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Detecting DUI (Non) deterrence: A macro-methodology to uncover "restrictive v permissive" county jurisdictions in California

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ABSTRACT

This paper builds a method to detect the apparent restrictiveness or permissiveness of communities towards drunk-driving. A framework of three mutually interacting community domains is used to motivate a minimum set of DUI patterns to be expected from an appropriately deterrent environment. Based on the (simplified) system dynamics model, an empirical estimation strategy and scoring methodology is outlined. This "macroscopic" approach is demonstrated using results from time-series panel analyses of California's 58 counties for the years 1990 to 2010 (Van Vleck et al., 2017). The process successfully classified three-quarters of California counties, encompassing almost 90% of the state population. The paper demonstrates a potential tool to classify communities' systemic behavior toward drinking-and-driving and other enforcement-sensitive subjects.

1. Introduction

Drinking and driving is a complex phenomenon; it is the intersection of multiple layers that includes drinking drivers, the communities that shape social learning and behavior over time, and the particular enforcement activities deployed in response. Prevention science in this area is concerned with systemic risk factors, such as evolving social norms, changing community conditions, and learning from prior experiences. Even so, analytical methods to address these complexities have yet to be fully articulated. Complex systems are characterized by: interrelatedness, feedback loops, nonlinearities, multiple layers, adaption of the system, and temporal dynamics. The aim of systems science is to advance methods to account for such complexities and inform the next generation of interventions for this and other complicated problems. One systems science approach is "systems dynamic modeling" (SDM), which incorporates multiple causal relationships and accumulations within a system over time to model an organic and evolving set of relationships rather than a deterministic, mechanical clockwork. The efficacy and longevity of policy tools critically depends on our abilities to assess whether the system is behaving as intended and under what circumstances. Describing the scope of complexity for the prevention fields is ably addressed by other authors (see, for example, Lich et al., 2013).[1]

This paper proposes a means to evaluate drunk driving at a macroscopic level, using a minimally complex system.[2] In Section 2, a simple, dynamic DUI environment involving three domains (community, police, and courts) generates a minimal scaffold of behavioral patterns to be expected from a deterrent system. Importantly, systems can exhibit success, failure, or ambiguity with respect to the intended objective. Section 3 outlines a "2 × 2 game matrix" scoring rubric to assess the behavioral interactions. Domains' *Strict* or *Lenient* (apparent) stances are inferred empirically with time-series analyses to detect the system patterns. The *Restrictive-Permissive* diagnostic aggregates these scored observations. In Section 4, the diagnostic is demonstrated concretely, using time-series panel results obtained for all California counties over a twenty-year span. Known caveats and limitations are acknowledged in the conclusion, Section 5.

2. Motivating the restrictive/ permissive framework

The success or failure of prevention initiatives depends crucially upon the attitudes and social norms of the target communities. Social psychologists Harrington and Gelfand (2014) documented striking regional variation in the "tightness or looseness" of Americans' attitudes toward various scenarios of deviance. Indicators of religiosity, corporal punishment in schools, the death penalty, same-sex unions, and marijuana violations were used to assess prevailing social norms by state. These norms can also be seen in the polarized political sphere; California's fractious history with (ballot) propositions has been tied to "shared mental models" (McFerrin and Adkisson, 2012). Historically, alcohol and drunk-driving are also topics of extreme divisiveness, and are still evident in the political geography of "wet/ dry/ moist" counties 80 years after Prohibition (Frendreis and Tatalovich, 2010) and in modern consumption and accident patterns (Baughman et al., 2001;

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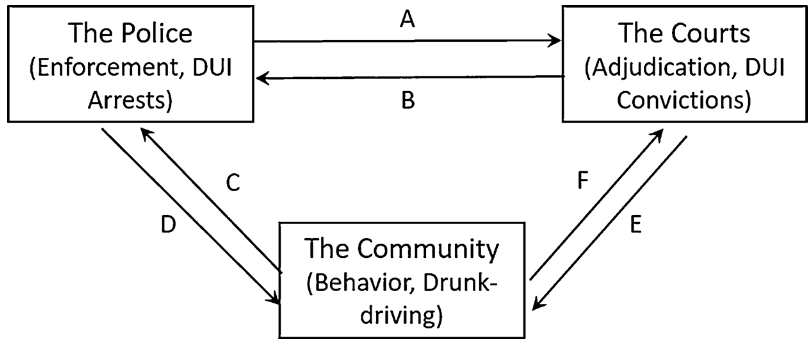

Fig. 1. Three-Domain Enforcement-Adjudication Feedback System.
Source: Van Vleck & Vera (2017).

