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Stand up and Be Counted: Using Traffic Cameras to Assess Voting Behavior in Real Time

Bryce J. Dietrich
Purdue University, bjdietri@purdue.edu

Hyein Ko
University of Illinois at Urbana-Champaign

Payel Sen

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Stand up and be counted: Using traffic cameras to assess voting behavior in real time

Bryce J. Dietrich[1], Hyein Ko[2] and Payel Sen[3]

Abstract
Despite their ubiquity, few have used traffic camera networks for social science research. Using 1,312,977 images collected from 768 London-based cameras leading up to the 2015 UK general election, this study not only demonstrates how traffic camera data can be used to effectively measure same-day turnout, but we also provide ways such data can be used to assess political behavior more broadly. Such automated enumeration is especially important in countries where official results are only returned for the current election, making it difficult for those interested in assessing turnout at lower levels of aggregation, even when those elections are next on the calendar. Although we are not the first to suggest the value of images-as-data, this study hopes to underline the importance of video-as-data, while simultaneously offering an important foundation for future research.

Keywords
computer vision, voter turnout, traffic cameras

Introduction

It is still unknown how many traffic cameras there are in the world, with some estimates putting the number in the hundreds of millions (Cosgrove, 2019). Unfortunately, there are substantially fewer studies that have used this data for social science research. This study uses 1,312,977 images collected from 768 London-based cameras in the days leading up to the 2015 United Kingdom (UK) general election to not only demonstrate how traffic camera data can be used by social scientists, but also to gain new insights into voting behavior.

From a practical standpoint, being able to automatically count the number of people outside a polling location is extremely important (Stein et al., 2020). For example, in the United States, there are real-time demands on Election Day for staffing and equipment (e.g., Burden and Milyo, 2015; Hostetter, 2020; Jones and Stein, 2021). Video-based measures of turnout could help election officials meet these demands without disturbing or preventing voters from casting their ballots. Similarly, in other countries, like the UK, election results are only released at a single level of aggregation, making it difficult for candidates, parties, and officials to predict turnout in the next election. Traffic camera footage could not only help alleviate this problem, but it could also help with the allocation of election resources before the first ballot is ever cast. This benefit, in addition to many new research opportunities, makes the use of traffic camera footage something that should be actively considered, a process this study aims to begin.

[1]Department of Political Science, Purdue University, USA
[2]Department of Political Science, University of Illinois, Urbana-Champaign, USA
[3]Social Science Research Service, USA

Corresponding author:
Bryce J. Dietrich, Department of Political Science, Purdue University, 100 North University Street, West Lafayette, IN 47907-2050, USA.
Email: bjdietri@purdue.edu

Turnout, traffic cameras, and the 2015 UK general election

Since perhaps Powell (1986), understanding aggregate turnout has been a staple of political behavior research (for review, see Cancela and Geys, 2016). For example, a recent meta-analysis found 130 peer-reviewed journal articles that used turnout at the national, regional, or local level as the dependent variable (Stockemer, 2017). These studies have typically offered institutional, socioeconomic, and election- specific variables as the main determinants (Blais, 2006). Although considerable work has been done on properly measuring turnout (e.g., Berent et al., 2016), less attention has been paid to same-day turnout which is often estimated using exit polls (Frankovic, 2008). However, the accuracy of these polls has been called into question due to the well-known problems associated with self-selection and interviewer effects (McDonald and Thornburg, 2012).

These general problems are especially pronounced in countries, like the UK, where election results are not released at lower levels of aggregation, forcing firms to rely on higher-level data for exit polling, making inaccuracies more prevalent (Pavía, 2010). Moreover, many countries only release results for the election at-hand, meaning those interested in studying local, county, and municipal turnout have no way to do so in off years, despite their theoretical importance (for review, see Warshaw, 2019). For example, understanding the extent to which people voted in London district councils in 2015 is important for those potentially running for those seats in 2016. However, such assessments are difficult when the only official estimates are from 2014.

If turnout was low in that cycle, then campaigns and researchers may conclude that something about 2016 caused turnout to decline. Such a conclusion could prove spurious, if 2015 turnout data showed that a downward trend was already underway. Unfortunately, such levels of granularity are often unavailable.

