INTERNATIONAL POLICY CENTER
Gerald R. Ford School of Public Policy
University of Michigan

IPC Working Paper Series Number 67

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November, 2007

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Preliminary Draft: 11/30/2007, Comments Welcome

Abstract

We examine the effect of political decentralization on pollution spillovers across jurisdictional boundaries. Upstream water use has spillover effects on downstream jurisdictions, and greater decentralization (i.e. a larger number of political jurisdictions managing the same river) may exacerbate these spillovers, as upstream communities have fewer incentives to restrain their members from polluting the river at the border. We use GIS to combine a panel dataset of 9,000 water quality measures collected at 321 monitoring stations across Brazil with maps of the evolving boundaries of the 5500 Brazilian counties to study (a) whether water quality degrades across jurisdictional boundaries due to increases in pollution close a river's exit point out of a jurisdiction, and (b) what the net effect of a decentralization initiative on water quality is, once the opposing impacts of inter-jurisdictional pollution spillovers and increased local government budgets for cleaning up the water are taken into account. We take advantage of the fact that Brazil changes county boundaries at every election cycle, so that the same river segment may cross different numbers of counties in different years. We find evidence of strategic enforcement of water pollution regulations; there is a significant increase in pollution close to the river's exit point from the upstream county, and conversely a significant decrease in pollution when the measure is taken farther downstream from the point of entrance. Pollution increases by 2.3% for every kilometer closer a river gets to the exiting border, but in the stretch within 5 kilometers of the border this increase jumps to 18.6% per kilometer. Thus the greatest polluting activity appears to be very close to the exiting border. Our theoretical model coupled with the empirical results are strongly suggestive that these results are evidence of strategic spillovers rather than spurious correlation between county splits and pollution stemming from changing population density. Even in the presence of such negative externalities, the net effect of decentralization on water quality is essentially zero, since some other beneficial by-products of decentralization (in particular, increased local government budgets) offsets the negative pollution spillover effects.

We thank Marianne Bertrand, Erin Mansur, Bernardo Mueller, numerous water management practitioners at the federal and various state water agencies in Brazil, and seminar participants at the University of Colorado at Boulder, Yale University, University of Michigan, Harvard University, Wesleyan University, the 2007 NBER Summer Institute in Environmental Economics, 2007 BREAD conference and the 2006 ISNIE conference for helpful discussions and comments. All errors are our own.

1. Introduction

Water is a publicly provided good of fundamental importance. Over one billion people in the world lack sufficient water, and over 90 percent of sewage and 70 percent of industrial wastes are dumped into surface water untreated (Revenga 2000). Diarrhea, whose incidence is related to the lack of access to clean water, kills 1.3 million children every year and accounts for 12 percent of under-5 mortality (WHO 2003).

The hundreds of international and intra-national conflicts over water sharing throughout history (Wolf 2002) are symptomatic of the microeconomics of water quantity and quality degradation. The flow of rivers creates 'upstream' and 'downstream' regions, and water conflicts are often related to the opening of a diversion gate upstream or the discharge of pollutants into the water as it flows downstream. With negative spillovers on downstream users, water use may be 'inefficient' from a societal perspective in the absence of inter-jurisdictional coordination.

Decentralization initiatives promoted by international organizations as a way to improve public service delivery (World Bank 2003, Bardhan 2002) may actually exacerbate cross-border spillovers once jurisdictions start making unilateral decisions. For example, a reduced role for the central authority in favor of sub-national (e.g. state or county) government management could lead to upstream water policy that promotes over-usage and over-pollution, as costs to downstream communities are not considered during planning processes. On the other hand, if decentralization increases local government budgets or otherwise reallocates resources toward environmental or sanitation spending, it has the potential to improve water quality. These issues are not unique to water quality, and are relevant for any publicly provided good with spillovers.

For example, local governments may under-invest in health programs if the positive spillover benefits of improvements in health status (e.g. Miguel and Kremer 2004) to those residing outside the jurisdiction are not taken into account.

This paper empirically examines the effect of a particular form of decentralization - the geographic splitting of counties leading to a larger number of counties managing the same river segment - on negative water quality spillovers on downstream users in Brazil. We combine a rich panel dataset of water quality measures collected at monthly intervals at 321 upstream-downstream pairs of monitoring stations located in all eight major river basins across Brazil with GIS maps of evolving county boundaries to examine (a) whether water quality degrades due to increases in pollution close a river's exit point out of a jurisdiction, and (b) the net effect of decentralization on water quality, accounting for both spillovers and budgetary impacts. We find substantial evidence that Brazilian counties strategically pollute close to the river's downstream exit point out of the county (and conversely, remain clean at upstream locations where the river enters the county), but no evidence that the decentralization initiative causes an overall deterioration in water quality, suggesting the presence of offsetting budgetary effects.

We can replicate Sigman (2002)'s empirical approach for analyzing pollution in international rivers to examine whether there are differentially larger drops in quality at monitoring stations downstream from a jurisdictional boundary (or more generally, when a river crosses a larger number of boundaries). However, the number of boundary crossings is likely correlated with other characteristics of the counties through which the river flows including major economic activities in the county, population heterogeneity, and environmental spending. Some characteristics correlated with both water quality and county size (which in turn is correlated with distances to county borders and boundary crossings) are not observed in the data and this can introduce bias in estimated spillover effects.[1]

We then take advantage of the fact that Brazil redraws county borders (the number of counties increased from 4492 in 1991 to 5562 in 2001), thereby changing both the number of boundary crossings and distances to nearest borders for the same river segment over time. This enables us to more precisely identify the effects of changes in proximity to borders and decentralization on the inter-temporal *change* in water quality deterioration by controlling for fixed effects for each station-pair (or the river segment defined by that pair). Since each county has some policy-making authority over environmental regulatory standards and over sanitation spending, the splitting of counties leads to *de facto* decentralization in the sense that more separate jurisdictions gain control over water quality in a river segment.[2] Management of water at the baseline is already somewhat "decentralized" in the usual sense of the word, but examining the effects of changes in distances to borders and in the number of counties managing the same water is a particularly useful way of honing in on the inter-jurisdictional spillover effects.

Our dependent variable is the change in *Biochemical Oxygen Demand* (BOD) from the upstream to the downstream location in each station pair: $\Delta BOD = BOD_d - BOD_u$.[3] For the same station-pair the county re-districting can change

[1] Sigman (2002) notes the need to include monitoring station fixed effects to account for such heterogeneity, but is unable to do so since her border variables of interest do not vary over time.

[2] Sigman (2004) on the other hand uses variation in which U.S. states are authorized to enforce Clean Water Act regulations to study the border spillover effects stemming from such authorization. This allows her to control for a station-fixed effect, but since distances to borders do not vary over time, that variable remains omitted, which may be of concern if the placement of monitoring stations is not random.

[3] Sigman (2002) also uses BOD to study pollution in international rivers. BOD is relatively easily measured by standard procedures, helping to ensure data quality. BOD tends to travel farther downstream than some other pollutants, which makes it appropriate for a study on inter-jurisdictional spillovers. We use ΔBOD

the distance the river traverses in the "upstream county" (i.e. where the upstream station is located), the distance traversed in the "downstream county", and the number of county boundary crossings between the pair of stations. We use variation in all three dimensions in order to analyze both strategic pollution spillovers and the net effect on water quality from the decentralization that results from county splitting. The theoretical framework we develop shows that under strategic behavior, counties shift polluting activity to near their downstream exit border and remain clean in the upstream part of their own jurisdiction. Thus pollution level in the upstream county would be greater when measured closer to the exit border, and conversely, pollution level in the downstream county should be lower when measured further away from the upstream entering border. We find strong statistical evidence for both effects, suggesting the presence of spillovers due to such strategic behavior by counties. Further our theory also suggests that under strategic pollution shifting, water quality should fall more dramatically in the upstream county the closer we get to the exiting border, and our regression estimates indicate precisely this type of dynamic for changes in BOD in Brazilian rivers. When we allow for non-linear effects of distance to border, we find that BOD increases by 2.3% for every kilometer closer a river gets to the exiting border, but in the stretch within 5 kilometers of the border this increase jumps to 18.6% per kilometer. Thus the greatest polluting activity appears to be very close to the exiting border.

In spite of such clear evidence on cross-boundary spillovers, we find that the net effect on water quality of having extra boundary crossings induced by county splitting is

(rather than, say, BOD_d) as the dependent variable since pollution at any point on a river is determined by the entire "spatial history" of the river (tributary inflows and dumping at any point upstream), and BOD_u acts as an effective control variable for the determinants of pollution anywhere upstream of point *u*. Our empirical models are then left with the simpler task of explaining the change in pollution from the upstream point to the downstream point as a function of the characteristics of counties in between the two points.

statistically indistinguishable from zero. County splitting may be associated with potentially countervailing benefits from (a) the increased aggregate public services budgets that accompany decentralization, and (b) the possibly greater homogeneity in population that results. Each county in Brazil receives a fixed transfer from upper-level governments in addition to a portion of the taxes collected in their jurisdiction. Thus the replacement budget for the smaller counties after a split exceeds the original county's budget. County fixed effects regressions show that per-capita sanitation spending increases by 20% in counties that are split, which potentially explains the improvement in water quality offsetting the negative spillover effects. Further we find that the net effect of decentralization on water quality is negative when we condition on monitoring stations located closer to borders (as opposed to the nil effect in the full sample). Close-to-border is also where spillovers are larger, so this further buttresses the case that there appears to be a spillovers-budgets tradeoff inherent in this process of decentralization.

A key concern with our estimation strategy is whether factors correlated with increases in pollution affect a county's propensity to split. For example, increasing population density may be correlated with both the propensity to split and with changes in pollution. It is not obvious that such a story would explain the specific pattern of strategic pollution shifting we report (that pollution increases non-linearly and more dramatically in the upstream county the closer we get to the exiting border), but nonetheless we want to be as careful as possible in differentiating evidence of true strategic behavior from spurious correlations. We therefore theoretically model this specific form of endogeneity (where a jurisdictional split occurs endogenously in an area with high population density), and examine the spatial pattern of pollution both upstream and downstream of county borders that would result under scenarios where endogenous population density-induced pollution is present, and in another scenario where it isn't. This yields an empirical test of that particular form of endogeneity (that splits occur in high density areas), and the data show that the specific spatial pattern of pollution that we report is not consistent with the hypothesis that endogeneity due to population density is the main driver of the relationship between decentralization and pollution spillovers.

