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Urban Domestic Wastewater: How to reduce individual injection?

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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.

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

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

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

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

92

93 **2 Methodology of Research**

94 **2.1 Hydrodynamic Simulation**

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

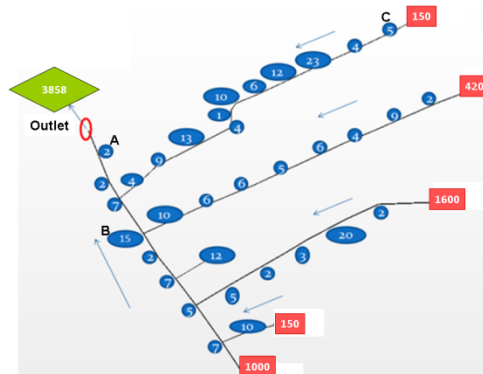
100 is investigated numerically (see De Marchis et al. 2013 for a similar approach based on a 1D
101 numerical model to simulate the dispersion of *E. coli*). The following paragraphs highlight the
102 selected methodology.

103 The separated sewer network presented in Fig. 1 is selected in the St Priest city (close to
104 Lyon, France). It is located within a 1 km² area, mainly comprising individual houses. The GL
105 water management services provided maps and GIS data detailing: i) the topology of the
106 sewer network, ii) the slope and diameter of each conduit and iii) the location of the inlets and
107 corresponding number of connected houses (see Fig. 2).



108

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



111

112 *Figure 2: Simplified sketch of the selected network with the number of houses located within*
113 *the catchment watershed and connected to the branches of the present network (red squares),*
114 *connected to each inlet (blue ellipses). The total number of involved houses finally equals*
115 *3858 (end-of-pipe green diamond). Three specific injection locations noted A, B and C will be*
116 *used for analyzing the numerical results in Figs. 4 and 5.*

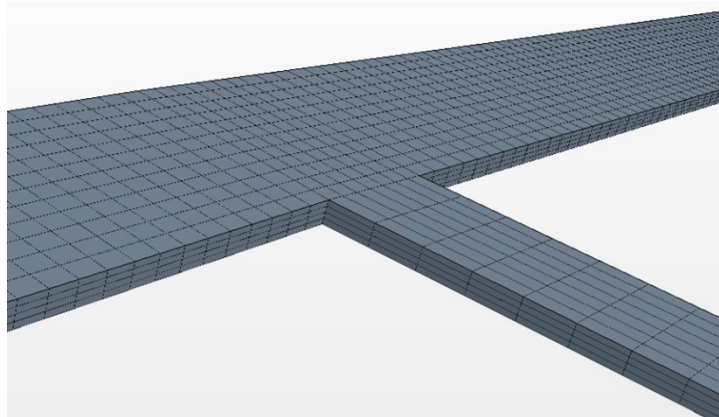
117 The discharge entering the network at each inlet is assumed to be equal to the number of
118 houses connected to this inlet multiplied by four inhabitants per house and multiplied by the
119 average individual water consumption at 9:00 am (0.31 L per minute per inhabitant)
120 according to the standard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

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

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

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

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



156

157

Figure 3: Computational mesh near a junction.

158 2.2 Household Waste Behavior

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

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

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

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

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

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

204

205 **3 Results and Discussion**

206 **3.1 Concentration profiles in sewer pipes**

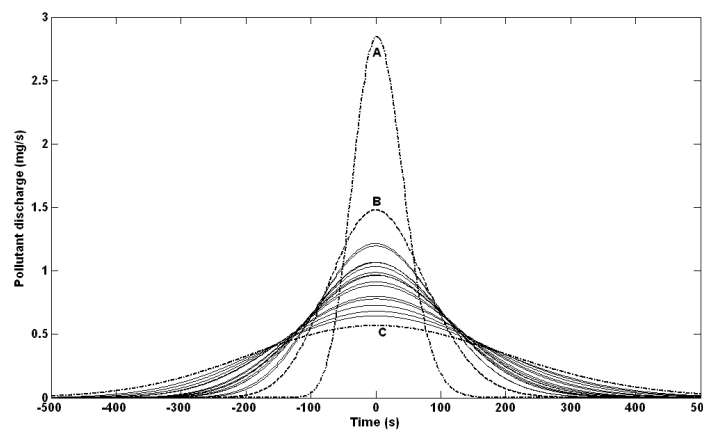
207 For each simulation, the pollution propagation is computed from the corresponding inlet to
208 the downstream section. The pollutant cloud appears to be conveyed with the main current
209 and to diffuse laterally, vertically and along the streamwise direction. Moreover, complex
210 turbulent mixing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

