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 risky driving behavior. Information on this little-explored measure of risk-taking is obtained from the traffic citations dataset of 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 statistical area socio-economic and demographic characteristics, geographic centrality and access, and traffic enforcement, results indicate substantial variation in risk-related traffic violations by political belief. Results show that statistical areas that support liberal parties exhibit, on average, 20–25 percent fewer risk-related traffic citations than those statistical areas that support conservative parties. Findings provide new insights as to the prediction of risk-related traffic violations and inform specification of community traffic enforcement and messaging protocols so as to reduce injury and enhance safety.

Keywords: Risky driving; traffic citations; political belief.

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1 Introduction

Risky driving is a major contributor to road accidents, injuries, and fatalities. In 2022, for example, 29 percent of all traffic fatalities in the United States were linked to driving above the posted speed limit (speeding).[1] In yet another indicator of the human costs of risky driving, 2023 data indicate that of the roughly 24,000 U.S. passenger vehicle traffic fatalities, nearly 50 percent involved those not wearing a safety belt.[2] The understanding of factors associated with risky driving behaviors and methods for reducing related accidents and injuries hence poses an ongoing and salient public policy challenge. In this study, we explore whether driver political belief is systematically associated with driver risk-taking on the road. Further, we discuss how an understanding of this risk factor may provide new insights for effective road safety policy response.

The literature provides numerous examples of the role of political belief in perception and decision-making. 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 companies that are less socially responsible. Financial research has illuminated other consequences of misalignment of prevailing political belief with the political party in power, including increased pessimism among investors (Bonaparte et al., 2017); larger corporate debt spreads (Dagostino et al., 2023); 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

[1] See "Traffic Safety Facts, 2022 Data" National Highway Traffic Safety Administration, U.S. Department of Transportation, July 2024.

[2] "Seat Belts", National Highway Traffic Safety Administration, U.S. Department of Transportation, 2024, https://www.nhtsa.gov/vehicle-safety/seat-belts#:~:text=Improperly%20wearing%20a%20seat%20belt,seat%20belts%2C%20not%20replace%20 (visited on August 17, 2025).

Huber, 2010; and Gillitzer et al., 2021).[3] Bartels (2002), Gaines *et al*. (2007), and Curtin (2018) provide further evidence that partisan political bias as proxied by party identification shapes individual reaction to political events.

While the above literature speaks to the role of political belief in information processing and cognitive reasoning, research on the association of political belief with risky behaviors is limited and inconclusive. We do know that risky behaviors play a key role in cognitive and emotional processing.[4] Further, based on meta-analysis of 88 samples from 12 countries, Jost et al. (2003) find that conservative beliefs are positively associated with sensation seeking, and that sensation seeking provides a reliable indicator of risk-taking behaviors (see Wong and Carducci, 1991; Horvath and Zuckerman, 1993; and Grinblatt and Keloharju, 2009).[5] Indeed, these findings suggest that drivers with conservative political beliefs may be more prone to risky behaviors. Moreover, conservatives may exhibit lower *perceived* risk in domains where personal freedom and skepticism toward regulation are salient. Indeed, in the 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; and Ben-Shahar et al. (2023) found that politically conservative households were associated with higher levels of both COVID-19 virus transmission and vaccine resistance.[6]

Consistent with the above studies, conservatives may perceive of government regulatory control—in our case, in the form of traffic regulations—as less necessary or more intrusive. This could lead to their lower compliance with traffic laws and higher

[3] 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.

[4] 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.

[5] Among the limited experimental evidence, Moore et al. (2010) and Choma et al. (2014) find higher levels of financial risk tolerance among conservatives compared to liberals, whereas 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.

[6] For additional studies on Covid-19-related social distancing and vaccine uptake behavior see, for example, Sandlin (2025) and Allcott et al. (2020).

citation rates, particularly for rules perceived as overly restrictive. And further, in reference to moral foundation theory (e.g., Haidt and Joseph, 2004), Graham et al. (2009) find that conservatives and liberals differ in moral priorities: whereas liberals emphasize care and fairness, conservatives emphasize loyalty, authority, and purity. These could lead to differences in perceived justification for risky behaviors on the road, where liberals might be more likely to consider traffic transgressions a violation of fairness or harm (endangering others), whereas conservatives might not prioritize these same moral concerns, especially if driving is viewed as a private or individual domain. Consistent with the above evidence, we hypothesize that right-of-center political beliefs are associated with riskier behaviors on the road, as manifested by their greater rate of traffic citations.

