Modeling Organizational Buffering and Performance: A Bayesian Approach[*]

Ling Zhu
Department of Political Science
TAMUS 4348
Texas A&M University
College Station, TX 77843
lingzhu@polisci.tamu.edu

and

Kenneth J. Meier
Department of Political Science
TAMUS 4348
Texas A&M University
College Station, TX 77843
kmeier@polisci.tamu.edu

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Abstract

Organizational buffering is a key aspect of public management yet little work has examined the practice and much of that has not been able to disentangle management behavior devoted to buffering from organizational structures that perform the same function. We use a Bayesian model to isolate managerial behavior in regard to buffering. Theoretically, managers decide to buffer based on changes in past performance, environment shocks and other factors. We treat this as an organizational learning process and estimate it using a simple Bayesian model. The Bayesian-derived measure performs better than a similar survey measure in predicting future organizational performance in a panel study of several hundred public organizations. The paper concludes with a discussion of how the present technique can be extended to deal with more complex processes of organizational learning and different decision rules.

Introduction

Considerable literature focuses on how organizations handle environmental shocks (Aldrich 1999; Boyne and Meier 2009; Lynn 2005; Meier and O'Toole 2008; Meyer and Rowan 1977; Meznar and Nigh 1995).[1] Systematic empirical research gauging how organizational buffering dampens negative environmental shocks, however, is lacking. One key challenge is that it is difficult to quantify a measure of organizational behavior in buffering. The core question we address in this research, thus, is how one might estimate an organization's effort to buffer environmental influences and what difference it makes.

Meier and O'Toole (2008) measure organizational buffering by combining elements of both structure and management. We extend this conceptualization by providing a theoretical model that explicitly models learning and the information updating process. We contend that organizational buffering is more dynamic than prior work conceptualized. While both internal structures and managerial processes are critical to reducing the negative impact of environmental shocks, an organization can adjust its level of buffering based on how it assesses various shocks and how effective prior buffering was.

Building on the theoretical model for organizational behavior in buffering, which specifies a Bayesian decision-making process, we use a Markov Chain Monte Carlo (MCMC) procedure to empirically estimate a dynamic measure of organizational buffering. In the first step, organizational buffering is conceptualized as a latent variable. A baseline measure for

[1] How to conceptualize organizational behavior in reaction to environmental changes is a fundamental question to students who study organizations. March and Simon (1958) first offered a rational-choice model to systematically study how activities may be initiated "to restore a favorable balance," when "the conditions within or surrounding an organization change in such a way as to affect adversely its inducements-contribution balance and endanger its survival (128)." Following March and Simon(1958), organizational theorists have emphasized the importance of studying the connection between environmental contexts and devision-making processes for handling external threats to organizational survival (Boulding 1975; Miles and Snow 1978; Kaufman 1985; Pfeffer and Salancik 1978; Thompson 1967).

buffering at time t is estimated based on managerial assessment of environmental shocks and information learned from performance feedback (Greve 2003). In the second step, an MCMC approach is used to make inferences about the level of buffering, which is not directly observable. We then use empirical analysis of actual data to show the viability of the Bayesian measure. Last, we empirically evaluate how the adaptive buffering process is linked to organizational performance.

In terms of theory, this research contributes to the existing literature on organizational behavior by showing how organizations adapt buffering strategies based on the outcome of prior efforts. The Bayesian updating approach is more consistent with how organizations decide than existing empirical works and can be applied to other organizational processes. This research also offers empirical verification for the proposed theoretical model. The quantitative measure generated from the theoretical model can potentially benefit other empirical research that focuses on evaluating the link between organizational behavior and performance.

A Theoretical Model for Organizational Buffering

Elements of Organizational Buffering: Assumptions and Definitions

We start from a few general assumptions about organizations and the norms of rationality (March and Simon 1958;Thompson 1967).[2]

Assumption 1: Organizational survival is contingent upon the organizational performance,

[2]These assumptions are made to generalize the theoretical model across different organizational types. In both the public administration and organizational theory literature, there is a long-standing debate regarding whether there are distinctive lines between public, private, and non-profit organizations (Rainey and Bozeman 2000). Here, we assume that there are some generic patterns in organizational behavior across various types of organizations. The homogeneity assumption is made to reduce complexity of the theoretical model.

measured by some forms of outputs ($O_{i,t}$).[3]

Assumption 2: Organizational activities are determined by organizational members who are decision makers and problem solvers (March and Simon 1958, 25).[4]

Informed by the literature on organizational theory and public management, we then identify four elements that may affect organizational outputs and in turn influence how buffering activities may be initiated. First, *Organizational Characteristics* ($S_{i,t}$) refers to the set of factors that characterize how an organization is organized internally. More specifically, it includes internal structure (e.g. hierarchical or decentralized structures), monetary resources, skill assets, and so on (Evans and Davis 2005; March and Sutton 1997). Second, the *Environment ($X_{i,t}$)* generates turbulence and exogenous shocks to organizations (March 1991; Pfeffer and Salancik 1978).[5] The environment also affects how difficult the core organizational task is. It is related to how organizational members perceive the viability of their collective tasks as well as procedural and technological complexity for completing collective tasks (Bohte and Meier 2001; Campbell 1988). Third, *Organizational Memory (O_{t-k})* refers to organizational history that may affect the organizational output at the current time, t (Levitt and March 1988).[6] Last, but not least, *Managerial Inputs*($M_{i,t}$) refer to management strategies, inputs, and processes, etc. (Meier and O'Toole 1999).

[3]For example, in the private sector, the survivability of firms is dependent on their core products and technology. In the public sector, governmental agencies and public organizations are created based on public goods and services they provide to the public. As for the mathematical notation, i denotes organizations, and t denotes time.

[4]This assumption simplifies the reality that different organizational members might share different decision-making power in an organization. Because the theoretical focus of this research is to model organizational behavior based on the aggregated unit-of-analysis, we adopt March and Simon's (1958) proposition that an organization as a whole is able to generate decisions regardless of the actual sources of the decision-making power.

[5]Turbulence and shocks can take various forms. A shock can be tangible, such as a change in the political environment, a financial crisis, a natural disaster, etc. A shock also may be intangible, such as a change in inter-organizational relations, etc.

[6]This assumes some path-dependence of organizations. Generically, k denotes the memory structure, and $k \in \{0, 1, 2, 3....n\}$. If k=0, an organization has no memory of its past performance and all the decisions at time t are independent from its history. When $k = 1$, it refers to organizational inertia, whereby the organizational output at time t can be partly explained by the output at $t - 1$ (Meier and O'Toole 1999).

