Risk Sharing in Local Governments:
Are State-Wide Rainy Day Funds the Answer?

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Abstract

Rainy day funds are one of the primary tools that state and local policymakers employ to dampen the effects of downturns. However, since business cycles (across US States or across municipalities within a particular state) are not perfectly synchronized, theoretically there should be risk-sharing benefits to governments who pool their fiscal resources over the business cycle. For local governments, this implies that there may be fiscal benefits to institutionalizing a state-wide rainy day fund. In this paper, we explore the issues associated with local government risk-sharing and provide estimates of the potential benefits to for the municipalities within the state of Virginia. Our results suggest that a statewide rainy day fund would provide considerable fiscal benefits to local governments at a lower price than self-insuring through their own rainy day funds.

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I. Introduction

Although economic downturns create periods of fiscal distress for all levels of government, state and local governments are particularly vulnerable because they have smaller tax bases, more limited options for raising additional revenue, and face much more stringent fiscal rules. In fact, a recent study by The Pew Charitable Trusts found that 21 out of the nation's 30 largest cities had nominal revenues in 2011 that were below their pre-recession peak levels.[1] Moreover, cities such as Boston, Houston, Miami, Minneapolis, Orlando, Phoenix, Sacramento, and Tampa were still experiencing declining nominal revenues at the time of the study.

Unlike state and federal governments, local governments generally maintain sizable unreserved fund balances to help mitigate such periods of fiscal stress. These unreserved balances can be thought of as "savings" or "fiscal slack." In an examination of North Carolina counties over the period from 1990 – 2007, Wang and Hou (2012) found that the typical county maintained slack reserves of more than 20 percent of expenditures. There is obviously considerable variation in how local governments save both within and across different states, however the basic fact remains that local governments in the US are the most active savers of all levels of government.

Since smaller regions such as cities and/or counties will tend to be less economically diversified than larger regions, there is reason to believe that local business cycles will not by strongly synchronized across or within a given region or state. Similar to insurance, this diversity suggests that local government may benefit from pooling their fiscal resources over the business

[1] *America's Big Cities in Volatile Times: Meeting Fiscal Challenges and Preparing for the Future*, published by the Pew Charitable Trusts, November 2013.

cycle and be able to maintain fewer reserve funds in aggregate than each individual government would need to save individually. In other words, the lack of business cycle synchronization between different local cities may yield opportunity for diversification benefits, which we call the risk-sharing or pooling benefit.

Examining individual city or county-level data in Virginia, our objective in this paper is to estimate the size of the potential risk-sharing benefits that may exist between local governments. Our estimation and simulation results indicate that risk-sharing – or pooling fiscal resources over the business cycle – would provide local municipalities with a lower-cost solution to hedge fiscal shocks regardless of the time horizon or confidence level we examine. In fact, if every municipality shared the same objective to maintain a constant growth rate in their funds available to spend in three out of every four recessions that might occur in a given time period (or to be in the 75^{th} percentile), our results suggest that they could pool their resources and save nearly 50 percent less in aggregate than they would be required to save individually to reach the same target. This nontrivial amount implies that the formation of a statewide rainy day fund could provide meaningful fiscal benefits to Virginia's municipalities.

In the following sections of the paper we provide a very brief overview of local fiscal slack, outline the empirical and simulation methodologies, present our results, and offer concluding remarks.

II. Empirical Methodology

2.1 Background

Research investigating the savings behavior of local government is relatively scant despite the fact that total spending by local government exceeds that of their parent state governments. One recent study by Marlowe (2013) provides a very nice overview of the issues and unique challenges that arise in assessing the fiscal health of local governments. Without loss of generality, we will use the terms rainy day fund, savings, fiscal slack, and unreserved balances interchangeably as our objective is to explore how much local governments may wish to save rather than the precise manner in which they do so.

While bond rating agencies and early studies of state-level savings such as Gold (1983) have suggested that savings equal to 5 percent of expenditures/revenues would be a suitable target, several recent distribution-based empirical studies cast doubt this threshold.[2] For instance, Cornia and Nelson (2003) model the distribution of budget deficits in Utah using a value-at-risk approach and estimate that there is a 95 percent chance that Utah's deficit will be no worse than $135 million in a single fiscal year. Applying the same value-at-risk to municipal governments, Salin et al. (2004) conclude that College Station, TX and Columbia, MO can weather a downturn with 95 percent certainty with a rainy day fund (or savings more generally) that is slightly more than 5 percent of their expenditures.

One potential concern with how the value-at-risk approach has been applied in previous studies is that the analysis is limited to a single fiscal year. Considering that Owyang et al. (2005) find that the typical downturn for the nation and most states lasts longer than a single year, the value-at-risk approach will tend to underestimate the slack resources needed to mitigate an average recession.

In contrast to value-at-risk, Wagner and Elder (2007) apply Hamilton's (1989) Markov-switching model to a measure of each state's economy in order to formally model the distribution

[2] In general, the literature suggests that states with more stringent or rule-bound deposit and withdrawal rules governing their rainy day funds have experienced better fiscal outcomes. See for example Hou and Duncombe (2008), Wagner and Elder (2005), Wagner (2004), Knight and Levinson (1999), and Sobel and Holcombe (1996).

of both expansions and contractions that states are likely to face conditional on the past. This allows them to form empirical distributions and calculate the associated probabilities with any given expansion-contraction combination that may occur. For the median state, Wagner and Elder (2007) estimate that savings equal to 13 percent of revenue is sufficient to weather a typical (50^{th} percentile) recession. In order to have a higher level of certainty, say 90 percent, the median state would need a rainy day fund that is equal to 35 percent of their revenue.

In addition to national governments, Hamilton's (1989) Markov-switching model has been used to model the cyclical behavior of both state and local governments (Owyang et. al, 2005, 2008, 2013; Wagner and Elder, 2007; Elder and Wagner, 2013). Examining employment cycles in 58 large US cities, Owyang et al. (2013) find strong evidence of region-specific cyclical employment cycles, and that cycles are related to educational attainment, establishment sizes, and industrial diversity.