Berman et al., 2000; Hilton, 1988, and Greenfield and Room, 1997). How the prevailing, local accident environment affects residents' drinking-and-driving behaviors has only recently been tested (MacLeod et al., 2015). What does it take to induce (long-term) change in community norms? Increasingly, effective DUI initiatives can be frustrated and impede harms-reduction: efficacious sobriety checkpoints (Nelson et al., 2013; contra Dula et al., 2006) are avoided using mobile phones and apps (Branan, 2009; Stross, 2011); ignition interlock devices' adoption is limited by fiscal conditions or these may be subverted after they are installed (DeYoung, 2002). Social norms are both obstacles and opportunities. The disparate and evolving role of these social attitudes on DUI deterrence and other prevention activities is an important study area (see Savic et al., 2016). An empirically-based diagnostic could be useful.

This paper uses a much simplified system of three macro-level domains—the community, the police, and the courts—to model a localized *drunk-driving environment* and propose a diagnostic methodology.[3] The system is illustrated in Fig. 1; the domain boxes are labelled and the six possible behavioral channels are given by the lettered directional arrows1 A to F. The police and the courts work to induce community compliance with the law (arrows D and E, respectively). Increased enforcement and consequences are expected to decrease drunk-driving (the effect signs of D and E should be negative). Events in the community shape the police and courts' activities (arrows C and F). If drunk-driving becomes more prevalent, public agents are predicted to increase enforcement and sanctions (C and F should have positive effect signs). And the actions of the police and courts each impact the other (arrows A and B). Increased consequences should follow from increased enforcement (positive effect sign for A); and increased consequences should lead to reduced future enforcement needs (negative effect sign for B). In sum, the community should respond to effective policing and penalties; and the police and the courts should respond to the public safety conditions in the community. People, and systems, are expected to learn and change in the face of education, heightened surveillance, and penalties. Dissuading harmful behaviors is fundamentally a dynamic systems process.

Real systems may not achieve these. Police and courts may have minimal effect on the community (directional arrows D and E may be weak or absent—or may have the wrong effect sign). Communities may resist a law that the police (or other agents) and the courts are mandated to enforce. The enforcers themselves may be reluctant: when California enacted the "workplace smoking ban", local officials reported wishing an outsider were responsible rather than have to confront "neighbors and friends" (see Montini and Bero, 2008). The police and the courts may not be optimally coordinated because of differential capacities and/or priorities. A perfectly functioning system would not exhibit these inconsistencies. A functional and effective deterrent system, in static terms, does the following: 1) detects violations of the law and apprehends the violators; 2) (appropriately) punishes offenders; 3) deters offenders from recidivating; and 4) deters other community members from committing the violation themselves.

The real-time sequence of a drunk-driving event is: drinking, driving, then possible accident and/or arrest, followed by prosecution and sanctions. JD Sterman (2001) called this perspective "event-oriented." A macroscopic systems perspective, however, makes the processes endogenous: current enforcement and/or sanctions cause changes in the community. Future needs for police or court activity are thereby impacted by the prior system processes. In this way, the sequential "cause →effect" event expands dynamically to "$\text{cause}_1 \rightarrow \text{effect}_1 = \text{cause}_2 \rightarrow \text{effect}_2 = \text{cause}_3 \rightarrow \ldots$" with many subsequent branches and loops possible.

A minimum of three variables are needed to evaluate the behavior within this DUI system: 1) drunk-driving (the the community does/n't drink-and-drive), 2) DUI arrests (the police do/n't enforce), and 3) DUI convictions (the courts do/n't render consequences).[3] An appropriately deterrent dynamic system is both responsive and deterrent (preventative). Responsiveness occurs when: 1) serious DUI events (accidents) are followed by DUI arrests; and 2) serious DUI events are followed by DUI convictions. Deterrence happens when: 1) DUI arrests are followed by DUI convictions; 2) DUI arrests dissuade drunk-driving, and/or 3) DUI convictions dissuade drunk-driving, in both instances so that fewer future serious accidents occur. (These obtain the expected effect signs for each lettered arrow in Fig. 1.) If drunk-driving increases, responsive deterrence theory expects that the police would increase enforcement activities, and the courts would impose (increasing) consequences. The institutional domains are appropriately responsive. The behavioral assumption of community "learning" expects drunk-driving is deterred by increased enforcement and (negative) consequences; then the prevalence of future drunk-driving should decrease (arrow B should have a negative effect sign). When the prevalence decreases, less (drunk-driving) enforcement and adjudication activities are required (and other public safety needs will be addressed instead). Alternatively, if drunk-driving remains tolerated locally, non-decreasing enforcement and prosecution activities will be necessary.