We contend traffic cameras may provide a potential remedy, something we demonstrate by testing two main theoretical expectations. First, we expect *when more pedestrians appear on traffic cameras near polling places, those locations will have higher Election Day turnout*. We also expect to find that this general relationship will carry over to the next election. More specifically, *when more pedestrians appear on traffic cameras near polling places on Election Day, those locations will also have higher turnout in the next election*. If evidence consistent with these expectations is found, it will open new avenues of inquiry for scholars interested in studying aggregate turnout, especially in countries, like the UK, where certain types of election data are unavailable.

Data and methods

Data collection began 1 day prior to the 2015 UK general election (May 6, 2015) and ended on the day itself (May 7, 2015). On these days, images were scrapped every 6 min from all available traffic camera in the London metropolitan area ($N = 768$) beginning at 7 a.m. and ending at 7 p.m. local time. This resulted in 597,480 unique images. Pedestrians were then detected using Tensorflow and the Faster R-CNN with Inception-ResNet architecture, which has been found to be effective in identifying people (e.g., Haque et al., 2019). Figure 1 shows an example of the output, where green boxes indicate a detected pedestrian.[1] (Additional details are provided in the Appendix.)

After reviewing several batches of images, we found labels which had detection scores greater than the median tended to be accurate. Consequently, our final pedestrian counts only include instances where the detection scores were greater than the median, resulting in 234,154 and 269,901 identified pedestrians on the day before and Election Day itself, respectively. To ensure the accuracy of these counts, we randomly sampled 50 images. Within these images, 64 pedestrians were identified, of which 44 had detection scores greater than the median. In the latter group, 36 (or 81.82%) were actually pedestrians.[2] Further validation was obtained using Google Maps. As described in the SI, we identified streets in our data which had good (green) and bad (red) traffic on Election Day. These results are reported in Figure 2 which shows ResNet detected significantly fewer cars on the former as opposed to the latter (W = 159, 794, p-value = .002338). We also found a similar statistical differences between streets labeled green and orange (indicating a "medium amount of traffic") (W = 159, 794, p-value = .003547), suggesting ResNet returned reasonable results.

For each constituency, our main independent variable (see "Video Turnout" below) is the extent to which the number of pedestrians increased on Election Day as compared to the previous day, represented as a percent increase. Here, we aggregated the ResNet output to either the parliamentary or mayoral constituency level (depending on the model) using a weighted median, such that cameras that were closer to polling locations were given greater weight. (Additional details are provided in the Supplemental Material). Given that polling locations are often housed in schools, government buildings, and even grocery stores, it is difficult to use the raw pedestrian counts as our main independent variable. Indeed, what may be a higher number of pedestrians on Election Day may simply be people patronizing these popular locations. Although the controls we outline below help, similar concerns have arisen in related research (e.g., Chen et al., 2022). By comparing the number of pedestrians detected on Election Day to the number of

Figure 1. Example of pedestrian detection output on UK election day.

