The "impossible precision" of regulation:
How policies dynamically interact with people heterogeneity and learning.

Giorgio Rampa* & Margherita Saraceno♣

[PRELIMINARY DRAFT TO BE COMPLETED – PLEASE, DO NOT CITE OR CIRCULATE]

Abstract

The present dynamic Bayesian-learning model frames the problem of a policymaker that, given a socially optimal goal to pursue, hardly achieves its goal with precision because regulation effects results from a complex interaction between regulation and individual beliefs, compliance costs, and subsequent individual choices. Showing how heterogeneous agents decide –time by time– whether to comply with given rules based on their conjectures, the available information, and their private costs, we study the possible conjectural equilibria and prove that the policymaker can pursuit optimality by acting on various structural parameters of the model (corresponding to various kind of regulatory interventions) to align the conjectural equilibrium level of welfare losses to the optimal one. However, the policymaker must be aware that any kind of regulatory intervention implies dynamical effects that depend on both people's conjectures and learning staying behind individual choices. Finally the precise achievement of any policy goal cannot be taken for granted, while requiring time and perseverance.

JEL classifications: D83, K23, K32.

Keywords: Compliance, Conjectural Equilibria, Dynamical features, Learning, Regulation effectiveness.

* Dept. Economics and Management Sciences University of Pavia – Italy.

♣Dep. of Law, University of Pavia, Corso Strada Nuova 65, 27100 Pavia, Italy. Email: margherita.saraceno@unipv.it Corresponding author.
All errors are our own. Declarations of interest: none

1. Introduction

In order to contrast various negative externalities resulting in social welfare losses, the policymaker typically sets up specific rules aimed at reducing their impact. Those rules typically require a *sufficient* compliance by part of individuals to achieve social optimality. However, regulatory compliance is often insufficient and this calls for further initiatives aimed at supporting compliance (Posner 1997, Stiglitz 2009, Tummers 2019). Regulatory approaches are various and, even when rules are well designed, the policymaker fails to perfectly achieve the wished policy goals (Greenstone 2009, Howlett 2019, cp.4; McConnell 2015). The different regulatory outcomes can be partially explained by the fact policies interact with individual beliefs and consequent behaviours (Viscusi 2007, Barr et al. 2009, Yan et al. 2020, Gofen et al 2021). This last point is also empirically and experimentally established by the boundless political economy literature (Aghion et al. 2010, Alesina &Giuliano 2015, Ostrom 2005, North 1991).

There are lot of examples in this regard. The average welfare losses due to behaviour-related diseases (i.e. smoking-related diseases) can be reduced thanks to individual compliance with healthy practices. Given the insufficient compliance rate with healthy practices, some policies can be adopted including prohibitions and restrictions (mandatory compliance), nudging and subsidies supporting healthy habits and early diagnosis, informational campaigns, new treatments, etc. The same plocies may lead to different results depending on the targeted populations (Becker & Maiman 1975, Cleemput & Kesteloot 2002).

A further example for which spontaneous compliance rates are usually too low and therefore require regulatory interventions is that one of natural hazards. Welfare losses due to floods, earthquakes, hurricanes and so on might be reduced significantly both by applying proper building techniques and subscribing convenient insurance schemes. However, individuals are often under-insured and do not sufficiently comply with building rules. For these reasons, in many countries, public authorities aimed at reducing average welfare losses due to natural hazards opt for subsidizing or nudging the implementation of appropriate building techniques and provide capped-prize insurances or prescribe mandatory insurance (May 2005, Gizzi et al 2021, Gunningham et al. 1998, Wu & Babcock 1999).

Pollution-related welfare losses might be optimally reduced by a sufficiently high compliance rate with environmental regulation. However, individual compliance is often insufficient. Various interventions can help. Scientific and technological advancements can reduce welfare losses independently of compliance; nudging, subsidies, and sanctions can improve compliance with environmental practices finally reducing the related average welfare losses (Byerly et al. 2018, Coglianese & Nash 2001, Czaikowski et al. 2017, Kountoris 2022). Similar examples include problems of energy shortage and insufficient compliance with curtailment behaviors (Del Rio 2010, Pam & Garmston 2012, Sütterlin et al. 2011).

Further examples are related to the average welfare losses due road accidents that can be effectively reduced by a sufficient adherence with driving rules and prudential behavior. Nonetheless, the compliance with such rules and good behaviors is various and often insufficient to achieve the optimal level of welfare loss reduction. Not surprisingly various policies are implemented: sanctions in the case of non-compliance, but also nudging through apps for safe driving, subsidies for free rides for drunk drivers and information campaigns to make drivers aware of the risks related to non-compliance with good practices and rules (Allen et al. 2017, Bradford el al. 2015, Nagler 2013, Sarkar et al. 2005).