A few additional assumptions are proposed to keep the theoretical focus on activities of buffering.

Assumption 3: There is no uncertainty about task difficulty. There might be uncertainty about task difficulty for future times; but for the core task, uncertainty is low for each current time node, t.

Assumption 4: An organization has a finite strategy set. We assume that there are only a finite number of strategies that an organization can take when facing turbulence and shocks.

Assumption 5: We assume that there are no substitution effects between buffering and other actions.[7]

Assumption 6: We assume that turbulence and shocks, though different in format and generated by different sources, all affect organizational performance negatively because they raise the uncertainty for completing a task.

Assumption 7: We assume that buffering occurs because of the existence of uncertainty concerning information on potential damages that environmental shocks can generate.[8]

Assumption 8: We assume that organizations predominantly learn from themselves. [9]

[7] We assume this to focus on the action of buffering. In the reality, organizations can have a finite set of mixed-action strategies. For example, managers in an organization can take both buffering and exploiting the environment as their actions to deal with environmental changes. Following the basic assumption of decision-rationality, this assumption simply says that managers are not indifferent between buffering and other actions.

[8] Thompson (1967) provides a more thorough discussion on what specific buffering activities might be initiated. According to Thompson, "under norms of rationality, organizations seek to buffer environmental influences by surrounding their technical cores with input and output components; by smoothing input-output transactions; and by sealing their core technologies from environmental influences (19-21)."

[9] This assumption is to exempt the theoretical model from inter-organizational learning. It can be relaxed to allow a more complex learning network structure. For theoretical simplicity, we focus on endogenous learning in this research.

Based on the aforementioned assumptions, the theoretical exercise of this research is to model how organizational buffering occurs and changes according to two components: (1) information on shocks (i.e. changes in $X_{t,i}$ and changes in $S_{t,i}$) and (2) information on the prior organizational output, $O_{i,t-k}$.[10]

Organizational Buffering at Time t

O'Toole and Meier (1999) propose a generic model for organizational outputs as a function of various management actions, the organizational structure, and the external environment. The model is defined as:[11]

$$O_t = \beta_1(S_t + M_1)O_{t-1} + \beta_2(X_t/S_t)(M_3/M_4) + \epsilon_t, \tag{1}$$

The implicit assumption is that the process of generating organizational outputs is autoregressive. According to Assumption 4 and 5, we can simplify other managerial behaviors to be constant. Assume that $M_1 = M_3 = 1$. Then, equation (2) can be re-arranged into:[12]

$$O_t = \beta_1(S_t + 1)O_{t-1} + \beta_2(X_t/S_t)(1/M_4) + \epsilon_t, \tag{2}$$

The core theoretical interest is to model buffering (M_4) as a function of two types of shocks and endogenous assessment about whether past managerial actions are effective in

[10] Conceptually, information regarding X_t informs organizations about external turbulence, and information regarding O_{t-1} informs organizations about the effectiveness of past management strategies.

[11] O_t denotes some measure of output. S_t denotes organizational characteristics based on structural, procedural, and other elements that support internal stability. X_t denotes a vector of environmental forces. M_k refers to managerial factors. Specifically, M_1 is internal management, M_3 refers to activities that exploit the environment. M_4 refers to activities that buffer the environment. See O'Toole and Meier (1999) for detailed theoretical discussion on the proposed relationship among major elements. Empirical studies that test validity of the model can be found in various subsequent studies (Andrews and Boyne 2010; Hicklin 2005; Meier and O'Toole 2002; Nicholson-Crotty and O'Toole 2004; O'Toole and Meier 2003).

[12] Mathematically, the constant value that we assign to M_1 and M_3 is only a matter of scaling. Hence, to simplify the calculation, we assign them to be 1. Note that Assumption 5 exempts the model from possible dependency among different managerial actions.

sustaining organizational outputs. Hence, we can derive equation (3) from (2):

$$(\beta_2 X_t)/(S_t M_4) = O_t - \beta_1(S_t + 1)O_{t-1} - \epsilon_t \tag{3}$$

Solving equation (3) for defining the expected value of M_4:[13]

$$E(M_4) = E\{\beta_2(X_t/S_t)[O_t - \beta_1(S_t + 1)O_{t-1}]^{-1}\} \tag{4}$$

Equation (4) has following theoretical implications. First, at time t, the expected level of buffering (M_4), is a function of two types of shocks (X_t and S_t) and the "distance" between outputs at time t and $t - 1$. Second, (X_t/S_t) reflects the relative influence coming from the external shocks and the internal shocks. When the relative magnitude of external shock increases, $E(M_4)$ increases. Third, let $D = [O_t - \beta_1(S_t + 1)O_{t-1}]$. D can be viewed as some form of weighted difference between past and current organizational outputs. The past output is scaled jointly by the autoregressive parameter β_1 and the organizational characteristics, S_t. When D increases, $E(M_4)$ decreases. Note that this relationship is not independent from the presence of the external shocks, X_t. This is to say, when facing external shocks, if an organization is still able to generate a relatively large performance increase compared with last year's performance (i.e., D is positive), there might be little buffering activity. When facing external shocks, if an organization is not able to generate a large performance increase (D is negative or 0), there might be more buffering activity.

Note that equation (4) is a highly nonlinear form. Meier and O'Toole (2008, 939) demonstrate that a simplified model equation can be written as:

$$O_t = \beta_1 M + \beta_2 X_t + \beta_3 M_2 + \beta_4(SM_4) + \epsilon_t \tag{5}$$

[13]Proof: Based on equation (4), $M_4 = (\beta_2 X_t)/S_t[O_t - \beta_1(S_t + 1)O_{t-1} - \epsilon_t]$. Assume the error term ϵ_t is random, $E(\epsilon_t)$=0. Therefore, $E(M_4) = E(\beta_2(X_t/S_t)[O_t - \beta_1(S_t + 1)O_{t-1}]^{-1})$.