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

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

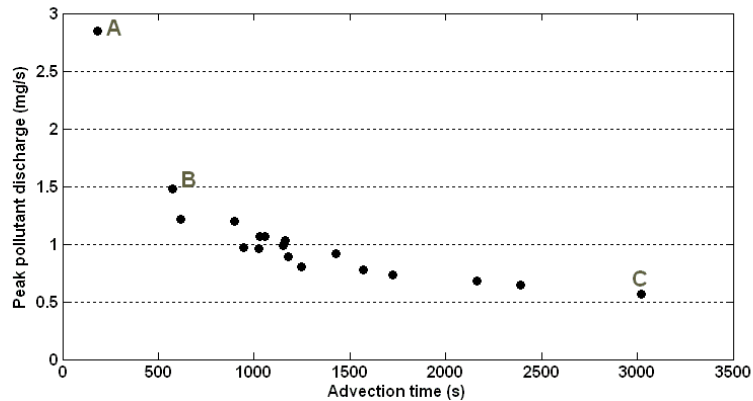
223 The peak concentration displayed on Fig.4 for each curve is plotted in Fig.5 as a function of
224 the convection time of the pollutant from the corresponding injection inlet to the downstream
225 section. A fine correlation is obtained: as the convection time increases, the pollution cloud
226 diffusion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

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



240

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



245

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

250 3.2 Survey and Econometric Model

251 The data proceed from a survey administered in April and May 2013 on the Saint Priest
 252 municipality (to encompass the hydrodynamic simulations context). The questionnaire has
 253 been designed jointly with GL; it is quite in-depth, so that relatively a lot of information is
 254 extracted from each observation, as shown below. The response rate was rather high, around
 255 20 to 30%, considering that it was not possible to make an appointment beforehand. The
 256 respondents chose to participate before knowing the subject of the survey, so that we can
 257 exclude sample selection bias. 101 complete and usable questionnaires have been collected, in
 258 face to face interviews using a planned random sampling procedure designed to avoid all
 259 forms of spatial clustering. In spite of its small size, the sample appears quite representative of
 260 the municipality in terms of age and gender, somewhat less in terms of professions.

261 The main question of the survey is summarized in Table 1; it shows that respondents are well
 262 aware of what their household does with each type of waste as there are very few “don’t
 263 know” or “other/unspecified” answers (6th and 8th columns). Those wastes that are discarded
 264 via the exterior network, e.g. storm drains, are also marginal (5th column of Table 1).
 265 Depending on the waste category, the three main ways of discarding are the general waste bin
 266 (0 to 91%), the recycling bin (0 to 79%), or the home wastewaters system (0 to 85%). Seven
 267 categories of waste are never (or 1%) discharged into the home wastewaters network: Solid
 268 foodstuffs, Phytosanitaires, Hydrocarbons, Pharmaceuticals, Cosmetics & hygiene: solids,
 269 Cigarette stubs and Soil/sand.

270 *Table 1: Statistics sorted from the answers to the questionnaire. The question asked to the*
 271 *respondents was (translated here from French to English): “For each of the following refuse,*
 272 *indicate how you usually discard it. This question is about your own habits; later, you will be*
 273 *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
Phytosanitaires	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

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

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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 :

282

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

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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.

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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).

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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.

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303

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
	Phytosanitaires	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 unrepresented 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

304

305 Table 2 shows very different intercepts for each type of waste, as is expected from Table 1 on
306 behaviors. The probability of discarding in the home network changes dramatically (from
307 about 85% to virtually 0%) among waste types. That is reflected by the high significance (p-
308 values much smaller than the conventional 5%) of the 12 variables indicating the waste type
309 in Table 2. On the other hand, none of the classical socio-economic variable is statistically
310 significant (p-values larger than the conventional 5%) to explain the discarding decision: age,
311 gender, education, family composition, presence of pet, home ownership; in other words, no
312 socio-economic characteristic has a statistically discernible effect on the discarding decision.
313 But also the regressors that could indicate “public good / altruism” motivated respondents –
314 the respondent “Lived a long time in the region”, “Knows what treatment plants are for”,
315 “Knows if home network connect to treatment plant”, “Worried by water pollution” or “Has
316 water-based leisures” – have no statistically significant influence (p-values higher than 5%),
317 or in any case, no influence that is similar among all respondents.

