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Abstract

The present paper aims to identify ways to reduce pollution injected by residents in the urban wastewaters network system. Two approaches are considered. The first one uses flow and pollutant calculation to test whether a polluter can easily be identified in a neighborhood. The second approach uses a survey to examine what incentive would be most effective to influence residents' behavior. Hydrodynamic simulation results show that concentration profiles at the network outlet corresponding to all possible polluters are similar and thus do not point out specific resident source of pollution. Household level survey results show that most socio-economic and public good-related characteristics do not play a significant role in explaining choices to discard in the home wastewaters network. Apart from the nature of the waste itself, by far, the belief that the respondent has about her neighbors' and relatives' discarding behavior is the main driver of the choice.

Keywords. Household wastewaters behavior; Panel-data logit; Prosocial behavior; Sewage Hydrodynamic Simulation; Reynolds time- Averaged Navier-Stokes.

1 Introduction

Wastewater treatment is a significant and growing cost for communities. In 2008, according to the French Ministry of Ecology and Sustainable Development and Energy, it amounted to 53% of the water bill for the domestic user (MEDDE 2015). The Greater Lyon Metropolitan Area (GL hereafter) estimated the volume of water collected in its sewer network at about 200 million cubic meters per year, consisting of approximately 60 % rainwater and 40% wastewater of all kinds. In addition to this volume, some additional rainwater is collected in separate networks through stormdrains and gutters. Collected wastewaters are sent to treatment plants designed to degrade the traditional domestic pollutants during dry or light rain weather. Treated water is then discharged into receiving water bodies (rivers, watercourses, etc.). If specific pollutants or excessive rain water volumes are collected in the sewer network, the hydraulic capacity of the treatment plant is exceeded and part of the wastewaters may be discharged directly through combined sewer overflow structures without treatment. Consequently, the quality of the collected wastewaters in part determines the quality of the water that will eventually be released into the natural environment.

Wastewaters are heavily loaded with organic matter and nitrogen; these substances are properly treated thanks to the processes involved in wastewater treatment plants. In addition, they also convey concentrations of phosphates, sulfates, chlorides, PAHs (polycyclic aromatic hydrocarbons), metals and pesticides, among others (see Padhye and Tezel 2014 for a review of most available rejected substances). Some of these substances are classified as dangerous by the European Water Framework Directive – WFD (2000) and the French Order of 25 January 2010 (JO 2010) on the evaluation of ecological and chemical state of surface water.

Most of the residues of these substances are trapped in the sludge for which it is necessary to find beneficial reuse or pay the landfill.

GL has already taken steps to reduce industrial wastewater injections and would like to extend this approach to individuals. Indeed, households cause pollution by occasionally discarding in the wastewaters network some wastes that should normally be brought to a waste disposal facility, including: paint, white spirit, motor and cooking oils, solid waste (wipes, cotton, ...), pesticides. However, GL perceives that residents may have a wrong perception of the issues of wastewaters and a very incomplete knowledge of where to release them. To address this perception issue, GL engaged in education and environmental-awareness activities, for example, educational visits of treatment plants for children, with free information leaflets along the path, for each participant; but this falls short from ambitious action plans. Furthermore, even though GL is in charge of the overall urban drainage system, sewer and treatment networks, for most cases, the water companies, instead of GL, are in direct contact with the residents about their water use and habits. This contact is however very much confined to sending and payment of the water bill (that include some information on the cost of treatment).