3. Implementation: framework to diagnostic

Several steps are required to construct the diagnostic from the skeletal framework above: channels must be identified, signed, and scored; channel interactions are evaluated for (in)consistency with effective deterrence; and an aggregating rubric devised. The rationale for "channel interactions" is described in general terms first using a "2 × 2 game matrix" to organize information.

Game theory is a powerful tool widely used in social sciences to model the interdependence of system outcomes upon the (independent) actions of domains (or "players").[4] Logic obtains that how the police and the courts seem to interact will signal to the community an apparent ethos toward drunk-driving. The behavioral interaction—the "game"— is illustrated in Fig. 2, using the notation *Police* ⊗ *Courts*.[5] The police are the row player; the courts are the column player. Each

		Courts: Strict	Courts: Lenient
Police	Strict	Positive reinforcement; consequences for offense. Deterrent to (re)offenses.	Police arrest but Courts do not "follow through" with convictions. Inconsistency.
	Lenient	Courts (would) convict but Police do not arrest. Inconsistency.	Negative reinforcement; offenses unpunished. No deterrent to (re)offenses.

Fig. 2. A 2 × 2 Matrix interacting Police and Courts stances.

domain will exhibit either a *Strict* (restrictive) or *Lenient* (permissive) stance toward the offense.[6] The presumptive aim of both domains is to deter drunk-driving with mutually reinforcing signals; the upper-left hand outcome, (*Strict, Strict*), obtains the expected result. The lower-right outcome, (*Lenient, Lenient*), denotes a mutually reinforcing pattern—but not producing an ethos consistent with effective deterrence. *De facto* permissiveness is possible. As described in Section 2, the actions of system domains can also be misaligned. Outcomes from conflicting stances, (*Lenient, Strict*) or (*Strict, Lenient*), may exert some deterrence but are unlikely to be as impactful as either mutually reinforcing scenario. The interaction of police and courts' actions sets one element of the *apparent* environment.

An interaction is formed between each possible pair of channels by "diassembling" Fig. 1. The triangular system with three domains, six channels, yields fifteen behavioral interactions to be examined (A⊗B, A⊗C, A⊗D, A⊗E, A⊗F, B⊗C, … E⊗F).[7] Channel "stances" are inferred using the signs from time-series analyses; then the channels are interacted following the generic matrix above. The result obtains the (apparent) influence, or ethos, exerted on the system by each element. Indicator-values will be assigned to each category of outcome (+1, restrictive; 0, conflicted; and -1 permissive) to aid evaluation.

An overall *Restrictive-Permissive (RP)* score for the system is the sum of N ($\leq$15) empirically-identified interactions observed. The system *Restrictive-Permissive, RP,* score can take-on values between -N to + N. Perfect (restrictive) consistency obtains $+1 \cdot N = N = RP$ (positively signed, all +1 indicator-values); whereas, a consistently permissive pattern of all (*Lenient, Lenient*) outcomes obtains -1 indicator-values, equaling $-1 \cdot N = -N = RP$ (negatively signed). In-between scores occur when the system displays *conflicted* patterns (0 s) or because of offsetting restrictive (+1) and permissive (-1) elements. The ordered pair (N, *RP*) encapsulates the examined system. A plot of the point into an (x,y)-space, bounded by a wedge with slopes ± 1, offers a simple, accessible visual aid: points above the horizontal axis indicate apparent degrees of restrictiveness (and permissiveness falls below the axis). Behavioral interactions can be absent, weak, or conflicting, so that points to the right obtain (somewhat) greater confidence than points at the left. Because DUI laws in the United States are established by each state, state systems are made up of component county systems, and counties are tasked with DUI prosecutions, the *Restrictive-Permissive* framework is expanded for panel application. A system comprised of multiple jurisdictions ($i = 1,\ldots,M$) obtains ordered pairs (N_i, RP_i) for all evaluable units. The resulting diagnostic visual renders a scatter-plot of each unit comparatively within the whole.

