POLITICAL BELIEF, ATTITUDES TOWARD RISK, AND BEHAVIOR ON THE ROAD

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Abstract

We utilize unique information on traffic citations to explore the role of political belief in risk-taking behaviors. Information on this little-explored measure of risky behaviors while driving is obtained from the Israel Police for 2019–2022. We identify political belief based on voting outcomes by small statistical area for the 2019 Israel parliament elections. Controlling for local area socio-economic and demographic characteristics, geographic centrality and access, and police enforcement, results indicate substantial variation in risk-related traffic violations by political belief. Consistent with findings in the finance and public health literatures, results show that liberal voters, compared with politically conservative voters, are associated with fewer risky behaviors behind the wheel, as indicated in an average 20–25 percent lower number of risk-related traffic citations. Outcomes are robust across various sample selection and test design specifications.

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1 Introduction

Recent studies provide new insights as to the role of political belief in perception, decision-making, and behavior. In financial markets, for example, Kaustia and Torstila (2011) present evidence that left-wing investors are less likely to invest in stocks, whereas Hong and Kostovetsky (2012) find that mutual fund managers donating to Democrats underweight stock investment in less socially responsible companies. Financial research has illuminated other consequences of misalignment of political belief with the political party in power, including more pessimism among investors about the market (Bonaparte et al.2017); higher loan spreads for corporate debt (Dagostino et al., 2022); and higher likelihood of downgrades in corporate credit ratings (Kempf and Tsoutsoura, 2021). Meeuwis et al. (2022) found that Republican (Democrat) investors selected into riskier (safer) investment portfolios following the 2016 election of Donald Trump; similarly, Mian et al. (2023) found that in the aftermath of the 2008 and 2016 elections, views of future economic conditions varied with partisan affiliation (also see related studies of Gerber and Huber, 2009; Gerber and Huber, 2010; and Gillitzer et al., 2021).[1] Elsewhere, in assessment of Covid-19 pandemic health risk, Barrios and Hochberg (2021) and Gollwitzer et al. (2020) showed that counties with higher shares of Trump voters were associated with both lower perception of virus risk and reduced adherence to social distancing guidelines; further, Ben-Shahar et al. (2023) found that politically conservative households were associated with higher levels of both COVID-19 virus transmission and vaccine resistance. Also, Bartels (2002), Gaines *et al*. (2007), and Curtin (2018) provide evidence that partisan political bias as proxied by party identification shapes individual reaction to political events whereas Fox *et al*. (2017) find that smoking prevalence varies with state political ideology.

While the above research provides recent evidence on the role of political belief in information processing and cognitive reasoning, research on how political belief is associated with risky behaviors—a key factor in cognitive and emotional processing[2]—is limited and inconclusive. Among the limited experimental evidence, Moore et al.

[1] Relatedly, studies also indicate that financial behavior diverges based on religious beliefs. For example, Shu et al. (2012) find that areas with lower Protestant or higher Catholic concentration exhibit greater return volatilities, while Abakah and Li (2023) show that banks in areas with higher concentration of Catholics (relative to Protestants) assume lower risk.

[2] See, for example, Hsu et al. (2005) on the neural effect of decision-making that involves risk in behavioral choices. Also, see Loewenstein et al. (2001) on the emotional effect of risk.

(2010) and Choma et al. (2014), for example, show higher levels of financial risk tolerance among conservatives compared to liberals, whereas Morris et al. (2008) find no clear association between the choice of risky financial options and Democrat/Republican affiliation.[3] Further, based on meta-analysis of 88 samples from 12 countries, Jost et al. (2003) find that conservatism is negatively associated with tolerance of uncertainty, but positively associated with sensation seeking, where the latter has been found to serve as a reliable indicator of risk-taking behaviors (Wong and Carducci, 1991; Horvath and Zuckerman, 1993; and Grinblatt and Keloharju, 2009).

In this paper, we apply unique information on traffic citations to explore the role of political belief in risky behaviors. Indeed, driving behavior—and related citations—provide a little explored activity in which capricious risk-taking often plays a central role. Specifically, the analysis employs data on the universe of risk-related traffic violations recorded by the Israel Police over the period 2019–2022. These citations are classified into six types: speeding, violating red-lights, ignoring road signage and related traffic instructions, reckless driving, failure to use a child's car seat or safety belts, and failure to operate the vehicle with due care and attention. To that end, we develop small statistical area (akin to U.S. census tracts) information on the above categories of traffic violations with that on voting outcome in Israel national parliament elections.[4] We merge this information with extensive statistical area population socio-economic, demographic, geographic access and centrality, and civic participation controls, as well as those for traffic violation enforcement in the area where the citation is recorded.

Results of panel estimation indicate substantial divergence in risky behaviors among left- and right-leaning small statistical areas, as proxied by area number of traffic violations per person (aged 16 and over). Findings show that, compared to households from politically conservative areas, households residing in liberal areas were associated, *ceteris paribus*, with an average of roughly 20 percent lower number of risk-related traffic violations per capita. This outcome is robust to a series of sample and test design specifications. Moreover, model estimation for traffic light violations—controlling for traffic light camera enforcement—indicates an average 25 percent lower

[3] Also, Han et al. (2019) find a mediating effect: conservatives' financial risk-tolerance increases with their self-efficacy, while liberals' financial risk-tolerance is invariant to their self-efficacy.
[4] As described below, outcomes are robust to basing the estimation on the (end of sample period) 2022 parliament elections.

number of per capita traffic light citations among left-leaning statistical areas. Note that the model controls for measures of statistical area access and geographic centrality that affect traffic flows and related variation in citation incidence.

Our findings make a number of contributions to the literature. First, while there is a growing interest in understanding how political belief and worldview affect information processing and cognitive reasoning, there exists only limited and inconclusive evidence on the association between political belief and attitudes toward risk. Also, the existing evidence is based largely on experimental/survey methods and focuses on financial risk. In contrast, our study draws from actual risky behavior behind the wheel as manifest in traffic citations—a framework that serves as a natural setting for risk-related behaviors.[5] Similarly, our assessment of political belief is not survey-based, but proxied instead by the revealed preference of voters in small statistical area in national elections.

In addition, our study contributes to the social and political sciences of transportation. Existing evidence demonstrates the role of individual characteristics in risky-driving (see Iversen, 2004; Pereira et al., 2022; McIlroy et al., 2022). For example, it has been shown that risky driving behavior is associated with Big Five personality traits (positively correlated with neuroticism and negatively correlated with conscientiousness, agreeableness, and openness; Luo et al., 2023) as well as personal attributes such as impulsiveness, sensation seeking, boredom proneness, and time perspective (Zimbardo et al., 1997; Dahlen et al., 2005). Also, studies find that road behavior is impacted by risk perception (Ulleberg and Rundmo, 2003; Huda & Ismail, 2020; and Jing et al. 2023); and socio-demographic factors, including age (Reason et al., 1990; Rhodes and Pivik, 2011; Voogt et al., 2014; and Factor, 2018), gender (Reason et al., 1990; Factor, 2018; Høye, 2020; Balasubramanian and Sivasankaran, 2021), race and ethnicity (Factor et al., 2008; and Adanu et al., 2017), education (Factor et al., 2008; and Itskovich & Factor, 2023), and employment status (Adanu et al., 2017).[6] Controlling for those factors in our estimation, our results provide new insights

[5] Studies show that risky driving behavior is related to other risk-taking behaviors such as financial and labor market decisions (Abay & Mannering, 2016); smoking, drug use, and antisocial behaviors (Bina et al., 2006) and gambling (Wang et al., 2011)—implying that risky driving arguably represent a systematic risk-taking behavior in decision-making.