Since GL seeks to reduce sources of polluting waste, it seems relevant to know which means can be used to efficiently influence residents' behavior. There is a dual approach for this issue. The first approach relates to understanding the diffusion of pollutants released in a wastewaters network to assess local policy effects. Understanding pollutant diffusion could also help identifying polluters based on available pollution concentration measurement, maybe at the level of a neighborhood; in that case, financial incentive might be used in a kind of polluter-pay principle. The second approach is based on non-monetary and non-individualized incentives. This second approach focuses on understanding how residents decide what to discard in the wastewater network and what could motivate a behavior change; how to influence this change, with what information. Despite the existence of an EU WFD, the 1991 Urban Waste Water Treatment Directive (UWWTC 1991), the literature, broadly in behavioral sciences, appears rather silent on such prosocial behaviors (that is, behaviors beneficial for the public good, at large) in the domain of wastewaters. OECD (2008) summarizes studies and papers on "Household Behaviors and the Environment" that state the interest in understanding heterogeneity of behaviors and people's "private" and "public" motives. Among others it reviews solid wastes generation and residential water use, but fails to identify works on household wastewaters behaviors.

Therefore, the paper aims to i) simulate the pollutant transport and diffusion into a selected sewer network in order to to evaluate how pollutant concentration profiles away from the injection location may help identifying the origin of the pollution and ii) survey the users to detect residents' knowledge of wastewaters issues, and motivations to avoid disposing of liquid pollutants in the wastewater network, and maybe bring them to a facility. The paper is organized as follows. The methodological basis of the two approaches mentioned above is first presented, followed by the results and discussions. The last section concludes regarding the best-suited measures which the demander should apply to reduce the pollutant concentration is its network.

2 Methodology of Research

2.1 Hydrodynamic Simulation

This approach aims to identify a source of pollution by means of the analysis of pollutant concentrations at the outlet of a wastewaters separated sewer network (where a sensor would be implemented). It is assumed that the signature of a pollution at the downstream section of the sewer network changes according to the location of the pollution injection. In order to check this assumption, the propagation of a pollutant concentration in a typical sewer network

is investigated numerically (see De Marchis et al. 2013 for a similar approach based on a 1D numerical model to simulate the dispersion of *E. coli*). The following paragraphs highlight the selected methodology.

The separated sewer network presented in Fig. 1 is selected in the St Priest city (close to Lyon, France). It is located within a 1 km^2 area, mainly comprising individual houses. The GL water management services provided maps and GIS data detailing: i) the topology of the sewer network, ii) the slope and diameter of each conduit and iii) the location of the inlets and corresponding number of connected houses (see Fig. 2).

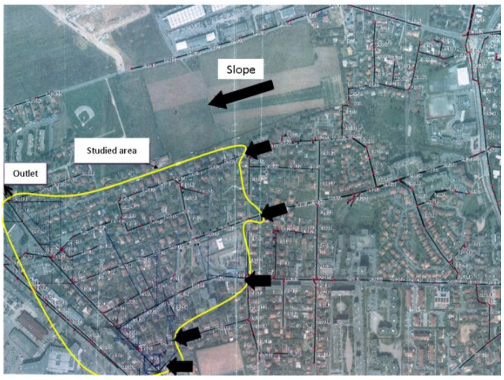

Figure 1: Selected studied area within St Priest city detailing each conduit (black lines) and corresponding slope and each inlet (red dots).

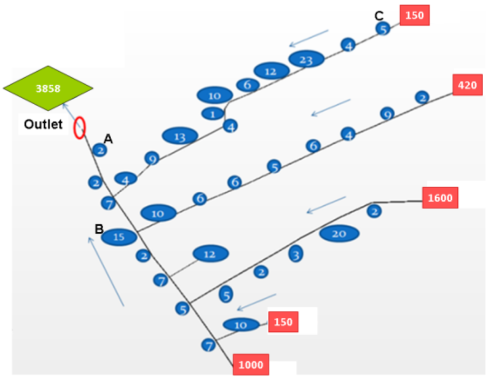

Figure 2: Simplified sketch of the selected network with the number of houses located within the catchment watershed and connected to the branches of the present network (red squares), connected to each inlet (blue ellipses). The total number of involved houses finally equals 3858 (end-of-pipe green diamond). Three specific injection locations noted A, B and C will be used for analyzing the numerical results in Figs. 4 and 5.