Time-series panel empirics are used to identify the relevant lettered channels within each observational unit (such as counties or states). The needed time-series analyses were already executed by Van Vleck et al. (2017), using a relatively new test for "heterogeneous panel Granger-non-causality" (Dumitrescu and Hurlin, 2012). Granger-causality is an analytical technique to detect statistical linkages (signals) between variables (Granger, 1969, 2003). Simple Granger-causality tests for the power of one data series $VARIABLE_1$ to predict another data series $VARIABLE_2$, with current and delayed effects and "own" inertia. It statistically identifies whether variables share an underlying data-generating process, but offers no structural estimates of the precise mechanisms. Advanced Granger-causality allows for multivariate and panel analyses. The Dumitrescu-Hurlin test has been applied most often to sectoral contributions to economic growth in macroeconomic research. The Van Vleck and Vera paper is the first known application of this advanced tool to injury prevention. The earlier paper severely limited its focus to cases consistent with deterrence. California counties were classified as "police-led", "courts-led", "responsive" or "reactive"; anomalies were noted but not examined further. Therefore, this paper extends the prior analytics and addresses the potential for systems to be ineffective. The framework is refined to detect both restrictiveness and permissiveness.

A unique time-series panel was assembled for that paper from the Annual Report of the California DUI Management Information System (1992-2012) and the Annual Report of the Fatal and Injury Traffic Collisions (1990-2012) for California's 58 counties, covering twenty years. The California DUI-MIS was established by 1989 legislation to tabulate "DUI arrests, convictions, court sanctions, administrative actions and alcohol-involved crashes" and recidivism at the county-level, based on arrest-matched administrative data from multiple reporting systems (CA DUI-MIS). It is a frequent source for snapshot demographics for DUI in California, but has seldom been used for time-series analyses (see, for example, Tashima and Masten, 2011). Two data series were drawn from the CA DUI-MIS: the number of DUI arrests (ARRESTS) and ensuing the DUI conviction rate (CONVICTIONS) by county and year. The California Highway Patrol's "Statewide Integrated Traffic Records System (SWITRS)" compiles a database of crash records from the many law enforcement agencies across the state; each crash record details the particulars of the event: date, location, roadway, violation type, collision severity, fatalities and injuries, alcohol-involvement, etc. Summary aggregates of trends, timing, involved persons & vehicles, and alcohol-involvement for counties and larger cities are given in the annual reports. The number of fatality and injury crashes involving alcohol (ARC, "alcohol-related crashes"; here termed serious crashes) by county and year were taken from those. The earlier paper describes the time-series panel and the econometric methodology used in detail.

4. Framework demonstration

In total, almost 90% of California's population, three of every four California counties, is in this catchment. The lettered columns in Table 1 correspond to the respective lettered channels in Fig. 1; the counties listed were identified with the Dumitrescu-Hurlin Wald-tests for similar underlying Granger-causalities. The upper and lower panels sort the identified counties according to apparent effect signs (upper panels, positive; lower panels, negative). Column A lists twenty counties: El Dorado, Fresno, Glenn, Imperial, Kings, Lake, Madera, Marin, Monterey, Nevada, Plumas, Riverside, Sacramento, San Mateo, Santa Barbara, Santa Clara, Shasta, Sutter, Trinity, and Ventura. Five of these—El Dorado, Imperial, Lake, Plumas, and Santa Barbara—display consistency with deterrence expectations. In these counties, the courts' DUI convictions activity is positively Granger-caused by prior police DUI arrest activity. The other fifteen counties listed in column A exhibit patterns of DUI arrests negatively Granger-causing (subsequent) DUI convictions. The remaining columns of Table 1 are similarly divided (and shaded) according to dynamics discussed in Sections 2 & 3.

The pairwise interactions generalized in Fig. 2 (*Police⊗Courts*) are detailed in Fig. 3 (A⊗B). The intersection of twenty counties in column

Table 1
Summary of statistically-significant Granger-causalities by Effect Sign.
Source: Van Vleck & Vera (2017).

	A lnDUI→lnCONV	B lnCONV→lnDUI	C lnARC→lnDUI	D lnDUI→lnARC	E lnCONV→lnARC	F lnARC→lnCONV
ρ > 0 (positively Granger-cause)	El Dorado† Imperial Lake† Plumas Santa Barbara†	Amador Fresno Madera Mendocino San Diego† Siskiyou†	Fresno Imperial Inyo Los Angeles Mono† Napa† Orange Riverside Sacramento San Bernardino† San Francisco San Joaquin† San Mateo Ventura	Colusa Del Norte† Kern Lassen Los Angeles Modoc San Benito† San Bernardino Santa Clara Santa Cruz Sierra† Solano Tulare Yuba	Colusa Del Norte Inyo Kern Madera Mariposa Merced Riverside Sacramento† San Bernardino San Luis Obispo Yolo	El Dorado Imperial Lake Mariposa Tehama† Trinity† Yuba
ρ < 0 (negatively Granger-cause)	Fresno Glenn† Kings Madera Marin Monterey Nevada Riverside Sacramento San Mateo Santa Clara Shasta Sutter Trinity† Ventura	Glenn Kings Lake† Lassen Los Angeles Modoc San Joaquin† Sonoma† Sutter† Ventura†	Alameda† Amador Butte† Plumas Tuolumne	Humboldt† Kings† Plumas	Alameda† Alpine Amador† Butte Fresno Humboldt Modoc Mono Napa Orange Placer† Plumas San Benito San Diego† San Mateo Shasta† Solano	Butte Contra Costa Kings Los Angeles Madera† Marin Mendocino† Mono Monterey Orange Plumas San Bernardino San Diego San Joaquin Santa Barbara Santa Clara Santa Cruz Shasta Tulare Yolo