While Mattoon (2003) first proposed the idea of the 'national' rainy day fund for US states that would be based upon the existing unemployment insurance trust fund, recent work by Elder and Wagner (2013) and Wagner and Elder (2014) has investigated the potential benefits that might arise from a multi-regional rainy day fund because of the lack of business cycle movements across different regions. In both US states and EU member nations, they find considerable evidence that "risk-sharing" benefits exist across these respective governmental units because of asymmetries in the cyclical movements of their economies. From a local perspective, if there is more variation in the structure of local economies within a given state that what we observe between states or between countries, then the risk-sharing benefits may be even larger for municipalities.

2.2 Measuring economic activity and Markov-switching model and estimates

Rather than relying solely on employment data as our measure of each city's or county's economy, we follow Stock and Watson (1989) and Crone and Clayton-Matthews (2005) and estimate an economic index for each city and county using a dynamic factor model. Each municipality's coincident economic index is calculated by estimating a latent common state variable from four different monthly observable data series: employment, labor force, unemployment rate, and taxable sales over the period from 1990:M1 – 2014:M8. Employment, labor force, and the unemployment rate are from the Bureau of Labor Statistics (LAUS), while taxable sales data were interpolated from quarterly data at the city level and are provided by the Wheldon Cooper Center at the University of Virginia. Each city's (or county's) measure of economic activity is the estimated unobserved common component of the four (stationary) data series that is rescaled to have a trend monthly growth rate that is equal to the city's (implied) mean monthly growth rate derived from its annual personal income over the period from 1969 to 2012. In other words, we are simply adapting the exact methodology employed by the Federal Reserve Bank of Philadelphia to estimate their widely used state-level coincident indexes originally developed by Crone and Clayton-Matthews (2005). Of course, our indexes do differ somewhat because they are derived from a different set of variables due to the limited availability of high frequency local economic data. The growth rate in each local city's or county's index provides us with a consistent metric to estimate the cyclical characteristics of economic activity at the local level.[3]

[3] Virginia has a total of 134 independent cities and counties. We exclude Bedford City because of missing data. Each city's level of employment, labor force, unemployment rate, and taxable sales were also seasonally adjusted using the Census X-13 ARIMA-SEATS program and deflated using the CPI-U before estimating the dynamic factor model.

Markov-switching models have a long record of accurately mimicking business cycle movements for states and national governments, yet only Owyang et al. (2008, 2013) have applied the model to local governments (focusing on employment in each instance). If we express the monthly index growth rate at time *t* for any individual municipality as $\dot{g}_t$, then the two-regime Markov switching model may be expressed as:

$$\dot{g}_t = \mu_{S_t} + \varepsilon_t ,$$

$$\text{(1)} \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2),$$

$$\mu_{S_t} = \mu_0 + \mu_1 S_t, \ \mu_1 > 0;$$

where μ denotes the mean growth rate and ε_t is the zero-mean innovation at time *t* assumed to be normally distributed with variance σ_ε^2. An unobserved regime variable, $S_t = \{0,1\}$, is assumed to exogenously govern the regime changes in the mean growth rate (μ) in (1). If $S_t = 0$, which we call the low-growth regime, g_t is assumed to follow a stationary AR(0) process and to have been generated from a normal distribution with a mean of μ_0 and a variance of σ_ε^2. When S_t switches to the high-growth regime, which occurs when S_t changes exogenously from 0 to 1, $\dot{g}_t$ follows a stationary AR(0) process and is assumed to have been generated from a normal distribution with a mean equal to $\mu_0 + \mu_1$ and a variance equal to σ_ε^2. In short, the model assumes that each municipality's growth rate is a mixture of two normal distributions having the same variance but potentially different means, with one normal distribution describing the behavior of expansions and the other distribution describing the behavior of recessions.

By assuming that the regime variable (S_t) follows a first-order, two-state Markov chain, it can be estimated. The transition matrix is as follows:

(2) $$\boldsymbol{P} = \begin{bmatrix} P(S_t = 0 \mid S_{t-1} = 0) & P(S_t = 1 \mid S_{t-1} = 0) \\ P(S_t = 0 \mid S_{t-1} = 1) & P(S_t = 1 \mid S_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} P_{HH} & 1 - P_{HH} \\ 1 - P_{LL} & P_{LL} \end{bmatrix},$$

where P_{ij} is the transition probability of $S_t = i$ given that $S_{t-1} = j$. Hence, P_{HH} is the probability that economic activity is in an expansion (or high-growth regime) in period t conditional on having been in the high-growth regime in period t-1.

We follow Owyang et al. (2005, 2008, 2013) and estimate the switching model using the Bayesian Gibbs-sampling approach developed by Kim and Nelson (1998). Their approach, which is very carefully detailed in Kim and Nelson (1999), models the unobserved region variable (S_t) and other parameters (μ_0, μ_1, P_{HH}, P_{LL}, σ_ε^2) as unknown random variables that can be evaluated from sampling from the appropriate conditional posterior distributions.[4]

We apply the model to 133 municipalities in Virginia (plus the Commonwealth as a whole) and report the parameter estimates in Table 1.[5] The parameter estimates are the means of the estimated posterior distributions. Since our objective is primarily in *using* the parameter estimates, we only briefly discuss the Markov switching results.

Table 1 shows each municipality's estimated expansion growth rate, $g_{i,H}$ $(= \hat{\mu}_{i,0} + \hat{\mu}_{i,1})$, estimated contraction growth rate, $g_{i,L}$ $(= \hat{\mu}_{i,0})$, and the estimated probabilities of high growth/low growth next period conditional on high growth/low growth this period (P_{HH}/P_{LL}).

[4] We set all of the priors and estimation parameters equal to those of Owyang, Piger, and Wall (2005), which is the approach followed by Wagner and Elder (2007), Owyang *et al*. (2008), and Owyang, Piger, and Wall (2013). The joint posterior distributions were simulated using 10,000 replications with an additional 2,000 burn-in replications. We also assumed that the mean parameters (μ_0 and μ_1) are normally distributed with means of -1 and 1 respectively, and that the variance-covariance matrix is equal to the identity matrix. The transition probabilities, P_{HH} and P_{LL}, have prior Beta distributions given by $\beta(9,1)$ and $\beta(8,2)$, implying means of 0.9 and 0.8 respectively. We also gratefully acknowledge the use of the computer routines described in Kim and Nelson (1999).