The discharge entering the network at each inlet is assumed to be equal to the number of houses connected to this inlet multiplied by four inhabitants per house and multiplied by the average individual water consumption at 9:00 am (0.31 L per minute per inhabitant) according to the standard dry weather flow components (Dorval, 2011).

The discharges being known at each inlet and thus everywhere in the network, the normal water depth (referring to a uniform open-channel flow) and the corresponding wet cross-section are computed within each conduit of the sewer network. In order to better control the geometry (with junctions, drop structures etc.) and increase the quality of the computational mesh, an equivalent rectangular wet cross-section is assumed with the same free surface width as within the actual circular conduit.

Adding all the conduits, the geometry of the water volume is finally generated and meshed, using 1.1 million cells (about 8 cells per conduit width and 4 per conduit depth) as shown on Fig. 3. A robust 3D calculation of the flow with clear water (without pollution) is performed using StarCCM+ CFD code solving the 3D-steady-RANS (Reynolds time-Averaged Navier Stokes) equations using the k-epsilon turbulent closure scheme, the rigid lid representation of the free surface and the standard wall functions for the wall boundary conditions. Regarding the pollutant propagation, the 3D advection-diffusion equation is solved considering a passive scalar (assuming same density) and a timely and spatially constant turbulent Schmidt number equal to 0.9 (see Romero-Gomez *et al*. (2008) or Franck *et al*., 2010). It is used to compute the turbulent diffusivity coefficients from the turbulent viscosity coefficients obtained through the hydrodynamics calculation. Momplot *et al*. (2012 and 2013) and Riviere *et al.* (2015) showed that this 3D numerical methodology, despite the use of a rigid-lid, fairly reproduces the complex hydrodynamics which occurs in the downstream branch of an individual junction. Similarly, Riviere *et al.* (2015) showed that this numerical approach also reproduces the pollutant dispersion in these junctions.

It was notably observed by Riviere et al (2015) and Dalmon et al (2015) that as the velocity of the flow entering from the lateral (or tributary) inlet exceeds that entering from the main inlet (see Fig. 3), the flow pattern in the downstream branch exhibits a complex helicoidally secondary motion (previously described by Shakibainia *et al*., (2010) which deeply enhances the pollutant homogenization in the downstream branch (see also Lane *et al.*, 2008). The length for complete mixing of the downstream branch as proposed by Fischer *et al.* (1979) can then pass from about 100 to 15 branch widths, in a similar way as the consequence from a bed discordance at the intersection (see Gaudet and Roy, 1995) or a density ratio between both incoming fluids (see Rice *et al*., 2008). A pollutant concentration is then injected at each inlet point of the sewer network one after the other, by replacing the generated clear water by passive tracer during 14 seconds. This permits the simulation of a pollutant load of 0.27 liter generated by each house.

Analysis of pollutant diffusion in the sewer until reaching the outlet is finally performed by post-processing the numerical results as detailed in section 3.

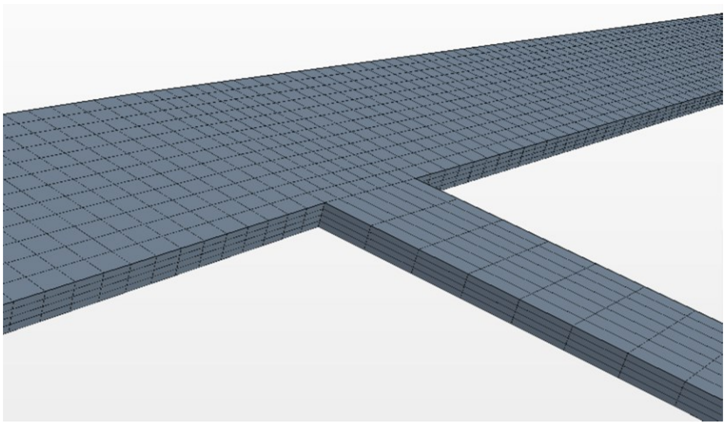

Figure 3: Computational mesh near a junction.

