they know the light is about to change, for example, it increases the chances that a collision occurs as well as the chances of more severe collisions occurring. When many road users use the information in the same way, countdown signals can reduce welfare overall.[8]

Our venue for assessing the impact of pedestrian countdown signals is the city of Toronto. The venue has three features that are particularly useful for the present study. The first is that decisions about where and when to install countdowns were based on cost considerations rather than the collision history of each intersection. As a result, the installations provide exogenous variation for identifying the effects on the behavior and safety of road users.

The second is that the installations were gradual and eventually covered every eligible intersection in the entire city. We control for citywide trends in collisions because, at most points in time, we observe some intersections with countdowns and some without. That countdown signals eventually covered the entire city lessens concerns that intersections with countdowns are, in some inadvertent and unseen way, different from ones without.

The third is that the decision to adopt pedestrian countdown signals was unrelated to the collision history of the city as a whole. The decision to adopt the signals was incidental to a citywide initiative to retrofit streetlights with more energy-efficient lamps. Because

[8] In addition to providing a natural testing ground for economic theory, what happens in this setting affects the well-being of millions of people each day. For example, the U.S. Department of Transportation estimates that 2.24 million Americans were injured in motor vehicle crashes in 2010 alone. They further estimate that these crashes resulted in nearly 33,000 fatalities and that, among these, nearly 6,700 fatalities happened at intersections. For more details, see http://www-nrd.nhtsa.dot.gov/Pubs/811552.pdf.

there was nothing specific about the collision history of Toronto that led to the adoption, our conclusions should apply to other settings where policymakers are deciding whether they should share information with the public.

We complement the rich variation generated by the city's natural experiment with detailed retrospective monthly collisions data collected over a 5-year span. The data describes every collision that occurred in the city, including injuries and fatalities to the involved parties, the precise location of the collision, and which party was at fault and for what reason. We exploit the wealth of detail to identify specific mechanisms that drive the increase in collisions. We investigate whether whether countdowns provide road users with information that they use to act more aggressively and whether increased acts of aggression harm others on the road.

Our empirical analysis reveals that countdown signals resulted in about a 5 percent increase in collisions per month at the average intersection. The effect corresponds to approximately 21.5 more collisions citywide per month. The data also reveals starkly different effects for collisions involving pedestrians and those involving automobiles only. Specifically, although they reduce the number of pedestrians struck by automobiles, countdowns increase the number of collisions between automobiles. Additionally, we find that collisions rose largely because of an increase in tailgating among drivers, a finding that implies drivers who know exactly when traffic lights will change behave more aggressively.

To assess the welfare implications of countdown signals, we consider the effects on various types of injuries, various types of accidents, and on the number of pedestrians and cars who transit through intersections. We find that although countdowns reduced the number of minor injuries among pedestrians, they increased the number of rear ends among cars. We show that the number of pedestrians who transit intersections with countdowns is the same as or more than the number who transit ones without. We also show that the number of cars who transit intersections with countdowns is the same as or less than the number who transit ones without. Altogether, the findings imply that fewer pedestrians were injured or struck by automobiles *for every pedestrian on the road* and that there were more collisions and rear ends *for every car on the road*. We conclude that welfare gains can be attained by disseminating information to pedestrians and hiding it from drivers.

The present study contributes to the empirical literature on the role of information in markets. Most existing studies analyze the effect of policies that increase the information that participants on one side of a market have about participants on the other side (Jin and Leslie [2003], Dranove et al. [2003], and Ippolito and Mathios [1990]).[9] We instead focus on the impact of a policy which increases the information that participants on all sides have about an event that is in their common interest.[10] In these regards, our finding that countdowns increase collisions between drivers complements the finding of [Dranove et al., 2003], who show that on average cardiac surgery report cards worsen outcomes for at-risk patients.[11]

Our finding that information benefited pedestrians at the expense of drivers speaks to questions about the role of transparency in public policy. Specifically, we provide an empirical contribution to the philosophical debate over whether governments with privileged access to information should share it with the public.[12][13] While the debate focuses on whether they should share or hide information, our findings point to the importance of considering *who* they share information with.[14]

[9] For papers that study the effect of these policies on consumer choice, see [Dellavigna and Pollet, 2009], [Bundorf et al., 2009], [Dafny and Dranove, 2008], [Dranove and Sfekas, 2008], [Hastings and Weinstein, 2008], [Jin and Sorensen, 2006], [Wedig and Tai-Seale, 2002], and [Beaulieu, 2002]. For papers that study their effect on the behavior of organizations or of their representatives, see [Jacob, 2005], [Jacob and Levitt, 2003]. [Dranove and Jin, 2010] provides an extensive review of these and other papers.

[10] In this way, our paper also relates to a large finance literature on the effects of macroeconomic news on the behavior of investors. See [Tetlock, 2010], [Pasquariello and Vega, 2007], [Green, 2004], and [Fleming and Remolona, 1999] for examples.

[11] The idea that public information can worsen outcomes is known to theorists. [Morris and Shin, 2002], for example, shows that public information can have adverse welfare effects when agents also have private information.

[12] An early summary of the broad debate can be found in [Stiglitz, 2002].

[13] There is a spirited debate about the role of transparency for monetary policy. These papers argue about whether or not central banks should publicly disclose their goals and intentions. For a summary of arguments from both sides, see [Morris and Shin, 2005].

[14] In general, political economy considerations make the role of transparency in public policy a difficult

2 A Textbook Example

To better understand why intersections might be more dangerous with countdowns, we consider a very simple textbook example of driver interaction,[15] where drivers can choose to act aggressively or cautiously. We modify the textbook example by introducing uncertainty, on the part of all drivers, about the time until a light change, an impending event that matters to all drivers. We show that under rather innocuous assumptions equilibrium collision probabilities are larger when drivers know the time that remains. The intuition for why more collisions are expected is as follows. A driver who is informed that the time remaining is greater than what he expected becomes more aggressive in his approach, while one who is informed that it is less becomes more cautious. However, the increased aggression of the driver who learns he has more time is greater than the increased caution of the driver who learns he has less. Consequently, drivers become more aggressive, on average, when they are informed about the time until light changes.

2.1 The Setup

Suppose that two drivers approach an intersection from different directions.[16] As they approach, each driver can choose either to proceed with caution (C) or to act aggressively (A). A driver who acts cautiously either slows down or stops, yielding the right-of-way to the other driver. A driver who acts aggressively either continues at the same speed or speeds up without conceding the right-of-way. We assume each driver prefers the right-of-way to waiting for the other to pass. However, if both drivers act aggressively costly collisions or

issue to study. The difficulty lies in the fact that governments often provide the public with information that has a direct bearing on whether politicians get re-elected. The public uses the information to evaluate the performance of incumbent politicians. As a result, incumbents have strong incentives to manipulate what information gets provided to the public. In this sense, the advantage of our setting is that information about light changes has no direct bearing on whether politicians get re-elected.