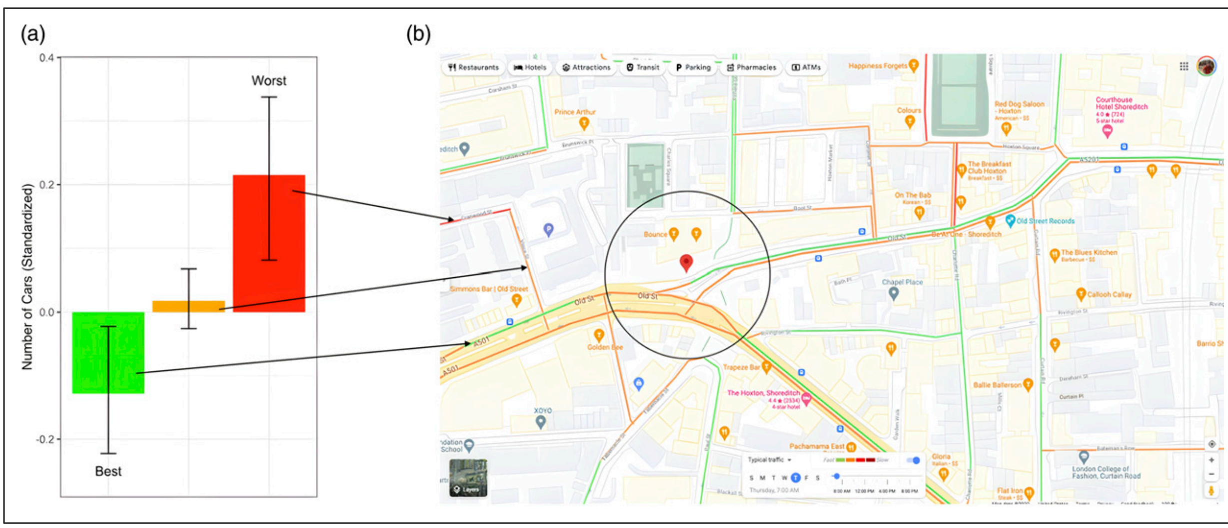

Figure 2. Traffic speed validation. *Note:* Results from our traffic speed validation exercise Panel A shows the median for the standardized number of cars for hours where traffic delates either were (red) or were not (green) present. In this panel, the orange bar indicates "medium amount of traffic." Bootstrapped 95% confidence intervals are shown around each bar and an example of Google Maps' "Typical traffic" tools is sown in Panel B.

pedestrians detected on the previous day, we gain some traction on this point, since any patronizing attributed to the location itself should be captured in what was counted the previous day. In the SI, we include a model in which we predict hour-by-hour turnout using a similar approach, which also should help alleviate these concerns.

Finally, to provide a point of comparison, we created a similar measure using the 2015 and 2010 British Election Study (BES). For each constituency, we calculated the proportion of respondents who said "Yes, I voted" in the 2015 and 2010 parliamentary elections. In both instances, the denominators are the number of respondents who answered the question. We then calculated the extent to which the 2015 proportion increased as compared to the 2010 proportion, represented as percent increase. In the analyses below, this variable is called "BES Turnout." Finally, our main dependent variable is turnout in the 2015 UK General Election and the 2016 London Mayoral Election.

Results

Table 1, Model 1 tests our main expectation by regressing the turnout in the 2015 UK general election on our video-based turnout measure, which again, is the median number of pedestrians on Election Day as compared to the previous

Table 1. Automated Pedestrian Counts From Traffic Cameras Can Effectively Predict Same-Day Turnout in the 2015 UK General Election.

	Dependent variable:			
	Parliamentary turnout			
	(1)	(2)	(3)	(4)
Constant	0.010**	−0.081**	0.015**	−0.063*
	(0.004)	(0.033)	(0.007)	(0.035)
Video turnout	0.600**	0.700**		
	(0.286)	(0.296)		
BES turnout		−0.001	−0.005	
			(0.020)	(0.020)
65+ Pop		0.004***		0.003**
		(0.002)		(0.002)
Unemploy. Rate		−0.00003		−0.0004
		(0.001)		(0.001)
Foreign Pop.		0.001***		0.001***
		(0.0004)		(0.0004)
Observations	68	68	68	68
Adjusted R^2	0.048	0.132	−0.015	0.056

Note: Ordinary least squares models predicting parliamentary turnout in the 2015 UK election. "Video Turnout" is the number of pedestrians on Election Day as compared to the previous day, represented as a percent increase. The unit of analysis is the constituency, so this measure is aggregated to that level. All other variables are described in the main text. Levels of significance are reported as follows: $* p < .1$; $** p < .05$; $*** p < .01$. Standard errors are reported in the parentheses.

Table 2. Automated Pedestrian Counts From Traffic Cameras Can Effectively Predict Future Turnout in the 2016 London Mayoral Election.