In the absence of a suitable instrument for county splitting we also adapt the Altonji, Elder and Taber (2005) methods to assess the potential bias in our estimates from the possibility that counties split for other unobserved reasons correlated with water quality. If the selection on county splits due to the set of observed explanatory variables (e.g. changes in population density or GDP per capita) is any guide, then the bias stemming from unobservable determinants of county splits is not likely to be very large, and can explain away only a small portion of our results on spillovers. Finally, we also conduct sensitivity checks to ensure that these results are not driven either by the selective addition of new stations in areas where the pollution problems are worsening, or extreme values of BOD measures, or by changing population density in re-districted counties.

2. The Literature on Decentralization and Water Quality Spillovers

Decentralization has been one of those "buzz-words" promoted by many development scholars and practitioners as a way to improve public service delivery and rural development outcomes. The World Bank 2004 *World Development Report* on service delivery devotes large sections to the topic, and the World Bank has also made loans aimed at localization of projects, technical assistance based on local capacity building, and conducted budget analyses of inter-governmental transfers necessary for decentralization to be successful. Many other multi-lateral development institutions have policies encouraging decentralization. The UNDP's Decentralized Governance Program works with national level governments to support the empowerment of local governments. The FAO has a policy of prioritizing work with local governments and encouraging rural and local governments to take a leading role in their projects. However, the relative merits of decentralized versus centralized organization of public services remains a debated topic in the scholarly literature. At issue is balancing the objective of improving accountability and responsiveness of the public sector with the difficulty of providing public goods with benefits or costs that cross jurisdictional boundaries. Identifying conditions under which decentralization improves the efficiency of the public sector remains a key policy challenge.

In its early stages, the contribution of the economics literature to the decentralization debate was primarily theoretical. Oates (1972)'s seminal work on the topic argues that decentralization improves efficiency if it enables communities to take advantage of heterogeneity in preferences over public goods provision. However, Oates (2001) argues that there are two major sources of inefficiency under decentralization. It allows communities to ignore the externalities that they impose on other regions and it causes duplication in management bureaucracy. List and Mason (2001) show that as long as such spillovers are not too high, decentralization will improve efficiency over a centralized government setting uniform pollution standards under heterogeneity in the costs of pollution across localities. Coate and Besley (2000), by contrast, note that when the budget is shared between localities and there is heterogeneity in preferences within communities, the optimal allocation of the public good need not be reached as each community does not pay the full marginal cost of local programs.

Insights from the environmental "race to the bottom" literature are also relevant for evaluating the merits of decentralization. Cumberland (1981) and others have argued that competition between jurisdictions to attract business investment may lead to a "race to the bottom" in environmental quality. In contrast, Oates (2001) suggests that a "race to the bottom" is unlikely to follow inter-jurisdictional competition, since environmental damage is capitalized into local property values, and as a result community members face the implicit shadow price of environmental damage even as they perceive the benefits of increased economic activity in their region.

The policy-making community has noted the relative paucity of empirical evidence for the various arguments in favor of and against decentralization (World Development Report 2000). This lack of empirical evidence is in part due to the difficulty of accurately measuring spillover effects, and in part a result of the impossibility of isolating the effect of decentralization when it is combined with a series of legislative reforms.

Sigman (2002) was the first to examine water pollution spillovers across jurisdictional boundaries. She finds that stations just upstream of international borders have higher levels of BOD than similar stations elsewhere. However, this effect is not robust to the inclusion of country fixed effects, and she herself warns of the dangers of interpreting correlations that may be driven by cross-country heterogeneity in some other unmeasured characteristic. Sigman (2005) improves this identification strategy in analyzing spillovers across U.S. states following the passage of the Clean Water Act. She uses variation in the time at which states were authorized to enforce the Clean Water Act within their boundaries in order to determine the impact of the decentralization of control over water policy. A key identifying assumption is that authorized states are comparable to other states at the baseline, and the timing and choice of states to authorize is essentially as exogenous event. Her estimation strategy requires identifying the location of monitoring stations relative to borders, and classifying each station as either upstream, downstream, or bordering a state boundary. Using a fixed 50-mile distance to the border to classify stations, she finds that a significant number of stations can be categorized in more than one group (i.e. they are both upstream of one boundary and downstream of another). The location of stations relative to state borders lacks any time variation, and empirical identification in the station-fixed-effect regressions comes from time variation in states' authorization status.

In contrast, our approach uses pairs of stations (rather than individual monitoring stations) as the unit of observation to examine changes in water quality from an upstream station to its nearest downstream station. Classification of "upstream' and "downstream" stations using GIS river flow vector maps is therefore natural and unambiguous. In addition, since our identification strategy takes advantage of the evolving county boundaries in Brazil over time, we have time variation in each station's distances to the nearest county exiting (i.e. downstream) and county-entering (i.e. upstream) borders. We identify the pollution effect of distance to border solely from *changes in that distance over time for the same monitoring station due to a change in the county boundary*. This reduces concerns about the strategic or non-random placement of monitoring stations relative to county boundaries. Unlike Sigman (2005), this also allows us to identify the effect of being an additional kilometer from the border, and examine non-linear pollution effects by distance to border (i.e. whether pollution increases more dramatically as the river flows downstream very close to the exiting border as opposed to further into the county, away from the border). We can also separately examine pollution attenuation once the river enters the downstream county, since that county has the reverse incentive to be more vigilant in deterring pollution at its own upstream locations close to its entering border. In addition to these distance variables, we also have variation in the number of county boundary crossings for the same river segment over time due to the re-drawing of county boundaries. This variable allows us to examine the *net effect* of the decentralization initiative, accounting for both inter-jurisdictional spillovers and changes in characteristics of the population or increased local government budgets that decentralization might afford.

Importantly, we examine the impacts of these three variables (distance to exiting border in the upstream county, distance to exiting border in the downstream county, and the number of boundary crossings) while controlling for a full set of station-pair fixed effects, which helps address concerns about omitted variable bias. Station pair fixed effects control for time invariant differences in population heterogeneity, geography, land use, and local economic structure. In addition, we directly control for changes in population density, county size, and GDP over time at all locations between the pair of stations. There is still the possibility of bias arising from the non-random re-districting of counties, which we discuss in greater detail in the next section, and address in the theory and empirical sections.

3. The Setting: Water, County Politics, and County Splitting in Brazil

Brazil's federal political system and the large variation in climates across its vast territory have meant that each region in Brazil has had a different experience with managing their water resources. States have devolved control over water management at different rates, and have encouraged varying levels of participation by civil society. Several case studies evaluate the decentralization of water policy in specific regions of Brazil. Brannstrom (2004) reports that decentralization policies encouraging interaction between all levels of government and the communities have been the most successful. Formiga-Johnsson and Kemper (2005) find that local sub-basin groups in the Alto-Tiete river basin have increased coordination following the growth of inter-county water management committees. The focus of and the conclusions the authors draw in these case studies point to the centrality of spillovers and the importance of inter-jurisdictional cooperation in managing a shared resource. These case studies show that inter-county management groups are important in enabling counties to negotiate for a reduction in the externalities imposed on them by their upstream neighbors.

A. Can Counties Affect Water Quality?

Although general environmental policy setting and enforcement is determined at the national and state levels, counties in Brazil have important powers over practices affecting the environment within their jurisdiction. Federal law establishes guidelines, norms, and minimum standards of environmental policy, but the importance of county government participation in environmental policy making has been continually acknowledged by both state and federal law since the 1977 Federal Water Law first established the principle of local participation in water quality management. The Federal Constitution empowers counties to pass laws complementary to federal and state laws, to establish local environmental standards, and to enforce standards within their jurisdiction. While county governments cannot institute standards lower than those passed by the state and federal government, they may enforce norms that are more strict (Engenharia and Projetos 2006). Virtually all counties in Brazil had either a ministry responsible for environmental issues or had an environment management council as of 2002, but less than 10% belonged to either an inter-county environmental management association or an inter-county water quality association (IBGE 2003).

Lack of sewage treatment is the most important source of water pollution across the densely populated areas of Brazil. Approximately 18 percent of counties report having open sewers which flood into major water systems. Farm runoff is the most important cause of water pollution in rural areas. Industrial dumping is also highlighted as a significant concern in approximately 10 percent of counties (see table 1).

The federal government devolved responsibility for sanitation services to the states in the 1970s. In the process of decentralization, states have allocated some authority over sanitation services to county governments. County governments have an important role in determining to which areas to extend sanitation services in peripheral regions that lack access to the sewer network. County governments also have the authority to either choose to continue publicly provided sanitation services through licensing them to the state sanitation agencies which are now privatized, or to implement their own sewage systems (Faria da Costa 2006).

Counties are able to fine and tax their community members for activities which cause pollution. In addition, they are able to forbid highly polluting practices and use zoning regulations to reduce direct runoff. They also manage programs for trash collection and sewage treatment (see table 2). The use of these enforcement mechanisms may not be evenly distributed within a county: the county administration has an incentive to increase spending on enforcement of pollution restrictions in areas of the county where pollution will be most harmful to community members.

B. The Process of Creating New Counties

Brazil created a large number of new counties by splitting larger counties during each election cycle in the 1990s, after the power to form new counties was devolved from the federal government to the state governments in the 1988 Federal Constitution. The reasons for creating new counties vary, but polls of mayors of new counties have highlighted the importance of disagreements over the amount of municipal funds used in the various districts of the original county, differences in economic activity across districts, and the large size of the original county (Bremaeker 1992). Other research suggests that the split can occur for purely administrative reasons and in order to better represent the political affiliation of the district which leaves the original county (de Noronha 1995). To the extent that counties have policy-making authority over any publicly provided good, the creation of new counties is a form of decentralization in the delivery of that public good (e.g. two smaller governments rather than one larger one are supplying the service to the same population).