2.2 Household Waste Behavior

The Bénabou and Tirole (2006) model of prosocial behavior is now used to model the (in principle simpler) case of wastewaters household behaviors. There is an abundant literature in economics on the topic of prosocial behaviors; the Bénabou and Tirole model has been adopted in the present paper because it has certainly been a milestone in this field and

synthetized several approaches. Bénabou and Tirole observed that individuals engaging in prosocial behaviors might not appear rational at first economic glance because such behaviors are costly in terms of time or effort, often without apparent economic benefit. Indeed, one may legitimately wonder why people do not discard more through the home wastewaters network and instead adopt behaviors (recycling or others) that are costly to them, at least in time and effort if not in money. Bénabou and Tirole propose that individuals engage in such prosocial behaviors following three broad types of incentives: "monetary", "altruism / public good", and "reputational".

Monetary incentives usually stem from fines in the case of pollution, but might also be subsidies to install more environmental-friendly equipment. Conventional wisdom has considered that wastewater is a nonpoint source pollution, that is, it is not possible to identify a particular pollution. If that is indeed the case, monetary incentives appear pointless even if they are sometimes enacted as it is not possible to fine or incent people for untraceable behavior. Whether wastewater is indeed a nonpoint source pollution is the object of the first approach of the present paper.

Altruism and public good considerations include such motives for an immaterial return of a prosocial action as caring for the well-being of others or the "health" of the aquatic environment in the area. Such motives require, in the case of wastewaters, a least some understanding of the water cycle and waste network.

Reputational incentives reflect the benefits that may be derived from the image of ourselves we send to others or to ourselves. The reflection of our own image may include such benefits as moral satisfaction or "warm glow" feelings, but also many immaterial benefits which have a more social nature : being accepted into a group, or on the contrary differentiating oneself from it, or networking benefits such as in a job or client search. The reputational incentives may exist with household wastewaters because of a partial observationality of the behaviors, e.g. while having friends over, or possibly during maintenance works.

The objective of assuming such a model is to seek leverages with which we might expect to influence behavior. With the Bénabou and Tirole model in mind, a household survey on such behaviors has been designed and administered with the purpose to test, using econometric analysis, whether different motives have a statistically significant effect on a resident's wastewaters behavior. Even though it is not possible to ask directly what the motivations of a respondent are, it is possible to examine the statistical significance of factors that would reveal whether each motive has a significant influence on the behavior. The public good motives might appear through such indicators of knowledge of wastewaters system, e.g. what is the use of a treatment plant? what is the destination of home wastewaters? does the individual have recreational or other use of the aquatic medium? is the person concerned by water pollution issues and does she feel that she can contribute to these issues ? The reputational motives have a significant effect for an agent *i* if her opinion of what her friends' or relatives' wastewaters behaviors matters for her own wastewaters behavior. The image of oneself appears difficult to measure without sophisticated psychological tests; instead, an indication of a willingness to change one's behaviors about waste has been used as a proxy.

3 Results and Discussion

3.1 Concentration profiles in sewer pipes

For each simulation, the pollution propagation is computed from the corresponding inlet to the downstream section. The pollutant cloud appears to be conveyed with the main current and to diffuse laterally, vertically and along the streamwise direction. Moreover, complex turbulent mixing takes place within the junctions with other pipes (Mignot *et al.*, 2013).

The time-evolution of pollutant concentration at the center of the downstream section (outlet) is presented for 18 selected injection locations in Fig.4. These time-evolutions are centered on

the arrival time of the concentration peak at this outlet (all injections are then performed at different negative times). The figure reveals that the shape of the curve is similar for each simulation, that is, for each injection location: the concentration data are normally distributed around a central maximum magnitude. Indeed, even though complex mixing occurs within each junction leading to a complex pollution cloud just downstream the junction, the distance before reaching the next junction (typically 100 meters in the case study) is much larger than the lateral and vertical dimensions of the flow section (typically 1 meter). Thus the flow recovery toward a uniform velocity and pollutant concentration distribution is systematically obtained before reaching the following junction (Mignot *et al.*, 2012). Nevertheless, the concentration peak and lateral diffusion appear to vary strongly between all simulations.