Note: Shaded blocks identify (pairwise) channels consistent with deterrence as outlined in the text. † indicates county "weakly" fits this category.

A ⊗ B		lnCONV → lnDUI Lenient ρ>0	lnCONV → lnDUI Strict ρ<0
lnDUI → lnCONV	Strict ρ>0		Lake†
lnDUI → lnCONV	Lenient ρ<0	Fresno Madera	Glenn† Kings Sutter† Ventura†

Fig. 3. Example Granger-causalities Interaction, Police and Courts.

A and sixteen in column B obtains seven counties in common (A ∩ B): Fresno, Glenn, Kings, Lake, Madera, Sutter, and Ventura. Arranged in the matrix by apparent strictness or permissiveness obtains: 1) Lake county displays (*Strict, Strict*); 2) Glenn, Kings, Sutter, and Ventura show (*Lenient, Strict*)); and 3) Fresno and Madera reveal permissive (*Lenient, Lenient*) patterns. The indicator-values assigned are: Fresno -1, Glenn 0, Kings 0, Lake +1, Madera -1, Sutter 0, and Ventura 0. These values are recorded in the first column in Table 2, labeled A⊗B, for aggregation. These steps are repeated for the fourteen remaining pair-wise interactions.[6] Counties' *Restrictive-Permissive* scores, RP_i, are the row-wise sums in Table 2. As an example, Alameda county was identified for behavioral channels C and E thereby interaction C⊗E. Alameda exhibits deterrence inconsistency with respect to channel C and consistency with respect to channel E; the interaction obtains a conflicted result and 0 indicator-value assigned. The *Restrictive-Permissive* ordered pair representing Alameda is (1, 0). The ordered pairs for a total of 44 counties were generated by this process. California counties' *Restrictive-Permissive* coordinates are plotted in Fig. 4. County-points can overlap, therefore each cluster is sized by total population share. Table 3 groups the counties by apparent *Restrictive-Permissive* type. (The 2010 population statistics and state population shares are also reported.)

Fig. 4 renders a picture of California's apparent *de facto* DUI environment: few California counties appear to be reliably "tough" on drunk-driving at a system-level. Twelve counties are plotted above the x-axis, generally restrictive. Five counties—El Dorado, Humboldt, Imperial, Lake, and Napa—appeared to display consistent restrictiveness, aligned on the positively sloped wedge boundary. The other seven—Modoc, Mono, Orange, Plumas, San Joaquin, San Mateo, and Ventura—are generally restrictive, plotted above the horizontal axis. A

Table 2
Restrictive/Permissive Scoring Summary.