The process of creating new counties begins with a feasibility study on the projected solvency of the potential county and a motion for a referendum on the proposal in the state legislature. Both the district newly acquiring county status and the county being split must ratify the proposal in a referendum. The referendums are followed by a state law passed by the state legislature and signed by the governor (Tomio 2002).

Counties receive transfers from both the federal and the state governments, and the incentives to create new counties are high. In addition to a portion of the income and industrial taxes collected in their jurisdiction, counties receive the Municipalities' Participation Fund (FPM). The amount transferred through the FPM is determined by population with 18 set steps, and the lowest amount is awarded to municipalities with less than 10,188 citizens. In response to the proliferation of new small municipalities, in 1996 a federal law was passed setting quotas for FPM by state (Tomio 2002).

The process of choosing counties to re-district is not random, and not necessarily uncorrelated with variables that affect water quality. For example, if a county is split due to significant ethnic or wealth differences between the separating district and the districts remaining in the county, the two new smaller counties may be more homogenous than the original larger county, which in itself may reallocate resources towards a variety of public goods including pollution abatement (Alesina, Baqir and Easterly, 1999). This is just an example of another mechanism that relates county splitting to water quality changes (along with spillovers and changes in local budgets), and therefore not a concern for the estimation, and may actually help explain the net effect of decentralization on pollution. An example of a different type of concern would be that counties with strong leadership or community involvement across districts are less likely to have districts separating, so that water quality would in general be lower in split areas. Since our regressions control for a full set of location fixed effects and inference is based only on *changes in water* *quality over time in the same river segment*, such level differences in water quality are not of concern for bias in the estimates. This may indicate, however, that our empirical identification comes from a 'special' set of counties, which limits the applicability of our results to other contexts.

The major concern here is that the non-random process of creating new counties may be endogenous to *changes in* water quality. The most straightforward example is that if districts with large increases in population density are more likely to separate from the county, then changes in boundary crossings would be correlated with changes in water quality for an independent reason (since population density likely contributes to pollution). We address this particular concern by always controlling for the changing population density in all counties between each pair of stations, but some residual concern might remain if the relationship between population density changes and county splitting is non-linear (e.g. counties split only after exceeding some population threshold). The next section therefore develops a theoretical model to predict the exact spatial pattern of pollution one might expect to see under endogenous population-based county splitting. This leads to an empirical test of the specific type of endogeneity we model, and our data strongly favor the case that strategic behavior rather than spurious endogeneity is the main driver of the pollution spillovers results we report.

One might also be concerned about other unobserved variables correlated with both county splitting and water quality changes. It is worthwhile noting that given the specific pattern of pollution spillovers we report (pollution increases at an increasing rate as the river heads toward the exit border and pollution decreases after it crosses the border), such observed variables would have to take a very specific form. It is difficult to rule out *all* possibilities, In the absence of a suitable instrument for county splitting, we adapt a bias estimation technique developed by Altonji, Elder, and Taber (2005) to estimate the maximum bias in our coefficients of interest stemming from unobservable factors affecting county splitting using as a guide the amount of selection in county splits that is due to other regressors that we have data on (such as population density, GDP etc.).[4] We find that the estimated bias cannot explain away the strong spillover effects we uncover.

4. A Theoretical Model of Pollution on a River

We model a river on a unit line flowing from left to right, with a population that consumes and pollutes distributed along the river according to a PDF $f(x)$ (see Figure 1). A person at location x consumes q_x, and there is a one-to-one relationship between this consumption and the pollution he emits into the river. Any pollution emitted at point x adversely affects people located downstream of x. This pollution exponentially decays as the river flows, and thus the pollution "felt" at downstream point t of the emission q_x is $q_x \cdot e^{-(t-x)}$. A social planner decides how much consumption (and pollution) to allow at each point within her jurisdiction by trading off the utility of consumption against the welfare cost of the pollution downstream, but subject to the constraint that pollution at any point x does not exceed $\bar{q}$, some natural limit on the 'need to pollute'. We begin

[4] Altonji, Elder and Taber (2005) study the effect of catholic school attendance in the presence of selection into catholic schools and the absence of an appropriate instrument for entry into catholic schools. There's an implicit assumption in this technique that the regressors we have data on are a random subset of all potential regressors correlated with both county splitting and water quality changes. This is quite a reasonable assumption, and in fact, we have data on population density, which is the most likely culprit for creating an endogeneity bias in our estimates.

with the case where the entire river falls under one jurisdiction, and later examine the effects of jurisdictional splits.

A. Pollution Prior to a Jurisdictional Split

At each point x the social planner chooses q_x to maximize the utility that the mass of individuals at x receive from consuming q_x net of the harm the associated pollution causes downstream: $W = f(x) \cdot u(q_x) - \int_x^1 q_x \cdot e^{-(t-x)} \cdot f(t) \cdot dt$ (subject to $q_x \leq \bar{q}$) (1)

This yields the first-order condition: $f(x) \cdot u'(q_x) = \int_x^1 e^{-(t-x)} \cdot f(t) \cdot dt \quad + \lambda$ (2)

where λ is the shadow value of the $\bar{q}$ constraint. In the simple case of the uniformly distributed population of mass 1 and log utility $[u(q_x) = \ln(q_x)]$, this yields the following solution for the per-person pollution allowance at point x: $q_x^* = \min(\frac{1}{1-e^{-(1-x)}}, \bar{q})$.[5] The solid blue line in figure 2 plots q_x^* for a $\bar{q}$ value of 40. Pollution and consumption allowances increase to the right, since the harm caused by upstream emissions is greater than the harm caused by emissions close to the exiting border out of the jurisdiction.

The actual pollution level felt at any point y on the river is the accumulation of all (decayed) pollution allowances to the left of point y: $P(y) = \int_0^y q_x^* e^{-(y-x)} \cdot f(x) \cdot dx$ (3)

[5] q_x^* switches from $\frac{1}{1-e^{-(1-x)}}$ to $\bar{q}$ at the point $\bar{x} = 1 + \ln(1 - \frac{1}{\bar{q}})$, to the right of which $\frac{1}{1-e^{-(1-x)}}$ gets too large. The $\bar{q}$ constraint is added to the model only for convenience – to avoid arbitrarily large pollution at the edge of the river. All our numerical simulations assume $\bar{q}$ =40, and at this value $\bar{x}$ is very close to the river's exit point out of the jurisdiction, so $\bar{q}$ does not play a numerically important role.

Even though there is no simple analytical solution for this integral, we can numerically integrate and plot the solutions for *P(y)* in figure 3. The figure shows that pollution level in a river increases as we head towards a river's exit point out of the jurisdiction, due to the county's strategic optimizing behavior to limit harm to its own constituents.

B. Effect of a Jurisdictional Split on Pollution

To examine the effect of a jurisdictional split on water pollution, we introduce a county split at 0.5 and solve for q_x^u and $P^u(y)$ for the upstream county, which is now only concerned about the harm its consumption decisions cause to its own constituents located in the interval [0,0.5], and for q_x^d and $P^d(y)$ for the downstream county, which is concerned about its own constituents at [0.5,1]. The dashed line in figure 2 shows that residents of the upstream half of the county are allowed to consume and pollute much more after the split, but the split causes no change in downstream county residents' pollution. The upstream county allows its residents to pollute more since part of the harm caused by the pollution is now an externality on the downstream county that does not enter its own optimizing calculus, whereas the downstream county experiences no such change in the tradeoff between utility and perceived harm. Figure 3 shows that overall pollution level in the river increases due to these "negative spillovers" brought about by the county split, and that downstream county residents are far worse off. The pollution function is no longer monotonically increasing since there is a sharp discontinuity in the consumption-pollution tradeoff calculus for the two social planners making decisions immediately to the left and to the right of the split.

C. Endogenous County Splitting with a Triangular Population Distribution

As discussed in the previous section, a key concern with our estimation strategy to identify the effect of decentralization on pollution spillovers is the possibility of endogenous splitting of jurisdictions in areas with high population density (where pollution problems are worsening for an independent reason). Under the particular form of welfare maximizing behavior by the county authority that we've assumed in the theory, there is actually no such endogeneity problem since the authority would respond to (say) a doubling of the population by simply halving each person's consumption allowance. With twice the population, each person's emissions cause double the harm, and so the county authority forces its citizens to cut back on consumption. However, to guide a careful empirical strategy we do want to allow for such endogeneity, so we will now assume that each person at location x emits ε_x in addition to the q_x, but that the ε_x emissions are un-monitored and beyond the control of the county authority. Thus we will model 'endogeneity' as follows: when population density increases at a location, counties are likely to split there, but there is also an independent effect on pollution at those locations since the ε component of emissions are now larger there. We have to also relax the assumption of a uniform population distribution in order to effectively model increasing population density.

Imagine that population doubles (from mass 1 to 2), and that *f(x)* now takes the form of a symmetric triangular distribution, so that the largest increase in population density occurs right around 0.5:

$$f(x) = \left| \begin{array}{ll} 4\text{x} & \text{for } 0 \le x \le 0.5 \\ 4(1-\text{x}) & \text{for } 0.5 \le x \le 1 \end{array} \right. \qquad (4)$$

We will examine the effect of a jurisdictional split at the location coincident with the peak of the distribution (at 0.5), since this is the form of endogeneity of greatest concern (i.e. that splits occur in areas where ε-type pollution increases for independent reasons).

