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The Impact of Collaborative Governance on Local Sustainability Policy Implementation

Author(s)
Angela YS Park, University of Kansas, USA, angelapark@ku.edu
Rachel Krause, University of Kansas, USA, rmkrause@ku.edu

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Introduction[1]

Research on collaboration has flourished over the past two decades as public, private, and non-profit institutions are increasingly forging relationships with each other to tackle the complex problems facing our societies. The multifaceted, interconnected, and trans-boundary nature of many contemporary policy problems challenge the ability of individual jurisdictions and organizations to effectively address them on their own and contributes to the development of collaborative partnerships in governance. Given its frequency of use, simply understanding collaboration as a phenomenon is important. The abundance of studies on the topic has enabled scholars to understand why and how it has arisen as an important public management form as well as what constitutes successful collaboration[2]. However, there has been a consistent call for research to move beyond developing descriptive understandings of collaboration and towards evaluations of its impact (Bryson, Crosby, and Stone 2006; Huxham 2003; McGuire 2006; O'Flynn 2009; Provan and Milward, 2001). This is particularly important given that the majority of the current literature makes an implicit assumption that collaboration is a normatively positive phenomenon that pools resources and capacity across different policy actors, ultimately yielding enhanced problem solving and governing ability. Although this positive impact is often taken for granted, the literature has not adequately established an empirically derived causal relationship between the presence of collaboration and superior policy outcomes. Indeed, increasing attention has recently been given to the potential unintended negative consequences of collaboration, including increased transaction costs and risk; nonetheless, to our knowledge, only a few public policy and management studies have empirically examined this question (e.g. Milward and Provan 2000;

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[2] We acknowledge that there is a great variation in the definition and operationalization of collaboration in the
[2] We acknowledge that there is a great variation in the definition and operationalization of collaboration in the literature and well-informed discussions about the definitions already exists, therefore we use collaboration as a general term encompassing those different definitions.

Newig and Fritsch 2009).

This study begins to help fill this gap by empirically examining the impact that collaboration has on organizational efficiency. Specifically, this research assesses the influence of collaboration on cities' efficiency in implementing policy initiatives and delivering public programs in the context of the federally-funded Energy Efficiency and Conservation Block Grant (EECBG) program. Using a novel dataset that merges a national survey on EECBG implementation with financial data on EECBG-funded activities, we examine cities' performance in implementing energy sustainability projects and evaluate the extent to which collaboration affects the efficiency of those projects.

The paper proceeds as follows: First, it briefly reviews the extant literature on collaboration, covering arguments on how it can have both positive and negative effects on policy outputs and outcomes. Following the literature review, we develop two competing hypotheses predict how these different theoretical expectations may be empirically borne out. Next, we introduce Stochastic Frontier Analysis (SFA), the statistical methodology utilized in this study to assess the effect that cities' use of collaborative partnerships has on the efficient production of outputs. SFA enables the generation of efficiency scores for each observation in a dataset and allows users to tease out the extent to which exogenous factors account for the sources of the inefficiency. We conclude with policy implications and suggestions for future research.

Literature Review

Collaboration as normatively good

Joint-production is present in almost every part and level of today's administrative system. The driving force behind this is the realization that many policy problems, such as those relating to environmental protection and social welfare, are so complex that no single agency has the capacity to efffectively tackle them (Huang and Provan 2006; Weber and Khademian 2008). Reflecting the increase in the use of collaboration among public agencies, the research aimed at understanding it has also proliferated in the over the past two decades. Some of the major threads within this literature include: the intellectual origin and history of collaboration (Berry et al. 2004; McGuire 2006); the definition and types of various collaborative contexts (Agranoff and McGuire 1999; Mandell and Steelman 2003; Thomson and Perry 2006); and the exploration of questions regarding how to create and maintain successful collaborations (Agranoff and McGuire 2001, 2003; Ansell and Gash 2008; Emerson, Nabatchi, and Balogh 2012; Hill and Lynn 2003; O'Leary and Vij 2012; Provan and Milward 1995; Thomson, Perry, and Miller 2009; Weber and Khademian 2008).