According to Meier and O'Toole (2008), M in equation (5) refers to other managerial variables such as managerial quality. M_2 refers to networking management. S refers to the structural characteristics of an organization. Similarly, under Assumption 4 and 5, we can derive the expected level of buffering at time t as:

$$E(M_4) = E[\frac{-(O_{t-1} - O_t) + (\beta_{2,t-1}X_{t-1} - \beta_{2,t}X_t)}{\beta_{4,t}S_t - \beta_{4,t-1}S_{t-1}}] \tag{6}$$

As equation (6) shows, the performance feedback $(O_{t-1} - O_t)$ is negatively associated with the expected level of buffering, meaning that as an organization generates a large performance increase, there might be little buffering. Changes in the environment $(\beta_{2,t-1}X_{t-1} - \beta_{2,t}X_t)$, however, are negatively related to the level of buffering, meaning that there might be high level of buffering when the external environment generates large shocks. Similarly, structural stability is inversely related to organizational buffering. Managers may put high level of efforts in buffering if the organizations do not have stable structures. In stable organizations, in turn, managers may put low level of efforts in buffering.

In sum, equation (4) and (6) generate consistent theoretical expectations in terms of how organizational buffering may vary based on changes in the environment, changes within organizations, and the past performance. We can summarize the expectations as follows.

Proposition 1: Organizational buffering is inversely related to performance feedback.

Proposition 2: Organizational buffering is inversely related to organizational stability.

Proposition 3: Organizational buffering is positively related to external shocks.

The conceptualization of organizational buffering hinges on the idea that organizational learning and decision-making are "routine-based, history-dependent, and target-oriented" (Levitt and March 1988, 319). Hence, "organizations are seen as learning by encoding inferences from history into routines that guide behavior (320)." This conceptualization may also apply to various political institutions, such as bureaucratic agencies, political parties, legislatures, etc.

Estimating Organizational Buffering as a Latent Variable: An Bayesian Approach

A major concern on models of adaptive organizational processes is that the adaptive behavior is not completely observable. As aforementioned, the expected level of buffering (M_4) is a function of changes in the environment (X_t), changes within the organization (S_t), and performance feedback (D_t) learned from prior organizational outputs. All these three key determinants can be directly observed. Although empirically, it is possible to observe if a manager takes a strategy of buffering or not, it is difficult to track his/her effort-level in buffering, because it involves a wide variety of decisions in response to a continual flow of demands. This not only is a conceptualization issue in the theoretical literature, but also is a hurdle for developing systematic empirical studies that link the adaptive processes to performance.

We propose a latent-variable model to empirically estimate organizational buffering. We contend that the process for organizational buffering follows an adaptive learning process, which combines information on changes and the assessment of past performance. Assume that organizational buffering is a latent variable Y^* mapped by an observed ranked-scale y. The observed ranked-scale y provides incomplete information on the level of organizational buffering. Figure 1 illustrates the mapping between the observed scale of buffering (y) and the latent scale of buffering (Y^*).

In Figure 1, the dashed-line represents empirical information that we could use to measure organizational buffering. The ranked-categories 1, 2, 3, and 4 represent different levels of

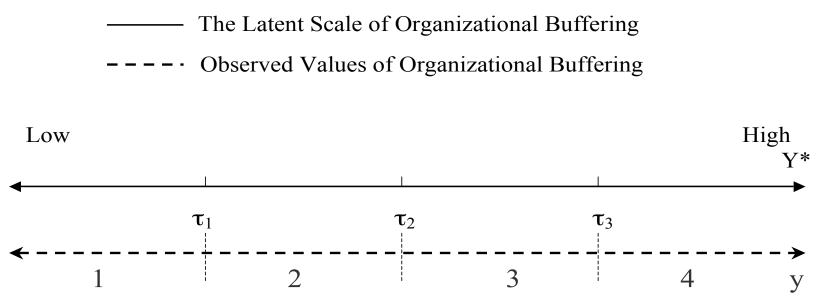

Figure 1: The Observed and Latent Scale of Organizational Buffering

buffering. The latent scale (Y^*), nevertheless, is defined by the three unobserved thresholds, τ_1, τ_2, and τ_3. In practice, one can parse the latent scale into more choice categories. The ordered scale, nevertheless, may not completely reveal the information on the unobserved thresholds that differentiate low levels of buffering from high levels of buffering.

To better estimate the level of organizational buffering, we begin with the latent linear probability regression function:[14]

$$y_i^* = X_i\beta + \epsilon_i, i = 1, 2, ...n \tag{7}$$

The probability of observing y_i in different values based on the scale y defined by the

[14]We demonstrate in the previous section that both equation (4) and (6) produce consistent expectations in terms of how organizational buffering may vary based on changes in the environment, within the organization, and the performance feedback. Here, we propose the linear probability function because it is a simpler model equation. It does not exclude the model-option that one can empirically estimate the measure by using a non-linear equation.

unobserved threshold points.

$$\begin{aligned} Pr(y_i = 1|X_i) &= Pr(y_i^* < \tau_1|X_i) \\ Pr(y_i = 2|X_i) &= Pr(\tau_1 \leq y_i^* < \tau_2|X_i) \\ Pr(y_i = 3|X_i) &= Pr(\tau_2 \leq y_i^* < \tau_3|X_i) \\ Pr(y_i = 4|X_i &= Pr(y_i^* \geq \tau_3|X_i) \end{aligned} \tag{8}$$

In equations (7) and (8), X_i is a vector of key determinants of organizational buffering. Based on equations (4) and (6), we focus on the three aforementioned key determinants: (1) environmental turbulence, (2) organizational stability, and (3) performance feedback. Equation (7) conceptualizes the baseline measure for estimating organizational buffering at time t. This latent-variable model for ranked values can render a joint-probability scale for each observed level of buffering. Because the thresholds $(\tau_j, j = 1, 2, \text{and}, 3)$ are not directly observed, uncertainty in the latent rank orderings may induce uncertainty in how each of the key determinants is linked to levels of organizational buffering.

Therefore, as our second estimation step, we use an MCMC procedure to make inferences for the cumulative ordered rankings. The number of parameters we need to estimate is determined by the length of the X_i vector and the number of thresholds in the observed scale. The third step is to convert a numerical measurement scale recovered from the joint-density for each observed level. In practice, there is more than one option to compute the measurement scale. For example, for each organization i, we can compute the probability of taking the lowest rank. We can also compute the probability of taking the highest rank. Given that our theoretical interest is to obtain an empirical measure for buffering, which is comparable across different organizations, we choose to compute the weighted-average probability scores across different rankings.[15]

[15]The mathematical formula for computing the probability measure is also contingent upon how the observed ordered rankings are developed. For example, if the observed scale is constructed based on a

The Bayesian approach is a particularly useful tool to measurement for latent variables. It allows incorporation of prior information based on an organization's past performance. It is flexible in handling different causal mechanisms. The MCMC procedure may also help to improve precision of the statistical inference and thus reduce measurement errors. Last but not least, the numerical scale recovered from the probabilistic updating process can vary across organizations and time and could be more informative than qualitative and categorical measures for organizational behavior.