[5] We use the Federal Reserve Bank of Philadelphia's coincident index for Virginia as our measure of the state's economy and apply the Markov-switching model to the same sample period (1990:M1 – 2014:M8) as our local economic indexes.

While the mean monthly expansion and contraction growth rates across all municipalities is 0.329 percent and –0.439 percent, expansion growth rates vary from 0.030 to 2.350 percent. For the entire Commonwealth of Virginia, our estimated (monthly) expansion and contraction growth rates are 0.236 and -0.174 percent, respectively. On an annual basis, the simple Markov-switching model for Virginia predicts a (mean) annual expansion growth rate of 2.87 percent and a (mean) annual recession growth rate of -2.06 percent. In terms of the average municipality, our models predict more volatility in both expansions and contractions than for the commonwealth as a whole. We estimate the typical municipality in the Commonwealth to have a (mean) annual expansion growth rate of 4.03 percent and a (mean) annual recession growth rate of -5.14 percent.

[Table 1 here]

For the mean municipality, we also estimate that there is a 0.964 probability of being in the high-growth regime in the current period conditional on having been in an expansion in the previous period. This is slightly below the Commonwealth's conditional probability of 0.984. In terms of low-growth regimes, the Commonwealth is estimated to have a 0.939 probability of remaining in a low-growth regime (conditional on last period), whereas the average municipality has a much lower estimated low-regime probability at 0.815. Relative to the Commonwealth as a whole, these estimates indicate that there is considerable variability in economic cycles between the municipalities.

In addition, because the expected length of each regime *j* may be computed as $E[t_j] = (1 - P_{jj})^{-1}$ for $j = H,L$, our estimates indicate that the expected duration of an expansion and contraction for Virginia over our sample period are 64.1 and 16.4 months, respectively. Again, we find substantial variation across municipalities with the average municipality experiencing 65.3 months of growth followed by 14.9 months of low-growth. We use the term low-growth, contraction, and recession interchangeably even though it is technically incorrect to do so. While most municipalities' economic cycles are similar to those of the Commonwealth, some areas, such as Lunenburg and Northampton Counties, are best characterized by long periods of very slow growth followed by short periods of rapid growth.

Table 1 also reports a concordance measure for each municipality. This measure, adopted from Owyang et al. (2005), is the percentage of time each municipality's economy shares the same business cycle regime with Virginia. If T is the number of time periods and $\hat{S}_{it}$ and $\hat{S}_{US}$ denote the estimated (smoothed) probability that area *i* and the Commonwealth are in regime 1 (a high growth regime) at time *t*, then municipality *i*'s concordance is given by:

(3) $$\text{Concordance} = \frac{1}{t} \sum_{t=1}^{T} \left[\hat{S}_{it}\, \hat{S}_{VA} + (1 - \hat{S}_{it})(1 - \hat{S}_{VA}) \right]$$

While the typical municipality is estimated to be "in synch" with Virginia's business cycle phase an average of 71 percent of the time, the estimates vary from a high of 93.6 (in Fairfax County) to a low of 24.1 percent of the time in Chesterfield County. As we hypothesized, the variation that we find across municipalities is considerably larger than the variation across state business cycles or European business cycles. Two municipalities are "in synch" with the Virginia economy more than 90 percent of the time, 18 are synched more than 80 percent of the time, and 92 match-up with the overall state economy more than 70 percent of the time. Twelve municipalities, that are primarily small and rural, have estimated concordances with Virginia that are below 50 percent over our sample period. Following the standard practice of assuming an estimated smoothed probability of 0.5 or higher indicates an expansion (and anything less a contraction), the average municipality is estimated to be in a high-growth regime 80 percent of the time and in a low-growth regime the remaining 20 percent of the time.[6]

III. Risk-Sharing Methodology

Our methodology is based on the approach of Elder and Wagner (2013), and estimates the potential pooling benefits over a fixed number of periods, k. Since the risk-sharing benefits are derived from municipalities being in different business cycle phases, we must first simulate the probability that each municipality is in an expansion regime/contraction regime in every time period.

Since revenue is assumed for simplicity to perfectly mimic each municipalities underlying economy, we simulate a k-period sequence of high and low-growth regimes for each municipality and use the sequence to calculate the budget position in each area. Each k-period sequence of high and low-growth regimes is simulated in a series of steps. First, we draw an initial regime for Virginia based on our estimated unconditional probabilities that Virginia is either in a low- or high-growth regime. These estimated probabilities, obtained from the Markov-switching output (but not reported in Table 1), are 80 percent for the high-growth regime and 20 percent for the low-growth regime, respectively. Hence, our initial regime for Virginia is based on a single random draw from a uniform (0,1) distribution. If the value is 0.80 or less, then Virginia is assumed to be in a high-growth regime, otherwise it is in a low-growth regime. Given Virginia's initial regime, the initial regime for each municipality is determined by the municipality's concordance with Virginia and a random draw from a U(0,1) distribution. For example, since Fredericksburg City has a concordance with Virginia equal to 0.844, if the

[6] The smoothed probability is a period-by-period estimate of the unobserved regime variable conditional on the most recent data available. This means that each period's estimate is updated in every subsequent period as new data become available. Since $S_t = 1$ denotes a high-growth regime, an estimated smoothed probability in any period t of 0.5 or higher is classified as an expansion.

random draw is less than 0.844, then Fredericksburg City's initial regime is the same as Virginia's initial regime. This process is repeated for each municipality until the first-period regimes for all the municipalities have been simulated.[7]