These studies all offer a critical base for understanding collaboration, yet a bulk of them treat collaboration as an outcome or ultimate goal when it is in fact an instrumental tool for governments to advance the quality of public programs and services in a cost-effective way. They less often treat collaboration as an explanatory variable or estimate its impact on organizational outputs and outcomes. Implicit in this treatment is a normative assumption that collaboration is desirable in and of itself. The presence of a collaborative relationship between agencies is often positively equated with improved programmatic and organizational outputs/outcomes with no or little empirical evidence (Andrews and Entwistle 2010; McGuire 2006; Milward and Provan 2000). Consequently, there is concern among scholars that the literature on collaboration tends to be "celebratory and rarely cautious" (McGuire 2006), which runs the risk presenting it as "the latest one best way" (O'Flynn 2009) or as a panacea (Bryson, Crosby, and Stone 2006; Huxham 2003).

The empirical assessment of collaboration's effects involves a range of challenges.

Collaboration itself is a complex multi-faceted concept that exists under various names – such as networks, partnerships and collective action – and its definition and scope require careful consideration and clarification before its impact on anything else can reasonably be examined (Berry et al. 2004; Moynihan et al. 2011). Such conceptual complexity breeds analytical challenges, since measuring performance in expansive and loosely connected administrative arrangements can pose unforeseen technical intricacies. Moreover, research in collaborative contexts often faces extensive endogeneity because collaborative networks are not a mere sum of independent elements, but a web of often loosely connected policy actors with blurred lines of accountability and divisions of labor (O'Toole and Meier 2004). Collaborative networks in the public sector pose particular challenges to assessing effectiveness, as they tend to have diversified stakeholder needs and interests. Financial performance cannot serve as the chief indicator of effectiveness as it does in the for-profit sector (Provan and Milward 2001). In this context, teasing out a direct causal relationship between an organization's collaborative actions and a particular outcome can be fairly difficult.

Possible Sources for Inefficiency from Working Together

Despite the conceptual and technical complications of measurement, developing an empirical understanding of the impact that collaboration has on policy outcomes and organizational performance is critical to the continued advancement of public management research. One view is that collaboration's net benefit is largely based on unsubstantiated assumption and devoid of context. Indeed, the relatively few existing studies that investigate the casual impact of collaboration on policy outcomes provides little empirical evidence for its consistently positive perceived effects (Milward and Provan 2000; Newig and Fritsch

2009). Despite its potential to improve policy effectiveness and efficiency, collaborative governance can be difficult and expensive to initiate and maintain. There are also risks that partnerships will not successfully hold together and meet the collective objective (Carr and Hawkins 2013; Feiock 2009, 2013).

Tempering its typical positive treatment, the literature points to at least two reasons why collaboration may not result in improved organizational performance: 1) structural instability; and 2) expensive coordination costs. First, collaborative relationships can be fairly unstable and unpredictable (Milward and Provan 2000). One of the chief virtues of collaborative networks is their flexible structures; they are often depicted as open, fluid systems where participants with necessary skill sets enter and exit to achieve a common or shared goal, allowing a series of inflows and outflows of people, resources and knowledge. This feature of being ‘light on their feet’ is believed to allow efficiency in resource allocation and flexibility to change and adapt to external needs (Milward and Provan 2000). However, the flipside of this flexibility is a loss of control or steadiness in organizational operations. Volatile policy environments can be detrimental to ensuring consistent policy goals and implementation across different partnering entities. Thus, compared to the stable and predictable bureaucracy, responsive yet volatile collaborative networks can lead to “inherently weaker forms of social action.” (Milward and Provan 2000)