To that end, in this paper, we apply unique information on traffic citations to explore the role of political belief in risky road behaviors. Specifically, the analysis employs data on the universe of risk-related traffic violations—roughly 840,000 observations—recorded by the Israel Police over the period 2019–2022. These citations are classified into six categories: 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. We aggregate the observations by small statistical areas (akin to U.S. census tracts) and match information on same-area voting outcomes in Israel national parliament elections.[7] We merge this information with extensive statistical area controls for population socio-economic, demographic, geographic access and centrality, civic participation, and traffic violation enforcement in the area where the citation is recorded.

Results of panel estimation indicate substantial divergence in risky behaviors, as proxied by area traffic violations per person (aged 16 and over), among left- and right-leaning small statistical areas. Findings show that, compared to statistical areas with greater support for conservative parties, those with higher support for liberal parties 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

[7] As described below, outcomes are robust to basing the estimation on the (end of sample period) 2022 parliament elections.

percent lower 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, the study contributes to the economics and social and political sciences of transportation. Existing evidence demonstrates the role of individual characteristics in risky-driving behaviors (see Iversen, 2004; Pereira et al., 2022; McIlroy et al., 2022). For example, it has been shown that risky driving is associated with the 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; and 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).[8] In line with this literature, we propose a new, underexplored attribute – political belief – as a behavioral determinant of risky behavior on the road, and show that ideological orientation is meaningfully correlated with traffic violations. Our analysis controls for important socio-demographic characteristics of driver's small statistical area of residence, including median age, SES, population density, proximity to central business district, average number of owned vehicles, and ethnicity distribution.[9]

[8] Donaldson et al. (2006) and Leveau & Vacchino (2015) also find that density and geographic location of driver's residence correlate with risky driving. Relatedly, Wang and Zhao (2019) show that risk preference is associated with the adoption of autonomous vehicles.

[9] Previous research shows that political beliefs may correlate with personality traits (e.g., Jost et al, 2008 and Cichocka and Dhont, 2018). However, as we proxy political belief by small statistical area general election outcomes in our macro-level estimation, our evidence does not control for personality traits. Hence, while our outcome on the association between ideological orientation and risky behavior on the road might capture, to some extent, driver personality traits, it is unlikely to be fully explained by drivers' personality traits.

Our findings have important implications for road safety protocols and policy. Specifically, our results support the idea that models of traffic safety can be improved by incorporating factors associated with political belief. Among other things, policy-makers can nuance and specify safety messaging across communities with differing political beliefs, such that the message resonates with the specific ideological orientation of the audience. Also, enforcement resources may be allocated in accordance with elevated traffic violation rates that correlate with the political orientation. Importantly, however, any use of politically correlated behavioral data must be accompanied by the necessary safeguards to maintain fairness and prevent profiling.

Finally, more generally, 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. Further, that evidence is based largely on experimental/survey methods and focuses on financial risk. In contrast, our study draws from actual behavior behind the wheel as manifest in traffic citations—a framework that serves as a natural setting for risk-related behaviors.[10] Similarly, our assessment of political belief is not survey-based, but proxied instead by the revealed preference of voting outcomes in national elections in small statistical areas.

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 840,000 observations across 6 violation categories) among roughly

[10] 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.

2,500 statistical areas (akin to census tracts) in Israel over the 2019–2022 period. The dataset – obtained from the Israeli National Traffic Police records – includes information on the type of traffic violation and the small statistical area where the violation occurred and where the violator resides.[11] 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.[12] As shown, speeding and failing to operate the vehicle with due care[13] are the most prevalent violations in the sample with an average of roughly 80,000 and 57,000 violations per year, respectively. The least prevalent violations in the sample include failing to obey a road sign and reckless driving with roughly 12,500 and 14,000 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.

[11] 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).

[12] 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 af 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 failing to operate vehicle with due care; Ivers et al. (2009) – for failing to use safety belt; Castanier et al. (2013) – for disobeying 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 five 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).

[13] 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).

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 Israel Central Bureau of Statistics (ICBS) socioeconomic index score (*SES*) to control for statistical area variation in household income, education, and standard of living.[14] 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%.[15] 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 area variation in geographic accessibility to central business districts and proximity to

[14] 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.

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

Tel Aviv, the "superstar" city and primary central business district of Israel (Ben-Shahar et al., 2020).[16]