To simulate the remaining *k-1* periods for each municipality, we assume that the period *t+1* regime depends on that municipality's period *t* regime *and* the period *t* regime of neighboring municipalities. We vary the number of neighboring municipalities between 2 and 5 as a robustness check and define neighbors based on the distance between municipality *i*'s geographic center and the geographic center of other municipalities. For instance, if municipalities are permitted to be influence by only two neighbors, then Fairfax City's second period regime will depend on its first period regime plus the first period regimes of its two closest geographic neighbors, Halifax and Prince Edward Counties. If all three municipalities were in a high-growth regime in the first period, then we refer to the matrix of smoothed probabilities to count how many times all three were estimated to be in a high-growth regime in the same period. Conditioning on those periods when all three municipalities were in a high-growth regime, then we count how many times Fairfax City was estimated to be in a high-growth regime in the subsequent period. If, for example, all three countries were in a low-growth regime ten times and of those ten times, Fairfax City was in a low-growth regime in the following period in three of those instances, then we assume that there is an 30 percent chance that Fairfax City will be in a low-growth regime in the period following a situation in which all three countries were in a low-

[7] Since we simulate data using the estimated concordances that are based on historical data, we are implicitly assuming that the future covariance structure between states will be the same as the past covariance structure. This may be a concern if the covariance structure changes over time. One simple approach to dealing with an evolving covariance structure would be to calculate a weighted concordance measure that gives more recent observations greater weight and to simulate each state's data using this alternative measure. Alternatively, in practice, parameter uncertainty could be handled as a coinsurance scenario such that the benefit payment is not paid in full if the state deviates excessively from its historical record. The risk pool could also hold funds in excess of any expected losses to cover contingencies.

growth regime in the previous period; Fairfax City's second period regime is assigned based on this probability by a random drawn number from a U(0,1) distribution. This process is then repeated k-1 additional times to establish a k period sequence of low- and high-growth regimes for every municipality. If a particular sequence is not found in the smoothed probabilities, then we default to each municipalities own history.

Given the simulated regime phase, we then utilize the estimated high-regime mean growth rate and low-regime mean growth rates from the switching output (in Table 1) to simulate a period-by-period revenue stream for each municipality (because we are assuming that each municipality's revenue is perfectly correlated with the economic index).[8] Each municipality is assumed to have a positive budget balance if actual revenues are above their geometric trend and a negative balance if revenues are below their geometric trend.[9] We also scale each municipality in our simulations based on the municipality's total personal income in 2012.[10]

Given the simulated and size-adjusted period-by-period budget positions for each municipality, we then calculate how much each municipality would need to accumulate individually prior to the k period of time so that they can withdraw from their accumulated savings in the event of a negative budget position and finish the time horizon with zero savings. This amount is simply equal to the sum of the negative budget positions for an individual country. We refer to aggregate savings required (for a given time period) across all

[8] The use of actual revenue data are too problematic because they are very low frequency (typically annual) and it is impossible to completely control for the effects of policy rate and base changes. By assuming revenue and the economic index are perfectly correlated, we are assuming a revenue elasticity of unity. Since many local governments derive a considerable share of their revenue from property taxes, which tend to be very stable over the business cycle, we could easily modify our analysis to allow individual elasticities that could be smaller or larger than one.

[9] We use the term "revenue" to describe the actual funds collected from various taxes and fees in a given period, whereas we use the term "operating budget" to refer to the government's trend revenue, which are the funds that are available to spend in a given period and is equal to the government's revenue net of any contributions to or withdrawals from the rainy day fund.

[10] The size of the smallest municipality is normalized to one.

municipalities as the “Aggregate Individual Savings” or “AI savings”. This figure is simply the total quantity of reserve funds required by all municipalities if each municipality saved individually and ended the period with zero slack.

To calculate the benefits of risk-sharing, we sum up, or pool, the period-by-period budget positions for all the municipalities and then sum the period-by-period pooled negative budget positions. This amount is how much the municipalities would have to accumulate as a collective to mitigate economic downturns that were widespread enough to cause the pooled budget positions to be negative. We call this metric the “Pooled Accumulated Savings” or “PA savings”.

After randomly generating a *k*-period sequence for each municipality based on the process discussed above, we repeat the process 10,000 additional times in order to form a distribution of both AI and PA Savings so that we may evaluate any potential benefits from risk-sharing.

IV. Simulation results

We refer to the total amount that the counties would have to save individually as aggregate individual savings (AI) and the total amount the counties would have to save if they pooled their fiscal resources as the pooled aggregate savings (PA). We report our simulation results as the *percentage reduction* that the pooled savings is relative to the aggregate individual savings, 100*(1 – (PA savings ÷ AI savings)). For instance, if the pooled savings is 2.5 and the sum of the individual savings is 4.2 then pooling reduces the sum of individual savings by 40.5 percent.[11] Figures closer to 100 represent a larger benefit of pooling, while numbers closer to 0 represent less of a risk-sharing benefit.

[11] To be consistent with more traditional insurance applications, resource pooling over the business cycle will not alter the expected value of each state’s operating budget but it will reduce the variance. So, while it is possible to

We examine four different time periods: 12, 24, 60, and 120 months. To further investigate the sensitivity of our results, we compare the AI savings to the PA savings at the 50th, 75th, and the 90th percentiles. Examining various points along the estimated distributions means that we do not have to make rigid assumptions about the actual objective function(s) of state policymakers. If, for example, policymakers would like to maintain a constant growth rate in their operating budget *on average* over a given time period, then the 50th percentile estimates would be appropriate. If the objective is instead to have a constant operating budget growth rate in three out of every four recessions that might occur in a given time period, then the 75th percentile estimates are relevant.

The results of our simulations are presented below in Table 2. The results should be interpreted as follows: suppose we are examining a time horizon of one year (N=12) and the data are simulated using two additional countries that are closest in terms of distance between population centers. If we are looking at a typical recession, for the 50th percentile, then the relevant figure in Table 2 is 52.1, which means that pooling fiscal resources reduces the total amount that countries need to save by at least 52.1 percent when compared to aggregate individual savings. Moreover, if we look at a time horizon of one year (N=12) and we use the 2 closest counties, the pooling benefit is estimated to be at least 37.0 percent at the 75th percentile.