Bayesian statistics also mimic how managers make decisions, that is, it is isomorphic with the data generating process. Managers select tactics based on observations of current performance interpreted relative to past performance and a set of expectations. Specific actions are selected because managers have prior expectations on the impact that those actions will have. These priors encompass organizational history and experience as well as managerial judgements. The priors also limit managerial choices to a more narrow range of options rather than the entire universe of managerial choice. Once implemented, managers observe outcomes to see if the results are an improvement. Based on this observation, the manager derives posterior probabilities, that is, knowledge about whether the action yielded the appropriate benefits. In a learning process, these posterior probabilities then become the prior probabilities for the next iteration of managerial decisions.

Estimating Organizational Buffering: An Empirical Application Using Public Education Data

Treating organizational buffering as a latent variable, the proposed Bayesian approach incorporates both the first-order knowledge (i.e., the factors that are linked to buffering

binary-outcome scale (e.g. 0= no buffering, 1=buffering), one can simply use the probability score of $y = 1$ as an empirical measure for organizational buffering. If the observed scale has more than two choices, one can measure high level of buffering by combining categories above the median thresholds. The weighted average across all choices simply reflects the average effort level of buffering for each organization i.

activities and constrain the level of buffering) and information uncertainty. The empirical data suitable for applying this theoretical approach need to meet following conditions.

First, the empirical data should provide a set of organizations, from which we can define a common core organizational task. Second, longitudinal data for the same set of organizations are needed for capturing the changes in the environment and within organizations. Empirical data for operationalizing the two shock variables (X and S) and some measures for the core organizational task are also needed.

We use a public education dataset for empirically estimating organizational buffering. The dataset includes more than 1,000 public school districts in Texas and includes educational performance data for these school districts from 2002 to 2009. The large number of cross-section units (public school districts) in each year-panel can render sufficient statistical power for estimating a robust first-order prior knowledge, i.e. to estimate M_4 based on equation (4). The longitudinal data for each school district allow a full exploration of the dynamic updating process. Performance on TAKS (Texas Assessment of Knowledge and Skills) is used as an empirical measure for the common core organizational task.[16] Public finance data on school employee turnover and revenue change are merged with the academic performance data for operationalizing internal and external shocks. Last, a longitudinal survey dataset on school district management is used for estimating the first-order equation and evaluating the validity of the weighting mechanism.[17]

[16] In Texas, TAKS is a standardized test mandated by the state and is the core task recognized by the Texas Accountability Rating System for education.

[17] This survey dataset is generated by the Project of Equity, Representation, and Governance (PERG) at the Texas A&M University. It is a bi-annual survey project, which focuses on studying how various managerial activities are adopted by public managers of Texas school districts. The first survey was launched in 2000. This management survey project has informed various empirical studies on topics of public administration, public policy implementation, quantitative management studies, and street-level political representation. Using this empirical application not only helps to assess the viability of the proposed theoretical model, but also can generate an improved empirical measure for organizational buffering and thus can extend the existing empirical research. The proposed theoretical model for measuring organizational behavior, nonetheless, is generic, and could be implemented with different empirical data on various organizations including political institutions.

Variables

We estimate the Bayesian measure for organizational buffering based on the theoretical expectations derived from equation (4) and (6). The empirical model for obtaining the joint-posterior density is constructed based on a Bayesian ordered-choice model proposed in equation (7) and (8). We draw data for the observed values of organizational buffering (M4) from Texas Superintendent Management Survey 2005-2009. In 2005, 2007, and 2009, we asked superintendents if they agree with the following statement: "I always try to limit the influence of external events on my principals and teachers." The observed values for the latent buffering variable are coded based on a 4-point scale: "Strongly Agree (=4)", "Agree (=3)", "Disagree(2)", and "Strongly Disagree (=1)". Figure 2 illustrates the overall sample distribution of the observed scale.

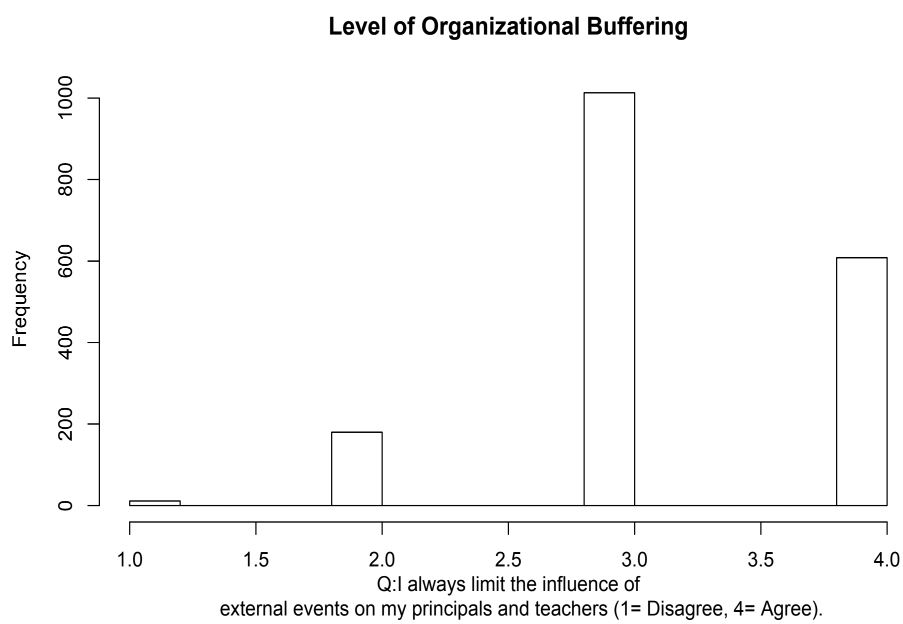

Figure 2: The Sample Distribution of Superintendents' Efforts in Buffering

Table 1 tabulates the observed values in each choice category in three surveys. Based on our full sample, 33.09% of the superintendents reported that they tried hard to buffer the influence of external events on their organizations. 56.15% of the superintendents reported that they somewhate tried to buffer the external turbulence. About 10.2% of the superintendents reported that they did not buffer the influence of external events.