Counties:	Identified Channels																Count Row Entries	2010 Pop	%
	A $\otimes$ B	A $\otimes$ C	A $\otimes$ D	A $\otimes$ E	A $\otimes$ F	B $\otimes$ C	B $\otimes$ D	B $\otimes$ E	B $\otimes$ F	C $\otimes$ D	C $\otimes$ E	C $\otimes$ F	D $\otimes$ E	D $\otimes$ F	E $\otimes$ F	Score			
Alameda											0					0	1	1,513,229	4.06%
Alpine																0	0	1,163	0.00%
Amador						−1		0			0					−1	3	37,863	0.10%
Butte											0	−1			0	−1	3	219,971	0.59%
Colusa													−1			−1	1	21,483	0.06%
Contra Costa																0	0	1,052,199	2.82%
Del Norte													−1			−1	1	28,543	0.08%
El Dorado					1											1	1	180,925	0.48%
Fresno	−1	0		0		0		0			1					0	6	932,343	2.50%
Glenn	0															0	1	28,144	0.08%
Humboldt													1			1	1	134,656	0.36%
Imperial		1			1							1				3	3	175,424	0.47%
Inyo											0					0	1	18,530	0.05%
Kern													−1			−1	1	841,158	2.25%
Kings	0		0		−1		1		0					0		0	6	152,693	0.41%
Lake	1				1				1							3	3	64,602	0.17%
Lassen							0									0	1	35,145	0.09%
Los Angeles						1	0		0	0		0		−1		0	6	9,825,247	26.33%
Madera				−1	−1			−1	−1						−1	−5	5	151318	0.41%
Marin					−1											−1	1	252,698	0.68%
Mariposa															0	0	1	18,194	0.05%
Mendocino									−1							−1	1	87,917	0.24%
Merced																0	0	255,886	0.69%
Modoc							0	1					0			1	3	9,649	0.03%
Mono											1	0			0	1	3	14,234	0.04%
Monterey					−1											−1	1	416,263	1.12%
Napa											1					1	1	136,811	0.37%
Nevada																0	0	98,625	0.26%
Orange											1	0			0	1	3	3,017,248	8.09%
Placer																0	0	350,272	0.94%
Plumas		0	1	1	0					0	0	−1	1	0	0	2	10	19,904	0.05%
Riverside		0		−1							0					−1	3	2,191,919	5.87%
Sacramento		0		−1							0					−1	3	1,420,255	3.81%
San Benito													0			0	1	55,332	0.15%
SanBernardino										0	0	0	−1	−1	−1	−3	6	2,038,518	5.46%
San Diego									−1						0	−1	2	3,102,904	8.32%
SanFrancisco																0	0	806,314	2.16%
San Joaquin						1			0			0				1	3	686,576	1.84%
SanLuisObispo																0	0	269,677	0.72%
San Mateo		0		0							1					1	3	719,667	1.93%
SantaBarbara					0											0	3	424,020	1.14%
Santa Clara			−1		−1									−1		−3	3	1,786,533	4.79%
Santa Cruz														−1		−1	1	263,182	0.71%
Shasta				0	−1										0	−1	3	177,457	0.48%
Sierra																0	0	3,229	0.01%
Siskiyou																0	0	44,896	0.12%
Solano													0			0	1	413,114	1.11%
Sonoma																0	0	484,030	1.30%
Sutter	0															0	1	94,645	0.25%
Tehama																0	0	63,476	0.17%
Trinity					0											0	1	13,705	0.04%
Tulare														−1		−1	1	443,086	1.19%
Tuolumne																0	0	55,146	0.15%
Ventura	0	0				1										1	3	825,061	2.21%
Yolo															−1	−1	1	201,328	0.54%
Yuba														0		0	1	72,336	0.19%

Notes: Column letters correspond to the directional arrows in Fig. 1 and column labels from Table 1; $\otimes$ indicates the interaction of Granger-causalities. Scoring: 1 = "consistent with restrictive/ deterrent interaction"; 0 = neither restrictive nor permissive, conflicted interaction; and -1 = "consistent with permissive/ non-deterrent interaction." Calaveras and Stanislaus counties not included because no significant Granger-causalities were identified.

zero *Restrictive-Permissive* overall score is either the result of offsetting instances of restrictiveness and permissiveness and/or of repeated instances of conflicted outcomes. Excluding the origin, fourteen counties fall along the horizontal axis, an overall neutral result. Exactly offsetting instances were obtained for Fresno, Kings, and Los Angeles. The eleven other counties aligned on the x-axis—Alameda, Glenn, Inyo, Lassen, Mariposa, San Benito, Santa Barbara, Solano, Sutter, Trinity, and Yuba—obtained repeated patterns of conflicted outcomes. The remaining identifiable cases display apparent permissiveness (below the x-axis). These eighteen counties appear to consistently contradict the patterns for effective DUI deterrence: Amador, Butte, Colusa, Del Norte, Kern, Madera, Marin, Mendocino, Monterey, Riverside, Sacramento, San Bernardino, Santa Clara, San Diego, Santa Cruz, Shasta, Tulare, and Yolo.