To control for possible differences in police enforcement of traffic rules and other unobserved factors that associate with locational incidence of traffic violations, we compute a time-varying statistical area locational violation intensity measure, $E_{s,t}$. Essentially, this measure reflects the intensity of traffic violation citations, thus controls for the location-based enforcement and other factors associated with the likelihood of receiving a traffic citation.[17] To generate $E_{s,t}$, we first denote the statistical area where the traffic violator resides and the statistical area where they committed the violation by s and c, respectively. For each statistical area c (where a violation is committed) and year t, we compute the per year total number of violations, standardized by the total area of c (that is, for each c, we divide the total number of traffic citations by the area in square-meters of that statistical area). We denote the outcome by $V_{c,t}$. For each violation i, we let $s(i)$ and $c(i)$ be the violator's residence statistical area and the statistical area where the violation occurred, respectively. Then, for each violation i committed in statistical area $c(i)$ in year t by a driver residing in statistical area $s(i)$, we assign the corresponding value $V_{c,t}$, denoting it by $V_{i,s(i),c(i),t}$. Finally, for each statistical area s, we average $V_{i,s(i),c(i),t}$ across all violations i committed at time t by a driver residing in statistical area $s(i)$, producing a measure of violation intensity in the areas where violations were committed at time t by drivers residing in s. We denote this measure by $E_{s,t}$ (see appendix for a formal derivation of $E_{s,t}$). Note that value of $E_{s,t}$ depends not only on the level of traffic enforcement in the areas where drivers from statistical area s tend to drive, but also on other unobserved locational factors such as road conditions and traffic volume – factors that may affect the intensity of traffic

[16] 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 geographically similar to our ICBS district classification. Hence, by including the district controls, we also further enhance our control for police enforcement.

[17] As $E_{s,t}$ is a macro-level, time-varying, location-based violation intensity control, it does not account for individual-level factors – such as individual driving behavior or the routes a specific driver chooses – that may be associated with the likelihood of receiving a citation.

violations and citations.[18] 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 measures of 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 political tendencies.[19] 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

[18] Proxying traffic enforcement based on the number of citations in the statistical area where the violations were committed is consistent with, e.g., Terrill et al. (2016) and Rezapour et al. (2017).

[19] 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).

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 risk-related traffic violations 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 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);[20] 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

[20] Controlling for *E* mitigates potential omitted variable bias: Suppose drivers originating from a politically right-leaning area (*Right*) are systematically more likely to drive in areas with a higher propensity for traffic violations – owing, for example, to stricter police enforcement or particular road conditions. In this case, omitting *E* in the estimation of equation (1) would bias the estimated relationship between *Right* and the incidence of risk-related citations. By controlling for *E*, we address this potential omitted variable bias.

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.[21]

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 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 a statistically significant and economically salient association between the number of risk-related traffic violations and political belief. 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

[21] 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).

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 $E \times Southern$; $E \times Central$ serving as the based category). Outcomes on the differences among political belief groups, however, are largely 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).[22]

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

[22] 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 ($0.0116 \times 15.7 = 18.2\%$).

1 percent levels, respectively).[23] 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 ($6.047 \times 0.006 = 3.63\%$). 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 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) with the full set of controls, (a) approximating political inclination across statistical areas based on Israel's November 2022 (instead April 2019) national parliament elections (that is, toward 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

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

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 observe the location of red-light police cameras by statistical area (available from the Ministry of National Security in Israel). Unlike the above analysis that is based on the entire sample of traffic violations – by which we generate the control variable E that captures location-based variations in traffic enforcement, road conditions, traffic volume and the like – information of the presence of red-light cameras allows us to directly control for location-based, time-varying *enforcement* of red-light violations.[24] 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 the violator was cited for the red-light violation by s and c, respectively. For each c and t, we then use an indicator $I_{c,t}$ ($I_{c,t} = 0{,}1$) that equals 1 if there is a red-light camera in the statistical area where the red-light violation was committed and zero otherwise. For each red-light violation i, we let $s(i)$ and $c(i)$ be the

[24] 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 discussions 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).

violator's residence statistical area and the statistical area where the violation occurred, respectively. Then, for each red-light violation i committed in statistical area $c(i)$ at year t by a violator residing in statistical area $s(i)$, we assign the corresponding value $I_{c,t} = 0,1$, denoting it by $I_{i,s(i),c(i),t} = 0,1$. Finally, we average $I_{i,s(i),c(i),t}$ across all i in $s(i)$ 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 (see appendix for a formal derivation of $RLC_{s,t}$). 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 columns 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.[25] 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.[26] 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 of April 2019) national parliament elections (that is, toward 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 Conclusion and Policy Implications

While research points to the role that political belief plays in information processing and decision-making, perception, and behaviors, little is known about how political belief affects risky behaviors. 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

[25] Results on the association between political beliefs and number of red-light violations per person in columns 2–5 are further robust to including E among the set of controls.

[26] 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 $0.25 \times 0.15 = 3.75\%$. Also, note that the Pearson correlation between RLC and the continuous version of the political beliefs, $Right\_Cont$, $Ortho\_Cont$, and $Arab\_Cont$ is -0.058, -0.076, and 0.136, respectively.