	Dependent variable:
	Mayoral turnout
	(1)
Constant	0.167***
	(0.021)
Video turnout	0.472**
	(0.209)
BES turnout	
65+ Pop	
Unemploy. Rate	
Foreign Pop.	
Observations	31
Adjusted R^2	0.121

Note: Ordinary least squares models predicting turnout in the 2016 London mayoral election. "Video Turnout" is the number of pedestrians on Election Day as compared to the previous day, represented as a percent increase. The unit of analysis is the constituency, so this measure is aggregated to that level using 2015 data. All other variables are described in the main text. Levels of significance are reported as follows: $*p < .1$; $**p < .05$; $***p < .01$. Standard errors are reported in the parentheses.

day, represented as a percent increase. Here, we not only find our video-based measure is a statistically significant predictor of the 2015 parliamentary turnout, and this relationship holds when a number of additional controls are also included (see Model 2).[3] Moreover, the turnout measure derived from the BES is not a significant predictor in either model, providing some evidence that our video-based measure yields distinctly different results than at least one survey-based estimate.

Table 2, Model 1 tests our second expectation which like the first expects turnout to be higher when more pedestrians are viewed by traffic cameras on Election Day as compared to the day before. However, unlike our first expectation, here we expect our video-based measure to be predictive of turnout in the next election. Not only do we find our measure is a statistically significant predictor of the 2016 mayoral turnout, but the relationship is more pronounced than what was found in Table 1 as indicated by the Adjusted R2 values. This suggests traffic camera data could be used to effectively assess turnout at two different levels of aggregation. The same cannot be said for our BES estimate which is again, not a statistically significant predictor.

In the SI, we also include two robustness checks and two supplementary analyses which further underline how traffic camera data could be used to assess political behavior. First, we include hourly measures of turnout which demonstrate significant differences in turnout as the day progresses. Not only does this analysis speak to democratic concerns over wait times at the polls (Stein et al., 2020), but it could also prove helpful for researchers and voters interested in choosing the most optimal time to vote on Election Day (King and Leemis, 2016). Second, we also present an analysis where the distance of each pedestrian from one another is the independent variable. We find this measure may be indicative of broader social connectedness in the area, a variable of interest to many scholars (for review, see Bailey et al., 2018).

Conclusion

This study demonstrates several ways traffic cameras could be used to better understand political behavior. Our main demonstration uses over a million images from the 2015 UK General Election. Ultimately, we find pedestrian counts from 768 London-based traffic cameras can be used to predict current and future turnout. In the UK, the former is important as a supplement to exit polls which have been found to be problematic in some instances. For researchers and practitioners interested in lower-level elections, traffic cameras may also help bridge gaps in official government releases, which are often restricted to the present election. Traffic cameras are all around us and this study will hopefully encourage scholars to begin to use this data for their own research.

With that said, traffic camera data comes with its own challenges. Not only are pedestrians sometimes missed when automated methods are used, but there are broader questions about whether such data should be publicly available in the first place. For example, it is impossible for pedestrians to consent to studies which utilize these data, which means issues related to privacy should always be a concern (Löfgren and Webster, 2020). Here, one of the main concerns is revealing sensitive information, like license plate numbers, using such data (e.g., Hoh et al., 2006). Fortunately, the present application poses a minimal risk since the data is "in the public domain and uses low-resolution imagery from which it is difficult or impossible to personally identify individuals" (Chen et al., 2021: 23). However, we hope this study shines some light on the ubiquity of traffic camera networks, leading to new research questions related to political behavior, but also a broader discussion over the networks themselves, including how best to disseminate the date for research use (Fan, 2018).

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ORCID iD

Bryce J. Dietrich https://orcid.org/0000-0002-9781-3088

Supplemental Material

Supplemental material for this article is available online.

Notes

1. As we discuss in the conclusion, there are privacy concerns about the use of traffic camera networks as a data source. Similar concerns have been levied against studies which use annotators to label videos of interviews or interpersonal interactions (e.g., Lasecki et al., 2015). In our study, we do not use any human annotation. Rather, we use an off-the-shelf machine learning algorithm to determine whether pedestrians are present. The authors did conduct a small validation exercise, but this was done internally in order to protect the privacy of those pedestrians identified by our algorithm.
2. Additional details are provided in Section S1 in the SI. In this section, we also provide more information justifying our validation approach.
3. We also include as controls the percent of the population over 65 (see "65+ Population") as well as the percent of the population born abroad (see "Born Abroad Population"). Finally, we include the unemployment rate (see "Unemployment Rate") as a control. Additional justifications of these variables are provided in the SI.

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