Another way that collaboration can negatively impact organizational performance is by increasing transaction costs. Collaborative partnerships – whether externally mandated or voluntarily forged – impose a unique decision process that can encompass a wide range of policy actors and decision points outside of one single agency. This plurality in policy making environment is what creates “the potential synergy” (Huxham 2003) in creating more innovative, efficient and effective solutions. Nonetheless, these diversified, heterogeneous and highly inter-connected characteristics can also result in high transaction costs rising from inclusive decision making process and coordination difficulties (Feiock, Steinacker, and Park 2009; Feiock 2013; O'Toole and Meier 2004). For example, if each collaborative partner can serve as a veto point, the decision and negotiation costs to settle disagreements among participating organizations are increased. Moreover, decentralized structures with fragmented authority complicate monitoring processes, often leading to higher enforcement costs. The avoidance of these transaction costs is a key reason why the traditional bureaucratic paradigm with a clear principal-agent relationship has long served as the predominant management form in public administration. The chief justification for having a centralized hierarchy was its potential for efficiency improvement by eliminating duplication and consolidating reporting points (Thompson 1975). On the other hand collaboration replaces a strong centralized authority with such concepts as trust, shared understanding and the norms of reciprocity, which are believed to generate social constraints to ensure credible commitment, thereby reducing transaction costs (Beccerra and Gupta 1999; Hindmoor 1998; Leroux, Brandenburger, and Pandey 2010). Yet, research indicates that the achievement of these informal enablers of collaboration is highly contextualized (Getha-Taylor 2012) and that the reliance on them alone is not often sufficient to ensure successful collaboration (Lynn, Heinrich, and Hill 2000; Provan and Milward 1995). Also, responsiveness to all relevant stakeholders potentially discourages a sound judgments informed by knowledge and expertise and can instead result in "diluted – and thus ineffectual plans and policies." (Coglianese 1999; Scott 2015) Therefore, while collaborative networks are conducive to resource pooling and flexibility, which may enable more efficient production of public goods and services, this is not always assured. Collaboration may also have negative consequences for organizational performance and policy outcomes by hampering organizational stability and incurring increased costs in coordinating actions.

Research Question & Hypotheses

Building upon the previous literature, we investigate the extent to which collaborative management shapes performance in policy implementation. Although performance is a multi-dimensional concept, which for public entities often includes effectiveness, equity, transparency and representativeness, here we focus exclusively on cost-efficiency in implementing policy initiatives. Given the resource constraints facing many local governments and increasing public demand for accountability to taxpayers, understanding the cost-efficiency implications of collaborative arrangements in delivering publicly-funded programs is important. The extant literature indicates that collaboration may either increase efficiency by helping entities better garner necessary information and resources OR decrease efficiency by incurring transaction costs from negotiating, monitoring and maintaining relationships with multiple partners.

We utilize cities as our unit of analysis and operationalize collaboration as the scope and strength of the ties each city has with other governmental and non-governmental entities to work on energy and climate issues. We empirically examine how collaboration moderates the efficiency of city governments in implementing policy initiatives that are designed to promote local energy sustainability and test the following two opposing hypotheses:

Hypotheses 1: Collaboration INCREASES organizational efficiency, particularly cost-efficiency with which policy outputs are achieved.

Hypothesis 2: Collaboration DECREASES organizational efficiency, particularly cost-efficiency with which policy outputs are achieved.

Data and Methods

Data

We examine these hypotheses in the context of U.S. cities' implementation of energy projects funded through Department of Energy (DOE)'s Energy Efficiency and Conservation Block Grant (EECBG) program. The EECBG program provided $3.2 billion in block grants and $40 million in competitive grants to local governments as part of 2009 American Recovery and Reinvestment Act stimulus package. The major goal was to support local governments' efforts initiating and implementing projects that simultaneously promoted energy and climate sustainability while creating jobs.

EECBG program provides an ideal context to study the impact of collaboration. Given that collaborative governance is a particularly useful administrative apparatus for addressing complex trans-boundary problems, we expect to see its frequent use in multilateral sustainability efforts, such as those promoted by the EECBG. Indeed, one of the key outcomes sought by the DOE in expending EECBG money was to improve inter-jurisdictional coordination of energy-related policies and programs with an aim to achieve cost-effective and lasting results (U.S. DOE 2010). We use a unique dataset of administrative records from DOE which provide disbursement records for each grant. Each grant recipients were required to submit monthly and quarterly reports that included information on project outcome metrics, fund outlays, activities, and progress on metrics (Terman et al. 2016). Information was extracted on EECBG-funded building retrofits implemented by US cities between 2009 and 2013 that includes EECBG dollars obligated the number of square feet retrofitted.

The majority of cities had multiple data points reported over the course of five years. In order to minimize reporting errors, each entry was inspected with care: each 'activity unique ID' was examined and entries were aggregated only when observations corresponded to each other (i.e. the square foot values were aggregated only when there were matching numbers on dollars obligated, and vice versa). The data were merged with the EECBG Grantee Implementation Survey, a national survey administered by the Askew School of Public Administration at Florida State University during late 2010 and early 2011. The survey, which is part of the larger Integrated City Sustainability Database (ICSD) (Feiock et al. 2014), gathered information about how cities have spent EECBG grant funds as well as their general administrative environment to carry out sustainability programs. The survey has a 77 percent response rate, which minimizes selection bias and helps assure the quality of data for this study. The final sample contains 232 city observations.