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

Results of model estimation show that, compared to residents in politically conservative zones, voters in politically liberal zones 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 control for variations in enforcement via the presence of a red-light camera—we find that more liberal 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 have important implications for safety protocol and policy intervention. First, results support the idea that predictive models of traffic safety can be improved by incorporating controls for political belief, similar to the inclusion of psychological and behavioral indicators (e.g. Ulleberg and Randmo, 2003 and af Wåhlberg et al., 2015). Transportation analysts can incorporate heterogeneity in political belief to predict the location and incidence of traffic violations and interventions in order to inform mitigation strategies and traffic planning. Also, as political affiliation is found to be informative predictor of risk-taking behind the wheel, researchers and policy-makers can use this factor to better understand why certain communities respond differently to enforcement or safety messaging. In this sense political beliefs may serve as a behavioral diagnostic tool, useful for understanding variations in road behavior patterns.

Moreover, our observed differences in risk-taking road behavior across political belief suggests that uniform safety messaging may not be equally effective across all communities. Regulators and authorities should thus adapt safety messaging that reflect different motivational frameworks that resonate with specific audiences: For example, this might be accomplished by emphasizing personal responsibility and economic consequences in some areas versus community outcomes and fairness elsewhere. Furthermore, enforcement resources, guided by empirical evidence, should address areas with elevated violation rates, which may correlate with political preferences and are justified by risk performance (not political classification). Such an approach would help to ensure fair enforcement while benefitting from the predictive value of our outcomes.

Finally, public trust in traffic safety systems depends on public perception that enforcement is objective and impartial. Therefore, any use of politically correlated behavioral data must be accompanied by the necessary safeguards to maintain fairness and prevent profiling. As we find political belief to be a meaningful correlate of traffic safety behavior, policymakers should use this knowledge to enhance the precision of enforcement and educational efforts so long as interventions remain behaviorally-based, transparent, and fairly implemented. We emphasize that policy and mitigation protocol interventions be limited to analytical use of information on political beliefs, rather than use of model findings for normative or ideological purposes.

References

Abakah, A. A., & Li J. (2023). Local religious beliefs and bank risk-taking. *Journal of Behavioral and Experimental Finance*, 40(C).

Abay, K. A., & Mannering, F. L. (2016). An empirical analysis of risk-taking in car driving and other aspects of life. *Accident Analysis & Prevention*, 97, 57–68.

Adanu, E. K., Smith, R., Powell, L., & Jones, S. (2017). Multilevel analysis of the role of human factors in regional disparities in crash outcomes. *Accident Analysis & Prevention*, 109, 10–17.

af Wåhlberg, A. E., Barraclough, P., & Freeman, J. (2015). The Driver Behaviour Questionnaire as accident predictor: A methodological re-meta-analysis. *Journal of Safety Research, 55*, 185‑212.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., and Yang, D. (2020). Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *Journal of Public Economics*, 191, 104254.

Balasubramanian, V., & Sivasankaran, S. K. (2021). Analysis of factors associated with exceeding lawful speed traffic violations in Indian metropolitan city. *Journal of Transportation Safety & Security*, 13(2), 206–222.

Barrios, J. M., & Hochberg, Y. V. (2021). Risk perceptions and politics: Evidence from the COVID-19 pandemic. *Journal of Financial Economics*, 142(2), 862–879.

Bartels, L. M. (2002). Beyond the running tally: Partisan bias in political perceptions. *Political Behavior*, 24(2), 117–150.

Begg, D. J., & Langley, J. D. (2004). Identifying predictors of persistent non-alcohol or drug-related risky driving behaviours among a cohort of young adults. *Accident Analysis & Prevention*, 36(6), 1067–1071.

Ben-Shahar, D., Gabriel, S., & Golan, R. (2020). Can't get there from here: Affordability distance to a superstar city. *Regional Science and Urban Economics*, 80, 103357.

Ben-Shahar, D., Gabriel, S., & Golan, R. (2023). The Role of Political Belief in COVID-19 Vaccine Resistance, Virus Transmission, and Closure Policy Response. *Vaccines*, 11(6), 1046; https://doi.org/10.3390/vaccines11061046.

Bina, M., Graziano, F., & Bonino, S. (2006). Risky driving and lifestyles in adolescence. *Accident Analysis & Prevention*, 38(3), 472–481.

Bonaparte, Y., Kumar, A., & Page, J. K. (2017).Political climate, optimism, and investment decisions. Journal of Financial Markets, 34, 69–94.

Castanier, C., Deroche, T., & Woodman, T. (2013). Theory of planned behaviour and road violations: The moderating influence of perceived behavioural control. *Transportation Research Part F: Traffic Psychology and Behaviour*, 18, 148–158.

Choma, B. L., Hanoch, Y., Hodson, G., & Gummerum, M. (2014). Risk propensity among liberals and conservatives: The effect of risk perception, expected benefits, and risk domain. *Social Psychological and Personality Science*, 5(6), 713–721.