[6] Donaldson et al. (2006) and Leveau & Vacchino (2015) also find that density and geographic location of driver's residence correlate with risky driving.

as regards to the role of political belief in risky driving behavior. The latter has important implications for enforcement policy and for mitigation of dangerous driving.

The remainder of the paper is organized as follows: Section 2 describes the data and the outcomes utilized in political belief classification. Section 3 presents the empirical model and results of assessment of the role of political belief in risk-related traffic citations. Section 4 provides robustness in assessment of the association between political belief and red-light citations, specifically controlling for variations in red-light camera enforcement. Finally, Section 5 provides a summary and concluding remarks.

2 Data

We observe the universe of all traffic violations associated with risky driving behavior (about 840K observations across 6 violation categories) among roughly 2,500 statistical areas (akin to census tracts) in Israel over the 2019–2022 period. The information is obtained from the Israeli National Traffic Police records.[7] We merge that data with information on household political belief based on statistical area voting outcomes in the general parliamentary elections held in Israel in April 2019 (available from the Israel Central Elections Committee). Finally, we merge these series with statistical area socioeconomic, demographic, geographic location, and enforcement controls, as are further described below.

Table 1 presents the sample number of risk-taking-related traffic violations per violation type and year.[8] As shown, speeding and failing to operate the vehicle with due care[9] are the most prevalent violations in the sample with an average of roughly 80.6K and 57.1K violations per year, respectively. The least prevalent violations in the sample

[7] According to Israel Central Bureau of Statistics (ICBS), Israel includes about 3,700 statistical areas. In our estimation, we drop statistical areas in the West Bank. Our traffic violation records include all statistical areas in which at least one violation was recorded. Results below are robust to omission of statistical areas with top and bottom 1% and 5% of traffic violations (results are not reported but available by request).

[8] The traffic violations types in our study are commonly used in risky-behavior measurements that assess risky driving propensity (e.g., West and Hall, 1997; Rowe et al., 2013; and Wahlberg et al., 2015). Other studies that use same violations as in our sample for analysis of risky-driving include Castanier et al. (2013), Watling et al. (2016), and Jonah and Boase (2016) – for speeding; Begg and Langley (2004) and Castanier et al., 2013 – for following too closely and fail to operate vehicle with due care; Ivers et al. (2009) – for fail to use safety belt; Castanier et al. (2013) – for disobey road sign; and Jantosut et al. (2021) – for red-light disobedience. Also noteworthy, according to the Israeli National Road Safety Authority (RSA), over the past 5 years, the violation types in our sample are consistently referred to as highly probable to associate with fatal traffic accidents (see RSA annual reports 2019–2023).

[9] This includes, for example, failing to maintain a safe distance from the vehicle ahead, disregarding relevant traffic signs or road markings, and failing to slow down in required areas (such as near pedestrian crossings or schools).

include failing to obey a road sign and reckless driving with roughly 12.7K and 13.1K violations per year, respectively. Figure 1A shows the statistical area (of violators' residence) incidence of traffic violations per person aged 16 and over. As shown, while traffic violations appear in all districts, their concentration is somewhat skewed toward the Tel Aviv and Center districts. Table 2 presents variable description and summary statistics for traffic violations and control terms by statistical area. As shown, the number of traffic violations per person aged 16 and over and year (V) is 0.028. Among controls, the average population density in a statistical area ($Density$) is 0.017 per square meter; the statistical area median population age (*Age*) is about 33; and the number of owned vehicles per 100 persons aged 17 and over in a statistical area (*Vehicles*) is 46.6. We use the ICBS socioeconomic index score (*SES*) to control for statistical area variation in household income, education, and standard of living.[10] As shown, the average socio-economic index score is about 0.18 (with min of -3.47 and max of 2.53), with a standard deviation of 1.09. The table also provides information on the ethnic distribution of statistical area population as determined by the ICBS 2008 census: defined as the statistical area share of population whose origin is (i.e., whose father was born in) either Asia or Africa ($AsiaAfrica$), Europe or America ($EuroAmer$), and Israel ($Israel$)—average of which is about 29, 37, and 34 percent, respectively. In addition, the table presents information on the share of non-voters among eligible voting population within the statistical area—proxying for civic engagement and social capital—the average of which is 32.5%.[11] We also include a couple of controls for geographic location: we use the standard ICBS geographic classification of Israel into six districts to control for the district in which the traffic violator resides—including North, Center, South, Tel Aviv, Haifa, and Jerusalem (*Northern*, *Southern*, *Central, TA*, *Haifa*, and *Jerusalem* districts, respectively). We also include the ICBS (2020) centrality index score (*Centrality*) to control for statistical

[10] The socioeconomic index is computed based on 14 indicators, including average years of schooling for the population ages 25–54; share of the population with academic degree ages 27–54; share of income earners ages 25–54; share of women ages 25–54 not in the workforce; share of income earners above twice the average wage; share of income earners below minimum wage; share of the population with income support; average per capita income; the number of owned vehicles per 100 residents over 17; the average vehicle license fee; average number of days abroad; median age; dependency ratio; and the share of families with 4 or more children. The socioeconomic index is generated by factor analysis that reduces the 14 indicators to three main factors that explain 86% of the variation among the statistical areas (see Agmon, 2016).

[11] See Inclan et al. (2005) and Obeid et al. (2014) for evidence on the positive association between civic participation and traffic violations.

area variation in geographic accessibility to central business districts and proximity to Tel Aviv, the "superstar" city and main central business district of Israel (Ben-Shahar et al., 2020).[12]

To control for potential divergence in traffic police enforcement among statistical areas where traffic violations are committed, we compute an enforcement measure, E, as follows: First, we denote the statistical area where the violator resides and the statistical area where she committed the traffic violation by s and c, respectively. We then compute for each statistical area c and year t, the per year total number of violations standardized by the total area of c (by dividing, for each c, the total number of violations by area in square-meters of the statistical area). Denote the outcome as $V_{c,t}$. To each violation i in year t that is committed by a resident in statistical area s, we match the value $V_{c,t}$ and denote it by $V_{i\in s,c,t}$. Finally, we average $V_{i\in s,c,t}$ across all i, $i \in s$ at time t—computing for each statistical area s at time t, a measure of violation intensity of area c as defined by violations committed by drivers residing in s—denoted by $E_{s,t}$.[13] This measure captures the extent to which the areas where drivers from s committed traffic violations were more prone to violations due to tighter enforcement or other unobserved factors. Figure 1b shows a heat map of the measure $E_{s,t}$. Consistent with the heat map in Figure 1a, the enforcement measure is elevated largely in the Tel Aviv and Center districts with scattered concentration in the Haifa, Jerusalem, Northern, and Southern districts. Also, as shown in Table 2, the mean and standard deviation of the enforcement measure (E) is 0.005 and 0.006, respectively.