Even average welfare losses due to tax evasion might fit the model. They can be reduced thanks to a sufficient tax compliance (in non-technical sense). Nevertheless, compliance rates are very different across countries and often too low with respect to social optimality. Sanctions in the case of non-compliance, nudging like pre-filled tax declarations, subsidies like tax discount in the case of early payments, etc. are some examples of policies aimed at reducing the average losses due to tax evasion (Coleman & Freeman 1997, Feld & Frey. 2007, Alm 2019).

Many other examples could be provided for problems whose average impact (average welfare loss) negatively depends on the compliance rate of population with rule/good practices, but the latter remains insufficient with respect to the achievement of the optimal welfare loss reduction. In these cases various regulatory approaches might be helpful. Nonetheless results of policies are various.

Starting from previous dynamic models (Rampa and Saraceno 2023, Rampa and Saraceno 2016, Bhattacharyya & Bauch 2010, Coelho & Codeço 2009), we develop a general model framing the problem of a policymaker that, given a socially optimal level of welfare losses to pursuit through regulation (Hethcote & Waltman 1973; Fine & Clarkson 1986, Szucs 2000, Donadel et al. 2021), hardly achieves the regulatory goal *with precision* because regulation effects results from a complex interaction between regulation and individual beliefs, compliance costs, and subsequent individual choices.

Specifically, we provide a dynamic Bayesian-learning setup with heterogeneous agents that shows how –time by time– people decide to comply with given *rules* aimed at reducing welfare losses based on their conjectures, the available information, and their private costs. Due to lack of precise information about the true relation existing between welfare losses and compliance, people decide based on the available information and their subjective beliefs. Time by time, people update their beliefs based on two common pieces of information communicated by the policymaker: the current compliance rate and the current average welfare loss. Then, we study the possible conjectural equilibria, i.e., those situations when individual decisions stop adjusting time by time because the learning process comes to an end.

Results show that that although the policymaker has various regulatory arrows in its quiver, it will hardly hit the target precisely. Leaving metaphors asides, the policymaker can pursuit optimality by acting on various structural parameters of the model (corresponding to various kind of regulatory interventions) to align the conjectural equilibrium level of welfare losses to the optimal one. However, the policymaker must be aware that any kind of regulatory intervention implies a dynamics that depends both on people conjectures and on the learning system staying behind individual choices. Finally the *precise* achievement of any policy goal cannot be taken for granted, while requiring time and a persistent approach.

2. The Model

2.1. Setup

At the beginning of date 0 (time is discrete), a social problem bursts forth. Define μ_t as the average welfare loss due to that problem, as can be observed at date *t*.

Define $B(\mu) = (1-\mu)^b, 0 < b < 1$ and $C(\mu) = (1-\mu)^c, c > 1$ as the social benefit and social costs, respectively, that are associated with the reduction of μ (here the time subscript is omitted because not relevant), where parameters b and c capture marginal benefits and costs, respectively, of μ reductions.

μ_t, can be considered as the main policy target-variable. Clearly, a trade-off exists between social benefits of reducing μ_t —milder consequences for individuals and a lower impact on institutions (health care and social security systems, fiscal system, the environment, etc.) — and social costs to achieve this reduction goal (public expenditure, social security costs to support affected people, costs of enforcement and detection, etc.).

We also assume that average welfare losses μ_t can be reduced thanks to the adherence with specific rules by part of population. Specifically, there exists a *true* random relation between μ_t and the compliance rate π_t such that $\mu_t \sim N(\alpha - \beta\pi_t; 1)$, $\alpha, \beta \in (0,1]$. Randomness and normality assumption seems to be quite reasonable; the linearity of the mean and the unitary variance are chosen for simplicity.

The parameters α and β are unknown to individuals. When the problem emerges at the beginning of $t = 0$, the policymaker clarifys that some compliance with specific rules can help to reduce welfare losses. At the end of each date *t*, the policymaker also observes μ_t and π_t and communicates them to the population.

Therefore, at each date $t \geq 0$ people must decide whether to comply with rules possible able to reduce welfare losses associated to the problem. Since compliance has temporary effects, at the beginning of each date each individual must decide once again. Individuals decide to comply by comparing the expected consequences (average welfare loss) resulting from the problem and their own compliance costs.

The overall population is composed of two components: subpopulation *A* and subpopulation *B*. The weight of sub-population *A* is $\gamma \geq 0.5$ and the weight of sub-population *B* is $1 - \gamma$. The individual compliance cost is a random variable distributed among each population according to a Uniform Distribution of support $[0, \theta_i]$, $i = A, B$ and $0 < \theta_A < \theta_B$.