The first-order conditions (2) yield the following solutions for pollution allowances in the upstream and downstream counties:

$$q_x^u = \min\left(\frac{1}{4[1+x-1.5e^{-(0.5-x)}]}, \bar{q}\right) \text{ and } q_x^d = \min\left(\frac{1}{4[e^{-(1-x)} - x]}, \bar{q}\right)$$

The dashed lines in Figure 4 plot the associated pollution function which only accounts for 'strategic' q-type pollution but not the unmonitored ε-type pollution. Pollution increases very sharply upto point 0.5 (and this pollution function is steeper than the corresponding one for the uniform distribution of population) because the strategic motives to pollute more and the effects of increasing population density coincide at locations just left of the split. Unlike the uniform distribution case, pollution monotonically decreases downstream of the split since the downstream county, concerned about the welfare of its citizens, allows relatively little new pollution within its border, and the unusually large inflows of pollution from the upstream county decay as the river flows. This particular difference in the shapes of the dashed blue lines in figures 3 and 4 (non-monotonic quadratic for the uniform distribution versus monotonically decreasing pollution downstream of county borders for the triangular distribution) yields a simple empirical test of the basic premise of the endogeneity concern – that county splits occur in areas of high population density. The intuition for the test is that with population-density based splitting, county borders are likely to be located in areas with high population density, so that when we move away downstream of borders, population density decreases, which lowers observed pollution. As we will see in the next section, our data are consistent with the population density based splitting, so the basic premise of this form of endogeneity is borne out.

Figure 4 also plots a "total pollution function" in solid orange, which aggregates the q-type with the unmonitored ε-type pollution. This function corresponds to the pollution that will be observed in the data (since the data is just "total pollution" aggregated across q-type and ε-type). The three panels of figure 4 vary the assumed levels of ε-type pollution. Since ε is the independent effect of population density on pollution that has nothing to do with strategic behavior, increasing values of ε correspond to assuming that larger amounts of "endogeneity" are present in our empirical analysis – that our regressions merely pick up fluctuations in pollution caused by population density changes that have nothing to do with strategic spillovers. The idea is to compare the shapes of the pollution functions under differing degrees of endogeneity to the empirically estimated shape of the pollution function to see whether the estimates based on the data correspond to large or small endogeneity concerns.

As we add larger amounts of 'endogeneity' (i.e. ε-type pollution), the shape of the total pollution function changes: total pollution keeps increasing to the right of the border, replacing the monotonically decreasing function associated with no endogeneity. This is because population density is largest close to the border, and this is where the emissions of per-person ε-type pollution is the greatest. A comparison of the shapes of the solid blue and the dashed orange lines across the three panels of figure 4 yields an empirical test of the quantitative importance of the endogeneity concern. If the correlation between distance to border to pollution is driven by population density rather than true strategic behavior, then the estimated relationship between pollution levels and distance downstream of border should follow a non-linear inverted-U shaped pattern. Observing a negative linear relationship between downstream distance and pollution would be more consistent with evidence of strategic spillovers. The key insight here is that if county splits occur in high density areas, that has implications for the spatial patterns of "endogenous" population density driven pollution around borders. Examining those spatial patterns allows us to make some empirical inferences on the extent to which the correlation is driven by population changes rather than strategic behavior by counties in the presence of spillovers. We allow for non-linear effects of downstream distance in our empirical work, and always find distance traversed downstream has a linear negative effect. The empirical results reported in this paper are thus likely evidence of strategic behavior as opposed to spurious correlation due to changing density.

5. Empirical Analysis

A. An Example of our Identification Strategy

Figure 5 presents example maps of the evolution of county boundaries from the state of Rio de Janeiro that help to illustrate our basic identification strategy. The points A, B and F in this diagram are locations of three water quality monitoring stations on the same river segment that flows from A to F. To explain the change in water quality from B to F in 1991, the three variables of interest are the location of the upstream station relative to the nearest exiting border (distance BD), the location of the downstream station relative to the nearest entering border (distance DF), and the number of county boundary crossings (1, at point D). Under the strategic spillovers logic, the pollution level at upstream point B is expected to be higher the closer B is to the exiting border, and the change is pollution from B to F should be more positive the more county boundaries that are crossed in between (e.g. figure 3). The effect of distance DF on the pollution level at downstream point F is less clear, and it's possibly non-monotonic depending on the nature of the population distribution around the river (figures 3 and 4).

It is difficult to empirically identify these spillover effects because for two different river segments of similar lengths located in two regions the number of boundary crossings and distances of stations to borders would be correlated with average county size and other county characteristics in those regions. Attenuation rate of pollution may also differ across station pairs, and has the potential to bias the results as geography may be more similar across counties in areas where counties are smaller (and therefore boundaries are more frequently crossed by the river). Since we have access to multiple water quality measures over time for each station, one potential solution is to add fixed effects for each river segment in our econometric models to control for fixed differences in county characteristics. However, our variables of interest – border crossings and distances to borders – are also usually 'fixed,' which implies that their effects would not be identified once location specific fixed effects are added. Luckily in Brazil we can take advantage of county splits which change distances to borders and border crossings over time for the same pair of monitoring stations even when the locations of those stations remain fixed. In this example, a district of Barra Mansa county outlined in red was recognized as a separate county by state law after the 1994 elections. Thus the distance of the upstream station B to the nearest exiting border decreased from BD to BC, and the number of border crossings for the segment BF increased from 1 to 2 in the middle panel of Figure 5. Prior to 1994 the Barra Mansa leadership was trading off the benefits of pollution allowance around B against the costs of pollution to all downstream constituents located along segment BD. After 1994 many of those downstream users were no longer Barra Mansa voters, and thus the political calculus that determines pollution allowances at B changes. Our regressions with the river segment fixed effects identify the *change in* pollution measured at B as a result of the *change in* B's distance to the nearest exiting border. Also, since the two new counties now have greater incentives to pollute just upstream of their respective exiting borders (i.e. close to points C and D), we should observe that after the split, water quality deteriorates more as the river flows from B to F due to such strategic spillovers. However, if the county split implies more money available for sanitation spending in the new smaller counties, or counties with more homogenous populations, there may be countervailing positive changes in water quality between B and F.

The bottom panel in figure 5 shows that in 2001 there was an additional split that reduced the distance of the downstream station from the nearest entering border. This second type of split allows us to identify the effect of downstream distance in the presence of river segment fixed effects. Since our dependent variable is measured as the change from upstream pollution to downstream pollution ($\Delta BOD = BOD_d - BOD_u$), we expect a positive coefficient on the distance from the upstream station to its nearest exiting border, and a negative coefficient on the distance between a downstream station and its nearest entering border. Further, based on the model in the previous section, we expect the effect of decreased pollution enforcement near exiting borders to be nonlinear: at stations very close to exiting borders, the jump in pollution should be larger than at stations farther away from exiting borders.

B. Data

Our unbalanced panel is comprised of water quality measures taken at 321 upstream-downstream station pairs across Brazil (see figure 6) in monthly intervals between 1975 and 2004, which results in an unbalanced panel of about 9,000 individual biochemical oxygen demand (BOD) observations. BOD measures the amount of oxygen consumed by micro-organisms which feed on organic matter in rivers. Higher BOD is associated with increased bacterial count and organisms in the water, which accumulate wherever there is a high level of pollution from organic matter. It is commonly used to measure pollution from industrial, sewage, and runoff sources, and indicates the general health of the river. Please see the Appendix for more details. Table 3 shows that BOD concentrations in Brazilian rivers are relatively high on average. Rivers with BOD greater than 4 mg/l is considered unacceptable for recreational use in the United States, and 40% of observations in our sample fall above this level, with a mean concentration of above 3.5.

Using Geographic Information Systems (GIS) modeling, we measure changes in BOD as the river flows from an upstream water quality monitoring station to a downstream station, and catalog the number of jurisdictional (e.g. county or *municipio*) boundaries the river crosses (see figure 7), distances traversed in each jurisdiction, a variety of political, economic, demographic and budgetary characteristics of each jurisdiction, and other aquatic conditions such as elevation, pollution attenuation and dilution through tributary inflows in addition to region, climate and seasonal controls (see table 3).

Brazil has re-drawn county boundaries three times between 1991 and 2001, which implies that each water quality observation for a station falls into one of four different county boundary regimes. The number of counties in Brazil has increased from 4492 in 1991 to 5562 in 2001. We merge digital maps of water monitoring stations, rivers, elevation and flow vectors, and the four different county boundary definitions in order to (a) identify the direction of water flow between each pair of stations (to classify them as upstream or downstream), (b) define river segments between station pairs, (c) identify the counties crossed by each river segment in each year, and (d) measure distances traversed within each of those counties. 32 of the 321 station pairs in the sample experienced at least one border change during the sample period. 1800 of the 9000 water quality observations (i.e. 20%) are for those 32 station pairs (see table 4). The river segments defined by station pairs cross 4 counties on average.

5. Results

Our regressions use each upstream-downstream station pair (or equivalently, the river segment in between) as the unit of observation, and the dependent variable measures the change in BOD from the upstream to the downstream station: $\Delta BOD = (BOD_d - BOD_u)$. Our primary estimating equation is the following station-pair (*stp*) fixed effects regression where the unit of observation is (station-pair x month):

$$\Delta BOD_{stp,t} = \alpha_{stp} + \delta_{basin-month} + \gamma_{year} + \beta_1 \cdot \text{Boundary\_Crossings}_{stp,t} + \beta_2 \cdot \text{Distance\_Upstream}_{stp,t} + \beta_3 \text{Distance\_downstream}_{stp,t} + \beta_4 X_{stp,t} + \varepsilon_{stp,t}$$

X is a vector time-varying control variables that have multiple observations for each station pair, including population density, GDP, area size of the county, all measured separately for the county where the upstream monitoring station is located, the county where the downstream station is located, and distance-weighted averaged for the other "intermediate" counties that the river segment flows through while getting from the upstream to the downstream station. We add year effects to account for the trend towards decentralization over time in Brazil, and 96 basin-month dummies (8 water basins x 12 months) to control for climactic varations Pollution attenuation on a particular river is a function of distance, rainfall, flow rate, water depth, elevation, and river gradient. Because many of the factors which affect the rate of pollution attenuation are geographic and non-time varying, station pair fixed effects controls for these issues. When omitting the fixed effect, we directly control for flow rate, water depth, elevation, and river gradient, which are obtained using GIS modeling on map data provided by the USGS. GIS techniques also allows us to measure distance along the river between stations (and in most cases this is longer than straight-line crow-fly distance).