Finally, we merge the above information with statistical area information on households political belief. To approximate political inclination across statistical areas, we employ data from Israel's April 2019 national parliament (Knesset) elections (available from the Israel Central Election Committee). Based on the methodology of Ben-Shahar et al. (2023), we calculate the distribution of votes by political party for each statistical area and apply a k-means clustering algorithm to classify each statistical areas into one of five distinct political belief groups, allowing for a nuanced analysis of

[12] The Kramer correlation between the district of residence and the district where the traffic violation is committed is roughly 0.75, indicating that, frequently, the violation is committed in the same district where one resides (also consistent with "the close to home effect"– e.g., McCarty and Kim, 2024). Also, police districts in Israel are fairly geographically similar to our ICBS district classification. Hence, by including the district controls, we also further enhance our control for police enforcement.
[13] Using the statistical area number of violations in the place where they were committed as an assessment for traffic enforcement is consistent with, e.g., Terrill et al. (2016) and Rezapour et al. (2017).

political tendencies.[14] Figure 1 presents the average vote rate for each political party in the April 2019 elections by political belief group. The groups include: $Right$, right-leaning statistical areas – dominated by votes for “Likud” (34 percent of statistical areas in the sample); $Left$, left-leaning statistical areas – dominated by votes for “Kahol-Lavan”, “HaAvoda” and “Meretz” (35 percent); $Center$, center-leaning areas, including roughly equal votes for right and left-leaning parties (18 percent); $Orthodox$, areas characterized by votes for the Jewish religious Orthodox parties – “Yahadut Hatora” and “Shas” (5 percent); and $Arab$, statistical areas defined by a high share of votes for Arab or Jewish-Arab parties “RaamBalad” and “HadashTaal” (8 percent). Table 3 presents summary information on statistical area traffic violations and socioeconomic and demographic controls by political group. As shown, left-leaning areas exhibit the highest average socioeconomic index score and the highest number of owned vehicles per 100 residents aged 17 and over. In contrast, Jewish religious Orthodox areas exhibit the lowest average socioeconomic index score, highest density, and lowest average of median population age. Finally, areas dominated by votes for Arab parties exhibit the highest uncontrolled average number of violations and lowest average centrality index.

3 Model and Results

Consider the following estimated equation:

(1)

$$ln\_V_{s,t} = \beta_0 + \vec{\beta}_1 P_{s,t} + \vec{\beta}_2 C_s + \beta_3 E_{s,t} + \vec{\beta}_4 D_s + \vec{\beta}_5 T_t + \varepsilon_{s,t},$$

where the dependent variable ln_V_{st} is the log of the time (year) t and statistical area of traffic violators residence s number of traffic violations (associated with risky road- and driving-behavior) per person aged 16 and over. The independent variables include P, a vector of political belief fixed-effects per statistical area, including $Left$, $Center$, $Orthodox$, and $Arab$ ($Right$ serving as the base category); C, a vector of statistical area characteristics comprised of $Density$, population density per square meter; Age, population median age; SES, socioeconomic index score; $Centrality$, centrality index score, controlling for the statistical area variation in geographic accessibility and

[14] As noted by Ben-Shahar et al. (2023), the k-means algorithm partitions a sample of observations into k distinct clusters, minimizing the variance within each cluster. The optimal number of clusters, k, is identified by the elbow method (Goutte et al., 1999).

proximity to the central business district of Israel; $Vehicles$, number of owned vehicles per 100 residents aged 17 and over; $EuroAmer$ and $AsiaAfrica$, share of population whose origin is Europe/America and Asia/Africa, respectively (share of population whose father was born in Israel serving as the base group); and $NonVoter$, share of nonvoters. The right-hand side of the equation also includes E, a control for the extent to which the statistical area where the traffic violation was committed is more prone to violations or experienced tighter enforcement (see computation of this variable in the data section); D, a categorical vector representing the larger Census region in which the statistical area (by traffic violators residence) is located—including $Northern$, $Southern$, $TelAviv$, $Haifa$, and $Jerusalem$ (and $Central$ Israel as the base category)—which controls for possible location-dependent variance in traffic violations associated with the place of residence of those receiving a citation; and T, a vector of time (year) fixed-effects. Finally, β_0 and β_3 are estimated parameters, $\vec{\beta}_1$–$\vec{\beta}_2$ and $\vec{\beta}_4$–$\vec{\beta}_5$ are vectors of estimated parameter, and ε is a random disturbance term.[15]

Results

Table 4 presents the results of panel estimation of equation (1) of the log of the number of risk-related traffic citations per capita issued to residents in statistical area *s* over the four-year period 2019–2022. Column 1 presents benchmark outcomes from estimating the model, controlling only for political belief group ($Right$ serves as a base group) and time (2019 serves as the base year) fixed-effects. As shown statistical areas dominated by $Left$ (left-leaning votes) exhibit the lowest number of traffic violations per person, followed by $Orthodox$, *Center*, $Right$ and $Arab$ (differences among groups significant at the 1 percent level with the exception of the insignificant difference between *Right* and *Center*). In column 2, we re-estimate the model with the full set of statistical area controls, including the socioeconomic index score (*SES*), periphery index score (*Centrality*), median age (*Age*), population density (*Density*), regional district (*Northern, Southern, Jerusalem*, *TA* and *Haifa*; Central serves as a base

[15] Studies show that men are more likely to commit traffic violation (Reason et al., 1990; Factor, 2018; Høye, 2020; Balasubramanian and Sivasankaran, 2021). Indeed, our data shows that about 70 percent of the sample violations are committed by men. Yet, as our unit of estimation is statistical area, there is little variation in this variable across statistical area. We therefore omit gender from our estimation. Results, however, are robust to (*a*) controlling for the share of men committing violations in the statistical area on the right-hand side of equation (1); and (b) estimating (1) on a stratified sample that includes men violation only (result are not reported but available upon request).

group), ethnicity (*EuroAmer*, *AsiaAfrica*; *Israel* serves as a base group), share of non-voters (*Nonvoter*), and enforcement measure (E). As shown, while the inclusion of the vector of small area controls somewhat mediates the effect of variations in political belief, results show significant association between the number of risk-related traffic violations and political inclination. Specifically, we find that compared to $Right$ areas (base group), $Left$ areas are associated with roughly 19 percent lower per person number of traffic violations, whereas $Arab$ are associated with about 18 percent greater number of violations per person (both significant at the 1 percent level). Upon accounting for the vector of controls, outcomes show no significant difference among $Right$, $Center$, and $Orthodox$ areas. In column 3, we re-estimate the model, supplementing the full set of controls with interaction terms between enforcement (E) and regional districts, controlling for possible variation in enforcement effects among districts. Indeed, as shown, the coefficients on the interaction terms are all significant at the 1 percent level (except for $Enforcment \times Southern$; $Enforcment \times Central$ serving as the based category). Outcomes on the differences among political belief groups, however, are robust: compared to $Right$ areas, $Left$ areas are associated with roughly 19 percent lower per person number of traffic violations and $Arab$ areas are associated with about 20 percent greater number of violations per person (both significant at the 1 percent level; with insignificant differences among $Right$, $Center$, and $Orthodox$ areas).