Method

We employ Stochastic Frontier (SF) analysis to assess how cities' collaboration with external partners affects the efficiency of achieving their policy outputs. Initially proposed by Aigner, Lovell and Schmidt (1977), the SF analysis is motivated by an interest in determining high and low performing economic agents (i.e. observations) in a given sample. Performance in the SF model is represented by efficiency scores calculated from the ratio of outputs to inputs from all observations in the sample data. In other words, a set of observations that maximize outputs by utilizing an optimal mix of various inputs serves as a baseline or a yardstick against which the rest of sample is compared. This provides an interesting contrast to OLS models: while ordinary regression models focus on average behavior, SF analysis is primarily interested in understanding the optimal or "frontier" behavior of economic agents. From this point of view, an implicit assumption under the SF model is that "more is better," which aligns with efficiency expectations, whereas the OLS model can be regarded as “middle is better” situation (Troutt, Shanker, and Acar 2001). The SF model is specified as the following:

$$y_i = f(x_i, \beta) + v_i - u_i$$

where $\mathbf{y_i}$ is output; $\mathbf{x_i}$ is the vector of inputs; **f (*)** is the production function of inputs into the outputs**;** $\boldsymbol{\beta}$ is a vector of parameters; $\mathbf{v_i}$ is a random error; $\mathbf{u}_i$ is a non-negative inefficiency. The model is composed of two parts or stages: 1) the frontier stage ($f(x_i, \beta)$) estimates efficiency scores for each observation through a specified production function; and 2) the error term $(v_i - u_i)$, which accounts for both inefficiency and random error, which results from the first stage frontier model.

The first stage forms an ideal, stochastic efficiency frontier, which essentially serves as a ceiling and represents the best possible performance that no economic agents can exceed. Any deviations from this frontier are considered inefficiencies, which are estimated as part of the error term. Quantities of a particular output are modeled for a production frontier (y_i), while inputs (x_i) typically consist of standard factors of production, such as labor and capital, and affect the location of specific observations on the frontier (Kumbhakar, Wang, and Horncastle 2015). Parameters are estimated by Maximum Likelihood (ML) estimation and a Cobb-Douglas production function is employed.

The error term has two components: a one-sided, non-negative error that represents inefficiency and a stochastic component that accounts for random shocks and statistical noise. Since SF analyzes cost-efficiency maximization, the estimation of inefficiency (i.e. u_i), rather than the model parameters, is of primary interest (Greene 1992). The inefficiency error u_i gives the log difference between the maximum and the actual output with a value closer to 0 implying a dynamic that is closer to fully efficient. While v_i is assumed to be two-sided and normally distributed, like an ordinary error term in any OLS model, u_i is assumed to be non-negative with a half-normal distribution[3].

Variables

Our Dependent Variable (DV) is the total square footage of buildings retrofitted using EECBG funds by each city, which represents the policy output in frontier estimation. Recalling that the SF model has two distinct components (i.e. a production frontier part and inefficiency part), the input variable in the production frontier part of our model is EECBG dollars obligated to building retrofits. It is critical that the production frontier component only contains quantities as outputs and the inputs that contribute to producing those outputs. In an ideal situation, we would also include other standard inputs of production, such as labor and time, to gain a more complete picture of returns of scale. Nonetheless, given the lack of available data on these metrics – a common challenge in such research – and the fact that production elasticity of inputs is tangential to our primary focus, we argue the current model is sufficiently justified. Using this information, the SF model estimates the frontier – the best possible performance, or the greatest output achievable with a given input.[4]

For the inefficiency portion of the SF model, we include the following variables: collaboration index, staff capacity, private contract, and program type. Variables were selected based on two criteria: 1) either the variable has an established theoretical justification for explaining organizational efficiency or 2) the variable has a program-specific

[3] While the SF model has been extended to other distributional assumptions, including truncated normal or gamma distributions, it has been suggested that accurate estimation of these later extensions is challenging (Ritter and Leopold 1997; Troutt et al., 2001).