[Table 2 here]

In general, the results in Table 2 show that the risk-sharing benefits are greatest at the 50th percentile and diminish noticeably at higher confidence levels. For example, considering a time horizon of 5 years (N=60), the pooling benefit is at least 57.3 percent at the 50th percentile, at least 39.7 percent at the 75th percentile, and falls to at least 23.7 percent at the 90th percentile (all

measure the pooling benefits in terms of the reduced variance, we opted to report the benefit as the reduction in savings to make our results (somewhat) more comparable to the rainy day fund literature. However, the variance in operating budgets will be directly related to the reduction in savings.

using the 2 closest counties). Since a higher confidence level increases the likelihood that a very severe recession will arise, the risk-sharing benefits decrease because more states are likely to be in the same regime in any given period in such instances. To put it another way, the benefits are largest for a 50th percentile recession because considerably fewer countries will be in the same regime in any given period, which raises the pooling benefit.

In addition, to test whether the benefits are being driven by large municipalities (Fairfax, Manassas, Prince William, and Virginia Beach are significantly larger than the median municipality), we perform additional simulations where all the countries are assumed to be the same size. Since the largest municipality (Fairfax) is over 400 times larger than the smallest country (Highland) in terms of personal income, it is possible that the pooling benefits in Table 2 are the result of low concordances between a small number of very large municipalities. All else equal, the larger the municipality, the more weight that country is given when calculating the pooled and individual savings.

Assuming that all municipalities are equally sized, we find the pooling benefits to be nearly identical indicating that the "Actual Size" pooling benefits are not being driven by the concordances between a subset of large municipalities. These results are shown below in the first four columns of Table 3.

To get a sense of how much of the pooling benefit is being driven by the level of synchronization of the municipalities being examined, an additional simulation is conducted where the matrix of smoothed probabilities is replaced by a completely random set of zeros and ones. With this structure, any synchronization should be completely random and the pooling benefits should be greater. These results are shown in the fifth column of Table 3, and in general, the pooling benefits are significantly larger at higher percentiles (and are comparable to the numbers shown in Table 2 under the column headed by “3”). Not surprisingly, due to the large number of municipalities, the benefits with the completely random smoothed probabilities are very high; at the median, the individual aggregate savings pooled savings amount is only approximately ten percent of the individual aggregate savings amount for a ninety percent reduction in the savings amount when fiscal resources are pooled.

Assuming policymakers can agree on the size of the shared pool, one remaining question is how much should each municipality contribute in order to establish it? One simple method to establish contribution amounts could be that each municipality contributes to the pool in proportion to its size. For example, based on this algorithm, Fairfax would contribute over 150 times as much as some of the smaller counties such as Bland, Bath, Craig, and Highland counties regardless of how much has to be accumulated. As an example, the total pooled savings for k=60 (and the 3 closest counties) at the 75th percentile is 13.0. Based on the relative sizes of the municipalities, the amount that each should contribute is shown in column three of Table 4 (column headed by “Contribution (Relative Size)”). Again, under this algorithm, Fairfax always contributes the most to a pooled fund, followed by Manassas, Prince William, and Virginia Beach, while Bland, Bath, Craig, and Highland Counties contribute very little.

[Table 4 here]

An alternative to estimate how much each municipality may contribute to establish a pooled fund could be based on the benefit that each particular municipality receives from belonging to such a group. This would set an upper bound on a municipality's contribution amount. To estimate this amount, we calculate how much each municipality would have to save if had no access to a pooled fund. For example, again assuming k=60 and considering the 75th percentile, the amounts that each municipality would have to save on its own are shown in the first column of Table 4. These individual savings amount sum to 26.3. Normalizing the sum of these amounts to be equal to the required pooled amount, results in a 52.9% reduction relative to the individual savings amounts (note that the pooling benefit for N=60, at the 75% percentile, using the 3 closest counties is 47.1%). The amounts that each municipality would contribute under this algorithm are shown in the second column of Table 4 (column headed by "Contribution (Individual Savings)").

V. Conclusion

Given the diversity that exists in the industry structure of local governments both within and across states, the variation in economic cycles for municipal governments is much greater than the variation between US states or EU countries. Much like insurance, this diversity in business cycle fluctuations suggests that risk-sharing benefits may exist such that municipalities can pool their fiscal resources and reach the same level of recession preparedness at a lower cost than self-insuring.

Examining monthly data for Virginia and its municipalities over the period from 1990:M1 to 2014:M8, we find that the pooled or risk-shared savings required by municipalities to be roughly 50 percent lower (depending on the time horizon) than the total savings required when each municipality savings individually to reach a given a target level of fiscal slack. Our results demonstrate that, at least for Virginia, a statewide rainy day fund-type instrument for municipal governments would substantially lower the cost of preparing for future unexpected shocks and downturns. Practical elements of precisely how such a fund might be structure remain unresolved, however our findings imply that this could be a very fruitful area of future research.

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Table 1 – Markov Switching Parameter Estimates