318 The dichotomous variable “Neighbors reject same waste in home network” takes the value
319 one if the respondent believes that neighbors and relatives discard the corresponding waste in
320 the home wastewaters network; this variable is called “mimic” for short. Mimic is certainly
321 striking as potentially endogenous in the sense that it may be governed by the same, possibly
322 unobserved, variables as the variable of interest (Reject in home wastewaters network, 0/1);
323 that is, the respondents might rationalize or justify their behavior by stating that they are not
324 worse or better than their neighbors. Tests show however that this is not the case and this
325 gives a causal sense to the mimic regressor in the sense that changing (or informing) the
326 perception that residents have from their neighbors or relatives discarding behavior, for
327 example through a public awareness campaign, certainly would cause a change in residents’
328 behavior. A detailed account of the testing is given by Polome (2013). Mimic is highly
329 significant (p-value much smaller than 5%); its $\hat{\beta}$ sign is positive (“if I think others discard in
330 the network, it is more likely that I do it myself”) and the coefficient is relatively large when
331 compared to the dichotomous variables that indicate the type of waste.

332 Another variable, “Ready to change [one’s] habits”, may be categorized as reputation effect in
333 the sense of Bénabou and Tirole (2006) because it is an attempt to demonstrate a form of
334 goodwill to the outside world (or at least to the interviewer). Its p-value is close to 10%,
335 which, although not significant, is the smallest one except mimic and the waste types; that is
336 another sign that the reputation effects are the main, if not the only, drivers of household
337 wastewater behaviors.

338

339 4 Conclusions

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

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

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

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

383
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387 **References**
388 Bénabou R. and Tirole J. 2006 Incentives and prosocial behavior. *American Economic*
389 *Review*, **96**(5),1652–1678.

390 Cameron A. C. and Trivedi P. K. 2005 *Microeconometrics Methods and Applications*.
391 Cambridge University Press.

392 Dalmon A., Mignot E., Riviere N., Lipeme Kouyi G., Momplot A., Gonzalez C. and
393 Escauriaza C. 2015 Mélange à l'aval d'une confluence d'écoulements à surface libre, 22e
394 Congrès Français de Mécanique, Lyon, August, 2015, in French.

395 De Marchis M., Freni G. and Napoli E. 2013 Modelling of E. coli distribution in coastal areas
396 subjected to combined sewer overflows, *Water Science and Technology*, **68**(5), 1123-1136.

397 Dorval F. 2011 Mise au point de techniques de traitement de données en continu pour
398 l'identification des composantes de débit à l'exutoire des bassins versants urbains : Etude de
399 cas des bassins versants Django Reinhardt et Ecully (in French). PhD thesis, INSA LYON.

400 Fischer H.B., List E.G., Koh R.C.Y., Imberger J. and Brooks N. H. 1979 *Mixing in Inland
401 and Coastal Waters*, Academic Press, New York, NY.

402 Frank T., Lifante C., Prasser H.-M., and Menter F. 2010 Simulation of turbulent and thermal
403 mixing in T-junctions using {URANS} and scale-resolving turbulence models in {ANSYS}
404 {CFX}. *Nuclear Engineering and Design*, **240**(9), 2313 – 2328.

405 Gaudet J.M. and Roy A.G. 1995 Effect of bed morphology on flow mixing length at river
406 confluences. *Nature*, **373**, 138-139.

407 Hausman J.A. 1978 Specification tests in econometrics. *Econometrica*, **46**, 1251–1271.

408 JO 2010 Journal Officiel du 25 janvier 2010 relatif aux méthodes et critères d'évaluation de
409 l'état écologique, de l'état chimique et du potentiel écologique des eaux de surface. Journal
410 Officiel (France).