At $t = 0$, when the problem emerges, given that the true relationship between μ_t and π_t is unknown, people get an idea on that relation. In particular, they correctly assume that the average welfare loss is a random variable with a given mean μ_t^e and unitary variance. However, given that the *structural* parameters (α, β) are unknown, individuals formulate subjective priors on the parameter that determine μ_t^e . In particular, the prior on (α, β) for subpopulation *i* is a normal bivariate, and the mean and precision parameters of this subjective distribution at date 0 are vector $\mathbf{z}_{i,0} = \begin{bmatrix} \alpha_{i,0} \\ \beta_{i,0} \end{bmatrix}$ and symmetric "precision"[1] matrix $\mathbf{H}_{i,0} = \begin{bmatrix} \eta_{i,\alpha,0} & \eta_{i,\alpha\beta,0} \\ \eta_{i,\alpha\beta,0} & \eta_{i,\beta,0} \end{bmatrix}$, $i = A, B$. $\alpha_{i,0}$ and $\beta_{i,0}$ are the initial parameters conjectured by subpopulation *i* on α and β, respectively; $\eta_{i,\alpha,0}$, and $\eta_{i,\beta,0}$ are positive, whereas we assume $\eta_{i,\alpha\beta,0} = 0$ because people have no reason to hypothesize any specific initial value for co-variances. Since at the beginning of date *t,* individuals do not know the actual π_t when formulating their expectation μ_t^e, they provisionally assume that the compliance rate remains constant from *t*-1 to *t*. Therefore, at t=0 subpopulation *i* expects $\mu_{i,0}^e = \alpha_{i,0} - \beta_{i,0}\pi_0$.

In general, define *hyperparameters* $\alpha_{i,t}$, $\beta_{i,t}$ as the *mean* hyperparameters, while $\eta_{i,\alpha(\beta),t}$ as the *precision* hyperparameters of the model. Therefore, at each date they expect $\mu_{i,t}^e = \alpha_{i,t} - \beta_{i,t}\pi_{t-1}$.

[1] *Precision (or robustness)* of the subjective prior is related to the inverse of the variance: indeed the matrices $\mathbf{H}_{i,0}$ are the inverse of the variance-covariance matrices conjectured by the populations.

At the end of each date *t*, once the individual compliance decisions have been taken, people learn μ_t and π_t and formulates a posterior along a Bayesian learning process, by updating the prior based on μ_t and π_t. The posterior at date *t* becomes the prior for date *t*+1.

2.2. Learning, conjectural equilibria, and optimality

The individuals of each subpopulation decide to comply at the beginning of each date *t* if and only if: $\mu_t^e > \theta_i$. Given Assumption 5, the share of each subpopulation who decides to comply is:

$$\pi_{i,t} = \frac{\alpha_{i,t} - \beta_{i,t}\pi_{t-1}}{\theta_i},\ i=A, B \tag{1}$$

The overall compliance rate at date *t* is:

$$\pi_t = \frac{\gamma}{\theta_A}\left(\alpha_{A,t} - \beta_{A,t}\pi_{t-1}\right) + \frac{1-\gamma}{\theta_B}\left(\alpha_{B,t} - \beta_{B,t}\pi_{t-1}\right) \tag{2}$$

corresponding to the observed mean:

$$\mu_t = \alpha - \beta\left[\frac{\gamma}{\theta_A}\left(\alpha_{A,t} - \beta_{A,t}\pi_{t-1}\right) + \frac{1-\gamma}{\theta_B}\left(\alpha_{B,t} - \beta_{B,t}\pi_{t-1}\right)\right] \tag{3}$$

Now, let us define the vector $\mathbf{x}'_t = [1 \quad -\pi_t]$, that is, the vector of the "regressors" of the equation $\mu_{i,t}^e = \alpha_{i,t} - \beta_{i,t}\pi_t$ that people would conjecture after being informed of π_t, given their previous prior. Under our assumptions, the updated hyper-parameters are as follows (see De Groot 1970):

$$\mathbf{z}_{i,t+1} = \mathbf{z}_{i,t} + \left[\mathbf{H}_{i,t} + \mathbf{x}_t\mathbf{x}'_t\right]^{-1}\left[\mathbf{x}_t\left(\mu_t - \mathbf{x}'_t\mathbf{z}_{i,t}\right)\right] \tag{4}$$

The final parenthesis contains the *forecasting error* for subpopulation *i,* $e_{i,t} \equiv \left(\mu_t - \mathbf{x}'_t\mathbf{z}_{i,t}\right)$, given that μ_t is the *true* average welfare loss at the end of time *t*, communicated by the PA together with the actual π_t, while $\mathbf{x}'_t\mathbf{z}_{i,t}$ is the one that would be computed by population *i* on the basis of its prior and of the actual π_t. Observe that $\mathbf{z}_{i,t+1} = \mathbf{z}_{i,t}$ *if and only if* the individuals of subpopulation *i* learns from the PHA that $\mu_t = \mathbf{x}'_t\mathbf{z}_{i,t}$, that is, if the forecast $e_{i,t}$ error is null. On the other side, because the precision matrix grows over time, the strength of the correction mechanism reduces in time. Therefore, the updating process becomes increasingly slower.