The peak concentration displayed on Fig.4 for each curve is plotted in Fig.5 as a function of the convection time of the pollutant from the corresponding injection inlet to the downstream section. A fine correlation is obtained: as the convection time increases, the pollution cloud diffusion increases and thus the concentration peak at the outlet decreases. However, for one measured peak concentration at the outlet, the number of possible injection locations equals the number of main branches of the sewer network (equal to four in the present case).

To conclude, the analysis of the pollutant concentration data, from a sensor supposed to be located within the sewer network (as in Namour *et al.*, 2010) does not permit the pollution origin to be identified even if the sewer network is perfectly known, and in spite of hypotheses made in the present study (mainly: same water consumption from each inhabitant in the area and sudden release of non-mixing pollutant load). This prevents further attempts to detect the source of pollution within a network using only measurements at the outlet, and to develop corresponding inverse methods. The only possible approach to identify sources of pollution would be to deploy a large sensor network, with at least one sensor per principal branch, which is impractical due to access complexity and prohibiting cost. Thus non-monetary, non-individualized incentives must be sought after, such as described in the next subsection.

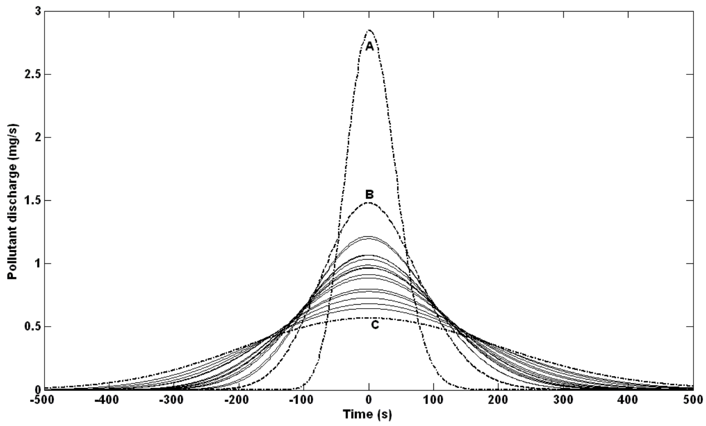

Figure 4: Time evolution of the simulated pollutant concentration at the center of the outlet section for 18 selected simulations (corresponding to 18 different injection locations) with t=0s the peak concentration arrival time at the outlet for each of them. The curves noted A, B and C, correspond to the injection locations indicated on Fig. 2.

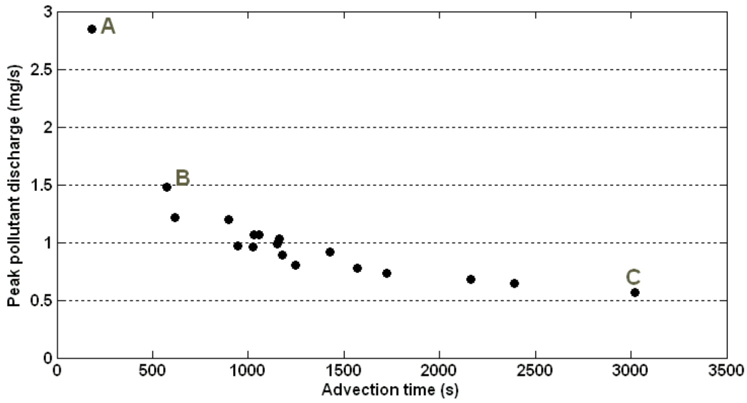

Figure 5: Outlet concentration peaks (obtained from Fig.4) as a function of the pollution advection time from its injection location to the outlet section (small advection times, such as A, refer to inlet injections located near the outlet on Fig.2, high advection times, such as C, refer to injections located near the inlet branches on Fig.2).