We typically expect upstream and downstream county characteristics to have opposite effects on the change in water quality. For example, an increase in population density in either the downstream county or in counties located in between should lead to an increase in pollution downstream ($BOD_d - BOD_u$ increases), but holding constant downstream density, an increase in population density upstream should increase BOD_u, thereby decreasing ($BOD_d - BOD_u$). Economic activity could affect water quality in either direction: with higher GDP per capita the demand for clean water may increase, but greater economic activity may be associated with greater incidence of industrial waste.

The net effect of the number of border crossings will depend on the relative strengths of the spillover effect versus other changes associated with county splitting such as increases in sanitation budgets or a change in population heterogeneity. The first model in table 5 shows that the net effect of border crossings is not statistically distinguishable from zero, but that the point estimate is negative (i.e. water quality improves with a larger number of border crossings).

With pollution externalities that are internalized within a political jurisdiction but not across jurisdictions, BOD_u should decrease with the distance traversed within the upstream county. If the upstream county strategically pollutes closer to their exiting border due to the spillovers present, we would expect BOD_u to be greater (and therefore $\Delta BOD = BOD_d - BOD_u$ to be lower) at low values for *Distance_upstream*. Hence the coefficient β_2 is expected to be positive in the presence of spillovers. Conversely, we expect BOD_d to *generally* decrease with distance traversed within the downstream county (which decreases $BOD_d – BOD_u$ and leads to a negative β_3), but the model in section 4 raises the possibility that this latter effect is non-monotonic and ambiguous.

The last two columns in table 5 provide strong support for spillovers and strategic polluting behavior by counties. The negative coefficient β_3 in column 2 implies that the pollution level decreases by 1.4% for every extra kilometer further the river travels before BOD is recorded in the downstream county. Conversely, BOD increases by 1.5% in the upstream county every kilometer closer we get to the exiting border. Our conversations with water management practitioners in Brazil indicate that the primary mechanism underlying this effect is that counties are less forceful in enforcing pollution permit regulations for firms and municipalities in downstream locations relative to portions of the county further upstream (and it's not that pollution intensive industries are physically relocated downstream).

If the upstream county is behaving strategically, they would want to dump all the pollution very close to the river's exit point out of the county. In that case, we would expect the pollution effect of distance traversed upstream to be larger when that distance is very small (i.e. when we are close to the border). In table 6, where we allow for a non-linear effect of *upstream_distance* show precisely this type of behavior. Within 5 kilometers of the exit border, getting closer to the border increases pollution by 18.6% every kilometer, whereas outside this range getting closer to the border increases pollution by only 2.3% per kilometer, and this difference is highly statistically significant. A similar pattern emerges when we split the effect by a 10-kilometer-of-exit-border cutoff (7.6% within 10km of border, and 2.8% outside that range). When we allow for more cut-offs in the piece-wise linear specification in column 3, we see that pollution increases 3.1% every kilometer closer we get to the border, but that this increase jumps to 6.4% within 10km of the exit border, and jumps further to 21% per kilometer within 5km of the river's exit point out of the jurisdiction. The pairwise differences between these 3 coefficients are jointly statistically significant. We illustrate this pattern for the pollution function with a heuristic diagram in Figure 8. Pollution keeps increasing more and more dramatically the closer we get to the exiting border.

The coefficient on the variable 'distance traversed in the downstream county is always estimated to be negative. We find very little evidence of any non-linear effects. Taken together with the predictions of the theoretical model in section 4, this implies that these spillovers results are not likely being driven by some spurious correlation between pollution and border locations stemming from population density. There is evidence of strategic behavior.

The specifications in Table 7 uses only stations close to a county border, and these results are supportive of the story of the apparent trade-off between spillovers and offsetting budgetary impacts inherent in the process of decentralization. When we condition on pollution measures taken only at stations close to the border where the spillovers and county strategic behavior is strongest, we find that the net effect of decentralization (i.e. additional boundary crossings) is to increase pollution levels. The coefficient on border crossings is +0.11 in this restricted sample, compared to -0.15 in the full sample. In this restricted sample, spillovers are also quite large (BOD increases by 21% every kilometer closer the river gets to the exit border), which suggests that strategic spillovers dominate the countervailing beneficial effects of decentralization, leading to an overall negative effect for border crossings.

In table 8 we check whether extreme values of BOD drives the results, but the coefficients of interest appear robust to excluding the extreme 6% (top 3% and bottom 3%) and the extreme 10% of observations. The coefficients of interest are also robust to excluding the cases of zero border crossings between two monitoring stations.

Table 9 presents some ancillary evidence of the budgetary impacts of county splitting. The county fixed effects regression shows that when counties are split, the new smaller counties see the county health and sanitation spending increase by R$13.2 per person over the spending in the larger county that they were a part of in the previous year. For the average county in Brazil, this translates into a 20% increase in expenditures. Thus the story of water quality improving due to increased local government budgets following decentralization, and offsetting the degradation due to greater spillovers appears plausible.

If some unobserved characteristics of counties is correlated with both changes in water quality and with county splits, that could introduce some bias in the estimated effects. Such an unobserved characteristic would have to take a very specific form in order to explain the non-linear patterns in the pollution function that we estimate, and as our theoretical model coupled with the empirical results show, something that shares the characteristics of population density would not do. If such an unobserved variable exists, one way to deal with the issue directly would be to identify an instrumental variable for county splits that is uncorrelated with water quality changes, but no plausible instrument is available. Therefore, to deal with the issue less directly, we borrow an idea from Altonji, Elder, and Taber (2005) to estimate the potential size of the bias stemming from some such unobservable using the amount of selection from the observed explanatory variables as a guide.

Using the Altonji et al. (2005) estimation strategy for this purpose requires us to make a few key assumptions. First, we assume that the observed variables (such as GDP changes and population density changes) are a random subset of the set of variables that potentially determine county splits (i.e. changes in the number of borders crossed). Second, we assume that there is a large enough set of variables determining border crossings, and that no other unobservable variable completely dominates the determination of border crossings or water quality changes. While these are restrictive assumptions, we do not believe that they are necessarily violated in our dataset: there are many possible reasons that counties may split, and GDP and population density are likely to explain splits at least as well as the other potential causes of county splits.

Table 10 presents a summary of the bias estimate results. Both variables measuring distance traversed by the river in the upstream county and the downstream county (the two variables that had non-zero statistically significant impacts in our regressions) appear to be slightly biased away from zero, and therefore need to be adjusted. However, the size of the maximum possible bias is small relative to the estimated coefficients. Our estimate of a 1.4% increase in BOD for every kilometer closer we get to the exiting border from the last column in table 4 gets revised to a 0.9% increase in BOD per kilometer. And after the adjustment on the variable measuring distance traversed in the downstream county, pollution is estimated to decrease by 1.8% (coming down from 2.4%) for every extra kilometer further the river travels before BOD is recorded in the downstream county.

In table 11, we test our model against a “naïve” “quasi cross-sectional” specification where we do not control for station-pair fixed effects, to assess whether there is any omitted variable bias from the unobserved fixed characteristics of locations. Coefficients on the variables of interest are substantially different in the naïve specification, indicating a need for caution in testing for spillovers using cross-sectional variation across localities.

7. Conclusion

Make comments on Coase Theorem, and what is going on in Brazil recently with the river basin committees.

This paper provides evidence of opposing effects on the quality of an important publicly provided good of the particular form of decentralization that results from the re-districting of jurisdictions. The results suggest that decentralization increases the incentives for counties to allow pollution close to borders, but that this effect is wholly offset by some other beneficial side-effects of the process of decentralization, such as increases in local budgets and (possibly) the replacing of a heterogenous jurisdiction with multiple homogenous communities.

We find evidence of selective enforcement of pollution regulations: water quality is more likely to degrade between two stations if the upstream station is farther from its nearest exiting border, and more likely to improve between two stations if the downstream station is farther from its upstream border. This is consistent with the hypothesis that counties will enforce pollution more in areas where their constituents will be more likely to be harmed from increased levels of pollution. The spillovers and strategic behavior by counties is largest closest to jurisdictional borders, and suggests that policy-makers and institutions such as the United Nations and the World Bank promoting decentralization ought to be more vigilant in assessing the potential spillover costs of decentralization close to border areas. Our results also suggest that there could be important gains from cooperation between upstream and downstream communities through negotiation and transfers. Strategic cooperation among counties in pollution abatement is a potentially interesting avenue for future research.

The results described above survive several robustness checks. There is a remaining possibility that the main source of identification – county border crossings – is driven by unobservables that are correlated with changes in water quality. If the amount of selection on border crossings based on the other observed variables is any guide, then these potential unobservables explain only a portion of the negative cross-border spillover effects reported in this paper.

In summary, while there may be many advantages and disadvantages to decentralizing the management of water resources, this paper shows that the inter-jurisdictional spillovers generated from county-level management of water can be large in magnitude, particularly close to borders. In assessing which is the proper geographic or administrative unit that ought to be in charge of a publicly provided good, the potential cost of such spillovers should be taken into account.