Now, we introduce the concept of conjectural equilibria in order to study whether and how the updating process can reach a position of rest, so that the compliance rates stabilize to certain levels (Hahn 1977, Fudenberg-Levine 1993, and Dekel-Fudenberg-Levine 2004). We define a *conjectural equilibrium* (*CE*, hereafter) as a configuration of subpopulations' hyperparameter such that, if the *learning dynamical system* is set in one of these positions, it stays there except when a further shock perturbs the system. In such situations, people (of both subpopulations) have no reason to modify their beliefs and the related compliance decisions.

Since the *CE* definition implies that equilibrium variables remain constant in time, we omit the time subscripts. From the definition above and from equations (2) and (4), the *CE* condition can be represented by the following system:

$$\begin{cases} \alpha_A - \beta_A\pi = \alpha - \beta\pi \\ \alpha_B - \beta_B\pi = \alpha - \beta\pi \\ \pi = \beta\left[\frac{\gamma}{\theta_A}\left(\alpha_A - \beta_A\pi\right) + \frac{1-\gamma}{\theta_B}\left(\alpha_B - \beta_B\pi\right)\right] \end{cases} \tag{5}$$

By solving (5), we obtain the *CE* average welfare loss and compliance rate:

$$\pi_{CE} = \frac{\left(\frac{\gamma}{\theta_A}+\frac{1-\gamma}{\theta_B}\right)\alpha}{1+\left(\frac{\gamma}{\theta_A}+\frac{1-\gamma}{\theta_B}\right)\beta} \qquad \mu_{CE} = \alpha - \beta\frac{\left(\frac{\gamma}{\theta_A}+\frac{1-\gamma}{\theta_B}\right)}{1+\left(\frac{\gamma}{\theta_A}+\frac{1-\gamma}{\theta_B}\right)\beta}\alpha \tag{7}$$

By inspecting (7), we can conclude that the precise location of π_{CE} and μ_{CE} does not depend on the subpopulations' conjectures (priors). There is a unique equilibrium compliance rate-welfare loss couple depending only on the structural parameters.

In spite of this uniqueness result, things are quite different as regards the configuration of the *CE conjectures* of the two subpopulations. Indeed, by replacing from (5), we are able to conclude that the *CE* mean hyperparameters of each subpopulation are characterized by the relations $\beta_{CE,i} = \frac{\alpha_{CE,i}-\alpha}{\pi_{CE}} + \beta \; i = A, B.$ Hence, we observe that there exist a doubly-infinite set of quadruplets of hyperparameters that are compatible with *CE*. More technically, we have a two-dimensional CE manifold in the four-dimensional space of the subpopulations' mean hyperparameters. The infinity of possible *CE* situations implies that the two subpopulations end up, in equilibrium, with different interpretations of the steady state: even if they correctly guess the *local* relationship between compliance rate and welfare loss, they envisage different relationships between the two variables. It is even possible that one subpopulation conjectures a positive relationship, meaning that they believe that complying with good practices/rules results in a further burdensome source of loss. Said differently: given an exogenous change in the overall compliance rate, the two subpopulations predict different (possibly, quite different) changes in the average welfare loss.

The policymaker is now able to derive the μ_{CE} and compare it with the socially optimal level of μ^*. The latter can be derived by trading off social benefits and costs of reducing average welfare losses. The socially optimal average welfare loss μ^* must satisfy the usual first-order condition $B'(\mu^*) = C'(\mu^*)$, $0 < \mu^* < 1$. In particular, given the assumed functional forms, the socially optimal average welfare loss is $\mu^* = 1 - \left(\frac{b}{c}\right)^{\frac{1}{c-b}} \in (0,1)$. Clearly, the socially optimal welfare loss may differ from the existing *CE* welfare loss. The PA interested in aligning the μ_{CE} to μ^* must be aware that only shocks affecting the structural parameters can be effective to achieve the purpose. loss do not depend on welfare loss reduction and can be simply added as an additional fixed cost to $C(\mu)$.
In the next section we will consider the impact of changes in structural parameters aimed at realigning μ_{CE} to μ^*.

2.3. Effects of changes in structural parameters and dynamical implications

In order to appreciate the impact of changes in the structural parameters on μ_{CE} we compute the *elasticity* of μ_{CE} with respect to each policy parameter. The elasticity is the ratio of the percentage variation in μ_{CE} and the percentage variation in the structural parameter. The elasticities provided below describe the percentage average variation in the policy target due to a one per cent variation (increase or decrease, depending on the policy) in a given policy parameter.