[15] See *Approaching Cars* on page 130 of [Osborne, 2004].

[16] To be precise, we suppose that pairs of randomly matched drivers are drawn from a single population.

fines may occur.[17]

Let $v > 0$ be the payoff from obtaining the right-of-way without a fine, $c > 0$ the cost of collision, and $b > 0$ be the cost of a fine to a driver caught crossing the intersection when the light is red. We assume that $c > b$. Let p be the probability that an collision occurs when both drivers act aggressively. Let $P_T(\omega)$ be the probability that a driver is caught and fined when he acts aggressively. ω is a random variable that represents the number of seconds until a light change (from green to yellow). Its probability distribution is given by $F(\omega)$. We assume that $P_T(\omega)$ decreases as ω increases. We do so because the probability of a fine when acting aggressively, $P_T(\omega)$, naturally depends on the amount of time left before the light changes from green to yellow. For example, driving through a red light is more likely when the driver acts aggressively with little time remaining than when he acts aggressively with lots of time remaining. In this way, the later the driver crosses (the smaller is ω) the greater the chances of punishment.

ω is known to drivers when countdowns are installed and unknown to drivers when they are not.[18] When ω is known, drivers have better information about the chances of having to wait for the next light change or of having to concede the right-of-way to another road user. At times, this information demands that drivers act more aggressively in order to avoid longer wait times.

The normal form for the simple game we consider is presented in Figure I, where one driver chooses a row and the other a column. Payoffs are symmetric. The matrix lists the payoffs for the row player. $\pi(\omega)$ is the payoff to acting aggressively when the other driver

[17] The setup describes several common interactions that occur at intersections. One such interaction occurs when a driver who is traveling straight through an intersection meets another who is turning left from the opposite direction. Another occurs when a driver is again traveling straight through but meets a driver who is turning right from the adjacent street. In both cases, there is a common space both drivers will have pass through to reach their destinations. A collision occurs if at least one driver fails to yield the right-of-way and both are in the common space at the same time.

[18] In principle, the probability of an collision occurring p could depend on ω as well. However, it is unclear why, conditional on both players being aggressive, collisions are more or less likely when little time remains on the countdown.

	Cautious	Aggressive
Cautious	0	0
Aggressive	$\pi(\omega)$	$p[-c] + (1-p)\pi(\omega)$

Figure I: The game when countdowns are active.

acts cautiously, where

$$\pi(\omega) = P_T(\omega)[-b] + (1 - P_T(\omega)))v. \tag{1}$$

We assume that $\pi(\omega) \geq 0$. If $\pi(\omega) < 0$ being cautions is the dominant strategy for both players and we never observe collisions in equilibrium.

2.2 Informing the Public Increases Collision Probabilities

Under these assumptions, the game has three Nash equilibria: two asymmetric pure strategy Nash equilibria where one driver is cautious and the other aggressive; a symmetric mixed strategy Nash equilibrium (MSNE) where each player acts cautiously with probability

$$q^*(\omega) = \frac{pc - (1-p)\pi(\omega)}{p(c + \pi(\omega))}. \tag{2}$$

We focus our analysis on the MSNE for three reasons. The first is that pure strategy equilibria are at odds with what we observe in the data, as they suggest that collisions never happen. On the other hand, when drivers use mixed strategies, the equilibrium probability that an collision occurs is given by:

$$\begin{aligned} P^*(a|\omega) &= (1 - q^*(\omega))^2 p & (3)\\ &= \frac{1}{p}\Big[\frac{\pi(\omega)}{c + \pi(\omega)}\Big]^2. & (4) \end{aligned}$$

The second reason we focus on MSNE is that the MSNE is the only symmetric Nash equilibrium of the game. The pure strategy equilibria each require one driver to defer to the other by social convention. However, we are unaware of any social convention that would lead one of these equilibria to be the norm. Third, we assume that drivers are drawn and matched randomly from the same population, so that the MSNE is the 'steady state' of interactions at intersections. Some fraction of the population of drivers act cautiously while the other fraction acts aggressively (See pp.37-39 of Osborne and Rubinstein [1994]).[19]

Figure II describes the game where drivers are unable to observe countdown signals and are therefore uninformed about the time until a light change. $E\pi(\omega)$ is the expected payoff

	Cautious	Aggressive
Cautious	0	0
Aggressive	$E\pi(\omega)$	$p[-c] + (1-p)E\pi(\omega)$

Figure II: The game when countdowns are inactive.

to acting aggressively, where the expectation is taken with respect to ω.[20] Similar to the case where drivers are informed about ω, the unique MSNE probability of being cautious is given by:

$$q^*(F) = \frac{pc - (1-p)E\pi(\omega)}{p(c + E\pi(\omega))}. \tag{5}$$

We can use the unique MSNE to solve for the collision probability when drivers are uninformed

$$P^*(a|F) = (1 - q^*(F))^2 p \tag{6}$$

$$= \frac{1}{p}\Big[\frac{E\pi(\omega)}{c + E\pi(\omega)}\Big]^2. \tag{7}$$

To evaluate the role of information for driver-driver interactions, we can compare the

[19]In the language of evolutionary game theory, the MSNE is the unique evolutionarily stable strategy of our game.

[20]We assume that driver beliefs about the time until a light change are consistent with the true distribution $F(\omega)$.

expected collision probability when drivers are informed about the next light change to the expected probability when they are not. This comparison reveals that, when drivers are informed, collisions are more likely if and only if:

$$E\left[\frac{1}{1-\frac{-c}{\pi(\omega)}}\right]^2 > \left[\frac{1}{1-\frac{-c}{E\pi(\omega)}}\right]^2. \tag{8}$$

In the theoretical appendix we show the inequality is always satisfied, so that more collisions can be expected when pedestrian countdown signals are active. Mathematically speaking, the result is driven by the fact that the MSNE probability a driver is aggressive is convex and increasing in ω.

To fix intuition about the result, we suppose that 1 second remains before a light change. We compare changes in the MSNE probability that a driver is aggressive when the time remaining decreases to 0 seconds to changes when it increases to 2. The decrease in this MSNE probability that comes with decreasing the timer to 0 is smaller in magnitude than its increase when the timer increases to 2.[21] As a result, by averaging over the possible values of the countdown, the probability of aggressive behavior is larger in the presence of a countdown than in its absence.