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Appendix: Chemical Properties of Biochemical Oxygen Demand

Biochemical oxygen demand (BOD) is a measurement of organic pollution in a water body. BOD increases as micro-organisms accumulate to degrade organic material. BOD is expected to have trends opposite to those of dissolved oxygen: in areas where dissolved oxygen is high, organic pollution is low, and BOD levels will also be low. High levels of organic pollution and BOD are associated with river eutrophication.[7]

Organic pollution may be derived from a variety of sources. Common organic pollutants include: phenols which are common in industrial food manufacturing, surfactants which are a by-product of detergents and are common in both household and industrial wastes, sewage, agricultural and urban run-off, and domestic waste.[8] Industries which emit pollutants to which BOD levels are particularly sensitive include: food processing, oil extraction and refining (sugar cane refining is a particularly large industry in Brazil, and untreated waste waters from sugar refineries carry high organic pollution loads), pulp and paper industries, and textiles. BOD is also sensitive to pollutants from chemical and pharmaceutical industries, mining, metallurgy, and machine production.[9]

Water Type	BOD Level
Unpolluted	2
Highly Polluted	10
Treated Sewage	20-100
Raw Sewage	600
Industrial Waste	up to 25,000[10]

BOD is an approximation of theoretical oxygen demand, or the total oxygen which would be necessary to decompose the organic matter present in the sample. It is measured as the oxygen consumption in a given water sample at twenty degrees Celsius over a period of five days. Consumption is determined as the difference in dissolved oxygen content between the beginning of the incubation period and at the end of five days. A gestation period of five days is given as the oxygen consumption of the micro-organisms is initially high, but decreases as organic pollutant concentrations decrease.[11]

Attenuation rates of organic pollution depend on a host of local factors. Weather can affect decomposition rates as low temperatures increase the half-life of organic pollution and slow the process of decomposition. High levels of water evaporation may increase the concentration of organic pollution while increased rainfall may contribute to the dilution of the pollution loads. High levels of rainfall may, however, also lead to local flooding and increased contamination from erosion. Geological factors such as local soil and rock types affect the absorption of pollutants into the river bed. Geographical factors such as slope, elevation, discharge, and depth affect attenuation; water velocity increases the oxidation of the organic pollutants in the water—high flow rates cause increased churning and oxygenation.[12]

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[7] Chapman, 1996, p. 276-278.
[8] Chapman, 1996, p. 102-111.
[9] Chapman, 1996. P. 122.
[10] Chapman, 1996, p. 88.
[11] Hounslow, 1995. P. 302.
[12] Chapman, 1996, p. 246-276

Figure 1: Model of a River

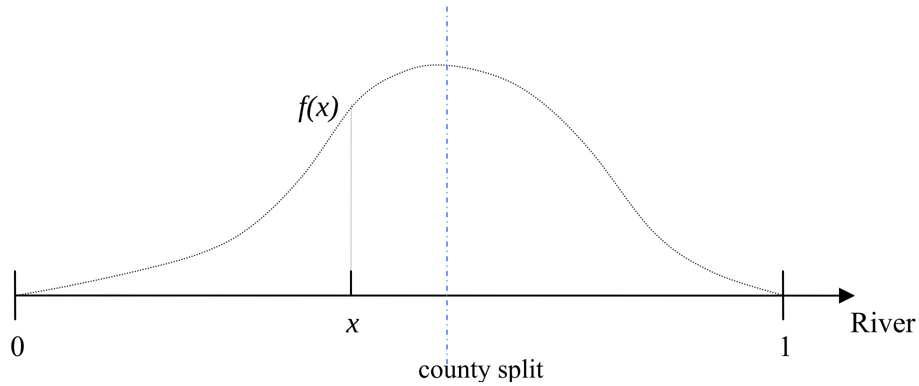


Figure 2: q_x Allowances Before and After the County Split (Uniform Population Dist.)

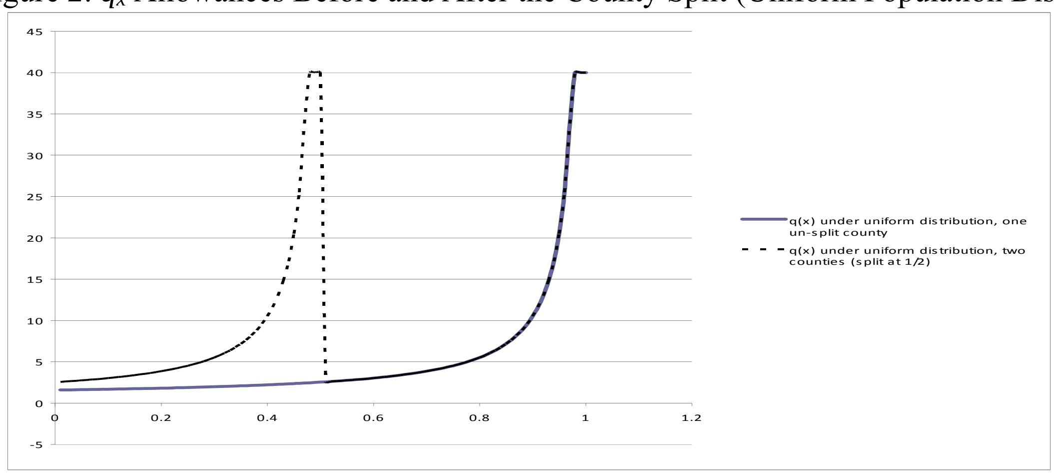


Figure 3: The Pollution Function *P(y)* for a County with Uniformly Distributed Population before and after the Jurisdictional Split at 0.5

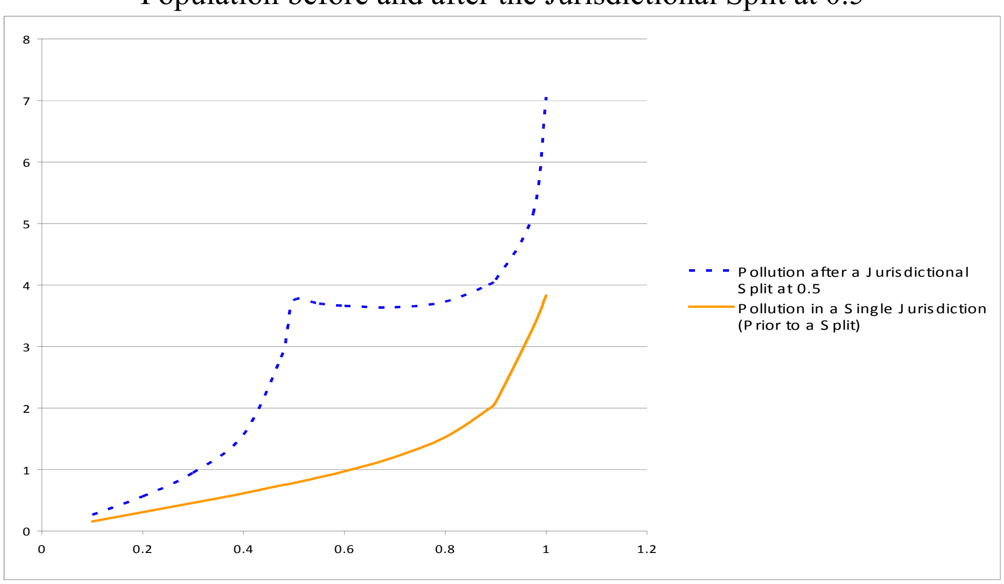
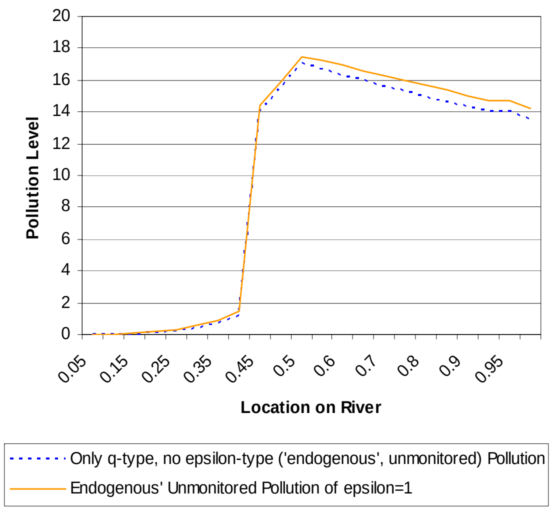
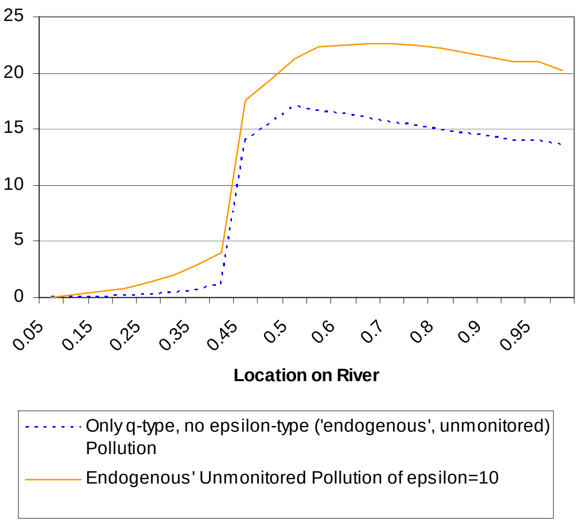


Figure 4: Endogenous Population Density Based Split under a Triangular Population Distribution: Effect of Varying Levels of Unmonitored ε-type Pollution





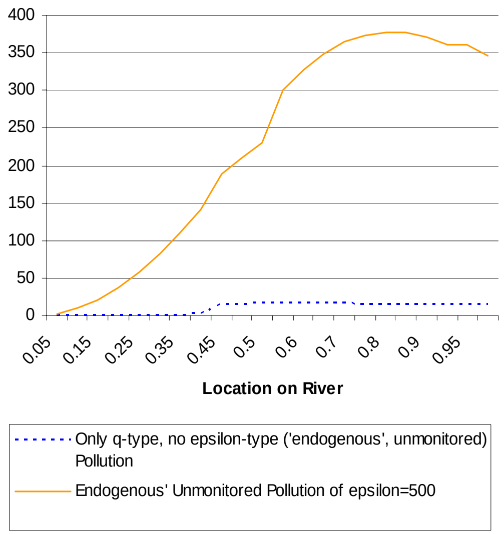


Figure 5: Example of the Evolution of County Boundaries in the State of Rio de Janeiro