Table 1: The Sample Distribution of Superintendents' Self-Reported Efforts in Buffering (Q: I always limit the influence of external events on my principals and teachers.)

Year	N	Strongly Agree (4)	Agree(3)	Disagree(2)	Strongly Disagree(1)
2005	621	40.74%	52.50%	6.60%	0.16%
2007	693	29.15%	58.73%	11.54%	0.58%
2009	593	29.68%	57.00%	12.14%	1.18%
Full Sample	1907	33.09%	56.15%	10.12%	0.63%

The first key determinant of organizational buffering is performance feedback. Based on equation (4) and (6), managers assess the performance feedback by gauging the distance between past performance and current performance. Our theoretical expectation is that the effort level of buffering would increase if an organization's performance at time t becomes worse than its past performance. Equation (4) refers that some discounting rate (β_1) is applied to the performance in last year. Equation (6) uses a one-period difference between past and current performance. We calculate a three-year average trend for changes in average TAKS pass rates as an empirical indicator for performance feedback. For example, for school district i in 2005, its performance feedback (from previous years) is calculated based on annual changes in 2004, 2003, and 2002. We would expect a rational decision-maker to establish priors based on a consistent level of past performance rather than a single year's outcome that could be distorted by unique events.

We then measure external shocks by using public finance data. Specifically, we calculate annual revenue changes based on the per pupil revenue in each school district and use it as a proxy for environmental turbulence. Revenue change is one of the major forms of environmental turbulence to public school districts, because school districts do not control the external economic conditions and the budgetary process. The variable for revenue change is measured as the percent change in per pupil revenue from year t-1 to year t. We then use data on personnel stability to evaluate changes within organizations. Specifically, we gauge both employee turnover and managerial stability in school districts. School districts are highly professionalized organizations and rely on their professional workforce to generate organizational performance. Therefore, changes in personnel stability are likely to have substantial impact on performance. To empirically measure internal changes based on personnel stability, we create a two-item factor index by combining the variable of employee stability and managerial stability. Employ stability is measured by the percentage of teachers hired by a district in year $t-1$ who continue work in the same district in year t. Managerial stability measures the number of years a superintendent has worked in the school district.[18]

In addition, we include managerial networking as a control variable for managerial activities that are taken to exploit the environment. This measure is constructed based on a principal-component analysis of a set of survey items that report school district top managers' behavior as they interact with the important parties in the district's environment (Meier and O'Toole 2003). The managerial networking index is calculated based on four survey items, including superintendents' interaction with the Texas Education Agency, other superintendents, state legislators, and local business leaders. All four items load positively in one factor, with an eigenvalue of 1.80 in with the 2005 survey data, an eigenvalue of 1.77 with the 2007 survey data, and an eigenvalue of 1.75 with the 2009 survey data.

Table 2 reports the descriptive statistics of the four variables included in our X_i vector. Both *Stability* and *Managerial Networking* are factor indexes. For these two variables, higher scores refer to higher levels of internal stability and managerial networking. The descriptive statistics for *Revenue Change* and *Performance Change* show that individual school districts

[18]We create a factor index for organizational stability based on the principal-component factor analysis. the two variables load in one factor with an eigenvalue of 1.15.

can face substantially different environmental shocks and can have very different performance feedback.

Table 2: Descriptive Statistics for the Key Determinants of Organizational Buffering

Variable	Obs.	Mean	Std. Dev.	Min	Max
Stability	1907	-1.58e-09	1.00	-5.54	3.23
Managerial Networking	1907	-0.10	0.91	-2.80	4.04
Revenue Change	1801	4.99	18.34	-70.88	99.45
Performance Change	1812	-1.05	5.17	-26.97	15.67

Estimation

Our estimation procedure contains three steps.[19] Firstly, we implement a Bayesian ordered logit model to obtain a joint posterior density for seven parameters. Because the outcome variable is constructed based on a 4-point ordered scale, we need to estimate the posterior distribution for three cut-points. We include four explanatory variables, furthermore, in the linear probability equation. Hence, we also need to estimate the posterior distribution for each slope parameter, β_i.[20] In this step, we first remove the small amount of missing data via list-wise deletion and store the OLS parameter estimates as start values for the MCMC algorithm. In the second step, we use the JAGS program in R to run an MCMC algorithm. We request 10,000 iterations and store every 10th value for the β_i coefficients and cut-points(τ_i). In the model output, we obtain a 1000-observation sample of the posterior distribution for each estimated β_i and τ_i. To implement the MCMC algorithm, we set the prior for the four β coefficients to be a multi-variate normal distribution, with means of 0. We also define the priors for the threshold parameters τ_i to be normal distributions with means of 0. For both sets of priors, the precision measures are defined as .01.

[19]See the Appendix A for the BUGS code of our Bayesian model. See the Appendix B for JAGS and R code that are used to compute the Bayesian measure. The BUGS code are adapted from Jackman (2009, 403).

[20]To simplify the computation process, we do not include the intercept in our model.

Table 3 reports results of the MCMC analysis for the ordered logit model. We find that two of the four predictors exhibit considerably larger effects on organizational buffering that are distinguishable for zero. The level of organizational buffering is negatively associated with performance change and positively associated with managerial networking. We estimate our Bayesian ordered logit model using mean-centered predictors, this model specification has the effect of changing the location of each cut-point, τ_i. Mean-centering predictors, however, does not affect the relative positions of these three cut-points mapped on the latent probability scale. Both organizational stability and revenue change, in addition, do not exhibit statistically significant impact on the level of organizational buffering. The posterior means of these two variables, however, are both negative. This is consistent with our theoretical expectations. It is conceivable that managers might put more efforts into buffering the influence of external events if their organizational structures are not stable. It is also likely that the effort of buffering might decline if a school district's revenues increase. The effort of buffering might increase, on the contrary, if a school district loses revenues compared to the prior year.