	$\hat{\mu}_0 + \hat{\mu}_1$	$\hat{\mu}_0$	$\hat{P}_{HH}$	$\hat{P}_{LL}$	$\hat{\sigma}_{\varepsilon}^2$	$\mathrm{E}[t_H]$	$\mathrm{E}[t_L]$	Concordance
accomack.county	0.131	-0.813	0.987	0.623	0.036	74.3	2.6	0.727
albemarle.county	0.262	-0.072	0.989	0.891	0.025	87.0	9.1	0.869
alexandria.city	0.240	-0.395	0.988	0.809	0.037	85.8	5.2	0.734
alleghany.county	0.099	-0.491	0.973	0.752	0.029	36.7	4.0	0.730
amelia.county	0.225	-1.016	0.991	0.704	0.073	109.1	3.4	0.734
amherst.county	0.177	-0.127	0.982	0.891	0.024	57.1	9.2	0.805
appomattox.county	1.129	0.145	0.723	0.983	0.046	3.6	60.3	0.277
arlington.county	0.234	-0.592	0.980	0.777	0.033	50.7	4.5	0.738
augusta.county	0.206	-0.083	0.980	0.923	0.020	51.2	12.9	0.872
bath.county	0.131	-0.764	0.984	0.715	0.113	61.1	3.5	0.723
bedford.county	0.278	-0.075	0.979	0.828	0.033	48.3	5.8	0.840
bland.county	0.153	-0.770	0.983	0.794	0.030	59.7	4.9	0.738
botetourt.county	0.301	-0.307	0.988	0.865	0.050	85.2	7.4	0.794
bristol.city	0.193	-0.356	0.938	0.786	0.028	16.0	4.7	0.738
brunswick.county	0.145	-0.794	0.996	0.789	0.028	283.8	4.7	0.752
buchanan.county	0.030	-1.109	0.989	0.666	0.056	92.9	3.0	0.730
buckingham.county	0.166	-0.690	0.972	0.793	0.051	35.8	4.8	0.738
buena.vista.city	0.772	0.142	0.819	0.987	0.029	5.5	77.0	0.280
campbell.county	0.084	-0.307	0.983	0.731	0.029	58.3	3.7	0.762
caroline.county	0.273	-0.188	0.983	0.813	0.054	58.6	5.3	0.794
carroll.county	0.704	0.117	0.860	0.990	0.025	7.1	95.8	0.277
charles.city.county	0.161	-0.354	0.966	0.731	0.060	29.7	3.7	0.794
charlotte.county	0.123	-1.321	0.993	0.726	0.038	142.7	3.7	0.741
charlottesville.city	0.254	-0.018	0.986	0.871	0.029	70.0	7.8	0.805
chesapeake.city	0.253	-1.026	0.992	0.719	0.023	127.0	3.6	0.734
chesterfield.county	0.664	0.202	0.857	0.988	0.028	7.0	80.4	0.241
clarke.county	0.268	-0.452	0.987	0.914	0.050	74.9	11.6	0.840
colonial.heights.city	0.119	-0.204	0.993	0.906	0.017	134.0	10.6	0.816
covington.city	0.074	-0.743	0.978	0.796	0.031	45.0	4.9	0.738
craig.county	1.921	0.154	0.818	0.990	0.037	5.5	95.7	0.738
culpeper.county	0.249	-0.630	0.985	0.620	0.052	64.9	2.6	0.734
cumberland.county	0.190	-0.322	0.984	0.800	0.048	61.9	5.0	0.748
danville.city	0.065	-0.579	0.991	0.732	0.033	111.0	3.7	0.745
dickenson.county	0.098	-0.674	0.969	0.704	0.057	32.7	3.4	0.730
dinwiddie.county	0.096	-0.882	0.993	0.727	0.021	144.8	3.7	0.734
emporia.city	0.200	-0.623	0.960	0.735	0.038	24.9	3.8	0.734
essex.county	2.350	0.171	0.819	0.990	0.031	5.5	97.2	0.266
fairfax.city	0.253	-0.272	0.989	0.884	0.030	87.6	8.6	0.727
fairfax.county	0.281	-0.068	0.985	0.926	0.031	66.9	13.5	0.936
falls.church.city	0.278	0.010	0.972	0.910	0.038	36.1	11.1	0.766
fauquier.county	0.269	-0.251	0.988	0.914	0.035	80.8	11.6	0.748
floyd.county	0.182	-0.359	0.987	0.753	0.038	79.1	4.1	0.777
fluvanna.county	0.433	0.091	0.986	0.920	0.036	73.5	12.5	0.766
franklin.city	0.123	-0.745	0.976	0.797	0.044	41.6	4.9	0.738
franklin.county	0.233	-1.295	0.993	0.726	0.036	147.7	3.6	0.734
frederick.county	0.278	-0.038	0.991	0.899	0.035	107.5	9.9	0.844
fredericksburg.city	0.347	-0.121	0.986	0.783	0.046	72.9	4.6	0.773
galax.city	0.141	-0.584	0.977	0.785	0.029	44.2	4.7	0.738
giles.county	0.084	-0.712	0.990	0.662	0.022	96.0	3.0	0.730
gloucester.county	0.186	-0.790	0.991	0.689	0.025	107.6	3.2	0.738
goochland.county	0.349	-0.254	0.988	0.801	0.071	81.7	5.0	0.780
grayson.county	0.048	-0.595	0.987	0.739	0.033	78.1	3.8	0.741
greene.county	0.474	0.237	0.968	0.956	0.039	31.3	22.9	0.624
greensville.county	0.092	-0.674	0.973	0.771	0.041	37.1	4.4	0.738
halifax.county	0.119	-0.657	0.978	0.759	0.030	46.0	4.1	0.734
hampton.city	0.141	-0.134	0.990	0.888	0.018	101.8	8.9	0.801