Cohn, E. G., Kakar, S., Perkins, C., Steinbach, R., & Edwards, P. (2020). Red light camera interventions for reducing traffic violations and traffic crashes: A systematic review. *Campbell Systematic Reviews*, 16(2), e1091.

Curtin, R. (2018). Consumer economic expectations: Persistent partisan differences. Working paper (2018 Ciret Conference, Brazil).

Dagostino, R., Gao, J., & Ma, P. (2023). Partisanship in loan pricing. *Journal of Financial Economics*, 150(3), 103717.

Dahlen, E. R., Martin, R. C., Ragan, K., & Kuhlman, M. M. (2005). Driving anger, sensation seeking, impulsiveness, and boredom proneness in the prediction of unsafe driving. *Accident analysis & prevention*, 37(2), 341–348.

Donaldson, A. E., Cook, L. J., Hutchings, C. B., & Dean, J. M. (2006). Crossing county lines: The impact of crash location and driver's residence on motor vehicle crash fatality. *Accident Analysis & Prevention*, 38(4), 723–727.

Factor, R. (2018). An empirical analysis of the characteristics of drivers who are ticketed for traffic offences. *Transportation research part F: traffic psychology and behaviour*, 53, 1–13.

Factor, R., Mahalel, D., & Yair, G. (2008). Inter-group differences in road-traffic crash involvement. *Accident Analysis & Prevention*, 40(6), 2000–2007.

Fosgerau, M. (2005). Speed and income. *Journal of Transport Economics and Policy*, 39(2), 225–240.

Gaines, B. J., J. H. Kuklinski, P. J. Quirk, B. Peyton, and J. Verkuilen (2007). Same facts, different interpretations: Partisan motivation and opinion on Iraq. *Journal of Politics*, 69(4), 957–974.

Gerber, A. S., & Huber, G. A. (2009). Partisanship and economic behavior: Do partisan differences in economic forecasts predict real economic behavior? *American Political Science Review*, 103(3), 407–426.

Gerber, A. S., & Huber, G. A. (2010). Partisanship, political control, and economic assessments. *American Journal of Political Science*, 54(1), 153–173.

Gillitzer, C., Prasad, N., & Robinson, T. (2021). Political attitudes and inflation expectations: Evidence and implications. *Journal of Money, Credit and Banking*, 53(4), 605–634.

Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *Journal of Finance*, 64(2), 549–578.

Gollwitzer, A., M. Cameron, W. J. Brady, P. Pärnamets, I. G. Freedman, E. D. Knowles, and J. J. Van Bavel, (2020). Partisan differences in physical distancing are linked to health outcomes during Covid-19 pandemic. *Nature Human Behaviour*, 4, 1186–1197.

Goutte, C., Toft, P. A., Rostrup, E., Nielsen, F. A., Hansen, L. K. (1999). On clustering fMRI time series. *NeuroImage*, 9(3), 298–310.

Graham, J., Haidt, J., & Nosek, B. A. (2009). Liberals and conservatives rely on different sets of moral foundations. *Journal of Personality and Social Psychology*, 96(5), 1029–1046.

Haidt, J., & Joseph, C. (2004). Intuitive ethics: How innately prepared intuitions generate culturally variable virtues. *Daedalus, Special Issue of Human Nature*, 133(4), 55–66.

Han, K., Jung, J., Mittal, V., Zyung, J. D., & Adam, H. (2019). Political identity and financial risk taking: Insights from social dominance orientation. *Journal of Marketing Research*, 56(4), 581–601.

Hong, H., & Kostovetsky, L. (2012). Red and blue investing: Values and finance. *Journal of Financial Economics*, 103(1), 1–19.

Horvath, P., & Zuckerman, M. (1993). Sensation seeking, risk appraisal, and risky behavior. *Personality and Individual Differences*, 14(1), 41–52.

Høye, A. (2020). Speeding and impaired driving in fatal crashes—Results from in-depth investigations. *Traffic injury prevention*, 21(7), 425–430.

Hsu M., Bhatt M., Adolphs R., Tranel D., & Camerer C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science*, 310(5754), 1680–1683.

Huda, L. N., & Ismail, S. (2020, May). The effect of car drivers risk perception and driving behaviour towards accident risk: A case study. In *IOP Conference Series: Materials Science and Engineering* (Vol. 801, No. 1, p. 012066). IOP Publishing.

Itskovich, E., & Factor, R. (2023). Economic inequality and crime: The role of social resistance. *Journal of Criminal Justice*, 86, 102065.

Ivers, R. Q., Senserrick, T., Boufous, S., & Stevenson, M. R. (2009). Novice drivers' risky driving behavior, risk perception, and crash risk: Findings from the DRIVE study. American Journal of Public Health, 99(9), 1638–1644.