[4] SFA is primarily interested in the distance between the frontier and the average or below average observations in a sample. Therefore outliers in SFA need to be treated with caution as they may carry important information useful for determining the frontier. Nonetheless, it is also possible that outliers are caused by data error or noise and may be misrepresented as highly efficient players or inefficient players. Most outliers caused by reporting error were detected during data cleaning and additional ones were examined and removed by inspection of leverage-versus-residual-squared plot.

characteristic that may influence the production function. Standard errors were clustered at state level to control for any unobserved state-specific influence. *Collaboration* serves as the main exogenous factor hypothesized to influence organizational inefficiency. It is operationalized as a count of the number of external sectors that a city partnered with on EECBG-funded energy programs weighted by the strength of each tie. There are a total of 8 types of collaborative partners – both governmental and non-governmental – and the strength of each collaborative partnership is estimated on a scale of 5 ranging from (1) not at all to (5) to a great extent. Although this weighted index may not fully capture the multi-dimensional and contextualized nature of collaborative networks in practice, it has been shown to be a sufficient proxy in other studies (such as Agranoff and McGuire 2003; Meier and O'Toole 2003). Details about partnership as well as the intensity of each partnership are offered in Table 1 Variable Description.

A second variable contained in the efficiency portion of the SF model is *Staff Capacity*, which indicates whether a city has staff members dedicated to administering and implementing sustainability efforts. It is an ordinal variable assigned 0 to cities that have no sustainability staff, 1 to cities that adopted staff program on/after the receipt of EECBG grants, and 2 to cities that already had dedicated staff prior to the receipt of EECBG grants. Compared to cities that hired sustainability staff upon the receipt of EECBG funding, those which already had dedicated staff are likely to have greater expertise and administrative capacity to handle retrofit projects and contracts. Next, *Private Contracting* is a binary variable that indicates if cities contracted with for-profit/private sector organizations when implementing EECBG-funded energy programs. This reflects a dominant perspective that the market-based organizations are more efficient in delivering products and programs than their counterparts in the public sector. This view was an impetus for reinventing government and

Table 1: Variables Used in SFA

Variable Name	Variable Description
Dependent Variable	
Sq ft. Retrofitted using EECBG funds	Total square feet of buildings that were retrofitted using EECBG dollars. *† Source: Department of Energy*
Input Variables	
$$ Obligated	EECBG grant dollars dedicated to retrofitting (only includes the amount that were directly involved in implementing retrofit activities, excluding the amount used to generate financial incentives & loans) *† Source: Department of Energy*
Inefficiency Variables	
Collaboration Magnitude	The scope of a city working collaboratively on energy issues with other organizations and the intensity of each tie ranging from (1) Not at all to (5) To a great extent. Potential partnering organizations include: other cities in the county; other cities within the region or MSA, universities, state agencies, federal agencies, utility companies, other private firms, and regional organizations. *† Source: 2011 EECBG Grantee Implementation Survey, a national survey administered by the Askew School of Public Administration at Florida State University*
Staff Capacity	If a city has dedicated staff to sustainability efforts (0==No; 1==adopted after the receipt of EECBG funds; 2== already adopted even before the receipt of EECBG funds) *† Source: 2011 EECBG Grantee Implementation Survey, a national survey administered by the Askew School of Public Administration at Florida State University*
Contract w/ Private Sector	If a city contracted with the private sector for implementing EECBG-funded sustainability activities (0=No, 1=Yes) *† Source: 2011 EECBG Grantee Implementation Survey, a national survey administered by the Askew School of Public Administration at Florida State University*
Retrofit Program Type	If EECBG dollars were used to initiate new retrofit projects or to expand ongoing retrofit efforts (0==ongoing, 1=new) *† Source: 2011 EECBG Grantee Implementation Survey, a national survey administered by the Askew School of Public Administration at Florida State University*