hanover.county	0.304	-0.245	0.987	0.870	0.039	76.2	7.7	0.826
harrisonburg.city	0.263	0.010	0.973	0.937	0.021	37.0	16.0	0.699
henrico.county	0.230	-0.224	0.984	0.903	0.028	63.0	10.3	0.883
henry.county	1.604	-0.028	0.819	0.990	0.027	5.5	97.2	0.266
highland.county	0.085	-0.939	0.988	0.641	0.040	81.0	2.8	0.730
hopewell.city	0.235	-0.019	0.984	0.910	0.019	60.9	11.1	0.897
isle.of.wight.county	0.269	0.016	0.983	0.867	0.039	57.8	7.5	0.794
james.city.county	0.360	-2.120	0.993	0.727	0.031	145.0	3.7	0.734
king.and.queen.county	0.147	-0.540	0.952	0.799	0.056	20.9	5.0	0.738
king.george.county	0.295	-0.601	0.973	0.795	0.050	37.6	4.9	0.738
king.william.county	0.207	-0.680	0.988	0.655	0.043	85.1	2.9	0.738
lancaster.county	0.135	-2.403	0.997	0.749	0.022	291.6	4.0	0.745
lee.county	0.149	-0.666	0.968	0.798	0.031	30.9	5.0	0.738
lexington.city	0.155	-0.865	0.993	0.727	0.031	144.5	3.7	0.734
loudoun.county	0.810	0.282	0.972	0.962	0.044	35.4	26.2	0.652
louisa.county	2.245	0.311	0.817	0.990	0.058	5.5	97.2	0.266
lunenburg.county	1.333	0.107	0.830	0.989	0.030	5.9	94.3	0.255
lynchburg.city	0.075	-0.659	0.964	0.789	0.034	28.2	4.8	0.738
madison.county	1.246	0.194	0.741	0.986	0.041	3.9	71.1	0.255
manassas.city	0.383	0.098	0.971	0.915	0.031	34.2	11.7	0.656
manassas.park.city	0.312	-1.231	0.993	0.727	0.038	145.0	3.7	0.734
martinsville.city	1.122	-0.026	0.817	0.990	0.032	5.5	95.3	0.738
mathews.county	0.196	-1.186	0.985	0.597	0.064	66.5	2.5	0.727
mecklenburg.county	0.170	-0.640	0.963	0.782	0.027	27.3	4.6	0.738
middlesex.county	0.207	-1.049	0.988	0.636	0.044	80.4	2.7	0.727
montgomery.county	0.193	-0.125	0.983	0.854	0.023	57.8	6.9	0.833
nelson.county	0.250	-0.684	0.986	0.742	0.057	72.2	3.9	0.741
new.kent.county	0.328	-0.048	0.974	0.865	0.029	39.1	7.4	0.805
newport.news.city	0.093	-0.780	0.990	0.681	0.023	100.7	3.1	0.738
norfolk.city	0.073	-0.487	0.969	0.784	0.038	31.9	4.6	0.738
northampton.county	1.775	0.099	0.819	0.990	0.096	5.5	95.9	0.266
northumberland.county	0.368	-0.020	0.978	0.972	0.108	44.8	35.2	0.504
norton.city	0.225	-0.094	0.961	0.946	0.031	25.9	18.6	0.294
nottoway.county	0.112	-0.791	0.987	0.628	0.034	75.2	2.7	0.741
orange.county	0.305	-0.342	0.950	0.794	0.039	19.9	4.8	0.738
page.county	0.106	-0.654	0.970	0.775	0.073	33.2	4.5	0.738
patrick.county	0.205	-0.044	0.933	0.958	0.027	14.8	23.7	0.461
petersburg.city	0.117	-0.276	0.978	0.801	0.023	44.9	5.0	0.752
pittsylvania.county	0.065	-0.544	0.988	0.780	0.035	85.5	4.5	0.741
poquoson.city	0.241	-0.667	0.987	0.624	0.032	75.7	2.7	0.727
portsmouth.city	0.107	-0.280	0.988	0.871	0.040	82.3	7.8	0.787
powhatan.county	0.425	-0.305	0.987	0.861	0.047	79.6	7.2	0.801
prince.edward.county	0.153	-0.357	0.991	0.741	0.024	112.7	3.9	0.730
prince.george.county	0.227	-0.038	0.985	0.897	0.020	68.9	9.7	0.787
prince.william.county	0.431	0.147	0.969	0.953	0.027	32.8	21.1	0.613
pulaski.county	0.159	-0.245	0.963	0.761	0.051	27.3	4.2	0.730
radford.city	0.234	-0.007	0.968	0.924	0.021	31.7	13.2	0.691
rappahannock.county	0.168	-1.602	0.990	0.674	0.066	99.6	3.1	0.738
richmond.city	0.125	-0.335	0.985	0.921	0.034	65.5	12.7	0.918
richmond.county	0.104	-0.593	0.987	0.711	0.042	79.4	3.5	0.734
roanoke.city	0.097	-0.663	0.989	0.742	0.028	91.3	3.9	0.734
roanoke.county	0.108	-0.674	0.986	0.691	0.035	70.8	3.2	0.745
rockbridge.county	0.161	-0.729	0.979	0.792	0.035	48.0	4.8	0.738
rockingham.county	0.222	0.010	0.960	0.842	0.028	25.0	6.3	0.748
russell.county	0.107	-0.463	0.992	0.732	0.024	119.2	3.7	0.730
salem.city	0.136	-0.122	0.984	0.908	0.020	61.2	10.8	0.865
scott.county	0.116	-0.218	0.982	0.814	0.025	54.3	5.4	0.738
shenandoah.county	0.345	-0.435	0.931	0.786	0.048	14.6	4.7	0.738
smyth.county	0.443	-0.386	0.897	0.822	0.025	9.7	5.6	0.730

southampton.county	0.104	-0.769	0.990	0.727	0.042	100.2	3.7	0.734
spotsylvania.county	0.448	0.128	0.978	0.958	0.030	46.3	23.7	0.621
stafford.county	0.387	-0.151	0.982	0.710	0.038	56.3	3.4	0.745
staunton.city	0.158	-0.027	0.986	0.902	0.032	73.6	10.2	0.833
suffolk.city	0.282	-1.446	0.993	0.726	0.048	144.8	3.7	0.734
surry.county	0.149	-0.711	0.987	0.674	0.053	76.8	3.1	0.730
sussex.county	0.113	-1.634	0.993	0.726	0.026	147.4	3.7	0.734
tazewell.county	0.150	-0.587	0.954	0.813	0.028	21.6	5.3	0.738
virginia.beach.city	0.159	-0.735	0.981	0.794	0.032	53.5	4.9	0.738
warren.county	0.244	-0.378	0.988	0.791	0.054	80.6	4.8	0.752
washington.county	0.197	-0.280	0.960	0.800	0.029	24.9	5.0	0.748
waynesboro.city	0.139	-1.165	0.992	0.709	0.027	122.2	3.4	0.741
westmoreland.county	0.193	-0.542	0.987	0.710	0.027	75.1	3.5	0.734
williamsburg.city	2.150	0.345	0.817	0.990	0.042	5.5	97.4	0.738
winchester.city	0.288	-0.071	0.991	0.915	0.031	116.0	11.8	0.848
wise.county	0.119	-0.239	0.986	0.863	0.045	72.6	7.3	0.656
wythe.county	0.107	-0.522	0.988	0.753	0.035	83.8	4.1	0.759
york.county	0.242	-0.630	0.971	0.796	0.039	34.9	4.9	0.738
Virginia	0.236	-0.174	0.984	0.939	0.028	64.1	16.4	NA
Mean	**0.329**	**-0.439**	**0.964**	**0.815**	**0.038**	**65.3**	**14.9**	**0.710**
Median	**0.205**	**-0.359**	**0.984**	**0.796**	**0.034**	**61.1**	**4.9**	**0.738**
Max	**2.350**	**0.345**	**0.997**	**0.990**	**0.113**	**291.6**	**97.4**	**0.936**
Min	**0.030**	**-2.403**	**0.723**	**0.597**	**0.017**	**3.6**	**2.5**	**0.241**

Notes: The reported parameters are the means of the posterior distributions. The mean, median, maximum, and minimum rows exclude the parameter estimates for Virginia. Monthly growth rates are reported in percentage terms.