Iversen, H. (2004). Risk-taking attitudes and risky driving behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, 7(3), 135-150.

Jantosut, P., Satiennam, W., Satiennam, T., & Jaensirisak, S. (2021). Factors associated with the red-light running behavior characteristics of motorcyclists. *IATSS Research*, 45(2), 251–257.

Jing, L., Shan, W., & Zhang, Y. (2023). Risk preference, risk perception as predictors of risky driving behaviors: the moderating effects of gender, age, and driving experience. *Journal of Transportation Safety & Security*, 15(5), 467–492.

Jonah, B. A., & Boase, P. (2016). Speeding and other risky driving behavior among young drivers. *Handbook of Teen and Novice Drivers*, 165–186.

Jost, J. T., Napier, J. L., Thorisdottir, H., Gosling, S. D., Palfai, T. P., & Ostafin, B. (2007). Are needs to manage uncertainty and threat associated with political conservatism or ideological extremity? *Personality and Social Psychology Bulletin*, 33(7), 989–1007.

Jost, J. T., Nosek, B. A & ,.Gosling, S. D. (2008). Ideology: Its resurgence in social, personality, and political psychology. *Perspectives on Psychological Science*, 3(2), 126–136.

Kaustia, M., & Torstila, S. (2011). Stock market aversion? Political preferences and stock market participation. *Journal of Financial Economics*, 100(1), 98–112.

Kempf, E., & Tsoutsoura, M. (2021). Partisan professionals: Evidence from credit rating analysts. *Journal of Finance*, 76(6), 2805–2856.

Leveau, C. M., & Vacchino, M. N. (2015). Residence place as a risk factor in different types of fatal car accidents. *International Journal of Injury Control and Safety Promotion*, 22(2), 95–99.

Loewenstein, G. F., Weber E. U., and Hsee, C. K., Risk as feelings. *Psychological Bulletin*, Vol. 127, 2001.

Luo, X., Ge, Y., & Qu, W. (2023). The association between the Big Five personality traits and driving behaviors: A systematic review and meta-analysis. *Accident Analysis & Prevention*, 183, 106968.

McCarty, D., & Kim, H. W. (2024). Risky behaviors and road safety: An exploration of age and gender influences on road accident rates. PLOS One, 19(1), e0296663.

McIlroy, R. C., Mont'Alvão, C., Cordovez, S. P., Vásconez-González, J., & Prado, E. O. (2022). The influence of fatalistic beliefs and risk perceptions on road safety attitudes in Latin America; A two-country study. *Transportation research part F*: *Traffic Psychology and Behaviour*, 90, 84–99.

Meeuwis, M., Parker, J. A., & Schoar A. (2022). Belief disagreement and portfolio choice. *The Journal of Finance*, 77(6), 3191–3247.

Mian, A., A. Sufi, and N. Khoshkhou (2023). Partisan bias, economic expectations, and household spending. *The Review of Economics and Statistics*, 105(3), 493–510.

Moore J., Felton, J., & Wright C. (2010). The influence of political orientation on financial risk taking. *American Journal of Business*, 25(1), 35–43.

Obeid, S., Gitelman, V., & Baron-Epel, O. (2014). The relationship between social capital and traffic law violations: Israeli Arabs as a case study. *Accident Analysis & Prevention*, 71, 273–285.

Pereira, V., Bamel, U., Paul, H., & Varma, A. (2022). Personality and safety behavior: An analysis of worldwide research on road and traffic safety leading to organizational and policy implications. *Journal of Business Research*, 151, 185–196.

Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: a real distinction?. *Ergonomics*, 33(10-11), 1315–1332.

Retting, R. A., Ferguson, S. A., & Shalom Hakkert, A. (2003). Effects of red light cameras on violations and crashes: A review of the international literature. *Traffic Injury Prevention*, 4(1), 17–23.

Retting, R. A., Ulmer, R. G., & Williams, A. F. (1999). Prevalence and characteristics of red light running crashes in the United States. *Accident Analysis & Prevention*, 31(6), 687–694.

Rezapour Mashhadi, M. M., Saha, P., & Ksaibati, K. (2017). Impact of traffic enforcement on traffic safety. *International Journal of Police Science & Management*, 19(4), 238–246.

Rhodes, N., & Pivik, K. (2011). Age and gender differences in risky driving: The roles of positive affect and risk perception. *Accident Analysis & Prevention*, 43(3), 923–931.

Rowe, R., Andrews, E., & Harris, P. (2013). Measuring risky-driving propensity in pre-drivers: The Violation Willingness Scale. *Transportation Research Part F: Traffic Psychology and Behaviour*, 19, 1–10.

Sandlin, E. W. (2025). The politicization of influenza: partisan changes in flu vaccination before and after COVID-19. *Journal of Public Health*, 47(2), 317–325.