Table 3: MCMC Analysis of Organizational Buffering

Variable	Posterior Mean	SD	Naive SE	Time-Series Error
Stability	-0.025	0.050	0.0016	0.0014
Revenue Change	-0.002	0.002	8.242e-05	8.9153-05
Managerial Networking	0.153	0.053	1.333e-04	1.344e-04
Performance Change	-0.043	0.009	1.680e-03	1.599e-03
Cut-Points				
τ_1	-5.146	0.309	9.801e-03	1.013e-02
τ_2	-2.152	0.077	2.495e-03	2.184e-03
τ_3	0.691	0.050	1.613e-03	1.662e-03

After obtaining the posterior distributions for β_i and τ_i, we extract the posterior means for each parameter and use the posterior means to compute posterior probability mass function over the four levels of organizational buffering. Figure 3 further illustrates the posterior probability mass functions over four levels of organizational buffering. As Figure 3 shows, the overall distribution of the posterior probability mass for each level of buffering corresponds well with the observed ordered scales. Based on the summary statistics in Table 1, we have the highest percentage of respondents who choose level 3, the second highest percentage is for level 4. As for the two categories of "no-buffering," we see the smallest proportion of respondents choose level 1. The Bayesian approach, nevertheless, adds more information on the latent scale for buffering. As Figure 3 shows, in each choice category, the converted posterior probabilities vary substantially among organizations. For example, the probability scores of choosing level 1 varies from, 0.004 to 0.011. The probability scores of choosing level 4 (the highest level of buffering) also has a wide range of variation now, from around 0.22 to 0.44. Because our Bayesian analysis is estimated by looping over each organization i, the posterior probability mass function (represented in Figure 3) produces a set of predicted probabilities for each choice category in observation i. Substantively, it reveals information on how likely an organization i will fall into the category for the high level of buffering, the moderately high level of buffering, the low level of buffering, and the very low level of buffering.

The third step of estimation is to calculate the organizational buffering measure for each organization i based on the posterior probability mass function. We simply calculate a weighted-average score by using the ordered-ranks as the base-value and use the set of predicted probabilities as the vector for weights. We use the weighted-average score as an empirical indicator for the level of buffering. This calculation produces a positive scale ranging from 0.357 to 0.806. Higher scores refer to higher levels of buffering and vice versa. This calculation is simple and straightforward. For an organization i, if the estimated probability of choosing level 1 (lowest level of buffering) is 1, then the estimated probabilities for choosing all other levels are zero. In such a case, the buffering measure takes a value of

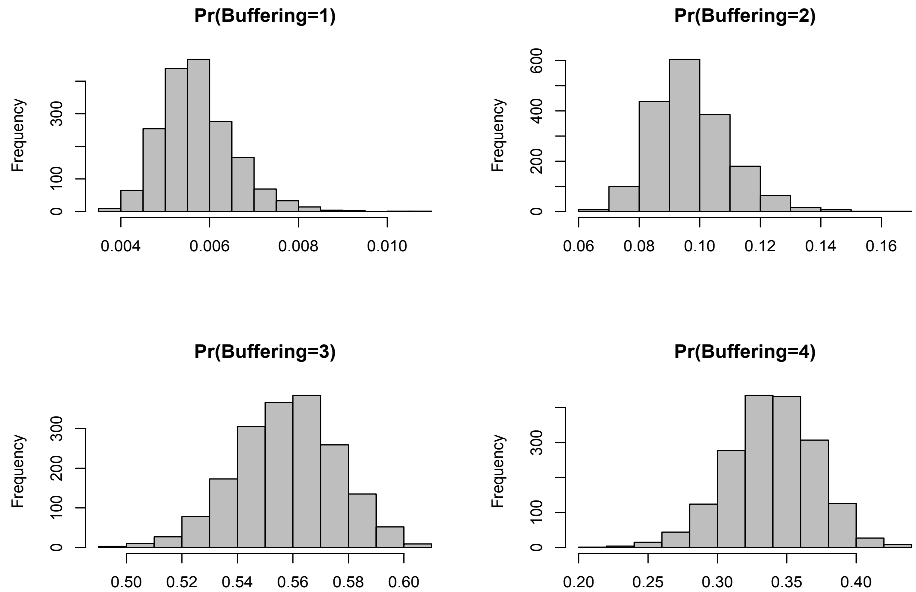

Figure 3: Histograms, Posterior Probability Mass Functions over Levels of Organizational Buffering

0.25. Conversely, if the estimated probability of choosing level 4 (highest level of buffering) is 1, then the probabilities for choosing all other levels are zero. In such a case, the buffering measure takes a value of 1.

The Impact of Buffering on Organizational Performance

We then evaluate the measurement validity by estimating the impact of the buffering measure on organizational performance. In theory, we expect that the level of managerial behavior in buffering may limit the influence of external events on organizations and thus contribute to increase organizational performance. We pool data on the average TAKS pass rate for each school district in 2005, 2007, and 2009. We then assess the impact of buffering by estimating two models. Model 1 is estimated based on the ordered-ranked buffering measure obtained from Superintendent Management Survey 2005, 2007, and 2009. Model 2 is estimated based on the Bayesian measure for managerial buffering. In order to compare model results, we include a common set of variables in two models, so that the only difference is in the buffering measure. We also normalized the originally survey responses into a scale bounded by 0 and 1, such that values of the two buffering measures are on the same numerical scale.[21] Because the average TAKS pass rate is an overall educational performance measure, we draw on the existing empirical literature and include a set of commonly used variables in the literature on educational production functions (Meier and O'Toole 2008).

Firstly, we include a set of managerial variables that may affect school districts' performance. Managerial networking is measured by superintendents' interactions with important parties in the environment. The interaction between superintendents and the school board is included as a variable for how managers deal with political oversight. Managerial stability measured by the superintendent tenure reflects consistency in management. We then include four variables related to teachers. Teachers' turnover is measured by the percentage of teachers who leave a school district i in a given year. We also include average years of teaching experience and teacher's salary measured by 1,000 dollars as two variables for teachers' characteristics. The percentage of non-certified teachers is included as a measure for teachers' quality. Thirdly, we include student demographics in the two models – the percentages of black, Latino, and low-income students. The percentage of state aid is included as a measure for financial resources. Lastly, we include total enrollment (1,000s) as a control for organizational size.

Because our analysis evaluates performance data in 2005, 2007, and 2009, we estimate the two empirical models for organizational performance by including dummy variables for year 2005 and 2007. Also with the consideration of across-organization heterogeneity, we

[21] We simply divide the original ordered ranking by 4, such that 1 is recoded into 0.25, 2 is recoded into 0.5, 3 is recoded into 0.75,and 4 is recoded into 1. When the two buffering measures take values on the same numerical scale, we can directly compare their coefficients in Model 1 and Model 2.

estimate the two models using robust standard errors. Table 4 reports estimation results for the two regression models. At the first glance, the two models produce comparable coefficients for most variables. The proportions of minority and low-income students are negatively associated with the average TAKS pass rate. Both models show that managerial stability and teachers' stability are important for promoting school districts' performance in educational tests.