3 Data and Context

3.1 How Countdown Signals Inform Road Users

Figure III displays walk signals in the city of Toronto before and after pedestrian countdown signals were introduced. The flashing hand indicates to all road users that a yellow light

[21] Alternatively, the MSNE probability that a driver is aggressive can be interpreted in steady state terms. In this case, we compare changes in the share of drivers who are aggressive when the time remaining decreases to 0 to that when it increases to 2. The reduction in the share that keeps a driver indifferent between being aggressive and being cautious when the timer decreases to 0 is smaller in magnitude than the increase that keeps them indifferent when the timer increases to 2.

for adjacent vehicular traffic is imminent. The timer begins when the orange hand starts to flash. It counts the time between the solid 'Walk' signal, as represented by a walking stick figure, and the solid 'Don't Walk' signal, as represented by a solid orange hand. The time counted is independent of the time of day, but it is longer at wider crosswalks.[22][23] Importantly, the time counted at each crosswalk was unchanged when the countdowns were introduced.

3.2 The Natural Experiment

The adoption of countdown signals was incidental to a citywide initiative that retrofits pedestrian and vehicular displays with more energy-efficient LED lamps.[24][25] The city's view was that installing countdowns alongside LED lamp installations was more cost effective than retrofitting the LED lamps with countdowns at a later date. As such, the original motivation for the adoption of countdowns was unrelated to the city's history of traffic collisions, fatalities, and injuries.[26]

Because adopting countdowns was secondary to the city's goal to reduce the energy costs of traffic signals as well as CO_2 emissions, the timing and locations of installations was unrelated to the collision history at each intersection. The installation dates and locations for the LED lamps were based on cost considerations and, moreover, were largely chosen before countdowns were included in the city's initiative. The first countdown was installed

[22] In Toronto, the duration of vehicular signals (green and red lights) is based on the time of day. These durations are based on historical traffic volumes in each direction at different times of the day.

[23] At intersections with side streets, vehicles and pedestrians can affect countdown signals along side streets. These intersections have sensors that detect the presence of vehicular traffic along side streets. Pedestrians along side streets can use push buttons to initiate the timers.

[24] The initiative was actually part of broader program to retrofit all city streetlights with more energy-efficient lamps.

[25] Originally, the streetlights were fitted with incandescent lamps. The program retrofits streetlights with Light Emitting Diode (LED) lamps. LED lamps use fewer watts to produce the same luminescence as incandescent lamps.

[26] These claims are supported by official city documents. These documents can be found at the city's website: http://www.toronto.ca.

in November of 2006. In the period that we study the last countdown was installed in December of 2008.

Figure IV graphically depicts the evolution of countdown installations over time. The figure supports the idea that installation dates and locations were motivated by cost considerations, as initial installations were geographically concentrated in a few central locations and diffused outwards thereafter. It supports the idea because geographically concentrating the installations is likely to reduce their costs.

3.3 A Description of the Data

Our sample is an extract from the internal collisions database maintained by the City's Transportation Services Division. The database contains information on all collisions that occurred between January, 2004 and December, 2008.[27] We restrict the sample to collisions that occurred at an intersection with traffic signals. The collisions data includes information on the parties involved, for example whether they were a cyclist, driver, or pedestrian and whether they incurred and injury or fatality,[28] which party was at fault and why, as well as the precise time and location of the collision. Our analysis rests on monthly level observations. Overall, we observe 1794 intersections during a five-year period for a total of 107,640 observations.[29]

Table I provides summary counts for the main variables used in our empirical analysis, which illustrate clear downward trends in several variables of interest. The total number of collisions decreased from 5058 in 2004 to 4194 in 2008, seemingly driven by a sharp decline in driver-driver collisions. While fatalities and major injuries are relatively stable, minor

[27] Collision information is retrospectively based on police reports.

[28] The data classifies fatalities as those persons who die within 366 days of a collision.

[29] We excluded intersections without traffic signals at the start of our sample period because the decision to install signals is endogenous to collisions. We also excluded ones that never receive a countdown. These intersections are typically located near emergency response operations, such as firehalls, where traffic signals are fitted with preemptive systems that facilitate quicker response times. The intersections did not receive countdowns because preemptive systems confuse the countdown's timing.

injuries decline from 267 in 2004 to 212 in 2008. Later we provide evidence which suggests the trends in collisions and injuries simply reflect a downward trend in traffic volumes.

4 Empirical Specification and Identification

The baseline specification that we consider is given by:

$$y_{it} = \alpha_i + \beta I(t \geq \tau_i) + \mathbf{X}_{it}\mathbf{\Gamma} + \gamma_t + \epsilon_{it}. \tag{9}$$

y_{it} is the number of collisions at intersection i at time t. The index t counts months, starting in January 2004 and ending in December 2008. α_i controls for time-invariant differences in the propensity for collisions across intersections, such as those that are generated by the number of lanes or the posted speed limits. τ_i is the installation date for intersection i. $I(t \geq \tau_i)$ is a binary variable that indicates whether the current date equals or exceeds the installation date, so that intersections with $I(t \geq \tau_i) = 1$ are in the treatment group. γ_t is a time-specific intercept. It allows for intersection-invariant differences across time in the propensity for collision, such as those that are generated by bad weather. ϵ_{it} is a random variable that measures idiosyncratic changes in collisions.

The random variables α_i and γ_t control for possible selection effects. For example, the city may have (inadvertently) installed the first countdowns at locations with collision propensities that fail to represent the typical intersection. In this case, intersection specific factors explain both observed installation decisions as well as observed collisions - excluding α_i would result in a biased estimate of the treatment effect. On the other hand, γ_t controls for time-based selection effects, in addition to trends in collisions. Specifically, it controls for the probability that an intersection receives a countdown, a probability that is increasing with time. Excluding γ_t would likely result in a (downward) bias in the estimated treatment effect.

Finally, although the pattern of installation indicates otherwise, $\mathbf{X}_{it}$ includes controls that allow for the possibility that intersections with a recent history of collisions are treated earlier than others. In particular, $\mathbf{X}_{it}$ includes lagged collisions. We show in the next section the evidence supports the city's claim that installations were unrelated to collision histories at intersections.

5 Results

5.1 Unintended Consequences

We study the unintended consequences of pedestrian countdown signals. We present estimates that suggest there were 5 percent more collisions per month (relative to the pre-treatment average) when road users were informed about the time until light changes. We also show that while, as intended, fewer pedestrians were struck by automobiles, there were more collisions between drivers.

We provide evidence in support of the model's main prediction, that collisions happen more frequently when individuals have better information about the timing of light changes. Table II presents estimates of the effect of countdown signals on collisions. The main finding is that countdown signals result in more collisions, once intersection- and time-specific factors are accounted for. The estimate in column (3) shows that there were 0.012 more collisions per month at the average intersection, where the estimate is statistically significant at the 5 percent level against a two-sided alternative. The increase in collisions represents a more than 5 percent increase over the mean number of collisions, which was 0.229 before countdown signals were introduced.