Table 2: Variable Summary Statistics

	N	Mean	Std Dev	Min	Max
ln (sq ft. retrofitted)	303	11.40	1.60	5.52	15.65
ln($$ obligated to retrofits)	303	12.14	1.40	8.34	15.26
Collaboration Magnitude	238	12.51	6.72	0	32
Staff Capacity	259	.788	.861	0	2
Contract w/ Private Sector	269	.743	.437	0	1
Retrofit Program Type	303	.257	.438	0	1

the New Public Management in the late 90s, and the introduction of practices like performance management public organizations (Gazell 1997; Savas 2000). The last variable, *Program Type* represents whether the EECBG funds were used to expand existing retrofit programs or generate new retrofit projects. This is relevant since generating a new program may require more labor and capital (not to mention the costs related with searching for the right contractor) than would expanding an existing program, which is likely to already have necessary infrastructure – both administrative and technical – in place. Or conversely, cities starting a new program may have blank slate with which to work and are thus able to select the retrofit projects that generate the largest “bang for the buck”. The following Table 1 lists variables as well as data sources for each variable and Table 2 provides summary statistics.

Model and Results

Using these variables, we examine how collaboration affects the efficiency with which cities utilize EEDBG funds to implement retrofit programs. We particularly assess the mediating effect that collaboration has on cities’ efficiency in translating given inputs to outputs. Our model is specified as follows:

$$\ln(\mathrm{sq.ft.retrofitted}) = \beta_0 + \beta_1 \ln(\$\$ \text{ dedicated to retrofits}) + v_i - u_i$$

where

$$u_i = \delta_0 + \delta_1 \mathrm{Collaboration} + \delta_2 \mathrm{Staff} + \delta_3 \mathrm{PrivateContract} + \delta_4 \mathrm{ProgramType}$$

Central to SF models is the presence of the one-sided error (u_i) that represents inefficiency in a given data sample. If no evidence for the presence of efficiency error is found, the SF model will provide results that would not be different from those of a standard OLS regression model (Kumbhakar, Wang, and Horncastle 2015)[5]. Therefore, we conduct two validity tests of the stochastic frontier specification prior to undertaking the SF analysis: 1) A simple skewness test on OLS residuals; and 2) A generalized Likelihood Ratio (LR) test of inefficiency.

First, negative skewness is a sign of the presence of u_i, because u_i is assumed to be non-negative one-sided error (i.e. $u_i \geq 0$), and thus the composed error (i.e. $v_i - u_i$) will always skew to the left (Schmidt and Lin 1984). Our sample is heavily skewed to the left with Coelli (1995)'s skewness statistic (also known as M3T) at -3.178. The M3T statistic for a normal distribution is 1.96, thus our M3T statistic shows ample evidence for the presence of inefficiency term (u_i,) in our data. While the skewness test serves as a simple pre-test, we further verify the model validity with a LR test, as it provides more precise and reliable evidence for u_i, (Kumbhakar, Wang, and Horncastle 2015). The LR statistic for our data has a critical value equal to 11.945 – a value that completely rejects the null hypothesis of no inefficiency in our data at less than the 1 percent significance level.[6] Both test results indicate there is an inefficiency error term clearly present in our sample and thus the SF model better fits our data than the restricted OLS estimation does.[7]

The maximum likelihood estimation results of the SF model are offered in Table 3. EECBG dollars obligated to retrofits has an output elasticity of 0.499 and is highly significant ($p<.001$). This implies that a 1% increase in dollars, ceteris paribus, would lead to a 50% increase in the number of square feet retrofitted. Our main variable of interest, *Collaboration*, is found to play a significant role in explaining organizational inefficiency. Note that because

[5] More precisely, the estimation of OLS will be consistent of that of SFA, but statistically inefficient in the presence of a one-sided non-negative inefficiency error (Buck and Young 2007).
[6] Critical values for the LR test are obtained from a tabulation developed by Kodde and Palm (1986). For further discussion on this topic, please refer to the original paper as well as the explanation offered in Kumbhakar et al. book (2015).
[7] Results of the model run as a standard OLS regression are available by request from the author.

Collaboration is included as inefficiency variable, a positive coefficient sign indicates increased inefficiency whereas a negative sign represents decreased inefficiency. Thus the negative coefficient of *Collaboration* means that collaboration has a positive impact on diminishing inefficiency in cities' performance in policy implementation. We compute the average marginal effects of *Collaboration* and find that a 1 unit increase in collaboration is associated with about a 4.3% reduction in inefficiency in cities' development of energy retrofit activities. Since the results are maximum likelihood estimates and *Collaboration* is an additive index ranging from 0 to 32, interpreting the notion of one unit change is not completely straightforward. Instead, we provide an overall picture of how collaboration positively moderates efficiency loss incurred in retrofit projects. Figure 1 shows the marginal effects of collaboration on cities' technical inefficiency.