Table 4: The Impact of Buffering on Organizational Performance (Dependent Variable: Average TAKS Pass Rate)

	Model (1)			Model(2)		
Variable	Coeff.	Std.Error	t-value	Coeff.	Std.Error	t-value
Buffering(Ordered-Scale)	**3.471**	**1.024**	**3.402**	–	–	–
Buffering(Bayesian)	–	–	–	**5.387**	**2.633**	**2.045**
Networking	0.219	0.196	1.118	0.330	0.199	1.656
School-Board Contact	-0.526	0.221	-2.380	-0.511	0.222	-2.301
Managerial Stability	0.015	0.018	0.845	0.016	0.018	0.902
Teacher Turnover	-0.298	0.024	-12.650	-0.298	0.024	-12.621
Teachers' Salary (000s)	0.130	0.069	1.886	0.128	0.069	1.848
Teacher Experience	0.272	0.008	3.274	0.268	0.084	3.211
Non-certified Teachers	-0.193	0.029	-7.287	-0.191	0.031	-6.164
Percent State Aid	-0.012	0.010	-1.238	-0.013	0.010	-1.324
Class Size(000s)	0.025	0.016	1.599	0.020	0.016	1.290
Percent Black Students	-0.163	0.018	-9.162	-0.161	0.018	-9.020
Percent Latino Students	-0.061	0.010	-5.996	-0.057	0.011	-5.393
Low-income Students	-0.283	0.015	-18.913	-0.282	0.015	-18.753
Residual SE	6.479			6.454		
N	1783			1783		

As for the two buffering measures, Model (1) and Model (2) report widely different coefficients. The buffering measure used in Model (1) is the 4-point ordered scale. Based on Model (1), managerial buffering has a positive effect on organizational performance. The average impact of a one-unit change in managerial buffering on performance is 3.471. Model (2) uses the Bayesian measure of managerial buffering, based on which the average impact of a one-unit change in buffering on performance is 5.387. While a one unit change exceeds the range of the data, the coefficients give an accurate view of the relative impact for smaller changes in buffering. We then calculate the standardized coefficients for the two buffering measures in Model (1) and (2). The standardized coefficient for the Bayesian measure is 0.078 and the standardized coefficient for the categorical buffering measure is 0.047.

It is conceivable that the Bayesian measure may help to improve the coefficient estimation of the buffering measure. The substantive impact of managerial buffering on performance is larger based on Model (2) than it is based on Model (1). It suggests that the 4-point ordered measure created by survey items may lead to an under-estimation of the substantive impact of managerial buffering. Why is this a case? We think this is because the categorical survey responses suppress possible data variations in the latent buffering scale, thus do not fully reveal the latent information regarding variations between different levels of buffering. The numerical scale ordered from 1 to 4 only roughly reflects different levels of managerial buffering. This buffering measure, moreover, does not vary a lot for the same organization in different year observations. The coefficient size of managerial buffering becomes larger in Model (2) because the Bayesian measure incorporates information regarding how the level of buffering are linked to its key determinants, accounts for the underlying adaptive decision-making process, and captures more data variation across different effort levels as well as across time.

The substantive findings on the managerial networking variable are also different in two models. The coefficient size of managerial networking is larger in Model (2) than it is in Model (1). Our empirical findings suggest that the effect of networking management might be underestimated in Model (1). It is likely managerial buffering and networking activities are positively correlated, therefore, measurement errors in the buffering measure could also affect estimation reliability of the networking measure. The lack of collinearity between networking and buffering for the Bayesian measure also suggests that the Bayesian technique has generated a measure with greater discriminant validity.

Comparing the model-fit statistics of the two models, the residual standard error (RSE) is reduced by using the Bayesian measure. This suggests that the Bayesian measure of buffering may help to improve measurement precision and thus improve the overall model quality. In our empirical illustration, nevertheless, we set all our priors to be normal distributions with 0 means. These priors only express vague beliefs about our parameters (β_i and τ_i), hence, the estimation results are heavily weighted in favor of our observed data structure. This is the main reason why our estimated Bayesian measure improves model RSE, but does not reduce it substantially.

Discussion

How organizations behave in response to environmental changes is a core question in organizational theory. Modeling adaptive behavior at the organizational level, however, is challenging due to the uncertainty of the micro-foundations of the decision-making process and the uncertainty of how environmental changes might affect an organization's survivability. When the decision-making process of choosing management strategies is not directly observable, it is very difficult to develop valid empirical measures for managerial activities. This research proposes a generic model for empirically assessing organizational behavior in buffering. In this research, we use a Bayesian approach to make statistical inference of the underlying organizational processes. Both the theoretical model and the Bayesian approach to measuring latent organizational behavior can be generalized to other organizational behaviors, such as internal management, networked management, etc. This research project contributes to two broad literatures: the literature on measuring organizational behavior, and the literature on organizational learning.

Using public education data as an empirical illustration, we demonstrate both the validity of our research design and the viability of using a Bayesian approach to quantify empirical measures for managerial buffering. The theoretical advantage of using the Bayesian approach is that it takes account into how organizations adapts to its environment, internal changes, as well as managerial decisions based on performance feedback. Theoretically, this is a better approximation of how managerial decisions are made. The validity of an empirical measure is likely to be increased when it is developed based on the the micro-foundations of the behavior in question. The Bayesian approach, moreover, is a flexible estimation tool and allows researcher to incorporate complex causal mechanisms in terms of how various factors determine the level of buffering. In this research, we only use a simple linear probability link function to demonstrate that it is viable to estimate a Bayesian measure of buffering. Our empirical design, nevertheless, is not the only way to estimate the buffering measure. For example, one may include additional causal variables in the X_i vector when estimating the Bayesian measure. It is also feasible to relax the assumption of linearity and model non-linear probability link functions.

To make our Bayesian computation simple and straightforward, we made a few assumptions in the theoretical section, which can be relaxed. For example, we assume that organizations have a finite strategy set and only take pure managerial strategies at a certain time node (Assumption 4 and 5). This may not perfectly reflect what managers could do in practice. It is possible that managers may take a mixed-strategy when facing environmental turbulence–i.e. to buffer the environment and to exploit the new opportunities at the same time. It is also possible that managers combine their efforts in dealing with environmental changes with other efforts in enhancing internal management. When we relax these assumptions, equation (4) would become more complex. One possible way to model the complex relationship is to use a system of equations instead of a single equation to conceptualize the relationship between multiple managerial strategies and the proposed key determinants.