The sign change when we include time-specific controls (columns (2) and (3)) are consistent with a pre-existing downward trend in collisions[30] as well as with an upward trend in the probability that an intersection is assigned a countdown. Table II also shows that lagged collisions matter little for the estimated effect of countdowns.[31]

To further understand why there were more collisions at intersections with a countdown, we consider the countdown's effect on three classes of collisions: ones involving only drivers; ones involving drivers and pedestrians; ones involving drivers and cyclists. The estimates can be found in Table III. The evidence in Column (1) suggests countdowns resulted in more collisions between drivers. We estimate 0.012 ($p < 0.05$) more driver-driver collisions per month at the average intersection after countdowns were introduced.

Table III also illustrates that countdowns resulted in fewer collisions between drivers and pedestrians. The estimate in column (2) suggests that there were 0.0032 ($p < 0.1$) fewer driver-pedestrian collisions per month at the average intersection after countdowns were introduced. On the other hand, the estimate in column (3) suggests that countdowns had a positive but statistically negligible (at the 10 percent level) impact on collisions between drivers and cyclists.

Three explanations might justify the increase in collisions between drivers. The first, which is closely related to our simple textbook example, is that being informed about the precise time until a light change allows drivers to become *selectively aggressive* in their approach to an intersection. Specifically, in the effort to avoid stop lights, drivers might accelerate when they know just enough time remains than when they don't. The second explanation is that countdowns distract drivers. They divert the driver's attention away from the road and, in turn, increase the chances that a collision ensues. The third is that countdowns do not directly cause collisions, rather they indirectly cause them through third-

[30]This result illustrates the benefits of a relatively long history of data from before the first installation. These data allow us to more accurately capture time trends that existed before countdowns were introduced.

[31]In Appendix Table A.I, we show that the estimates are robust to the inclusion of more lags in our empirical specifications.

party responses to the countdown. Under this explanation, because countdowns induce pedestrians or cyclists to act more aggressively they cause more collisions among drivers. In their efforts to avoid these third parties, drivers collide with each other.

5.2 More Information Means More Aggression

We provide evidence in support of the model's prediction that information about light changes induced drivers to act more aggressively. Table IV provides estimates of the effect on collisions where at least one driver was exceeding the speed limit or tailgating.[32] [33] While the estimate of Column (1) suggests a small and statistically insignificant impact on speeding, the estimate of Column (2) suggests countdowns resulted in 0.0074 ($p < 0.05$) more collisions where at least one driver was tailgating another. As a result, the evidence supports a story where drivers act more aggressively when they are informed about the time until light changes.

5.2.1 It's more than just Inattention

We consider the possibility that countdown signals distracted drivers. Specifically, we consider whether collisions increase because countdown signals divert driver attention away from the road. To do so, we compare and contrast the lasting effects of collisions with the more immediate ones. Our hypothesis is that, if countdown signals distracted drivers, then their positive effect on collisions should be more pronounced in the periods immediately after their installation. Initially, because drivers are unsure as to how to best use the countdown signals, it further distracts their attention from the road, and collision becomes more likely. As time passes, countdowns impose less of a burden on driver attention because drivers adjust to the

[32] A driver is tailgating if they were reported as following another driver too closely.

[33] Tailgating is widely considered the model of aggressive behavior, and much effort, both by way of government policy and non-government initiatives, has gone into reducing tailgating among drivers. Examples of these efforts can be found at http://www.stopandgo.org/research/aggressive/tasca.pdf and http://www.dot.state.mn.us/trafficeng/tailgating/Tailgating-finalreport.pdf.

new environment they face. Consequently, the chance of a collision should decrease.

To evaluate these alternative models, we use the following specification to estimate short- and long-run treatment effects:

$$y_{it} = \alpha_i + \sum_{k=0}^{K} \beta_k I(t = \tau_i + k) + \beta_{K+1} I(t > \tau_i + K) + \mathbf{X}_{it}\mathbf{\Gamma} + \gamma_t + \epsilon_{it}. \tag{10}$$

The coefficients $\{\beta_k\}_{k=0}^{K+1}$ describe the collision trajectory that follows a countdown installation. The first K terms describe the transition - they capture the average effect of countdowns in a month following installation relative to the effect before the first installation. The last term captures the 'permanent' effects. This specification is less restrictive than the base specification, as $I(t \geq \tau_i) = \sum_{k=0}^{K} I(t = \tau_i + k) + I(t > \tau_i + K)$. We also include leads of $I(t = \tau_i)$ in $\mathbf{X}_{it}$ to evaluate the role of collision histories in treatment effect estimates[34] - the leads describe the collision trajectory before a countdown installation.[35]

In the case where collisions increase because drivers are more distracted from the road, we anticipate larger β_k in the periods k immediately following the initial installation. We also anticipate that β_k diminishes as we approach the long run, as defined by K, and that the permanent effect, β_{K+1}, is small. Conversely, where more collisions arise because drivers become more aggressive, we anticipate a large permanent effect and, when there are differences between the short- and long-run, a small temporary one.

In Table V we present estimates of equation 10 for different values of K. Two things are apparent from these estimates. The first is that, as we lengthen the short run, the count-

[34] Formally, the leads are $I(t = \tau_i - 1)$,$I(t = \tau_i - 2)$,...,$I(t = \tau_i - s)$ for some $s \geq 1$.

[35] While this approach ostensibly resembles an event study, conceptually the two approaches differ. An event study effectively evaluates the effects of a one time event that is temporary, but that may have lasting effects. Examples of such events include worker displacement [Jacobson et al., 1993], which may adversely affect future earnings, or EPA plant inspections [Hanna and Oliva, 2010], which may have lasting effects on plant emissions. We evaluate the effects of a one time event that is permanent, where these effects may vary from period to period. Specification 10 is appropriate for both cases.

down's estimated long run effect grows in magnitude. The estimated long run effect ranges from 0.029 more collisions on average in Column (1) to 0.045 more in Column (5). Each of these are statistically significant at the 1 percent level. The second is that the estimated short run effects of countdowns, while varying in magnitude and statistical significance, appear somewhat smaller than those estimated for the long run. This is particularly true for the periods immediately following the initial installations.

We plot the estimates from Column 5 of Table V in Figure V. The solid line plots the estimates for leads to the left of the red line and the estimates for lags to the right. The dashed lines plot the 90 percent confidence interval. Figure V illustrates that in all but one case we fail to reject the hypothesis that collisions followed their usual patterns in the months leading up to a countdown installation (because zero enters the confidence interval only once). In contrast, it supports the hypothesis that collisions departed from their usual pattern when road users were informed about the time until light changes.