Table 3: Maximum Likelihood Parameter Estimates

	Coefficients	Standard Errors	T Ratio
Frontier Model			
EECBG dollars	0.499	0.063	7.84 ***
Constant	6.002	0. 844	7.12***
Inefficiency Model			
Collaboration	-0.138	0 .065	-2.12**
Staff Capacity	0.299	0.325	0.92
Contract w/ Private	1.466	1.091	1.34
Program Type	-1.988	1.222	-1.63
Constant	0.553	1.106	0.50
Variance Parameters			
σ_v	0.439	0.135	3.24***
Γ $(\sigma_u^2 / \sigma_u^2 + \sigma_v^2)$	0.775		
Log-Likelihood	-399.14		
LR-Test	11.95***		
N	232		

** denotes statistical significance at p<0.05 *** significance at p<0.01

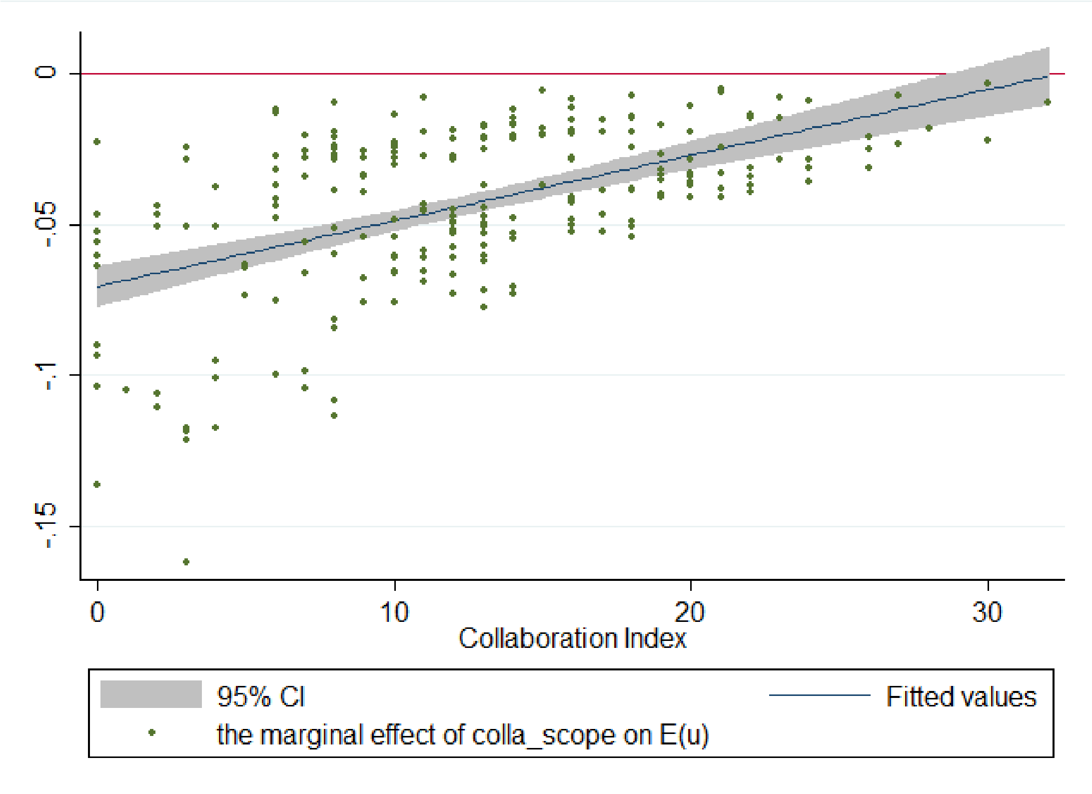

Figure1. Marginal Effects of Collaboration on Inefficiency

All observations show negative marginal effects, indicating that technical inefficiency decreases as the collaboration index scores increases. Nonetheless, the fitted line with 95% confidence intervals is clearly trending upward – suggesting diminishing returns where the size of negative effects (i.e. efficiency improving effects of collaboration) becomes smaller as the collaboration index scores increase and eventually reaches close to 0. In other words, collaboration always yields positive, efficiency-improving effects, but cities enjoy greater marginal benefits of working together when moving from no collaboration to the average level of collaboration than they do when moving from average collaboration to the maximum level of collaboration. Given that engaging in collaboration requires energy, time and resources, this result implies that collaboration and organizational efficiency are positively associated, but that the relationship is not linear.