In columns 4 and 5, we re-estimate the full model (with and without $E \times District$ interaction terms, respectively), substituting statistical area socioeconomic index score (SES) with one of its components that is directly relevant for the number of traffic violation—*Vehicles*, number of owned vehicles per 100 residents age 17 and over. As shown in columns 4 and 5, results on the effect of political beliefs are robust to these specifications. Moreover, as expected, the coefficient on the number of vehicles per 100 residents age 17 and over is positive and economically meaningful. Specifically, a one-standard deviation increase in the number of owned vehicles is associated with roughly 18.2 percent increase in the number of traffic violations (significant at the 1 percent level).[16]

[16] Provided that the estimated coefficient and sample standard deviation of $Enforcement$ is 0.0116 and 15.7, respectively, we get that a one standard deviation increase in $Vehicles$ is associated with 18.2 percent increase in the number of traffic violations ($0.0116 \times 15.7 = 18.2\%$).

Also, among controls, following columns 2–3 in Table 4, traffic violation enforcement (E), socioeconomic status index (SES), geographic accessibility and proximity to Tel Aviv ($Centrality$), and share of non-voters ($NonVoters$) are positively associated with the per person number of violations (all significant at the 1 percent level), whereas median age (Age) and population density ($Density$) are negatively associated with the per person number of violations (significant at the 5 and 1 percent levels, respectively).[17] Specifically, provided that the estimated coefficient and sample standard deviation of the enforcement measure (E) is 6.047 and 0.006, respectively, we find that a one standard deviation increase in E is associated with about 3.63 percent increase in the number of recorded violations per person ($6.047 \times 0.006 = 3.63\%$). Recall that E measures violation intensity in the area where a violation is committed—thus proxies enforcement level. Similarly, provided that the estimated coefficient and sample standard deviation of the socio-economic index score (SES) is 0.122 and 0.176, respectively, we find that a one standard deviation increase in SES is associated with about 2.15 percent increase in the number of recorded violations per person ($0.122 \times 0.176 = 2.15\%$). Also, increasing the share of non-voters by 1 basis point (holding the distribution of other votes fixed) is associated with increased number of violations per person of about 0.8 percent; whereas increasing statistical area median age by 1 year is associated with roughly 0.6 percent increased number of violations per person. Finally, ethnicity is associated with the number of traffic violations. In particular, compared to population whose father was born in Israel, increasing the share of population whose origin is Asia/Africa ($AsiaAfrica$) by one basis point (on the account of those whose father was born in Israel) is associated with a 1 percent increase in the per person number of violations (significant at the 1 percent level). Europe/America ($EuroAmer$) origination exhibits an insignificant difference from the base category (father born in Israel).

Finally, we re-estimate the model in (1), replacing the political belief group fixed-effects with a continuous specification of political belief terms, including $Right\_Cont$, $Orthodox\_Cont$, and $Arab\_Cont$, where those terms represent the share of votes in each statistical area for right-leaning, Orthodox, and Arab parties, respectively. Results from re-estimating this continuous version of equation (1) are

[17] The finding on the negative association between SES and number of traffic violations is consistent with, e.g., Atombo et al. (2017) and Fosgerau (2005).

presented in Table A1 in the appendix (with otherwise the same specifications as in Table 3). As shown, outcomes are robust to the continuous specifications of political beliefs. We also re-estimated the model in (1) as shown in Table 4, (a) approximating political inclination across statistical areas based on Israel's November 2022 (instead April 2019) national parliament elections (that is the end rather the beginning of our sample period)—using once again a k-means clustering algorithm to categorize each statistical areas into one of five distinct political belief groups (results reported in Table A2 in the appendix); (b) supplementing the right-hand side of the equation with interaction terms of regional districts with SES, Age, $Vehicles$, $Centrality$, $Density$, and E; and (c) omitting the 1 percent and 3 percent of the statistical areas with the greatest and smallest number of violations [results from items (b) and (c) are not reported but available upon request]. All obtained results are robust to these specifications.

4 Case Study: Red-Light Violations and Police Camera Enforcement

Running a red-light is a manifestation of risky driving behavior (e.g., Rettling et al., 2003 and Cohn et al., 2020). To gauge the robustness of our results on the association between political beliefs and risky road- and driving- behavior, we re-estimate our model for the subsample of red-light violations. In this analysis, we also observe the location of red-light police cameras by statistical area (available from the Ministry of National Security in Israel). We use the latter to control for police enforcement of red-light violations.[18] Specifically, we re-estimate equation (1), substituting the dependent variable ln_RLV_{st}, the log of the annual time t and statistical area s (violator's place of residence) number of red-light violations per person in place of ln_V_{st}; and substituting $RLC_{s,t}$, a measure of enforcement by red-light cameras of red-light violations committed at time t by violators residing in statistical area s in place of the enforcement control term, $E_{s,t}$. To derive $RLC_{s,t}$, we denote (as before) the statistical area where the violator resides and the statistical area where she was cited for the red-light violation by s and c, respectively. For each c and t, we then use an

[18] As noted on the Ministry of National Security website, red-light camera enforcement account for roughly 30 percent of the red-light violations (see https://www.gov.il/en/pages/traffic_enforcement_cameras). From conversations with Israel Police, most of the other red-light violations where enforced by traffic police patrol. Also, on the use of red-light cameras as an enforcement mechanism, see, e.g., Retting et al. (2003) and Shaaban and Pande (2022).

indicator $I_{c,t}$ that equals 1 if there is a red-light camera in the statistical area where the red-light violation was committed and zero otherwise. Next, for each red-light violation i committed in statistical area c at year t by a violator residing in statistical area s, we match $I_{i \in s,c,t} = 0{,}1$. Finally, we average $I_{i \in s,c,t}$ across all i, $i \in s$, and t—generating $RLC_{s,t}$, a measure of red-light violation enforcement intensity of violations committed at time t by violators residing in statistical area s. As shown in Table 3, the mean and standard deviation of RLC is 0.05 and 0.15, respectively.

Estimation results for the above red-light citation specification are contained in Table 5. As shown, empirical findings on the association between political belief and risky driving behavior are robust to the red-light citation specification. In column 1, we include only political belief fixed-effects ($Right$ serves as the base category). As shown, left-leaning ($Left$) statistical areas are associated with the lowest average number of red-light violations followed by $Orthodox$ and $Arab/Right/Center$ (results show an insignificant difference among $Arab/Right/Center$ areas; other differences in results among belief groups are significant at the 1–10 percent levels). In column 2 and 3, we re-estimate the model with the full set of controls, respectively omitting (column 2) and including (column 3) interaction terms between RLC and regional districts. As shown, compared to $Right$ areas (the base political belief group), $Left$ areas are associated with roughly 24–25 percent lower average number of red-light violations (significant at the 1 percent level), whereas $Center$ areas are associated with about 7 percent lower average number of violations (significant at the 10 percent level). There is an insignificant difference among $Arab/Right/Orthodox$ areas. In columns 4 and 5 of Table 5, we include $Vehicles$, defined above as the number of owned vehicles per 100 residents age 17 and over in the statistical area, in place of SES, the statistical area socioeconomic index score. The variable $Vehicles$, which is a component of SES, bears directly on the number of red-light citations issued in a statistical area. We then re-estimate the full model, respectively without (column 4) and with (column 5) the $RLC \times District$ interaction terms. As shown, results on the political belief groups are once again largely robust to these specifications. Also, per controls, it follows from column 2–5 that the coefficient on the enforcement measure (RLC) is positively associated with number of red-light violations (significant at the 1–5 percent levels). Specifically, it follows from columns 2 and 4 that a one-standard deviation increase in

RLC is associated with a roughly 3.75% increase in the number of red-light violations.[19] Also, estimates of controls in columns 2–5 are generally robust to those obtained in Table 3.