Shaaban, K., & Pande, A. (2018). Evaluation of red-light camera enforcement using traffic violations. *Journal of Traffic and Transportation Engineering*, 5(1), 66–72

Shu, T., Sulaeman, J., & Yeung, P. E. (2012). Local religious beliefs and mutual fund risk-taking behaviors. *Management Science*, 58(10), 1779–1796.

Terrill, T. T., Mashhadi, M. M. R., & Ksaibati, K. (2016). Developing a tool to help highway patrol in allocating resources to crashes. *International Journal of Police Science & Management*, 18(4), 231–241.

Ulleberg, P., & Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety Science*, 41(5), 427–443.

Voogt, A., Day, A., & Baksheev, G. N. (2014). Risky driving in young adults: A review of the literature. *Road & Transport Research: A Journal of Australian and New Zealand Research and Practice*, 23(2), 50–59.

af Wåhlberg, A. E., Barraclough, P., & Freeman, J. (2015). The driver behaviour questionnaire as accident predictor; A methodological re-meta-analysis. *Journal of Safety Research*, 55, 185–212.

Wang, P., Rau, P. L. P., & Salvendy, G. (2011). Chinese drivers' risky driving and risk taking in other life situations. *International Journal of Occupational Safety and Ergonomics*, 17(2), 155–164.

Wang. S., & Zhao, J. (2019). Risk preference and adoption of autonomous vehicles. *Transportation and Research Part A: Policy and Practice*, 126, 215–229.

Watling, C. N., Armstrong, K. A., Smith, S. S., & Obst, P. L. (2016). Crash risk perception of sleepy driving and its comparisons with drink driving and speeding: which behavior is perceived as the riskiest? *Traffic Injury Prevention*, 17(4), 400–405.

West, R., & Hall, J. (1997). The role of personality and attitudes in traffic accident risk. *Applied Psychology*, 46(3), 253–264.

Wong, A., & Carducci, B. J. (1991). Sensation seeking and financial risk taking in everyday money matters. *Journal of Business and Psychology*, 5(4), 525–530.

Zimbardo, P. G., Keough, K. A., & Boyd, J. N. (1997). Present time perspective as a predictor of risky driving. *Personality and Individual Differences*, 23(6), 1007–1023.

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	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 ($Violations$)

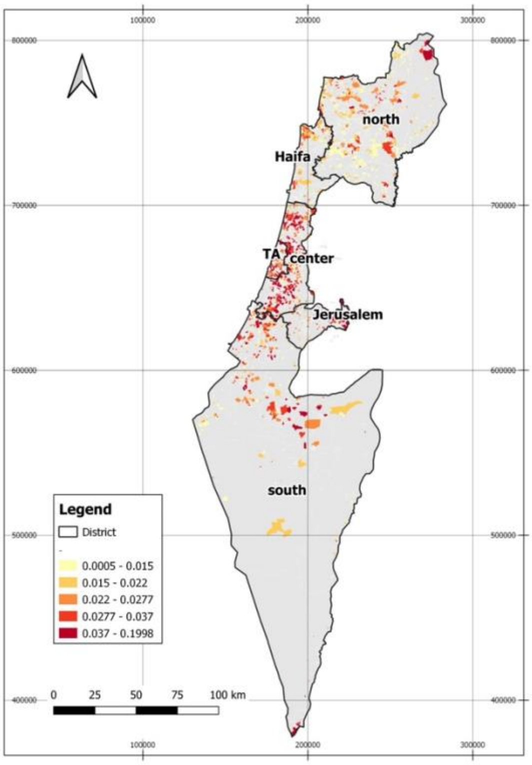


Figure 1b: Heat Map of the Enforcement Measure (E)