3.2 <u>Survey and Econometric Model</u>

The data proceed from a survey administered in April and May 2013 on the Saint Priest municipality (to encompass the hydrodynamic simulations context). The questionnaire has been designed jointly with GL; it is quite in-depth, so that relatively a lot of information is extracted from each observation, as shown below. The response rate was rather high, around 20 to 30%, considering that it was not possible to make an appointment beforehand. The respondents chose to participate before knowing the subject of the survey, so that we can exclude sample selection bias. 101 complete and usable questionnaires have been collected, in face to face interviews using a planned random sampling procedure designed to avoid all forms of spatial clustering. In spite of its small size, the sample appears quite representative of the municipality in terms of age and gender, somewhat less in terms of professions.

The main question of the survey is summarized in Table 1; it shows that respondents are well aware of what their household does with each type of waste as there are very few "don't know" or "other/unspecified" answers (6^{th} and 8^{th} columns). Those wastes that are discarded via the exterior network, e.g. storm drains, are also marginal (5^{th} column of Table 1). Depending on the waste category, the three main ways of discarding are the general waste bin (0 to 91%), the recycling bin (0 to 79%), or the home wastewaters system (0 to 85%). Seven categories of waste are never (or 1%) discharged into the home wastewaters network: Solid foodstuffs, Phytosanitaries, Hydrocarbons, Pharmaceuticals, Cosmetics & hygiene: solids, Cigarette stubs and Soil/sand.

Table 1: Statistics sorted from the answers to the questionnaire. The question asked to the respondents was (translated here from French to English): "For each of the following refuse, indicate how you usually discard it. This question is about your own habits; later, you will be asked about what you think neighbors and relatives do."

Behaviors (%) →	General waste bin	Recycling : facility, retailer, specialist, ...	Home wastewaters : sinks, toilets	Exterior wastewaters: gutters, drains	You do not know	You do not produce this refuse	Other
Cooking fat refuse	19.61	10.78	39.22	0	0.98	29.41	0
Liquid foodstuffs	12.75	2.94	74.51	0	0	8.82	0.98
Solid foodstuffs	91.18	2.94	0	0	0	3.92	1.96
Tea leaves & coffee	46.08	9.8	28.43	1.96	0	2.94	10.78
Home cleaning products	1.96	3.92	85.29	0	0	6.86	1.96
Solvents and paint remnants	6.86	47.06	8.82	0.98	0.98	33.33	1.96
Phytosanitaries	2.94	9.8	0.98	1.96	0.98	81.37	1.96
Hydrocarbons	0	63.73	0	0	2.94	32.35	0.98
Pharmaceuticals	11.76	79.41	0.98	0	0.98	5.88	0.98
Cosmetics & hygiene : liquids	38.24	6.86	22.55	0	2.94	29.41	0
Cosmetics & hygiene : solids	88.24	1.96	0.98	0	1.96	6.86	0
Toilet paper rolls	54.9	25.49	18.63	0	0	0.98	0
Cigarette stubs	25.49	0	0.98	0.98	0	69.61	2.94
Soil, sand or similar	11.76	17.65	0	3.92	1.96	46.08	18.63

The row and column titles are summarized for presentation; they are more complete and less technical in the questionnaire