The evidence fails to support the hypothesis that countdown signals distracted drivers. The results are unsurprising, mostly because a situation where countdowns cause inattention seems highly unlikely. This is because countdown signals and traffic lights are in the *same* line of sight for approaching drivers and because, consequently, drivers can use the information countdowns provide without having to look away from the traffic light. On the other hand, the evidence is consistent with the hypothesis that collisions increased because drivers became more aggressive when they were informed about the time until a light change. Specifically, if the information enables road users to better respond to their circumstances, and road users learn over time how timers can best be used to avoid getting caught waiting at intersections, then we would expect a more pronounced permanent effect of countdown signals and a less pronounced temporary one.

5.2.2 It's not just Third-Party Effects

We consider the possibility that changes in third-party behaviors explain the increase in driver-driver collisions. In particular, using more detailed collision information, we explore whether collisions among drivers increased because countdowns induced third parties to enter intersections at inopportune times. We argue that the estimates from Column 2 of Table III and Table VI suggest the increase in collisions is unrelated to the behavior of third-party pedestrians.

If third-party pedestrians are the source of more driver-driver collisions, it should be the case that pedestrians are placing themselves in more risky situations. The estimates from Column (2) of Table III and from Table VI suggest otherwise. The estimates in Table III, which show that countdowns resulted in fewer driver-pedestrian collisions, suggest that pedestrians might act more cautiously after the countdown installation.[36] The estimates from Table VI provide further support for this idea, as they show that in interactions where drivers are more likely to meet pedestrians (turns) the rise in collisions is smaller than in ones where they're not. Columns (1) and (2) suggest there were 0.0022 more collisions among drivers when they make right or left turns, though only the coefficient for right turns is statistically significant. Column (3) suggests there were 0.0075 more collisions ($p < 0.1$) among drivers where at least one driver was traveling straight through the intersection, a driving manoeuver that is unlikely to involve third parties.

6 Implications for Social Welfare

We approach the welfare effects of countdowns from three directions. First, we consider the effect of countdowns on various types of collisions, such as rear ends and sideswipes.

[36] The particular piece of evidence is also consistent with an alternative hypothesis. Under the alternative, drivers act more aggressively with each other, but less aggressively towards pedestrians, when informed about the time until a light change.

Second, we consider the impact on fatalities and injuries. Third, we study the effect on traffic and pedestrian volumes at intersections. Our major findings are that countdowns resulted in more rear ends, fewer minor injuries, and had a negligible effect on traffic and pedestrian volumes. The findings suggest that the welfare impacts hinge on a comparison of the additional costs of rear ends with the benefits of fewer minor injuries.

6.1 Injuries and Rear Ends

Columns (1)-(5) of Table VII suggests the costs of pedestrian countdown signals are comprised primarily by the costs of more rear ends. These columns provide estimates of the countdown's effect on various types of collisions, those where at least one driver: enters the intersection; collides with another at an angle; rear ends another driver; sideswipes another driver, or was turning when an collision occurred. The estimates show that countdowns resulted in 0.0108 more collisions per month ($p < 0.05$) where one driver rear ends another at the average intersection.

Columns (6)-(8) of Table VII suggests the benefits of pedestrian countdown signals are comprised primarily by the benefits of fewer minor injuries. Column (8) shows countdowns resulted in 0.0027 fewer minor injuries per month at the average intersection. This finding is consistent with our finding in Column (2) of Table III of a reduction in collisions between pedestrians and drivers, because most collisions involving pedestrians and drivers result in minor injuries.

6.2 Traffic and Pedestrian Flows

In order to more properly assess the welfare implications of reducing road-user uncertainty about light changes, we consider the effects of countdown signals on vehicular and foot traffic at the intersections in our sample. The specific goal is to determine whether countdown signals resulted in fewer pedestrian-driver collisions for every pedestrian on the road and whether they resulted in more collisions between cars for every car on the road. The finding that countdowns reduced driver-pedestrian collisions has positive welfare implications when the same or more pedestrians use intersections after countdowns were introduced. The implications are ambiguous when fewer pedestrians use intersections with countdown signals. Similarly, the finding that countdowns resulted in more driver-driver collisions has negative welfare implications when the same or fewer cars use intersections after countdowns were introduced. The implications are ambiguous when more cars use intersections with countdown signals.

To quantify the rise in collisions, and reduction in minor injuries, relative to the flow of road users, we draw on counts of pedestrian and automobile traffic at intersections throughout the city.[37]. In both cases, we estimate specifications of the form:

$$V_{it} = \delta_0 + \delta_1 T_{it} + \mathbf{X}_{it}\boldsymbol{\pi} + \upsilon_{it} \tag{11}$$

where t is the time of the count, V_{it} represents volume (pedestrian or automobile) that passes through intersection i at time t, T_{it} indicates whether a countdown is installed, and $\mathbf{X}_{it}$ controls for time and geographic factors that might affect variation in V_{it} and T_{it}. We note that counts are done at different (and irregular) points in time. In the case of pedestrians, counts are done only once, while automobile counts are done repeatedly for most intersections.[38]

Table VIII provides estimates of the effect of countdown signals on the number of pedestrians transiting intersections. The data reveals three things. The first is that Columns (3) and (4) show a downward trend in pedestrian traffic across years. This conclusion follows

[37] These counts were done for most of the intersections in our study.

[38] In fact, for many intersections we have multiple observations from the same time period. This is because at separate counts are done for traffic flowing in various directions. At a minimum, this provides another useful source of variation for identifying an effect of countdowns on traffic volume.

because intersections are more likely to have a countdown installed in the later years of our sample. The second is that Columns (5) and (6) demonstrate that excluding geographic factors results in overestimates of the countdown's effect on pedestrian traffic.[39] The third is that pedestrian traffic was unaffected by the presence of countdown signals once all of the time and geographic factors are controlled for.

The results for pedestrian traffic as well as the reduction in pedestrian-driver collisions (Table III) suggest that pedestrians benefited from the introduction of countdown signals. The estimate in Column (7) shows that they benefited because fewer pedestrians were struck by automobiles for every pedestrian on the road. A potential welfare improvement for pedestrians is unsurprising because a major motivation for introducing countdown signals is that they "have been proven to improve pedestrian signal understanding, and have particular benefit for vulnerable road users such as seniors, children and mobility-challenged pedestrians."[40] Pedestrians who were initially reluctant to use intersections may now feel safer doing so, and in fact are safer doing so.

We use Table IX to study the countdown's effect on the number of cars transiting intersections. The estimates suggest at best that countdown signals had a statistically insignificant effect on the number of automobiles per 24-hour period at the average intersection.[41] As with pedestrian flows, Table IX suggests that geographic and time factors matter for estimates of the countdown's effect on automobile flows. Specifically, a comparison of Columnes (3) and (4) reveals a downward trend in automobile traffic across years. Similarly, a comparison of Columns (5) and (6) demonstrates that excluding geographic factors results in overestimates of the countdown's effect on automobile traffic.[42]

[39] We view the estimates in Column 7 with caution. This is because of the significant burden that controls for street type place on regressions that use cross-sectional data.