Finally, for robustness check, we re-estimate the model in (1), replacing the political belief group fixed-effects with $Right\_Cont$, $Orthodox\_Cont$, and $Arab\_Cont$, continuous variables representing the share of votes in each statistical area for right-leaning, Orthodox, and Arab parties, respectively. As shown in Table A3 in the appendix, results are robust to the continuous specifications of the belief terms. We also re-estimated the model (a) approximating political inclination across statistical areas, using a k-means clustering algorithm, based on Israel's November 2022 (instead April 2019) national parliament elections (that is the end rather the beginning of our sample period) – results are reported in Table A4 in the appendix; and (b) supplementing the right-hand side of the equation with interaction terms of $Districts$ with each of the following: SES, Age, $Vehicles$, $Centrality$, $Density$, and E (results are not reported but available upon request). All results are robust to these specifications.

5 Summary and Conclusions

Accumulated evidence substantiates the role of political belief in information processing and related decision-making, perception, and behaviors. Prior findings, however, are inconclusive on how political belief affects risky behaviors. Indeed, attitudes toward risk are a key factor that underlies mental processing. In this paper, we explore the association between political belief and risky behavior via the unique prism of risk-related driving citations. To do so, we employ data on the universe of all risk-related traffic violations recorded by Israel police over the period 2019–2022. We merge this information with small statistical area voting outcomes for the 2019 Israeli parliament elections as well as information on population socio-economic,

[19] Provided that the coefficient on RLC is 0.25 (columns 2 and 4) and the sample standard deviation of RLC is 0.15, we get $0.25 \times 0.15 = 3.75\%$.
Note that previous studies show mixed results regarding the impact of red-light cameras on decreasing car crashes rates and red-light violations (Cohn et al., 2020; Li & da Silva, 2022; Llau & Ahmed, 2014; Erke, 2009). As opposed to these studies, we did not aim at evaluating the effectiveness of red-light cameras on the frequency of committing red-light violations, but merely alternating the proxy for the level of enforcement used in the main model, in order to control for variation of enforcement between statistical areas.

demographic, geographic access, civic participation characteristics, and traffic violation police enforcement.

Our findings show that, compared to likely-politically conservative voters, likely-liberal voters are associated, *ceteris paribus*, with roughly 20 percent lower number of risk-taking traffic violations per person aged 16 and over. This outcome is robust to a series of sample and test design specifications. Moreover, re-estimating the model only for red-light violations—for which we specifically observe red-light camera enforcement—we find that left-leaning statistical areas are associated with an average of roughly 25 percent lower number of red-light violations per person aged 16 and over.

Our findings contribute to the understanding of how political beliefs are associated with a fundamental cognitive process—risk attitude. Moreover, our evidence complements previous studies of the social sciences of driving behavior, suggesting important implications for enforcement policy and risky driving mitigation.

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Table 1: Type and Number of Traffic Violations by Year

Traffic Violation Type	2019	2020	2021	2022
Speeding	47,929	141,635	72,180	60,769
Fail to operate vehicle with due care and attention	49,407	58,749	64,570	55,719
Disobey a red-light	15,804	17,179	19,641	19,202
Disobey road sign	15,370	14,316	12,572	8,612
Reckless driving	13,107	11,956	17,831	13,315
Fail to use safety seat and safety belt	32,566	28,876	29,179	23,278

Table 2: Variable Description and Summary Statistics (Per Statistical Area)

Variable	Description	Mean	Std	Min	Max
$Violations$	Number of traffic violations per person aged 16 and over of statistical area	0.028	0.018	0.0005	0.29
$Area$	size of statistical area (in sqm)	1.3×10^{8}	4.6×10^{6}	17,662	1.4×10^{8}
E	Enforcement measure	0.005	0.006	6×10^{-7}	0.088
SES	Socioeconomic index score	0.176	1.088	-3.471	2.532
Age	Median population age	33.35	7.85	9.00	57.00
$Vehicles$	Number of owned vehicles per 100 residents aged 17 and over	46.64	15.70	5.149	93.522
$Centrality$	Measure of accessibility and proximity to central business districts and to Tel Aviv	1.097	1.648	-2.547	4.973
$Density$	Population per square meter	0.017	0.07	0	1.503
$Northern$	Dummy variable equals 1 if statistical area in Northern district	0.22	0.42	0	1
$Southern$	Dummy variable equals 1 if statistical area in Southern district	0.18	0.38	0	1
$Central$	Dummy variable equals 1 if statistical area in Central district	0.24	0.42	0	1
$Tel\ Aviv$	Dummy variable equals 1 if statistical area in Tel Aviv district	0.15	0.36	0	1
$Haifa$	Dummy variable equals 1 if statistical area in Haifa district	0.11	0.32	0	1
$Jerusalem$	Dummy variable equals 1 if statistical area in Jerusalem district	0.10	0.30	0	1
$Right$	Dummy variable equals 1 if statistical area is classified as right-leaning beliefs	0.34	0.47	0	1
$Left$	Dummy variable equals 1 if statistical area is classified as left-leaning beliefs	0.35	0.48	0	1
$Center$	Dummy variable equals 1 if statistical area is classified as center beliefs	0.18	0.38	0	1
$Orthodox$	Dummy variable equals 1 if statistical area is classified as Orthodox beliefs	0.05	0.22	0	1
$Arab$	Dummy variable equals 1 if statistical area is classified as Arab beliefs	0.08	0.27	0	1
$NonVoter$	Share of non-voters	0.325	0.133	0.015	0.95
$AsiaAfrica$	Share of population whose father was born in either Asia or Africa	29.01	11.26	1.8	74.6
$EuroAmer$	Share of population whose father was born in either Europe or America	36.65	13.91	3.3	93
$Israel$	Share of population whose father was born in Israel	34.38	13.03	3.1	81.7
$RedLight$	Per year average number of red-light disobedience violations per resident aged 16 and over	0.003	0.002	0.0001	0.4
RLC	Measure of red-light violation enforcement intensity	0.05	0.15	1×10^{-7}	0.0078

Table 3: Variable Description and Summary Statistics by Political Groups

Variable	***Right***		***Center***		***Left***		***Orthodox***		***Arab***	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Violations	0.030	0.015	0.030	0.016	0.022	0.015	0.024	0.012	0.041	0.031
SES	-0.23	0.55	0.59	0.56	1.47	0.44	-1.60	0.52	-0.91	0.73
Vehicles	42.52	9.92	52.72	10.88	61.06	11.82	20.87	8.89	45.69	7.41
Age	34.23	5.53	36.36	4.77	36.96	4.20	18.78	4.56	26.73	6.68
Centrality	0.73	1.42	1.53	1.58	0.90	1.73	2.37	1.61	0.17	1.04
Density	0.007	0.008	0.010	0.009	0.005	0.007	0.022	0.015	0.005	0.005
NonVoter	0.34	0.11	0.33	0.10	0.27	0.09	0.30	0.14	0.55	0.12
E	0.004	0.005	0.005	0.005	0.005	0.007	0.006	0.004	0.002	0.003

Notes: Table 3 presents summary statistics by political belief groups (according to the April 2019 national elections). The variable $Violations$ is average per year, for the period of 2019-2022.