The gamma parameter, which measures the variability of the two error terms (i.e. v_i and u_i) is 0.775, indicating that about 77 percent of error term in this model is due to inefficiency. Together with LR test statistic, discussed above, leads to the conclusion that the inclusion of inefficiency term in the model provides an estimation that is statistically more significant and efficient than OLS (Wijeweera, Villano, and Dollery 2010). Our goal in this analysis is to assess whether there is a statistically supported and reliable relationship between collaboration and organizational efficiency. The strong statistical significance presented in Table 3 indicates the presence of a valid and robust relationship supporting our first hypothesis that collaboration reduces technical inefficiency.

Conclusion

The joint-production of public services and programs through interagency collaboration are common and widespread today. The extant literature on collaboration provides considerable insight into understanding what collaboration is and how it is being practiced. Questions regarding the factors that enable and inhibit collaboration have received particular research attention. Much of this research carries the implicit assumption that collaboration yields positive net benefits, however, as critics increasingly note, empirical support for this view is lacking. This study is an attempt to empirically evaluate the impact that collaboration has on the implementation public programs in terms of one public goal: efficiency.

The literature claims that collaboration reduces organizational inefficiency by breaking down silos and aggregating the capability that individual entities may uniquely posses (e.g. resources, knowledge, information etc.). By contrast, inefficiencies can result from diffuse and inclusive collaborative governance which often entail more risk and require more monitoring. We examined how these contrasting theoretical expectations are borne out empirically using cross sectional data on U.S. cities' implementation of EECBG grants. Our study supports the idea that collaboration is beneficial for public programs and specifically indicates that it improves the cost-efficiency with which policy outputs are achieved. Nonetheless, the diminishing marginal effects of collaboration suggest that there is an optimal level of collaboration for cities to engage in, as it also takes time and resources for organizations to work together. While it will be ideal to carry out cost-benefit analysis to predict the exact point at which the benefits of collaboration are maximized, this also requires information on the costs and resources invested in collaboration for building retrofits, which are absent. We could only hypothesize the factors that moderate collaboration benefits, such as institutional and structural conditions of collaboration participants. The literature on collaboration documents well the particular conditions under which collaboration successfully develops, yet most work has not investigated how these conditions can also mediate collaboration outcomes. Future research can take advantage of the extant literature that lists various enablers of successful collaboration, and examine how these factors can explain the variations in marginal benefits of collaboration, particularly depending on the different level and scope of collaboration.

Future research could also make improvements in the areas of data, methodology, and measurement. First, with better data, the specification of production function in the SF model could be refined. The SF analysis models functional relationships between outputs and given inputs and this means that the correct specification of production function is important. Including additional variables as inputs beyond financial resources, such as a number of employees and hours expended on generating outputs could enhance understanding about the relationship between resources invested and outputs. However, although the use of SF analysis is increasing in many disciplines, the fields of policy and public management have not yet established a widely-accepted functional relationship between inputs and policy outputs. This lack of a clear functional relationship makes the specification of production functions somewhat tricky but open avenues for future inquiry. Methodologically, the production function might be improved through the use of different production function methodologies. The Cobb-Douglas production function, which is used in our analysis, is the most common and standard production function methodology and allows for a fairly easy estimation and interpretation of coefficients. But it also imposes restrictive assumptions, such as constant elasticity of substitution– or "smooth" substitution – among inputs (Klacek, Vošvrda, and Schlosser 2007). Alternative ways to relax these assumptions have been suggested, including Translog production function, which comes with a different set of limitations. Improving measures of collaboration is another important objective to which research attention should be drawn. A reliable and valid measure of collaboration is essential for accurately estimating and understanding its impact on organizational outputs and outcomes. The measure utilized in this paper – which combines the scope and strength of partnerships – is a reasonable approach, but one which no doubt could be improved upon. Future research should thus not only look for a causal relationship between an organization's partnership and its performance, but also seek to improve the measurement of collaborative dynamics.

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