The sequential nature of the responses in Table 1 is a panel: each respondent answers several times, once for each type of waste (i.e. each line of Table 1). In the following, we consider only the decision to discard in the home wastewaters network or not; that is, collapsing all the columns of Table 1 but the "home wastewaters" one. Formally, following Cameron and Trivedi (2005), such a dichotomic decision, in a panel-data setting, can be represented by the logit panel-data model :

$$\Pr\{y_{it} = 1 | \alpha_i, \beta\} = \frac{\exp(\alpha_i + x_{it}\beta)}{1 + \exp(\alpha_i + x_{it}\beta)} \qquad (1)$$

where $y_{it}=1$ if respondent i chooses to discard waste t in the home wastewaters system, and $y_{it}=0$ otherwise; x_{it} is a vector of regressors or explanatory factors; α_i is the respondent's unknown specific effect and β is a vector of unknown coefficients. Estimation of the β coefficients is classically by maximum likelihood and is implemented in many econometric packages. The sign of an estimated coefficient indicates its qualitative effect on $\Pr\{y_{it}=1\}$: if the sign is positive (negative), then an increase in the corresponding factor increases (decreases) $\Pr\{y_{it}=1\}$, other things equal. The full marginal effect can also be computed, but that is beyond the scope of this paper.

The Hausman (1978) test indicates unequivocally an absence of endogeneity on the individual-specific effects α_i; therefore, we prefer the so-called random-effects model for its statistical efficiency; that means in particular that unobserved individual factors, although certainly effecting the decision to discard, are uncorrelated with any of the factors that are included in the model – there is no confounding effect. Presumably there is a correlation between waste behaviors; for example, one might think that some people prefer recycling any waste wherever possible. The random-effects panel-data model assumes that the correlation is the same among all wastes and respondents (equicorrelation, Cameron and Trivedi, 2005).

The results are presented in Table 2 for the seven "chemical" wastes from Table 1, 5th to 11th rows, that is 707 observations for 101 respondents. The focus has been on the "chemical" wastes because it seemed intuitive to consider relatively homogenous wastes.

Table 2: Probability to reject in home wastewaters network various "chemical" wastes. Random-effects panel data logit.

Reject in home wastewaters network (Yes=1 / No=0)		Type	$\hat{\beta}$	p-value
Waste type	Reference: Home cleaning products	Constant	1.26	0.61
	Solvents and paints	0/1	-4.47	**0.00**
	Phytosanitaries	0/1	-6.19	**0.00**
	Hydrocarbons	0/1	-22.41	1.00
	Pharmaceuticals	0/1	-5.82	**0.00**
	Cosmetics & hygiene : liquids	0/1	-6.17	**0.00**
	Cosmetics & hygiene : solids	0/1	-3.15	**0.00**
8 unpresented non-significant socioeconomic regressors, see below.				
Public good / Altruism	Lived a long time in the region	0/1	0.09	0.86
	Knows what treatment plants are for	0/1	0.50	0.32
	Knows if home network connect to treat. plant	0/1	-0.22	0.66
	Worried by water pollution	0/1	-0.90	**0.13**
	Has water-based leisures	0/1	-0.11	0.83
Reputation	Ready to change habits	0/1	-0.83	**0.12**
	Neighbors reject same waste in home network	0/1	0.98	**0.00**