[40] http://www.transportation.alberta.ca/

[41] One caveat with this result is that with this data intersections are only observed with countdowns 6% of the time. However, it's likely that the number of observations more than compensates for the loss in statistical power this asymmetry generates.

[42] In contrast with the pedestrian count data these street indicators fail to distinguish between main and side streets. Instead they indicate the street along which the measured flow is traveling (street 1) as well as

The results for automobile traffic as well as the increase in driver-driver collisions (Table III) suggest that drivers suffered from the introduction of countdown signals. The estimate in Column (7) shows that they suffered because of more collisions between drivers for every driver on the road. As a result, the data reveals that countdowns may have had negative implications for the welfare of drivers who visit an intersection.

7 Conclusion

Most existing studies analyze the effect of policies that increase the information that participants on one side of a market have about participants on the other side. We instead focus on the impact of a policy which increases the information that participants on all sides have about an event that is in their common interest. We draw on a natural experiment conducted in the city of Toronto to evaluate the impact that pedestrian countdown signals have on the behavior and safety of road users. We find that the installation of countdown signals resulted in approximately 21.5 more collisions citywide per month, a more than 5 percent increase over the average without countdown signals. The data reveals starkly different effects for collisions involving pedestrians and those involving automobiles only. Although they reduce the number of pedestrians struck by automobiles, countdowns increased the number of collisions between automobiles. We show that countdowns cause fewer minor injuries among pedestrians for every pedestrian on the road and more rear ends among cars for every car on the road. Overall, the findings show that reducing road user uncertainty about the time until a light change makes life safer for pedestrians and more dangerous for drivers.

Our findings have important implications for public policy. The main implication is that welfare gains can be attained by creating asymmetries in information. That is, by disseminating information to pedestrians and hiding it from drivers. For example, in the

the intersecting street (street 2).

context of our study, rather than making countdowns visible, municipalities can announce the time until a light change through a speaker that only pedestrians can hear. While the announcement makes it more difficult for drivers to use the information for their personal gain, it continues to provide pedestrians with information that can make their lives safer. Because there was nothing specific about the collision history of Toronto that led to the adoption of pedestrian countdown signals, the implications should generalize to other settings where policymakers are considering disseminating important information to the public.

A Appendix

A.1 Theoretical Appendix

We show the inequality in Relation (8) follows from the assumption $c > b$ and Jensen's Inequality. Let $h(r) = \frac{\pi(\omega)}{c+\pi(\omega)}$ where $r = P_T(\omega)$. We define $f(t) \equiv \frac{1}{(1-t)}$ and $g(r) \equiv \frac{c}{r(b+v)-v}$ so that $h(r) = f(g(r))$. The functions f and g have the following properties: a) $f(t)$ is increasing and convex if $t < 1$; b) g is decreasing and convex in r. These properties imply that h is convex in r for $t < 1$. Or, equivalently, $h(r)$ is convex in r if and only if $-c < r(-b) + (1-r)v$. The inequality $-c < r(-b) + (1-r)v$ clearly holds when $c > b$. It follows that the square $h(r)^2$ is also convex in r. Since r is a monotone function of ω, applying Jensen's Inequality to $h(r)^2$ yields $V(F) > 0$, *i.e.* more collisions are expected when countdowns are active.

A.2 Robustness Checks

We verify the robustness of our main result when more lags are included in our estimates of Specification (9). Estimates that control for up to five lags are found in Appendix Table A.I. The estimates each show that the installation of pedestrian countdown signals resulted in 0.010 more collisions. The estimate in column (5) is marginally insignificant at the 10 percent level.

The coefficient estimates are similar when more than six lags are included in the base specification. However, as more lags are included, the statistical significance of our point estimates decline. Two factors might explain the decline in statistical significance. The first is that the statistical power of our estimator falls as we exchange more lags for fewer observations. The decline in statistical power makes it more difficult to detect small but statistically significant effects. The second is that the incidental parameters problem, which arises because autoregressive parameters mechanically depend on intersection fixed effects, is of greater concern as the cross-sectional dimension grows relative to the time-series dimension. This dimensionality problem reduces the chances of obtaining consistent estimates of the countdown's effect.

References

Nancy Dean Beaulieu. Quality information and consumer health plan choices. *Journal of Health Economics*, 21(1):43–63, January 2002.

M. Kate Bundorf, Natalie Chun, Gopi Shah Goda, and Daniel P. Kessler. Do markets respond to quality information? the case of fertility clinics. *Journal of Health Economics*, 28(3):718–727, May 2009.

Leemore Dafny and David Dranove. Do report cards tell consumers anything they don't already know? the case of medicare hmos. *The RAND Journal of Economics*, 39(3): 790–821, Autumn 2008.

Stefano Dellavigna and Joshua M. Pollet. Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749, April 2009.

David Dranove and Ginger Zhe Jin. Quality disclosure and certification: Theory and practice. *NBER Working Paper Series*, (15644), January 2010. URL http://www.nber.org/papers/w15644.

David Dranove and Leemore Sfekas. Start spreading the news: A structural estimate of the effects of new york hospital report cards. *Journal of Health Economics*, 27(5):1201–1207, September 2008.

David Dranove, Daniel Kessler, Mark McClellan, and Mark Satterthwaite. Is more information better? the effects of "report cards" on health care providers. *Journal of Political Economy*, 111(3):555–588, 2003.

Michael J. Fleming and Eli M. Remolona. Price formation and liquidity in the u.s. treasure market: The response to public information. *The Journal of Finance*, 54(5):1901–1915, October 1999.

T. Clifton Green. Economic news and the impact of trading on bond prices. *The Journal of Finance*, 59(3):1201–1233, 2004.

Rema Nadeem Hanna and Paulina Oliva. The impact of inspections on plant-level air emissions. *The B.E. Journal of Economic Analysis and Policy (Contributions)*, 10(1), 2010. Article 19.

Justine S. Hastings and Jeffrey M. Weinstein. Information, school choice, and academic achievement: Evidence from two experiments. *The Quarterly Journal of Economics*, 123 (4):1373–1414, November 2008.

Pauline M. Ippolito and Alan D. Mathios. Information, advertising and health choices: A study of the cereal market. *The RAND Journal of Economics*, 21(3):459–480, Autumn 1990.

Brian Jacob. Accountability, incentives and behavior: the impact of high-stakes testing in the chicago public schools. *Journal of Public Economics*, 89(5-6):761–796, June 2005.

Brian A. Jacob and Steven D. Levitt. Rotten apples: An investigation of the prevalence and predictors of teacher cheating. *The Quarterly Journal of Economics*, 118(3):843–877, 2003.

Louis S. Jacobson, Robert J. Lalonde, and Daniel G. Sullivan. Earnings losses of displaced workers. *The American Economic Review*, 83(4):685–709, September 1993.