411 Lane S.N., Parsons D.R., Best J.L., Orfeo O., Kostaschuk R.A. and Hardy R.J. 2008 Causes
412 of rapid mixing at a junction of two large rivers: Río Paraná and Río Paraguay, Argentina,
413 *Journal of Geophysical Research: Earth Surface* (2003–2012), **113**, F2, DOI:
414 10.1029/2006JF0007453.

415 MEDDE 2015, Statistiques du Ministère de l'Ecologie du Développement Durable et de
416 l'Energie : L'essentiel sur Eau et assainissement, gestion de l'eau potable et des eaux usées
417 [http://www.statistiques.developpement-durable.gouv.fr/lessentiel/ar/306/1168/prix-leau-](http://www.statistiques.developpement-durable.gouv.fr/lessentiel/ar/306/1168/prix-leau-domestique.html)
418 [domestique.html](http://www.statistiques.developpement-durable.gouv.fr/lessentiel/ar/306/1168/prix-leau-domestique.html), in French.

419 Mignot E., Bonakdari H., Knothe P., Kouyi G. L., Bessette A., Rivière N. and Bertrand-
420 Krajewski J.-L. 2012 Experiments and 3d simulations of flow structures in junctions and
421 their influence on location of flowmeters. *Water Science & Technology*, **66**(6), 1325–1332.

422 Mignot E., Vinkovic I., Doppler D. and Riviere N. 2013 Mixing layer in open-channel
423 junction flows. *Environmental Fluid Mechanics*, **14**, 1027-1041, DOI 10.1007/s10652-013-
424 9310-7.

425 Momplot A., Bonakdari H., Mignot E., Lipeme-Kouyi G., Riviere N. and Bertrand-Krajewski
426 J. 2012 Effects of computational meshes on hydrodynamics of an open channel junction
427 flow using cfd technique. In *9th International Conference on Urban Drainage Modelling*,
428 Belgrade, Serbia.

429 Momplot A., Lipeme Kouyi G., Bertrand-Krajewski J.-L., Mignot E., and Riviere N. 2013
430 Modélisation tridimensionnelle des écoulements multiphasiques en régime instationnaire au
431 droit d'ouvrages spéciaux présents en réseau d'assainissement : performances des modèles
432 et analyse de sensibilité, *La houille blanche*, **4**, 16-24, in French.

433 Namour P., Lepot M. and Jaffrezic-Renault N. 2010 Recent trends in monitoring of european
434 water framework directive priority substances using micro-sensors: A 2007–2009 review.
435 *Sensors*, **10**(9), 7947–7978.

436 OECD 2008 Organization for Economic Co-operation and Development: Household
437 Behaviour and the Environment : Reviewing the Evidence, available at:
438 <http://www.oecd.org/environment/consumption-innovation/42183878.pdf>.

439 Padhye L. P. and Tezel U. 2014 Fate of Environmental Pollutants. *Water Environment*
440 *Research*, 2014 Literature Review, **60**, 1714-1773

441 Polome P. 2013 Mimic behavior in home waste-waters management. *GATE-LSE Working*
442 *Paper* 1325, available at: <https://halshs.archives-ouvertes.fr/halshs-00855051>.

443 Rice S.P., Roy A.G. and Rhoads B.L. 2008 River confluences, tributaries and the Fluvial
444 Network. Wiley.

445 Riviere N., Cai W., Lipeme Kouyi G., Momplot A. and Mignot E. 2015 Mixing downstream a
446 90° open channel junction, Proceedings of the 36th AIRH World Congress, Delft-the Hague,
447 The Netherlands, June-July 2015.

448 Romero-Gomez P., Ho C. and Choi C. 2008 Mixing at cross junctions in water distribution
449 systems, i: Numerical study. *Journal of water resources planning and management*, **134**,
450 285–294.

451 Shakibainia A., Tabatabai M.R.M. and Zarrati A.R. 2010 Three-dimensional numerical study
452 of flow structure in channel confluences. *Canadian Journal of Civil Engineering*, **37**(5),
453 772-781.

454 UWWTC 1991 Urban Waste Water Treatment Council directive 91/271/eec of 21 may 1991
455 concerning urban waste-water treatment. OJ, L(135), 40–52, 30.5.1991.

456 WFD 2000 Water Framework Directive 2000/60/ec of the european parliament and of the
457 council of 23 October 2000 establishing a framework for community action in the field of
458 water policy. OJ, L(327), 1–73, 22.12.2000.

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