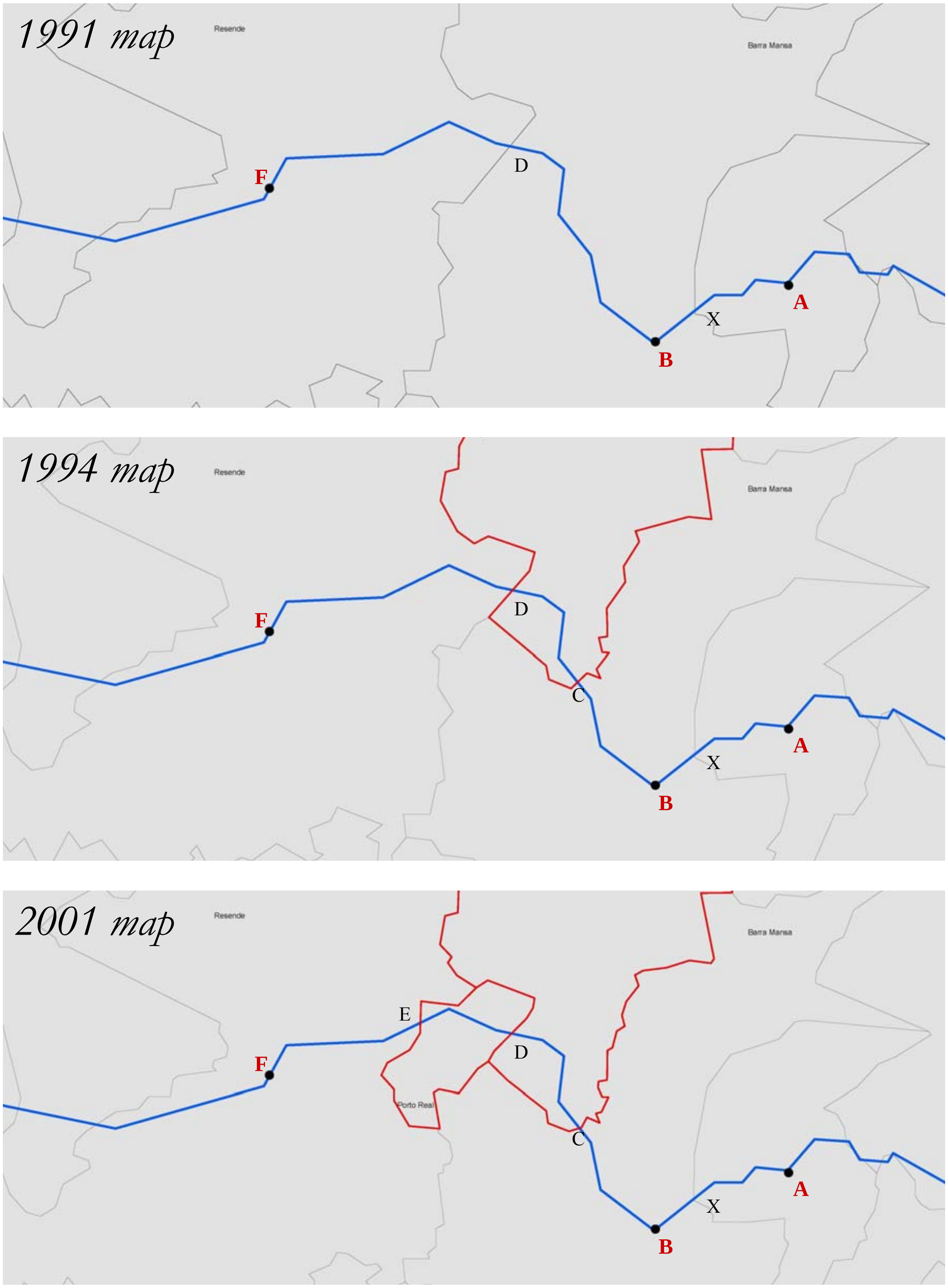


Figure 6: Rivers and Water Quality Monitoring Stations

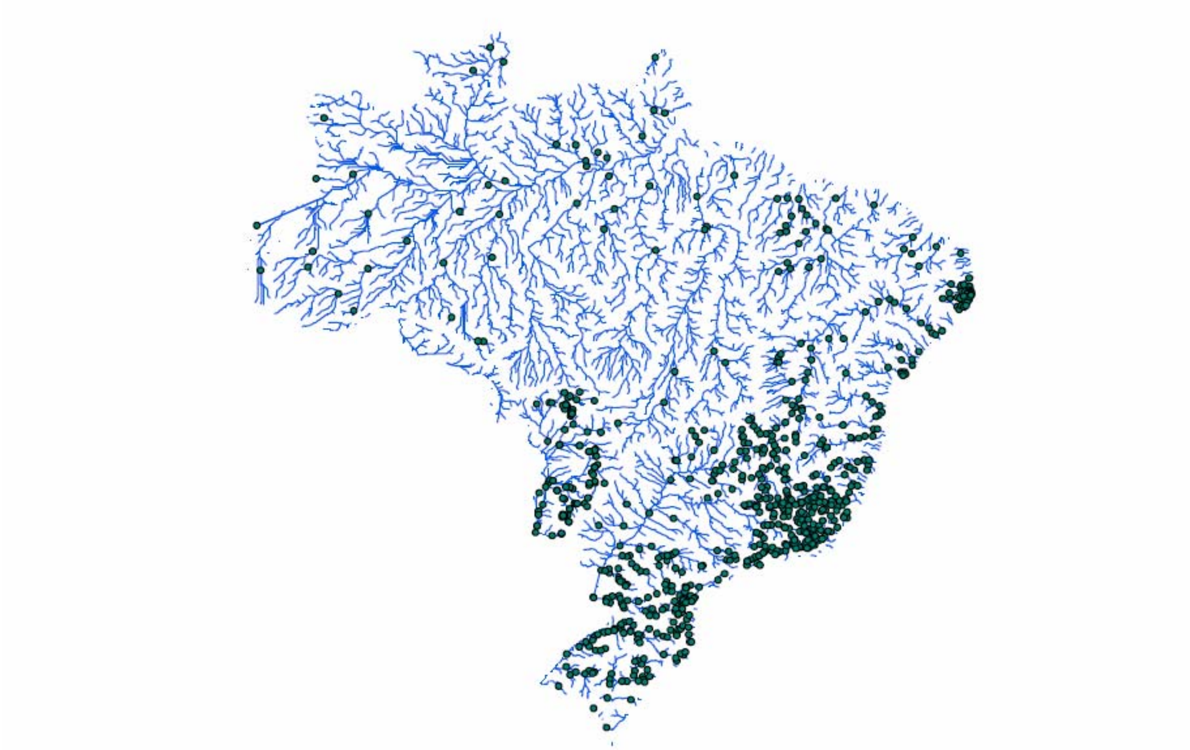


Figure 7: Water Quality Monitoring Stations and County Boundaries

Figure 8: A Heuristic Diagram of the Effects we Estimate

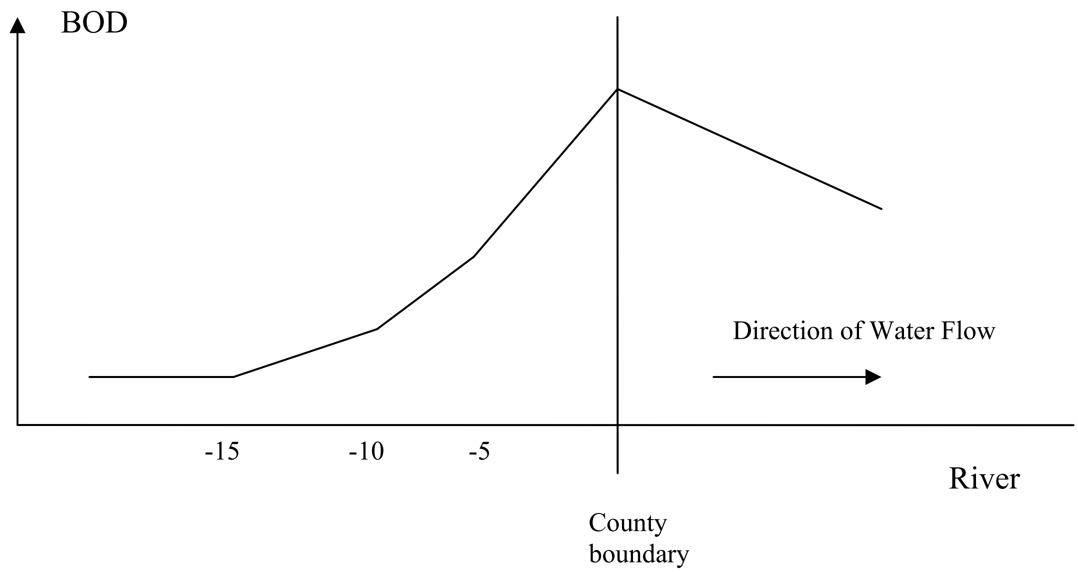


Table 1. County-Reported Causes of Water Pollution

Mining	235
Oil and gas from boats	81
Animal Waste	832
Materials from the Processing of Sugar	160
Industrial Dumping	521
Domestic Sewage	1595
Poor Solid Waste Management	821
Poor enforcement of river pollution regulations	648
Poor enforcement of underground water rights licensing	228
Use of Pesticides and Fertilizers	901
Others	160
Total Counties reporting Water Pollution	2121

*Counts are as of 2002. There were 5,560 counties in Brazil in 2002. Source: IBGE

Table 2. County Actions to Reduce Pollution

Fining Households with Inadequate Sewer Systems	2462
Fining Companies with Inadequate Industrial Waste Management Systems	1007
Monitoring of Potentially Polluting Industrial Activities	596
Taxing Mining Industries	1027
Taxing Automobiles	104
Management of Toxic Waste	483
Trash Collection Program	1654
Recycling Program	1082
Creation of Sewers	1949
Other	564

*Counts are as of 2002. There were 5,560 counties in Brazil in 2002. Source: IBGE.