$\varepsilon_{\mu_{CE},\alpha} = \frac{\partial \mu_{CE}}{\partial \alpha}\frac{\alpha}{\mu_{CE}} = 1$, positive and unitary.

$\varepsilon_{\mu_{CE},\beta} = \frac{\partial \mu_{CE}}{\partial \beta}\frac{\beta}{\mu_{CE}} = -\frac{\beta(\theta_A-\gamma(\theta_A-\theta_B))}{\theta_A\theta_B+\beta(\theta_A-\gamma(\theta_A-\theta_B))}$ negative and its absolute value is smaller than 1.

$$\varepsilon_{\mu_{CE},\theta_A} = \frac{\partial \mu_{CE}}{\partial \theta_A}\frac{\theta_A}{\mu_{CE}} = \frac{\beta\gamma\theta_B}{\theta_A\theta_B+\beta(\theta_A-\gamma(\theta_A-\theta_B))}$$ positive and smaller than 1;

$$\varepsilon_{\mu_{CE},\theta_B} = \frac{\partial \mu_{CE}}{\partial \theta_B}\frac{\theta_B}{\mu_{CE}} = \frac{\beta(1-\gamma)\theta_A}{\theta_A\theta_B+\beta(\theta_A-\gamma(\theta_A-\theta_B))}$$ positive and smaller than 1;

$$\varepsilon_{\mu_{CE},\gamma} = \frac{\partial \mu_{CE}}{\partial \gamma}\frac{\gamma}{\mu_{CE}} = -\frac{\beta\gamma(\theta_A-\theta_B)}{\theta_A\theta_B+\beta(\theta_A-\gamma(\theta_A-\theta_B))}$$ negative and its absolute value is smaller than 1.

Looking at the sign of the elasticities, we observe that when $\mu_{CE} < \mu^*$, regulation can intervene by decreasing α and θ_i or increasing β and γ. Vice versa, when $\mu_{CE} > \mu^*$interventions go in the opposite direction.

Furthermore, the higher impact (not surprisingly) is guaranteed by changes in α. Note that $\varepsilon_{\mu_{CE},\alpha} > |\varepsilon_{\mu_{CE},\beta}| > \varepsilon_{\mu_{CE},\theta_A} > \varepsilon_{\mu_{CE},\theta_B} > |\varepsilon_{\mu_{CE},\gamma}|$ where the last inequality is verified for $\frac{(1-\gamma)}{\gamma} > \frac{\theta_A-\theta_B}{\theta_A}$.

Comments in a narrative form must be added here. Add an explanation describing the type of policies affecting the structural parameters in the desired direction.

Now, in order to assess the dynamical implication of actions changing the structural parameters and finally moving the system towards a new *CE*, observe that the dynamical system whose stability properties we wish to examine is defined by equations (2) and (4), coupled with the formulation of the forecasting errors: therefore, five variables are involved. Defining the vector $\mathbf{y}_t \equiv (\alpha_{A,t}, \beta_{A,t}, \alpha_{B,t}, \beta_{B,t}, \pi_t)$, we have the following formal definition of our discrete-time dynamical system:

$$\mathbf{y}_t = F(\mathbf{y}_{t-1}) \tag{8}$$

The system of equations (8), besides being five-dimensional, is *non-linear*; hence, analyzing its global properties is quite difficult. Therefore, we propose to study the *local* stability of *CE*s. Following Gandolfo (1980), this requires computing the Jacobian matrix of system (8) evaluated at a *CE* that contains the partial derivatives of each variable at date t with respect to all variables at date $t-1$. In our case, it is a 5x5 matrix. Then, we study the eigenvalues of this matrix. The characteristics of the eigenvalues determine how the variables move after a tiny displacement from the *CE* at which the Jacobian and its eigenvalues are evaluated (details will be provided in the Appendix).

Since the *analytical* study of the relation between the eigenvalues and the structural parameter turns out to be quite difficult, we resort to numerical computations in order to obtain the *time of convergence* (TOC, hereafter) associated with different parameter combinations. The TOC is measured in terms of how many periods are required in order that a shock is reduced to 5% of its initial amplitude. The computation program (available upon request) is implemented by means of the open-source GNU Octave language (Eaton-Bateman-Hauberg-Wehbring 2023).

The TOC is quite sensitive to parameter changes. Consider that a positive TOC associated with each *CE* shows how rapidly the variables converge to that *CE* if they are slightly displaced from it. On the contrary, a negative TOC means divergence (the system would converge if it moved *backwards* in time). A lower positive TOC means faster convergence, while a lower negative TOC indicates slower divergence.