Table 4: Results from Estimation of Equation (1)

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$Constant$	-3.844*** (0.016)	-3.918*** (0.110)	-3.954*** (0.110)	-4.715*** (0.162)	-4.758*** (0.161)
$Left$	-0.379*** (0.026)	-0.186*** (0.046)	-0.193*** (0.046)	-0.168*** (0.038)	-0.174*** (0.038)
$Center$	-0.0002 (0.028)	-0.039 (0.030)	-0.043 (0.030)	-0.042 (0.028)	-0.045 (0.028)
$Arab$	0.261*** (0.054)	0.182*** (0.035)	0.197*** (0.033)	0.100** (0.048)	0.115** (0.047)
$Orthodox$	-0.214*** (0.045)	0.056 (0.067)	0.060 (0.067)	0.128** (0.058)	0.130** (0.058)
SES		0.122*** (0.029)	0.126*** (0.029)		
$Vehicles$				0.012*** (0.002)	0.012*** (0.002)
$Centrality$		0.042*** (0.015)	0.043*** (0.015)	0.061*** (0.015)	0.063*** (0.015)
Age		-0.006** (0.003)	-0.006** (0.003)	-0.007*** (0.003)	-0.007** (0.003)
$Density$		-10.76*** (1.87)	-10.64*** (1.88)	-8.20*** (2.21)	-8.06*** (2.22)
E		6.047*** (0.918)	9.430*** (1.767)	6.151*** (0.910)	9.501*** (1.756)
$E \times Northern$			-60.45*** (9.109)		-60.78*** (9.211)
$E \times Southern$			-0.146 (4.995)		0.093 (4.964)
$E \times TelAviv$			-4.062*** (1.437)		-4.033*** (1.433)
$E \times Haifa$			15.14*** (4.462)		14.81*** (4.452)
$E \times Jerusalem$			-10.05*** (2.092)		-10.04*** (2.085)
$Nonvoter$		0.824*** (0.183)	0.822*** (0.184)	1.240*** (0.206)	1.238*** (0.208)
$AsiaAfrica$		0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
$EuroAmer$		2×10^{-6} (0.002)	0.0002 (0.002)	0.002 (0.001)	0.002*** (0.001)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	2,549	1,003	1,003	1,003	1,003
Number of Observations	10,078	4,012	4,012	4,012	4,012
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R^2	0.165	0.468	0.473	0.488	0.494

Notes: Table 4 presents results from the estimation of the log of statistical area number of traffic violations per year and population over the age 16 for various model specifications. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.

Table 5: Results from Estimation of Equation (1) for Red-Light Violations

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$Constant$	-6.147*** (0.021)	-7.720*** (0.152)	-7.736*** (0.149)	-8.258*** (0.231)	-8.279*** (0.226)
$Left$	-0.617** (0.028)	-0.253*** (0.064)	-0.241*** (0.062)	-0.221*** (0.056)	-0.212*** (0.055)
$Center$	0.012 (0.035)	-0.070* (0.043)	-0.071* (0.041)	-0.064 (0.041)	-0.067* (0.040)
$Arab$	-0.098 (0.064)	0.263 (0.322)	0.256 (0.318)	0.212 (0.320)	0.203 (0.314)
$Orthodox$	-0.440*** (0.072)	0.007 (0.101)	-0.001 (0.10)	0.025 (0.094)	0.022 (0.093)
SES		0.107*** (0.038)	0.104*** (0.037)		
$Vehicles$				0.008*** (0.002)	0.008*** (0.002)
$Centrality$		0.239*** (0.020)	0.242*** (0.019)	0.253*** (0.020)	0.257*** (0.019)
Age		0.007* (0.004)	0.007* (0.004)	0.010* (0.004)	0.006 (0.004)
$Density$		-6.685** (2.66)	-6.826*** (2.60)	-5.092* (2.95)	-5.211* (2.89)
RLC		0.255** (0.118)	0.815*** (0.190)	0.253** (0.119)	0.827*** (0.190)
$RLC \times Northern$			-0.889*** (0.243)		-0.926*** (0.243)
$RLC \times Southern$			-0.399 (0.375)		-0.404 (0.373)
$RLC \times TelAviv$			0.005 (0.478)		-0.032 (0.472)
$RLC \times Haifa$			-1.035*** (0.299)		-1.044*** (0.299)
$RLC \times Jerusalem$			-2.079*** (0.384)		-2.067*** (0.388)
$Nonvoter$		1.037*** (0.250)	0.965*** (0.242)	1.262*** (0.284)	1.201*** (0.275)
$AsiaAfrica$		0.015*** (0.003)	0.015*** (0.003)	0.015*** (0.003)	0.015*** (0.003)
$EuroAmer$		0.004* (0.002)	0.004* (0.002)	0.005** (0.002)	0.005** (0.002)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	2,498	1,002	1,002	1,002	1,002
Number of Observations	8,394	3,930	3,930	3,930	3,930
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R2	0.024	0.347	0.361	0.350	0.364

Notes: Table 5 presents results from the estimation of the log of statistical area number of red-light violations per year and population over the age 16 for various model specifications. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.

Figure 1a: Heat Map of the Number of Traffic Violations Per Person Aged 16 and Over by residence of violator ($Violations$)

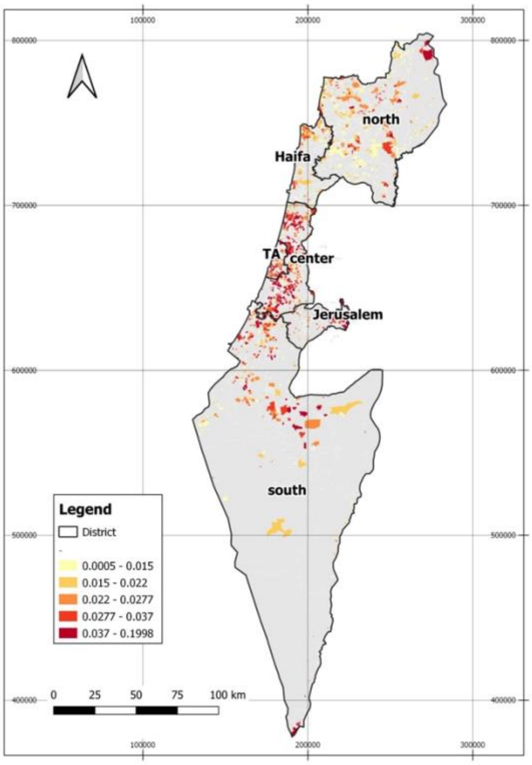


Figure 1b: Heat Map of the Enforcement Measure (E)