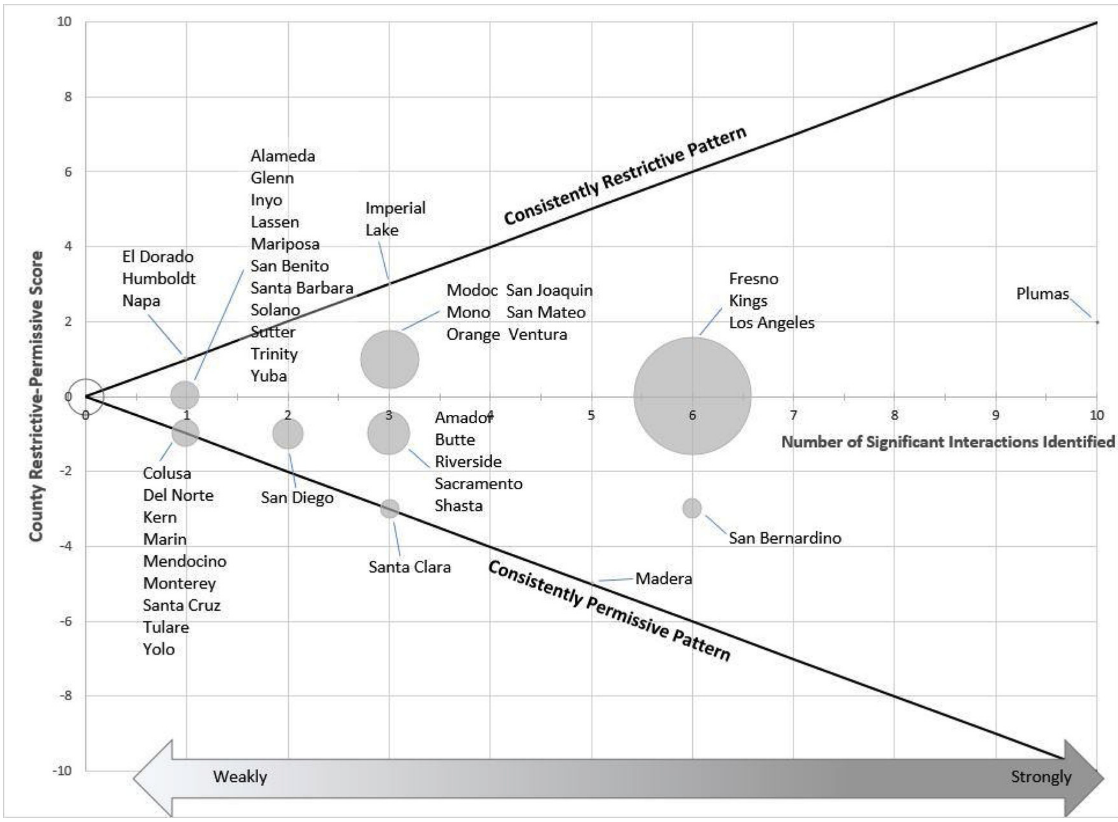

Fig. 4. "Restrictive-Permissive" Score plot, California counties.

Table 3
"Restrictive-Permissive" Summary.

Restrictive (12 counties; 16.1% state pop.)				Ambiguous/ Conflicted	(14 counties, 38.4%)	Permissive (18 counties; 36.6%)			
Consistently (5, 1.9%)		Generally (7, 14.2%)				Generally (7, 24.6%)		Consistently (11, 12.0%)	
El Dorado	0.48%	Modoc	0.03%	Alameda	4.06%	Amador	0.10%	Colusa	0.06%
Humboldt	0.36%	Mono	0.04%	Fresno	2.50%	Butte	0.59%	Del Norte	0.08%
Imperial	0.47%	Orange	8.09%	Glenn	0.08%	Riverside	5.87%	Kern	2.25%
Lake	0.17%	Plumas	0.05%	Inyo	0.05%	Sacramento	3.81%	Madera	0.41%
Napa	0.37%	San Joaquin	1.84%	Kings	0.41%	San Bernardino	5.46%	Marin	0.68%
		San Mateo	1.93%	Lassen	0.09%	San Diego	8.32%	Mendocino	0.24%
		Ventura	2.21%	Los Angeles	26.33%	Shasta	0.48%	Monterey	1.12%
				Mariposa	0.05%			Santa Clara	4.79%
				San Benito	0.15%			Santa Cruz	0.71%
				Santa Barbara	1.14%			Tulare	1.19%
				Solano	1.11%			Yolo	0.54%
				Sutter	0.25%				
				Trinity	0.04%				
				Yuba	0.19%				

Note: Omits counties without Granger-causality interactions (14 counties; 8.9% state population); see Table 2.

5. Conclusion

This has been a probative exercise; it is "tool for hypothesizing" (Goh et al., 2012). Key advantages to this kind of tool are: the data (may) already exist; and the analytical tools are available, with established properties and practices. What had been missing was to apply these in new ways to known research needs. The minimal, empirically-base structure proposed herein to detect (the appearance of) DUI *Restrictiveness-Permissiveness* is one possible application. A catalog of legal compliance issues at the macro-systems level(s) could include: child support, domestic violence, use-of-force by police, environmental regulation, water conservation policies, or tax evasion, among others. All of these are the results of complex interactions between agents, communities, and enforcement entities; addressing these relies on adapting and shaping evolving social norms. The next generation of interventions cannot be uninformed of real-world context and hope to have meaningful effects.