In Figure 1 we plot the stability of *CE*s, measured by the TOC, against different parameter values. This is done for different scenarios (different lines in the same graph, parameters are provided in the caption). As regards the first five graphs in Figure 1, we see that increases either in α or in θ_i lead to higher stability or lower instability (decreasing TOC) in all possible scenarios. Vice versa, higher values of β and γ induce lower stability or higher instability (increasing TOC) in all scenarios. On the other hand, the last graph in Figure 1 shows clearly that higher initial precisions (matrices $\mathbf{H}_{i,0}$) cause a more sluggish learning rate, hance implying a longer TOC.

Therefore, we are able to conclude that changes in structural parameters reducing μ_{CE} tend to push in the direction of slower convergence/faster divergence. Vice versa, changes in structural parameters augmenting μ_{CE} are associated with faster convergence/slower divergence.

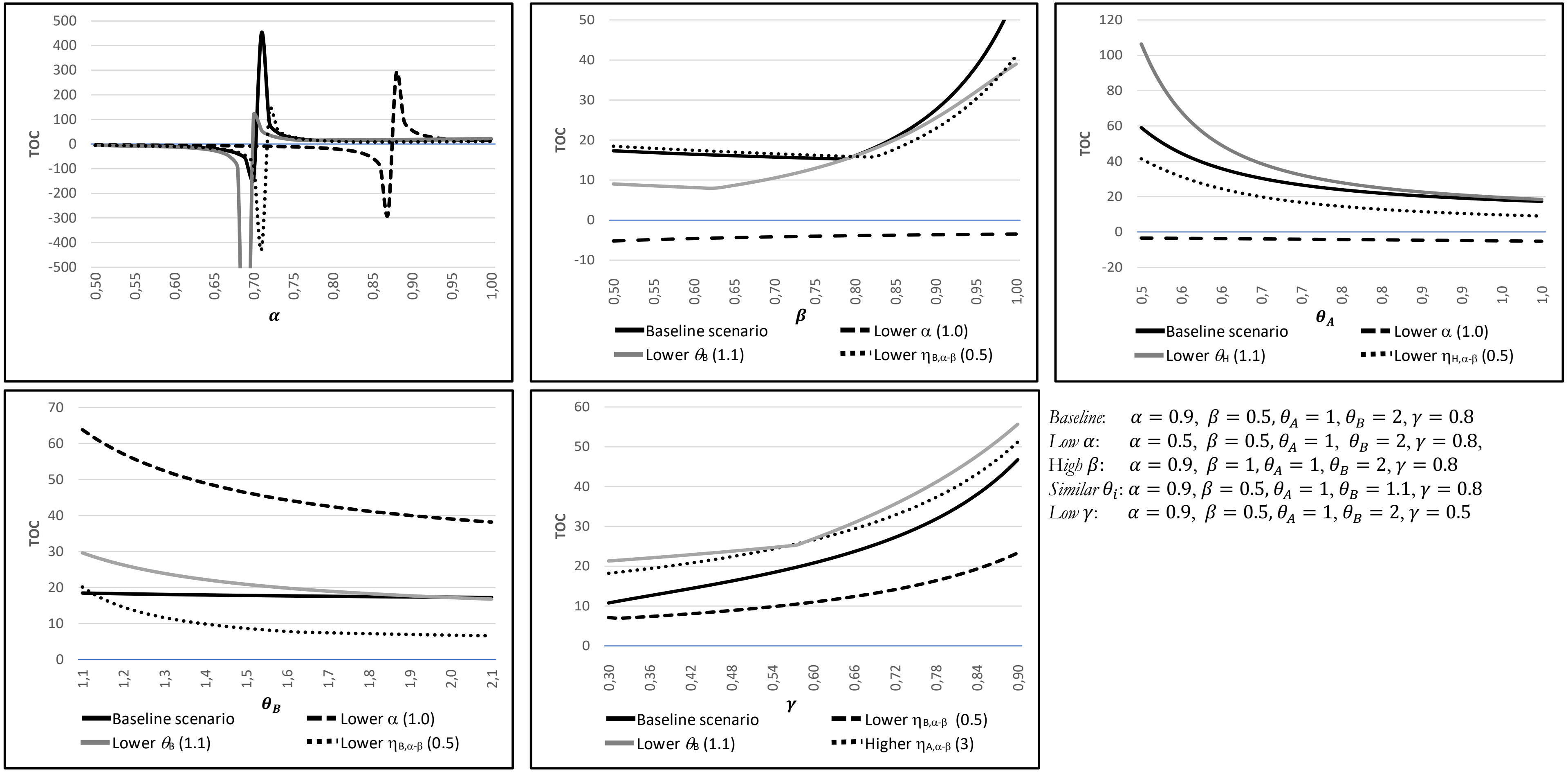
Concluding, when structural parameters change, not only the system shifts towards new *CEs*, but also the latter are characterized by different stability properties. In particular, some changes might lead to a longer convergence time/shorter divergence time. This must be very clear to the policymakers intervening on parameters to the end of reducing the average severity of a vaccinable disease. Each intervention should be carefully evaluated not only for its capacity to achieve a new desirable *CE*, but also in terms of its dynamic effects.