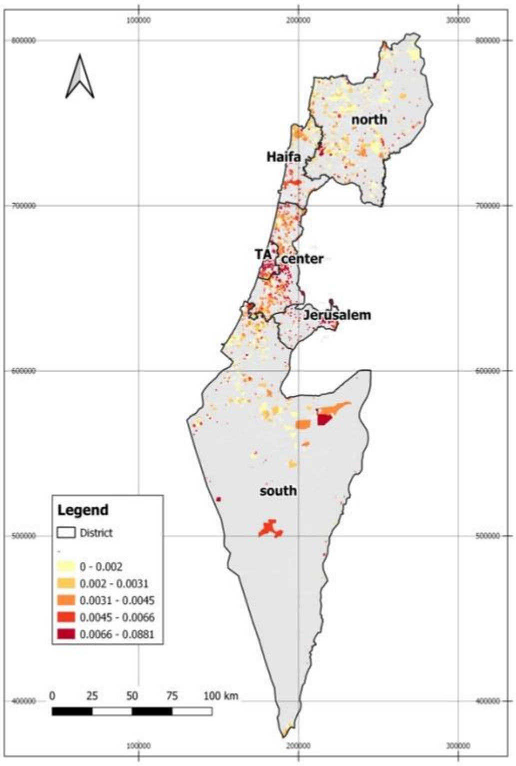
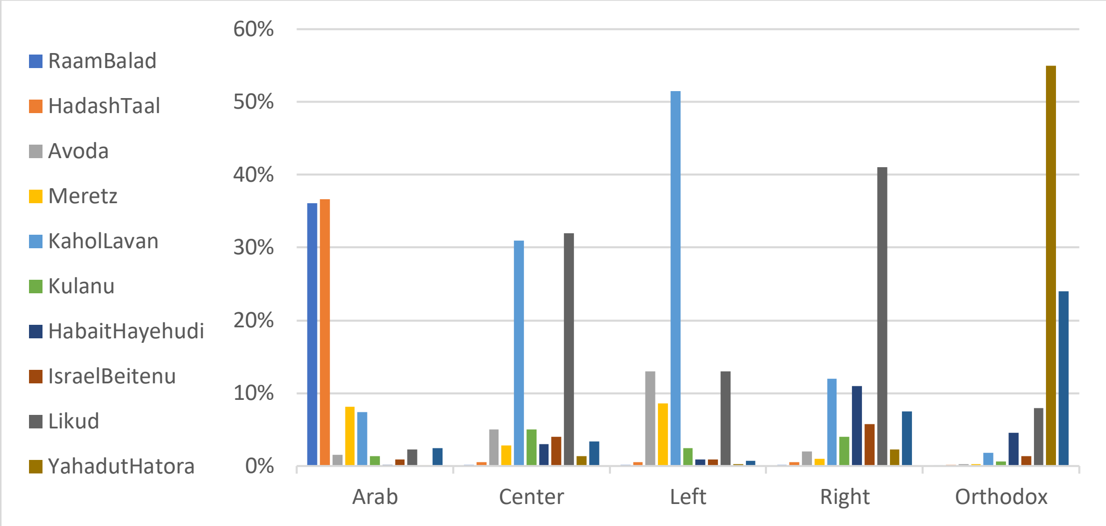


Figure 2: Average Vote Rate for Political Parties by Political Groups



Notes: Figure 2 shows the average vote share in the 2019 (April) national elections of each party by political belief group. Groups are determined by the k-means clustering method, where k, is determined by the elbow method. Political belief groups are labeled $Right$, $Left$, $Center$, $Orthodox$, and $Arab$ based on their respective vote share.

Appendix

Table A1: Results from Estimation of Equation (1) – Replacing Belief Fixed-Effects with Continuous Belief Terms

Column	(1)	(2)	(3)	(4)	(5)
$Constant$	-4.390*** (0.027)	-4.387*** (0.133)	-4.432*** (0.133)	-5.122*** (0.181)	-5.165*** (0.181)
$Right\_Cont$	1.172*** (0.071)	0.839*** (0.144)	0.860*** (0.145)	0.643*** (0.121)	0.660*** (0.121)
$Ortho\_Cont$	0.261*** (0.054)	0.558*** (0.143)	0.573*** (0.143)	0.532*** (0.100)	0.539*** (0.100)
$Arab\_Cont$	1.060*** (0.080)	1.630*** (0.334)	1.705*** (0.339)	1.342*** (0.321)	1.413*** (0.326)
SES		0.155*** (0.031)	0.158*** (0.031)		
$Vehicles$				0.012*** (0.002)	0.012*** (0.002)
$Centrality$		0.041*** (0.015)	0.043*** (0.015)	0.062*** (0.015)	0.063*** (0.015)
Age		-0.003 (0.003)	-0.002 (0.003)	-0.003 (0.003)	-0.003 (0.003)
$Density$		-10.41*** (1.88)	-10.28*** (1.89)	-8.07*** (2.19)	-7.94*** (2.21)
E		5.926*** (0.917)	9.156*** (1.765)	6.087*** (0.912)	9.338*** (1.757)
$E \times Northern$			-61.20*** (9.336)		-61.28*** (9.390)
$E \times Southern$			-0.046 (4.994)		0.154 (4.970)
$E \times TelAviv$			-3.911*** (1.431)		-3.935*** (1.429)
$E \times Haifa$			15.37*** (4.464)		15.03*** (4.451)
$E \times Jerusalem$			-9.988*** (2.101)		-10.02*** (2.091)
$Nonvoter$		0.875*** (0.185)	0.872*** (0.186)	1.233** (0.209)	1.226*** (0.210)
$AsiaAfrica$		0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
$EuroAmer$		-0.0005 (0.001)	-0.0004 (0.001)	0.001 (0.001)	0.001 (0.001)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	2,107	1,003	1,003	1,003	1,003
Number of Observations	8,360	4,012	4,012	4,012	4,012
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R^2	0.206	0.481	0.488	0.497	0.504

Notes: Table A1 presents results from the estimation of the log of statistical area number of traffic violations per year and population over the age 16 for various model specifications – replacing belief fixed-effects with continuous belief terms. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.