Ginger Zhe Jin and Phillip Leslie. The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics*, 118(2):409–451, May 2003.

Ginger Zhe Jin and Alan T. Sorensen. Information and consumer choice: The value of publicized health plan ratings. *Journal of Health Economics*, 25(2):248–275, March 2006.

Stephen Morris and Hyun Song Shin. Social value of public information. *The American Economic Review*, 92(5):1521–1534, December 2002.

Stephen Morris and Hyun Song Shin. Central bank transparency and the signal value of prices. *Brookings Papers on Economic Activity*, 2005(2):1–43, 2005.

Martin J. Osborne. *An Introduction to Game Theory*. Oxford University Press, 198 Madison Avenue, New York, New York 10016, 2004.

Martin J. Osborne and Ariel Rubinstein. *A Course in Game Theory*. The MIT Press, Cambridge, Massachusetts and London, England, 1994.

Paolo Pasquariello and Clara Vega. Informed and strategic order flow in the bond markets. *The Review of Financial Studies*, 20(6):1975–2019, 2007.

Joseph Stiglitz. Transparency and government. *The World Bank: The Right to Tell, The Role of Mass Media in Economic Development*, pages 27–44, 2002.

Paul C. Tetlock. Does public financial news resolve asymmetric information? *The Review of Financial Studies*, 23(9):3520–3557, February 2010.

Gerard J. Wedig and Ming Tai-Seale. The effect of report cards on consumer choice in the health insurance market. *Journal of Health Economics*, 21:1031–1048, 2002.

Table I: Descriptive Statistics - Counts by Year

	Year				
	2004	2005	2006	2007	2008
Collisions	5058	5166	4704	4500	4194
Driver-Pedestrian	266	322	301	296	295
Driver-Cyclist	124	127	136	128	129
Driver-Driver	4250	4185	3897	3740	3407
Fatalities	8	10	10	13	10
Major Injuries	67	95	76	82	63
Minor Injuries	267	244	232	243	212

Table II: Collisions and Pedestrian Countdown Signals

	(1)	(2)	(3)	(4)
Pedestrian Countdown Signal Activated	-0.055*** (0.006)	-0.022*** (0.004)	0.012** (0.006)	0.011* (0.006)
Controls				
Intersection	N	Y	Y	Y
Month-Year	N	N	Y	Y
Lagged Collisions	N	N	N	Y
R^2	0.001	0.001	0.002	0.012
Intersections	1794	1794	1794	1794
Observations	107640	107640	107640	105846

1. The dependent variable is number of collisions.
2. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.

Table III: Collision Involvements and Conditions

	Collisions Involving Driver-Driver	Driver-Pedestrian	Driver-Cyclist
Pedestrian Countdown	0.0117**	-0.0032**	0.0014
Signal Activated	(0.0052)	(0.0015)	(0.0011)
R^2	0.002	0.002	0.003
Intersections	1794	1794	2075
Observations	107640	107640	107640

1. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
2. All regressions include fixed effects for the intersection and month-year.

Table IV: Driver Actions and Conditions

	Collisions where a driver	
	Speeds	Tailgates
Pedestrian Countdown Signal Activated	0.0001 (0.0002)	0.0074** (0.0020)
R^2	0.0005	0.0028
Intersections	1794	1794
Observations	107640	107640

1. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
2. All regressions include fixed effects for the intersection and month-year.

Table V: Collisions and Pedestrian Countdown Signals - Dynamic Treatment Effects

	(1)	(2)	(3)	(4)	(5)
Months after installation					
0 months	0.015	0.017	0.019	0.018	0.023*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
1 months	0.005	0.007	0.009	0.009	0.013
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
2 months	-0.012	-0.010	-0.008	-0.008	-0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
3 months	0.016	0.018	0.020*	0.020	0.024*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
4 months	0.012	0.014	0.017	0.016	0.020
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
5 months	0.002	0.005	0.007	0.007	0.011
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
6 months		0.019	0.021	0.021	0.025*
		(0.014)	(0.014)	(0.014)	(0.015)
7 months			0.034**	0.033**	0.038**
			(0.015)	(0.015)	(0.016)
8 months				0.038**	0.043**
				(0.007)	(0.017)
9 months					0.029*
					(0.017)
After last month in specification	0.029*** (0.008)	0.034*** (0.009)	0.038*** (0.010)	0.037*** (0.010)	0.045*** (0.011)
Intersections	1794	1794	1794	1794	1794
Observations	107640	107640	107640	107640	107640
p-value for F-test that leads don't matter	0.15	0.19	0.22	0.30	0.21

1. The dependent variable is number of collisions.
2. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
3. Regressions control for intersection and month-year fixed effects. They also include leads for first installation date.

Table VI: Third Party Effects

	Collisions where driver		
	Turns Left	Turns Right	Not Turning
Pedestrian Countdown Signal Activated	0.0023 (0.0027)	0.0024** (0.0012)	0.0075* (0.0041)
R^2	0.0014	0.0008	0.0017
Intersections	1794	1794	1794
Observations	107640	107640	107640

1. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
2. All regressions include fixed effects for the intersection and month-year.

Table VII: Collision Types and Injuries

	Impact Type					Injury Type		
	Entering	Angle	Rear End	Sideswipe	Turning Movement	Fatalities	Major	Minor
Pedestrian Countdown	0.0003	0.0004	0.0108***	-0.0009	0.0021	-0.0003	0.0006	-0.0027*
Signal Activated	(0.0007)	(0.0022)	(0.0032)	(0.0015)	(0.0030)	(0.0003)	(0.0009)	(0.0016)
R^2	0.0010	0.0006	0.0056	0.0010	0.0014	0.0005	0.0005	0.0007
Intersections	1794	1794	1794	1794	1794	1794	1794	1794
Observations	107640	107640	107640	107640	107640	107640	107640	107640

1. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
2. All regressions include fixed effects for the intersection and month-year.

Table VIII: Countdowns and Pedestrian Flow

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Countdown Activated	1030.50 *** (129.96)	1017.06*** (130.02)	992.32*** (127.89)	1812.81*** (293.55)	1281.43*** (274.54)	137.48 (260.47)	-228.44 (669.40)
Controls							
Day of Week	N	Y	Y	Y	Y	Y	Y
Month	N	N	Y	Y	Y	Y	Y
Year	N	N	N	Y	Y	Y	Y
N-S/E-W	N	N	N	N	Y	Y	Y
Main Street	N	N	N	N	N	Y	Y
Side Street	N	N	N	N	N	N	Y
R^2	0.02	0.02	0.08	0.11	0.17	0.52	0.81
Intersections (Observations)	1912	1912	1912	1912	1912	1912	1912

1. The dependent variable is volume of pedestrians using the intersection over an 8-hour period.
2. Robust Standard Errors, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.