3. Conclusions

The policymaker can pursuit optimality by acting on various structural parameters of the model (corresponding to various kind of regulatory interventions) to align the conjectural equilibrium level of welfare losses to the optimal one. However, the policymaker must be aware that any kind of regulatory intervention implies dynamical effects that depend on both people conjectures and learning staying behind individual choices. Finally the precise achievement of any policy goal cannot be taken for granted, while requiring time and perseverance.

[To be completed]

FIGURE 1 Time of convergence (TOC) against different parameters, under various scenarios.



Baseline: $\alpha = 0.9,\ \beta = 0.5, \theta_A = 1, \theta_B = 2, \gamma = 0.8$

Low α: $\alpha = 0.5,\ \beta = 0.5, \theta_A = 1,\ \theta_B = 2, \gamma = 0.8,$

H*igh* β: $\alpha = 0.9,\ \beta = 1, \theta_A = 1, \theta_B = 2, \gamma = 0.8$

Similar θ_i: $\alpha = 0.9, \beta = 0.5, \theta_A = 1, \theta_B = 1.1, \gamma = 0.8$

Low γ: $\alpha = 0.9,\ \beta = 0.5, \theta_A = 1, \theta_B = 2, \gamma = 0.5$

References

Aghion, P., Algan, Y., Cahuc, P., Shleifer, A. (2010) "Regulation and Distrust." 125 Quarterly Journal of Economics 1015–49.

Agranov, M., Elliott, M. Ortoleva, . (2021) The importance of Social Norms against Strategic Effects: The case of Covid-19 vaccine uptake. 206 Economics Letters, 109979.

Alesina, A., & Giuliano, P. (2015). Culture and institutions. Journal of economic literature, 53(4), 898-944.

Allen, S., Murphy, K, Bates, L. (2017). What drives compliance? The effect of deterrence and shame emotions on young drivers' compliance with road laws.27.8 Policing and society pp.884-898.

Alm, J. (2019), What Motivates Tax Compliance?. Journal of Economic Surveys, 33: 353-388.

Barr, M.S., Mullainathan, S., Shafir, E. (2009) The Case for Behaviorally Informed Regulation in Moss D. & Cisternino j (Eds.) New Perspectives on Regulation. The Tobin Project, One Mifflin Place, Cambridge, MA 02138.

Becker, M. H., & Maiman, L. A. (1975). Socio-behavioral determinants of compliance with health and medical care recommendations. Medical care, 10-24.

Bhattacharyya S., Bauch, C.T. (2010) A game dynamic model for delayer strategies in vaccinating behaviour for paediatric infectious diseases. 267 J. Theor. Biol. 276–282.

Bradford, B., et al. (2015) Obeying the rules of the road: Procedural justice, social identity, and normative compliance." Journal of contemporary criminal justice 31.2 (2015): 171-191.

Byerly H, Balmford A, Ferraro P J, Hammond Wagner C, Palchak E, Polasky S, Ricketts T H, Schwartz A J and Fisher B 2018 Nudging pro-environmental behavior: evidence and opportunities Front. Ecol. Environ. 16 159–68

Cleemput, I., & Kesteloot, K. (2002). Economic implications of non-compliance in health care. The Lancet, 359(9324), 2129-2130.

Coelho, F., Codeço, C.T. (2009) Dynamic modeling of vaccinating behavior as a function of individual beliefs. 5, PLoS computational biology, e1000425.

Coglianese G. and Nash J. (Eds.), 2001. Environmental Management Systems: History, Theory, and Implementation Research. In Regulating from the Inside: Can Environmental Management Systems Achieve Policy Goals? Washington , DC : Resources for the Future.

Coleman, C., & Freeman, L. (1997). Cultural foundations of taxpayer attitudes to voluntary compliance. Australian Tax Forum, 13(3), 311-336.

Czajkowski M, Hanley N and Nyborg K (2017) Social norms, morals and self-interest as determinants of pro-environment behaviours: the case of household recycling Environ. Resour. Econ. 66 647–70

Del Río P. (2010). Analysing the interactions between renewable energy promotion and energy efficiency support schemes: The impact of different instruments and design elements. Energy Policy, 38(9), 4978–4989.

Dhaliwal, D., Mannion, C. and others (2020) Antivaccine messages on facebook: preliminary audit. 6 JMIR public health and surveillance,18878.

Donadel, M., Panero, M.S., Ametewee, L., Shefer, A.M. (2021) National decision-making for the introduction of new vaccines: A systematic review, 2010—2020. 39, Vaccine, 1897--1909

Dubé, E., Gagnon, D., Nickels, E., Jeram, S., Schuster, M. (2014) Mapping vaccine hesitancy—Country-specific characteristics of a global phenomenon. 32, Vaccine, 6649—6654.