Table A2: Results from Estimation of Equation (1) – Based on 2022 Election Outcomes

Column	(1)	(2)	(3)	(4)	(5)
$Constant$	-3.851*** (0.016)	-3.742*** (0.115)	-3.776*** (0.115)	-4.307*** (0.176)	-4.345*** (0.176)
$Left$	-0.350*** (0.025)	-0.174*** (0.043)	-0.180*** (0.043)	-0.164*** (0.037)	-0.169*** (0.037)
$Center$	0.017 (0.029)	-0.013 (0.028)	-0.017 (0.028)	-0.017 (0.027)	-0.020 (0.027)
$Arab$	0.266*** (0.053)	0.469*** (0.120)	0.487*** (0.119)	0.426*** (0.121)	0.444*** (0.118)
$Orthodox$	-0.205*** (0.053)	-0.024 (0.067)	-0.024 (0.066)	0.013 (0.061)	0.012 (0.060)
SES		0.096*** (0.027)	0.098*** (0.027)		
$Vehicles$				0.008*** (0.002)	0.009*** (0.002)
$Centrality$		0.031* (0.016)	0.033** (0.016)	0.044*** (0.016)	0.046*** (0.017)
Age		-0.007** (0.003)	-0.007** (0.003)	-0.008*** (0.003)	-0.007*** (0.003)
$Density$		-10.22*** (1.91)	-10.06*** (1.92)	-8.33*** (2.23)	-8.18*** (2.24)
E		6.261*** (0.938)	9.674*** (1.762)	6.351*** (0.931)	9.717*** (1.754)
$E \times Northern$			-61.47*** (9.317)		-61.64*** (9.384)
$E \times Southern$			-0.226 (4.787)		-0.151 (4.757)
$E \times TelAviv$			-4.103*** (1.443)		-4.055*** (1.442)
$E \times Haifa$			15.91*** (4.351)		15.68*** (4.345)
$E \times Jerusalem$			-10.87*** (1.994)		-10.91*** (1.988)
$Nonvoter$		0.375** (0.183)	0.371*** (0.183)	0.581** (0.234)	0.577** (0.234)
$AsiaAfrica$		0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.011*** (0.002)
$EuroAmer$		0.0005 (0.001)	0.006 (0.001)	0.002 (0.001)	0.002 (0.001)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	2,549	984	984	984	984
Number of Observations	10,078	3,936	3,936	3,936	3,936
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R^2	0.159	0.466	0.473	0.478	0.484

Notes: Table A2 presents results from the estimation of the log of statistical area number of traffic violations per year and population over the age 16 for various model specifications – based on 2022 election outcomes. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.

Table A3: Results from Estimation of Equation (1) for Red-Light Violations – Replacing Belief Fixed-Effects with Continuous Belief Terms

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	-6.219*** (0.028)	-8.221*** (0.195)	-8.219*** (0.189)	-8.613*** (0.266)	-8.616*** (0.258)
$Right\_Cont$	0.147** (0.074)	0.955*** (0.207)	0.957*** (0.201)	0.789*** (0.186)	0.796*** (0.182)
$Ortho\_Cont$	-0.375*** (0.083)	0.487** (0.212)	0.466** (0.206)	0.386*** (0.149)	0.373*** (0.145)
$Arab\_Cont$	-0.058 (0.076)	1.710*** (0.450)	1.809*** (0.443)	1.498*** (0.452)	1.605*** (0.444)
SES		0.118** (0.046)	0.116** (0.045)		
$Vehicles$				0.008*** (0.002)	0.008*** (0.002)
$Centrality$		0.240*** (0.020)	0.244*** (0.019)	0.254*** (0.020)	0.258*** (0.019)
Age		0.010*** (0.004)	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)
$Density$		-6.267** (2.675)	-6.461** (2.615)	-4.933* (2.953)	-5.132* (2.89)
RLC		0.258** (0.119)	0.862*** (0.191)	0.256** (0.119)	0.867*** (0.191)
$RLC \times Northern$			-0.985*** (0.241)		-0.983*** (0.243)
$RLC \times Southern$			-0.443 (0.372)		-0.511 (0.395)
$RLC \times TelAviv$			-0.054 (0.475)		0.244 (0.437)
$RLC \times Haifa$			-1.088*** (0.300)		-1.118*** (0.290)
$RLC \times Jerusalem$			-2.142*** (0.386)		-1.977*** (0.478)
$Nonvoter$		1.061*** (0.273)	0.975*** (0.262)	1.214*** (0.302)	1.133*** (0.291)
$AsiaAfrica$		0.012*** (0.003)	0.011*** (0.003)	0.012*** (0.003)	0.011*** (0.003)
$EuroAmer$		0.003 (0.002)	0.003 (0.002)	0.004* (0.002)	0.004* (0.002)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	1,946	1,002	1,002	1,002	1,002
Number of Observations	6,416	3,930	3,930	3,930	3,930
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R^2	0.017	0.351	0.366	0.353	0.368

Notes: Table A3 presents results from the estimation of the log of statistical area number of red-light disobedience violations per year and population over the age 16 for various model specifications – replacing belief fixed-effects with continuous belief terms. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.

Table A4: Results from Estimation of Equation (1) for Red-Light Violations – Based on 2022 Election Outcomes

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	-6.153*** (0.021)	-7.594*** (0.151)	-7.616*** (0.147)	-7.906*** (0.224)	-7.937*** (0.218)
$Left$	-0.050* (0.028)	-0.274*** (0.062)	-0.260*** (0.060)	-0.250*** (0.055)	-0.237*** (0.053)
$Center$	0.045 (0.036)	-0.046 (0.042)	-0.043 (0.041)	-0.041 (0.041)	-0.039 (0.040)
$Arab$	-0.118* (0.064)	0.362* (0.211)	0.380* (0.199)	0.336 (0.210)	0.355* (0.197)
$Orthodox$	-0.416*** (0.072)	-0.048 (0.099)	-0.048 (0.098)	-0.053 (0.094)	-0.051 (0.093)
SES		0.075** (0.035)	0.075** (0.034)		
$Vehicles$				0.005** (0.002)	0.005** (0.002)
$Centrality$		0.244*** (0.020)	0.249*** (0.020)	0.253*** (0.020)	0.258*** (0.020)
Age		0.007* (0.004)	0.007* (0.004)	0.008* (0.004)	0.007* (0.004)
$Density$		-6.796** (2.68)	-7.128*** (2.61)	-5.929** (2.91)	-6.229** (2.84)
RLC		0.257** (0.118)	0.851*** (0.191)	0.256** (0.118)	0.858*** (0.191)
$RLC \times Northern$			-0.963*** (0.243)		-0.983*** (0.243)
$RLC \times Southern$			-0.508 (0.395)		-0.511 (0.395)
$RLC \times TelAviv$			0.267 (0.440)		0.244 (0.437)
$RLC \times Haifa$			-1.114*** (0.290)		-1.118*** (0.290)
$RLC \times Jerusalem$			-1.982*** (0.478)		-1.977*** (0.478)
$Nonvoter$		0.487** (0.231)	0.446** (0.223)	0.570** (0.261)	0.533** (0.252)
$AsiaAfrica$		0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)
$EuroAmer$		0.005** (0.002)	0.005** (0.002)	0.005*** (0.002)	0.006*** (0.002)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
District fixed-effects	No	Yes	Yes	Yes	Yes
Number of Groups	2,498	983	983	983	983
Number of Observations	8,394	3,853	3,853	3,853	3,853
Prob (χ^2)	0.00	0.00	0.00	0.00	0.00
R^2	0.024	0.344	0.359	0.344	0.360

Notes: Table A4 presents results from the estimation of the log of statistical area number of red-light disobedience violations per year and population over the age 16 for various model specifications – based on 2022 election outcomes. Standard errors in parentheses. Three, two, and one asterisks, respectively, represent 1, 5, and 10 percent significance level.