Table 2 shows very different intercepts for each type of waste, as is expected from Table 1 on behaviors. The probability of discarding in the home network changes dramatically (from about 85% to virtually 0%) among waste types. That is reflected by the high significance (p-values much smaller than the conventional 5%) of the 12 variables indicating the waste type in Table 2. On the other hand, none of the classical socio-economic variable is statistically significant (p-values larger than the conventional 5%) to explain the discarding decision: age, gender, education, family composition, presence of pet, home ownership; in other words, no socio-economic characteristic has a statistically discernible effect on the discarding decision. But also the regressors that could indicate “public good / altruism” motivated respondents – the respondent “Lived a long time in the region”, “Knows what treatment plants are for”, “Knows if home network connect to treatment plant”, “Worried by water pollution” or “Has water-based leisures” – have no statistically significant influence (p-values higher than 5%), or in any case, no influence that is similar among all respondents.
The dichotomous variable “Neighbors reject same waste in home network” takes the value one if the respondent believes that neighbors and relatives discard the corresponding waste in the home wastewaters network; this variable is called “mimic” for short. Mimic is certainly striking as potentially endogenous in the sense that it may be governed by the same, possibly unobserved, variables as the variable of interest (Reject in home wastewaters network, 0/1); that is, the respondents might rationalize or justify their behavior by stating that they are not worse or better than their neighbors. Tests show however that this is not the case and this gives a causal sense to the mimic regressor in the sense that changing (or informing) the perception that residents have from their neighbors or relatives discarding behavior, for example through a public awareness campaign, certainly would cause a change in residents’ behavior. A detailed account of the testing is given by Polome (2013). Mimic is highly significant (p-value much smaller than 5%); its $\hat{\beta}$ sign is positive (“if I think others discard in the network, it is more likely that I do it myself”) and the coefficient is relatively large when compared to the dichotomous variables that indicate the type of waste.
Another variable, “Ready to change [one’s] habits”, may be categorized as reputation effect in the sense of Bénabou and Tirole (2006) because it is an attempt to demonstrate a form of goodwill to the outside world (or at least to the interviewer). Its p-value is close to 10%, which, although not significant, is the smallest one except mimic and the waste types; that is another sign that the reputation effects are the main, if not the only, drivers of household wastewater behaviors.

4 Conclusions

The aim of the present paper was for the Greater Lyon Metropolitan Area (GL) to identify ways to reduce the pollutions injected by residents in the wastewater network system. Two possibilities, corresponding to the two main parts of this study, were tested: i) is it possible to easily identify the polluter in order to focus on the house or neighborhood to work with for changing habits and ii) what incentives should be considered to induce changes in residents' habits of discarding waste in the wastewater network.

The first part aimed at verifying whether it is possible to identify a polluter from the analysis of the concentration signal acquired by a sensor located at the outlet of a wastewater watershed. To do so, the geometry of the wastewater sewer network of St Priest, a suburb of Lyon in France, is created and meshed and the typical 3D flow corresponding to the statistical water discharge consumed at 9am by the residents is computed. Pollutant injection from each house is modelled and the pollutant concentration responses at the outlet are compared to each other. It appears that all signals are alike, resemble normal distributions, and thus prohibit any identification of the polluter. The only information that could be sorted would be an estimation of the pollutant advection time which would be useful only for very restrictive configurations.

The second part of the paper presented results of a survey on the behavior of discarding wastes in the home wastewater network. Behaviors were seen to be markedly different among different types of wastes. The respondents appear well aware of how their households discard each type of wastes. A striking result is that none of the "typical" socio-economic factors are near standard statistical significance levels. Following Bénabou and Tirole (2006), factors are separated between those that might reflect "altruism / public good" and "reputational" motives for these behaviors (financial motives are non-existent in this case). It is surprising that none of the factors that might reflect an "altruism / public good" motive is significant. Therefore, it does not seem possible to influence the behavior of discarding in the home wastewater system through the "altruism / public good" motives, e.g. conscientization of the environmental impact wastewater is unlikely to effect individual behavior. Two factors reflect reputational motives: "Willingness to change one's habits" and "Whether the respondent thinks that his neighbors reject the corresponding waste category in the home wastewaters network". The latter is the only factor that has a clear statistically significant effect (in addition to the dichotomous factors that indicate each waste type). In other words, when a respondent thinks her neighbors discard a particular type of waste through the home wastewaters, it is much more likely she does it herself for the same waste. Statistical tests allows to interpret these results in a causal sense, that is to say, it is not because a respondent discards a particular type of waste in the home wastewaters network that she will declare that her neighbors do likewise.

Therefore, if one can influence the perception of what neighbors discard in the home wastewaters network, one could likely influence discharges into that network. The present study does not determine what form such influence should take, but the results clearly suggest that the most effective topic will likely be the behavior of neighbors or relatives, and not, for example, the effects on the environment, or images of water pollution. Campaigns like those on the proportion of the population that recycles batteries or lightbulbs would fit such description.

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