Table IX: Countdowns and Automobile Flow

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Countdown Activated	-1079.74 ***	-1097.60***	-996.12***	1479.03***	1456.83***	-655.97*	-346.34
	(389.78)	(363.41)	(362.41)	(459.51)	(471.90)	(340.79)	(224.89)
Controls							
Day of Week	N	Y	Y	Y	Y	Y	Y
Month	N	N	Y	Y	Y	Y	Y
Year	N	N	N	Y	Y	Y	Y
N-S/E-W	N	N	N	N	Y	Y	Y
Street1	N	N	N	N	N	Y	Y
Street2	N	N	N	N	N	N	Y
R^2	0.002	0.008	0.05	0.08	0.08	0.65	0.83
Observations	28996	28996	28996	28996	28996	28996	28996
Intersections	1637	1637	1637	1637	1637	1637	1637

1. The dependent variable is volume of automobiles using the intersection over a 24-hour period.
2. Robust Standard Errors, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.

Table A.I: Collisions and Pedestrian Countdown Signals

	(1)	(2)	(3)	(4)	(5)
Pedestrian Countdown Signal Activated	0.010* (0.006)	0.010* (0.006)	0.010* (0.006)	0.010* (0.006)	0.010 (0.006)
Controls					
Collision Lags	Two	Three	Four	Five	Six
Intersections	1794	1794	1794	1794	1794
Observations	104052	102258	100464	98670	96876

1. The dependent variable is number of collisions.
2. Robust Standard Errors clustered at the intersection level, *** for $p < .01$, ** for $.01 < p < .05$, * for $p < .1$.
3. Regressions include intersection and time fixed effects as well as a control for the months since the first installation.

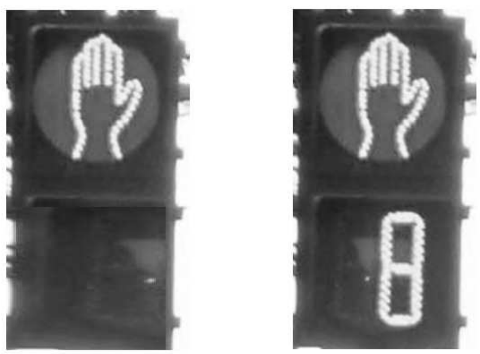
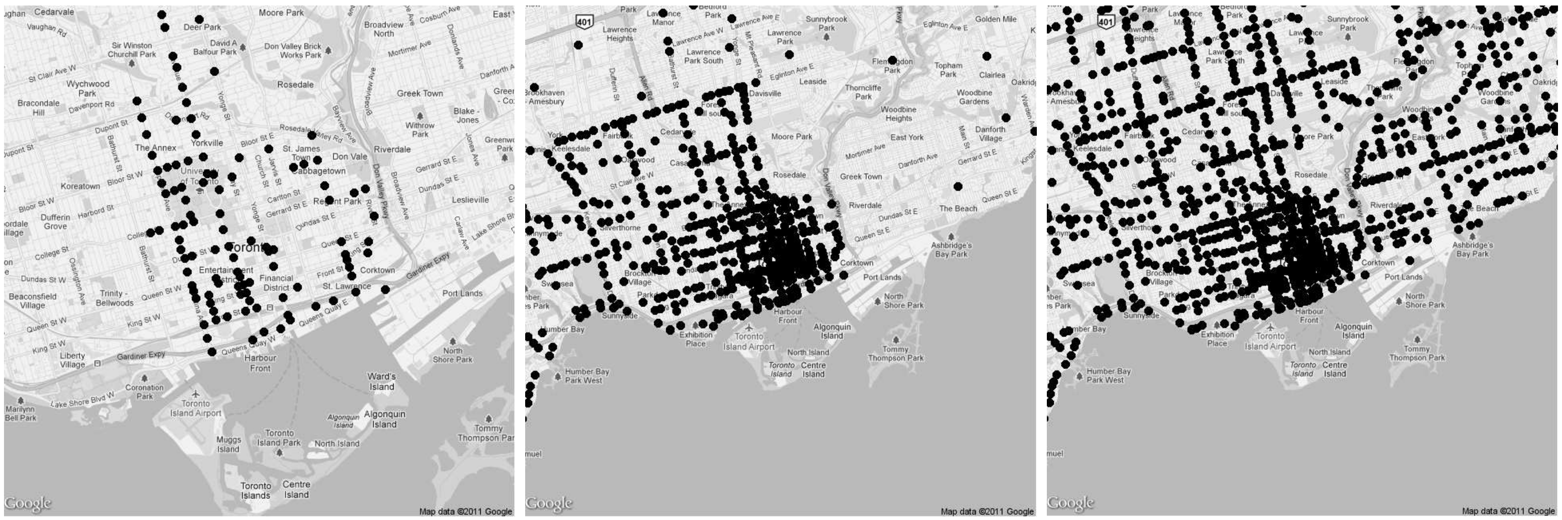


Figure III
Flashing Don’t Walk signal, with and without countdown



(a) 2006 (b) 2007 (c) 2008

Figure IV
Countdown Installations in the City of Toronto

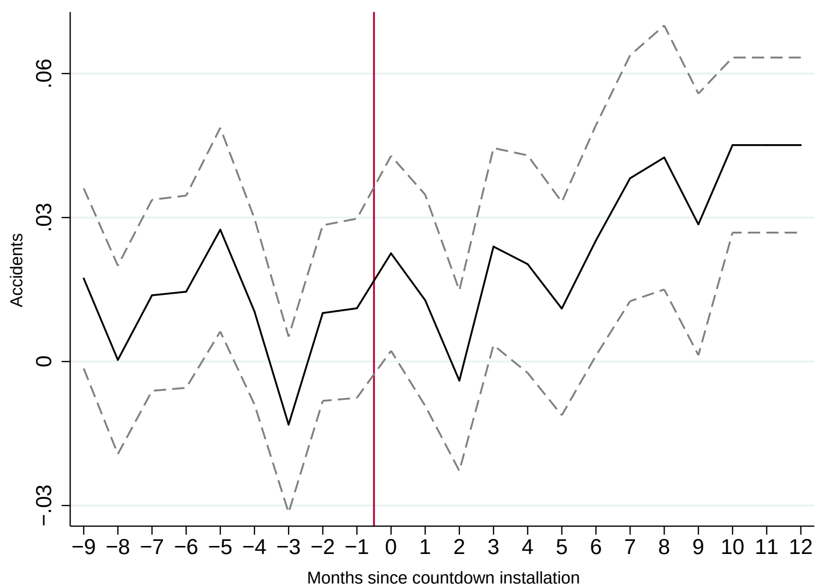


Figure V
Pedestrian countdown signals and their effects on collisions