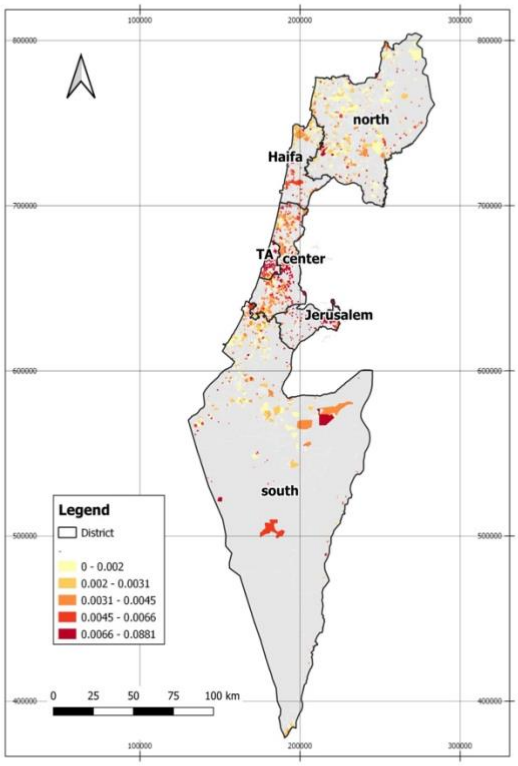
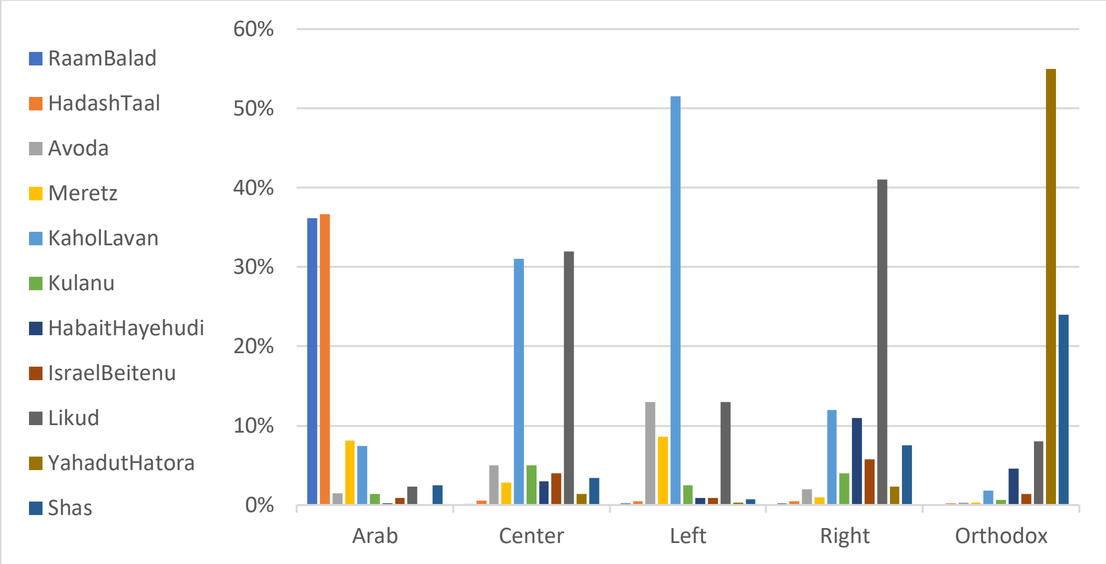


Figure 2: Average Vote Rate for Political Parties by Political Groups



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 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 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.

Appendix

Formal Derivation of $E_{s,t}$:

Let s, c, and t respectively denote the statistical area where the traffic violator resides, the statistical area where they committed the violation, and the year in which the violation was committed and let i be a violation committed in statistical area c in year t by a driver residing in statistical area s. Also, let $D_{c,t}$ and A_c be the total number of traffic violations committed in statistical area c during year t and the land area (in squared meters) of statistical area c, respectively. Then, for each c and t, we compute

$V_{c,t} = D_{c,t}/A_c$.

For each violation i, let $s(i)$ and $c(i)$ be the violator's residence statistical area and the statistical area where the violation occurred, respectively. Then, for each violation i committed in $c(i)$ at year t by a driver residing in $s(i)$, we define

$V_{i,s(i),c(i),t} = V_{c,t}$.

Finally, let $B_{s,t} = \{i\text{: violation } i \text{ in year t by a driver residing in } s(i)\}$ and $N_{s,t} = |B_{s,t}|$. We then compute

$E_{s,t} = \frac{1}{N_{s,t}} \sum_{i \in B_{s,t}} V_{i,s(i),c(i),t}$.

Formal Derivation of $RLC_{s,t}$:

Let s, c, and t respectively denote the statistical area where the red-light violator resides, the statistical area where they committed the violation, and the year in which the violation was committed and let i be a red-light violation committed in statistical area c in year t by a driver residing in statistical area s. Then, for each c and t, we compute

$I_{c,t} = \begin{cases} 1, & \text{if a red light camera is present in } c \text{ during } t \\ 0, & \text{otherwise} \end{cases}$.

For each red-light violation i, let $s(i)$ and $c(i)$ be the violator's residence statistical area and the statistical area where the violation occurred, respectively. Then, for each red-light violation i committed in $c(i)$ at year t by a driver residing in $s(i)$, we define

$I_{i,s(i),c(i),t} = I_{c,t}$.

Now, let $F_{s,t} = \{i\text{: red light violation } i \text{ in year t by a driver residing in } s(i)\}$ and $M_{s,t} = |F_{s,t}|$. We then compute

$RLC_{s,t} = \frac{1}{M_{s,t}} \sum_{i \in F_{s,t}} I_{i,s(i),c(i),t}$.