Table 3: Summary Statistics

Dependent Variable	Mean	Std. Dev.	Min	Max
BOD level in Upstream Station	4.14	5.17	0.20	42
BOD level in Downstream Station	3.85	4.73	0.20	39
Difference in BOD levels	-0.29	5.31	-39.17	37
Log difference in BOD levels	-0.07	0.90	-3.66	3.33
Variables of Interest				
Number of Counties passed through	4.33	5.34	0.00	54.00
Total Distance between Stations (in km)	80.73	112.67	0.05	1,147.87
Distance from upstream Station to Nearest Downstream Border (in km)	11.18	9.28	0.02	39.32
Distance from nearest upstream border to Downstream Station (in km)	11.19	10.41	0.02	37.93
Control Variables				
GDP of the Upstream County in millions of R$ (constant 2000) source: IPEA	560.67	1,587.30	4.26	21,781.34
upstream and downstream stations in millions of R$ (constant 2000) source: IPEA	600.54	1,538.60	1.14	13,456.99
GDP of the Downstream county in millions of R$ (constant 2000) source: IPEA	714.66	1,927.02	4.26	26,273.94
Population Density of Upstream County (People per square kilometer) source: SIDRA	148.23	518.21	0.72	6,506.20
Average population density in counties traversed by river between Upstream and Downstream Station weighted by distance (People per square kilometer) source: SIDRA	164.14	558.33	0.72	6,506.20
Population Density of Downstream County (People per square kilometer) source: SIDRA	198.29	729.76	0.68	6,744.58
Size of Upstream County (square kilometers) source: IBGE	688.50	1,331.06	0.06	17,777.47
between Upstream and Downstream Stations (square kilometers) source: IBGE	690.59	1,302.00	0.08	17,777.47
Size of Downstream County (square kilometers) source: IBGE	728.00	1,537.69	0.07	17,777.47

	Number of groups	No. of Observations per group
Station pair fixed Effects	321	27.87
Basin-Month Dummies	96	93.19
Year Fixed Effects	29	308.48

Geographic Controls (source: USGS)	Mean	Std. Dev.	Min	Max
Flow Accumulation at the Upstream Station	54,422.37	147,456.70	0	668,018
Flow Accumulation at the Downstream Station	96,162.39	209,616.10	0	816,557
Elevation at the Upstream Station	368.00	281.88	1	1,204
Elevation at the Downstream Station	303.82	261.49	1	941
Depth index at the Upstream Station	1,361.43	421.99	304	2,064
Depth Index at the Downstream Station	1,477.36	367.68	313	2,064
Slope at the Upstream Station	50.24	69.38	0	813
Slope at the Downstream Station	43.15	49.54	0	268

Table 4: Changes in Number of Counties Passed Through

Traversed by River between stations	Freq.	Percent	Cum.
0	1,682	18.8	18.8
1	871	9.74	28.54
2	1,625	18.16	46.7
3	1,098	12.27	58.98
4	812	9.08	68.05
5	772	8.63	76.68
6	316	3.53	80.21
7	342	3.82	84.04
8	257	2.87	86.91
9	70	0.78	87.69
10	93	1.04	88.73
More than 10	1,008	11.27	100
Total	8,946		

	All Cases		Restricted to Cases where Border Crossings Occur	
Station pairs	321		321	
Station pairs that experienced at least one split during the sample period	32		32	
Observations at station pairs that experienced at least one split	1804	20.17%	1777	24.46%
Observations at station pairs that did not experience a split	7142	79.83%	5487	75.54%

Table 5: Spillovers from Adding new Counties

	Biochemical Oxygen Demand		
	-0.1528		-0.1637
Number of Counties Traversed	(0.1321)		(0.1345)
Distance Traversed in Upstream County before		0.0154**	0.0141**
Reaching Exiting border		(0.0067)	(0.0069)
Distance Traversed in Downstream County from		-0.0141	-0.0242*
Entering Border to Monitoring Station		(0.0086)	(0.0129)
R-squared	0.046	0.044	0.048
N	8946	8946	8946

*All regressions include station pair fixed effects, year fixed effects, and basin-month fixed effects. Controls for GDP, population density, and county size upstream, downstream, and distance averaged between counties have been included but not reported. Standard errors have been clustered at the station pair level. The upper and lower 1% extreme values of the dependent variable have been removed from the sample.

Table 6: Nonlinear Effects of Distance

	Biochemical Oxygen Demand				
Distance river traverses in upstream county * (station is within 5km of exiting border)	0.1860***		0.2106***	0.2067***	0.1877***
	(0.0418)		(0.0369)	(0.0370)	(0.0421)
Distance river traverses in upstream county * (station is beyond 5km of exiting border)	0.0233***				0.0234***
	(0.0045)				(0.0046)
Distance river traverses in upstream county * (station is within 10km of exiting border)		0.0757*			
		(0.0324)			
Distance river traverses in upstream county * (station is beyond 5km but within 10km of exiting border)			0.0643**	0.0605**	
			(0.0217)	(0.0206)	
Distance river traverses in upstream county * (station is beyond 10km of exiting border)		0.0279**	0.0311***	0.0305***	
		(0.0096)	(0.0060)	(0.0059)	
Distance Traversed in Downstream County from Entering Border to Monitoring Station	-0.0140	-0.0129	-0.0131	-0.0564*	
	(0.0083)	(0.0082)	(0.0081)	(0.0257)	
Squared (Distance river traverses in downstream county)				0.0016	
				(0.0008)	
Distance Traversed in Downstream County * (station is within 5km of the border)					0.0143
					(0.0395)
Distance Traversed in Downstream County * (station is beyond 5km of the border)					-0.0127
					(0.0086)
R-squared	0.047	0.045	0.047	0.048	0.047
N	8946	8946	8946	8946	8946

*** 1% **5% *10%

	F-Statistics for Equality of Distance Coefficients				
F-Statistic for Equality of Upstream Distance C	16.9	3.84	14.32	13.67	16.98
p-value	0	0.05	0	0	0
F-Statistic for Equality of Downstream Distance Coefficients					0.59
p-value					0.44

*All regressions include station pair fixed effects, year fixed effects, and basin-month fixed effects. Controls for GDP, population density, and county size upstream, downstream, and distance averaged between counties have been included but not reported. Standard errors have been clustered at the station pair level. The upper and lower 1% extreme values have been removed from the sample.

Table 7: Conditioning on Stations Close to County Borders

	Upstream Station				Downstream Station	
	Less than 5 km from the Border		Less than 10 km from the Border		Less than 5 km from Border	
Number of Counties Traversed	0.1140 (0.1173)		0.1270 (0.1081)		0.0765 (0.2638)	
Distance Traversed in Upstream County before Reaching Exiting Border		0.2174*** (0.0525)		0.2456*** (0.0463)		0.1069 (0.0752)
Distance Traversed in Downstream County from Entering Border to Monitoring Station		-0.0192 (0.0256)		-0.0109 (0.0156)		-0.0465 (0.2520)
R-squared	0.062	0.066	0.047	0.050	0.071	0.072
N	3077	3077	4767	4767	3478	3478

*All regressions include station pair fixed effects, year fixed effects, and basin-month fixed effects. Controls for GDP, population density, and county size upstream, downstream, and distance averaged between counties have been included but not reported. Standard errors have been clustered at the station pair level. The upper and lower 1% extreme values have been removed from the sample.

Table 8: Sensitivity Checks

	Alternative Cleaning Levels						Cases of 0 border Crossings Removed		
	3% Extreme Values			5% Extreme Values					
	-0.1582			-0.1509			-0.1575		
Number of Counties Traversed	(0.1288)			(0.1240)			(0.1350)		
Distance Traversed in Upstream County before Reaching Exiting Border		0.0123 (0.0075)			0.0215*** (0.0046)			0.0150* (0.0067)	
Distance Traversed in Downstream County from Entering Border to Monitoring Station		-0.0065 (0.0095)	-0.0500 (0.0280)		-0.0131 (0.0085)	-0.0607* (0.0255)		-0.0142 (0.0091	-0.0608* (0.0256)
Squared (Distance river traverses in downstream county)			0.0016 (0.0009)			0.0018* (0.0009)			0.0018* (0.0009)
Distance river traverses in upstream county * (station is within 5km of exiting border)			0.1476*** (0.0274)			0.1236*** (0.0348)			0.2183*** (0.0371)
Distance river traverses in upstream county * (station is beyond 5km but within 10km of exiting border)			0.0391* (0.0180)			0.0490** (0.0178)			0.0645** (0.0218)
Distance river traverses in upstream county * (station is beyond 10km of exiting border)			0.0220*** (0.0056)			0.0304*** (0.0056)			0.0313*** (0.0061)
R-squared	0.055	0.052	0.054	0.061	0.060	0.061	0.063	0.061	0.065
N	8077	8077	8077	7477	7477	7477	7264	7264	7264

*All regressions include station pair fixed effects, year fixed effects, and basin-month fixed effects. Controls for GDP, population density, and county size upstream, downstream, and distance averaged between counties have been included but not reported. Standard errors have been clustered at the station pair level.

Table 9: Effects of County Splitting on County Budgets/Expenditures

	Assessed Municipal Share	Sanitation Spending (R$)
County split	65.6582***	13.2073***
	(1.5592)	(0.7384)
R-squared	0.631	0.517
N	52391	59712

* County fixed effects and year dummies are included in all specifications.

Table 10: Bias Estimates using Altonji, Elder, Taber method

	Bias	Max Bias	Adjusted Coefficient	Adjusted Confidence Interval	
Number of Counties Traversed	-0.00635 0.01209	-0.030044	-0.1227555	-0.382556	0.137134
Distance Traversed in Upstream County before Reaching Exiting Border	0.00004 0.00343	0.006757	.008643	-0.004539	0.021895
Distance Traversed in Downstream County from Entering Border to Monitoring Station	0.00004 0.00198	0.003926	-0.0180264	-0.034986	-0.001149

Table 11: Comparison of River Fixed Effects Regression with Station Pair Fixed Effects Regression

	River Fixed Effects			Station Pair Fixed Effects		
Number of Counties Traversed	0.0000			-0.1532		
	(0.0195)			(0.1321)		
Distance Traversed in Upstream County before Reaching Exiting border		-0.0021			0.0154*	
		(0.0037)			(0.0067)	
County from Entering Border to Monitoring Station		-0.0040	-0.0324**		-0.0141	-0.0565*
		(0.0049)	(0.0125)		(0.0086)	(0.0257)
Squared (Distance river traverses in downstream county)			0.0011*			0.0016
			(0.0004)			(0.0008)
county * (station is within 5km of exiting border)			0.0271			0.2067***
			(0.0410)			(0.0370)
county * (station is beyond 5km but within 10km of exiting border)			0.0026			0.0605**
			(0.0120)			(0.0206)
county * (station is beyond 10km of exiting border)			0.0003			0.0305***
			(0.0047)			(0.0059)
R-squared	0.064	0.065	0.071	0.046	0.044	0.048
N	8939	8939	8939	8939	8939	8939