Feld, L. P., & Frey, B. S. (2007). Tax compliance as the result of a psychological tax contract: The role of incentives and responsive regulation. Law & Policy, 29(1), 102-120.

Gandolfo, G. (1980), Economic Dynamics: Methods and Models, North-Holland, Amsterdam

Gizzi, F.T.; Porrini, D.; De Masi, F. Building a Natural Hazard Insurance System (NHIS): The Long-lasting Italian Case. Sustainability 2021, 13, 12269.

Gofen, A., Moseley, A., Thomann, E., & Kent Weaver, R. (2021). Behavioural governance in the policy process: introduction to the special issue. Journal of European Public Policy, 28(5), 633-657.

Greenstone, M. (2009) Toward a Culture of Persistent Regulatory Experimentation and Evaluation in Moss D. & Cisternino j (Eds.) New Perspectives on Regulation. The Tobin Project, One Mifflin Place, Cambridge, MA 02138.

Gunningham N., Grabosky P., Sinclair D. (1998). Smart regulation: Designing environmental policy. Clarendon Press.

Howlett, M. (2019). Designing public policies: Principles and instruments. Routledge.

Kountouris, Y. (2022). The influence of local waste management culture on individual recycling behavior. Environmental Research Letters, 17(7), 074017.

MacDonald, N.E., SAGE Working Group on Vaccine Hesitancy. (2015) Vaccine hesitancy: Definition, scope and determinants. 33, Vaccine, 4161—4164.

May, P.J. (2005), Regulation and Compliance Motivations: Examining Different Approaches. 65 Public Administration Review, 31-44.

McConnell, A. (2015). What is policy failure? A primer to help navigate the maze. Public Policy and Administration, 30(3-4), 221-242.

Nagler, M.G. (2013) Does social capital promote safety on the roads?." 51.2 Economic Inquiry 1218-1231.

North, D. C. (1991). Institutions. Journal of economic perspectives, 5(1), 97-112.

Ostrom, E. (2009). Understanding institutional diversity. Princeton university press.

Pan, W., Garmston. H. (2012) Building regulations in energy efficiency: Compliance in England and Wales. 45 Energy Policy 594-605.

Posner, R.A. (1997) Social norms and the law: An economic approach. 87 American Economic Review 365-369.

Sarkar, S., Andreas, M., De Faria, F. (2005) Who uses safe ride programs: an examination of the dynamics of individuals who use a safe ride program instead of driving home while drunk." 31 American Journal of Drug and Alcohol Abuse 305-325.

Siram, B. Shah, M., Panda, R. (2022) Vaccine Hesitancy in COVID-19: A Behavioural Economics Approach—A Systematic Literature Review. 2022 Studies in Microeconomics.

Shim, E., Grefenstette, J.J., Albert, S.M., Cakouros, B.E., Burke, D.S. (2012a) A game dynamic model for vaccine skeptics and vaccine believers: measles as an example. 295, Journal of theoretical biology, 194—203.

Silver, M. C., Neumann, P. J., Ma, S., Kim, D. D., Cohen, J. T., Nyaku, M., ... & Ollendorf, D. A. (2021). Frequency and impact of the inclusion of broader measures of value in economic evaluations of vaccines. Vaccine, 39(46), 6727-6734.

Standaert, B., Sauboin, C., DeAntonio, R., Marijam, A., Gomez, J., Varghese, L., & Zhang, S. (2020). How to assess for the full economic value of vaccines? From past to present, drawing lessons for the future. Journal of market access & health policy, 8(1), 1719588.

Stiglitz J. (2009) Regulation and Failure in Moss D. & Cisternino j (Eds.) New Perspectives on Regulation. The Tobin Project, One Mifflin Place, Cambridge, MA 02138.

Sütterlin, B., Brunner, T.A., Siegrist, M. (2011) "Who puts the most energy into energy conservation? A segmentation of energy consumers based on energy-related behavioral characteristics." 39.12 Energy Policy 8137.

Tummers, L. (2019). Public policy and behavior change. Public Administration Review, 79(6), 925-930.

Viscusi, W. K. (2007) "Regulation of health, safety, and environmental risks." Handbook of law and economics 1.

Yan, B., Zhang, X., Wu, L., Zhu, H., & Chen, B. (2020). Why do countries respond differently to COVID-19? A comparative study of Sweden, China, France, and Japan. The American review of public administration, 50, 762-769.

Wu, J.J., Babcock,B.A. (1999) The Relative Efficiency of Voluntary vs Mandatory Environmental Regulations, 38 Journal of Environmental Economics and Management, 158-175.

Appendix

Proofs and complete simulations will be provided here. [To be completed]