Several limitations are already known (or anticipated) about this exercise. First, California's DUI-MIS data may be uniquely suited to this application because of the particular way the data is compiled: adjudication and corrections records are cataloged according to the "arrest-year", not calendar year (see Van Vleck et al., 2017). Second, the framework as demonstrated is non-spatial. Each unit (county) in the Dumitrescu-Hurlin test exists in isolation. The DUI-externalities caused by California's infamous inter-county commute-traffic is not captured. Third, the end result obtains a static picture of a dynamic process; it does not address the evolution of the *Restrictive-Permissive* stances (as yet). The geographic and temporal adoption diffusion and/or erosion of

DUI enforcement is itself worthy of investigation. Fourth, the diagnostic is not directive; it cannot indicate why the underlying patterns were obtained nor if they are real or statistical. Inferential errors cannot be ruled out; the confidence measures for this, or similar, diagnostic approaches will have to be developed.

The preliminary snapshot of California obtains a disappointing assessment: more county jurisdictions, home to a majority of the state population, exhibited patterns indicative of ambivalence or resistance to DUI deterrence rather than compliance. Fewer than one-in-six Californians resided in a county broadly restrictive toward driving-and-drinking. Only two-percent lived where a consistently restrictive DUI ethos appeared. More than one-third (36%) of Californians are in apparently *de facto* permissive settings and more than one-in-ten (12%) are in apparently consistently permissive ones. Countervailing forces were detected in Fresno, Kings, and Los Angeles, encompassing almost thirty-percent of the state population. Consider that Fresno (city) has been acclaimed (NHTSA 2010, 2018) for policing strategies to reduce DUI and related harms (Davis et al., 2006; Fell, 2013). But, based on the indicators examined herein, Fresno (county) exhibits contravening patterns thereafter. Comparable circumstances undoubtedly occur in many locales. One element in isolation, even if effective, yields an incomplete picture of the larger scene.

Notes

[1] A few other "system dynamics" (SD) articles in this, and related, journals are: Goh et al. (2012); Lich et al. (2013); Mehmood (2010); Newnam and Goode (2015); Salmon et al. (2012), 2016, and Underwood and Waterson (2013). From the management field, JD Sterman acknowledged the expansive scope of SD saying "[it draws] on fields as diverse as anthropology, biology, engineering, linguistics, psychology, physics, and Taoism, and seeks applications in fields still more diverse" (2001, p. 24). The seminal roots of SD go back farther (see Mehmood, 2010).

[2] "Macroscopic" is a concise phrasing for "a higher level of system" (Salmon et al., 2016) or an "up and out" perspective (attributed to Dekker in Underwood and Waterson, 2013).

[3] There are many other known factors—domains and actions—involved in complete drunk-driving systems (e.g. alcohol outlets, tourism, etc.) One commenter on a much earlier iteration of this paper was offended by the implied priority for DUI convictions; s/he believed the difficult work of prosecutors was diminished or disrespected by omitting plea bargains or other alternative sentencing from the model. Disrespect was not intended. The scope of the system here is limited for demonstration purposes.

[4] Use of game theory was motivated, in part, by McAdams' discussion of paradigm dilemmas in Law (2009).

[5] The Kronecker product symbol (⊗) is a convenient symbol; the appropriation is not literal: *Police⊗ Courts* and *Courts⊗ Police* are equivalent here, which is not true mathematically. The other domain interactions to complete this general example are: 1) the police with the community, *Police⊗ Community*, and 2) the courts with the community, *Courts⊗ Community*. These two cases are illustrated by Figure A1 in the supplemental materials.

[6] The *Strict* stances (row or column) are each lightly shaded to aid the reader; *Lenient* actions are unshaded. Overlapping lightly shaded cells obtain a darker shaded cell and denote a (*Strict, Strict*) outcome, which are consistent with effective deterrence. Outcomes of (Lenient, Lenient) interactions retain unshaded format.

[7] The number of domains and number of actions (per domain) determine the number of system interactions to be evaluated. Conceptually, the framework can be expanded to include multiple activities per domain, more domains, and *intra*-domain coordination or conflict, but the complexity increases markedly. When it becomes possible to determine the relative strengths and magnitudes of the channels, a more continuous gradient could be derived.

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