In this research, we also assume that organizations primarily learn from themselves and conceptualize performance feedback based on objective measures. The assumption of endogenous learning can be relaxed. We contend that the key element to infer managerial decisions in buffering is to obtain an estimation on the organizational feedback. In practice, objective performance indicators may not be the only set of criteria used for performance appraisal. How managers assess their organizational performance may also be affected by their aspiration levels (i.e. their expectations on performance) and how peer organizations perform. Managers' aspirations and the learning-from-others mechanism are both subjective information that could affect organizational behavior in buffering. The Bayesian approach could be extremely useful for incorporation subjective beliefs. Using different types of informative priors in the estimation procedure can help to incorporate subjective beliefs on prior performance. This is also a situation suitable to Bayesian hierarchical modeling. For example, in our empirical example, we simply assume that all organizations have the same underlying decision-making rational and suppress the intercept. One may incorporate heterogeneous managerial expectations by adding a hierarchical prior for each organization.

We demonstrate that the Bayesian approach to measurement also has empirical advantages. Large organizations are likely to be inertial and thus it could be hard to empirically track changes in managerial activities. Conventional data-collection methods (such as large scale surveys) are essentially taking snapshots of managerial behaviors, thus may not capture across time changes well. For example, in our case of surveying school districts in texas, we track how school districts are managed biannually. Survey responses for the same organizations may not vary a lot across different years. Using the Bayesian approach to measurement, we can make inferences about how these values may vary across different time points. The empirical measure produced by the MCMC analysis varies across organizations and time, and thus is superior to the survey responses. The Bayesian measure also better approximates the data-generating process than the empirical data we collect from surveys.

To conclude, systematic research on how management is linked to organizational performance can be hindered by a lack of valid measures for organizational behavior and unsophisticated methodology for handling information uncertainty. The Bayesian approach is particularly appealing for dealing with both challenges. It alters the conventional way of thinking about empirically observed information and the underlying data-generating process. The Bayesian approach relies on strong theoretical justifications for defining causal variables and renders a flexible modeling procedure for updating our inference of the unknown based on the known (Gill and Meier 2000). Because organizations are seen as "learning by doing", they often capture historical lessons into future routines (Levitt and March 1988, 320-321). In both the theoretical and empirical literature of management and organizations, managerial routines and strategies are usually deemed as fixed. Conventional survey research is useful to collect information on organizational processes at fixed time points, but may not be very helpful to capture how managerial activities are transformed into favorable performance outcomes. The Bayesian approach is more suitable to modeling learning, information updating, and adaptive processes of choice.

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Appendix A: BUGS Code for Bayesian Estimation

```
 model{
       for(i in 1:n){ ## loop over observations
          ## form the linear predictor, no intercept
   mu[i] <- x[i,1]*beta[1]+
        x[i,2]*beta[2]+
        x[i,3]*beta[3]+
        x[i,4]*beta[4]

    ## cumulative logistic probabilities
    logit(Q[i,1]) <- tau[1]-mu[i]
    p[i,1] <- Q[i,1]
    for (j in 2:3){
           logit(Q[i,j]) <- tau[j]-mu[i] ##obtaining cdf.
   p[i,j]<- Q[i,j]-Q[i,j-1]
     }

    ## four choices, 3 cut-poits
    p[i,4]<-1-Q[i,3]
    y[i]~dcat(p[i,1:4]) ## 4 choices, p[i,] sums to 1 for each i.
       }

    ## Priors over betas
    beta[1:4]~dnorm(b0[ ],B0[ , ])

    ## Priors over cut-points
    for (j in 1:3){
             tau0[j]~dnorm(0,.01)
            }
         tau[1:3]<-sort(tau0) ## Only can be used in JAGS.
}
```

Appendix B: JAGS and R Code

```
library(foreign)
Buffering<-read.dta(file.choose())# load file pmra4.dta
attach{Buffering}

hist(buffer,
     main="Level of Organizational Buffering",
     xlab="Q:I always limit the influence of
     external events on my principals
     and teachers (1= Disagree, 4= Agree).")

ols<-lm(as.numeric(buffer)~stability+avecut
    +apasschange+network, data=Buffering, x=TRUE,y=TRUE)

##Variables for JAGS
# The call to JAGS from R.
forJags<-list(y=ols$y,
      x=apply(ols$x[,-1],2,function(x)x-mean(x)),
      n=length(ols$y),
      b0=rep(0,4),
      B0=diag(1E-08,4)
              )

##Setting Initial Values
# Using ols coefficients as starting values
inits<-list(list(beta=coef(ols)[-1],tau0=2:4))
require(rjags)

buffermodel<-jags.model(file="oLogit.bug",
data=forJags,
inits=inits)

out<-coda.samples(buffermodel, variable.names=c("beta","tau"),n.iter=10000,thin=10)

summary(buffermodel)
plot(buffermodel, smooth=TRUE)

# Checking Sampler-Lag Autocorrelations
autocorr(out, lags = c(0, 1, 5, 10, 50), relative=TRUE)
autocorr.plot(out)

# Checking the Trace Plot
plot(out, trace=TRUE)
```

```
## Posterior Means for each parameter
colMeans(buffermodel[[1]])

##Converting posterior means into probabilities
# Posterior probabilities-using posterior means
vector<-c(colMeans(out[[1]]))
beta1<-vector[1]
beta2<-vector[2]
beta3<-vector[3]
beta4<-vector[4]
tau1<-vector[5]
tau2<-vector[6]
tau3<-vector[7]

#Calculate mu[i]
mu <- stability*beta1+avecut*beta2+apasschange*beta3+network*beta4

#Calculate Q[i,j]
Q1<-(1/(1+exp(-tau1+mu)))
Q2<-(1/(1+exp(-tau2+mu)))
Q3<-(1/(1+exp(-tau3+mu)))

#Calculate p[i,j]
p1<-Q1
p2<-Q2-Q1
p3<-Q3-Q2
p4=1-p1-p2-p3

# Show probabilities for the 4 choices
library(lattice)
par(mfrow=c(2,2))
hist(p1, type="count", main="Pr(Buffering=1)", xlab="", col="gray")
hist(p2, type="count", main="Pr(Buffering=2)", xlab="", col="gray")
hist(p3, type="count", main="Pr(Buffering=3)", xlab="", col="gray")
hist(p4, type="count", main="Pr(Buffering=4)", xlab="", col="gray")
```