Table 2: Simulation Results

	Actual Size *Additional Municipalities* 2	3	4	5
	One year (N=12)			
50th percentile	52.1	51.4	51.7	51.5
75th percentile	37.0	36.2	36.1	36.7
90th percentile	25.0	25.6	25.1	24.9
	Two years (N=24)			
50th percentile	57.3	56.9	56.4	57.1
75th percentile	39.7	40.6	39.9	40.0
90th percentile	23.7	23.8	24.1	23.1
	Five years (N=60)			
50th percentile	70.0	69.8	70.2	71.5
75th percentile	49.8	47.1	47.2	49.4
90th percentile	26.9	26.1	27.3	29.0
	Ten years (N=120)			
50th percentile	81.3	80.8	82.8	84.7
75th percentile	58.8	56.8	56.7	60.1
90th percentile	36.5	35.9	37.9	40.1

Notes: The reported figures are the estimated percentage reduction in accumulated (or pooled) savings relative to aggregate individual savings.

Table 3

	Same Size *Additional Municipalities*				Random
	2	*3*	*4*	*5*	
	One year (N=12)				
50th percentile	51.5	51.8	51.8	51.4	94.8
75th percentile	36.2	36.9	37.3	36.6	81.3
90th percentile	24.7	25.3	25.7	25.1	62.1
	Two years (N=24)				
50th percentile	56.9	57.3	56.8	57.3	92.5
75th percentile	40.9	40.8	39.8	40.4	79.2
90th percentile	23.4	23.7	23.9	23.6	64.5
	Five years (N=60)				
50th percentile	70.7	70.0	71.2	72.8	91.2
75th percentile	48.7	49.2	49.0	50.6	79.1
90th percentile	26.6	26.7	27.9	28.6	65.1
	Ten years (N=120)				
50th percentile	81.4	80.1	83.9	84.3	89.9
75th percentile	58.3	57.2	59.0	60.2	77.8
90th percentile	37.0	35.9	38.4	39.8	65.2

Table 4 – Contributions by Municipality Based on the Benefit of Being in the Sharing Pool

County	Individual Savings	Contribution (Individual Savings)	Contribution (Relative Size)
accomack.county	0.16	0.08	0.02
albemarle.county	0.21	0.11	0.14
alexandria.city	0.34	0.18	0.23
alleghany.county	0.16	0.08	0.02
amelia.county	0.17	0.09	0.01
amherst.county	0.23	0.12	0.02
appomattox.county	0.09	0.05	0.01
arlington.county	0.00	0.00	0.35
augusta.county	0.17	0.09	0.08
bath.county	0.46	0.24	0.00
bedford.county	0.21	0.11	0.06
bland.county	0.00	0.00	0.00
botetourt.county	0.47	0.24	0.03
bristol.city	0.00	0.00	0.05
brunswick.county	0.39	0.20	0.01
buchanan.county	0.15	0.08	0.02
buckingham.county	0.00	0.00	0.01
buena.vista.city	0.11	0.06	0.02
campbell.county	0.25	0.13	0.08
caroline.county	0.34	0.18	0.02
carroll.county	0.05	0.03	0.02
charles.city.county	0.28	0.14	0.00
charlotte.county	0.19	0.10	0.01
charlottesville.city	0.21	0.11	0.14
chesapeake.city	0.16	0.09	0.19
chesterfield.county	0.07	0.04	0.28
clarke.county	0.54	0.28	0.01
colonial.heights.city	0.13	0.07	0.06
covington.city	0.00	0.00	0.02
craig.county	0.04	0.02	0.00
culpeper.county	0.15	0.08	0.03
cumberland.county	0.35	0.18	0.01
danville.city	0.15	0.08	0.07
dickenson.county	0.12	0.06	0.01
dinwiddie.county	0.13	0.07	0.06
emporia.city	0.11	0.06	0.01
essex.county	0.10	0.05	0.01
fairfax.city	0.47	0.24	1.57
fairfax.county	0.19	0.10	1.57
falls.church.city	0.32	0.17	1.57
fauquier.county	0.51	0.26	0.07
floyd.county	0.31	0.16	0.01
fluvanna.county	0.39	0.21	0.02
franklin.city	0.00	0.00	0.02
franklin.county	0.21	0.11	0.04
frederick.county	0.25	0.13	0.08
fredericksburg.city	0.30	0.16	0.13
galax.city	0.00	0.00	0.02
giles.county	0.12	0.06	0.01
gloucester.county	0.14	0.07	0.03
goochland.county	0.43	0.23	0.03
grayson.county	0.07	0.03	0.01
greene.county	0.34	0.18	0.01
greensville.county	0.00	0.00	0.01
halifax.county	0.11	0.06	0.02
hampton.city	0.14	0.07	0.11
hanover.county	0.45	0.23	0.09
harrisonburg.city	0.27	0.14	0.08
henrico.county	0.35	0.18	0.28
henry.county	0.07	0.04	0.04
highland.county	0.18	0.09	0.00
hopewell.city	0.18	0.09	0.05

isle.of.wight.county	0.23	0.12	0.03
james.city.county	0.32	0.17	0.09
king.and.queen.county	0.00	0.00	0.00
king.george.county	0.00	0.00	0.02
king.william.county	0.14	0.07	0.01
lancaster.county	0.43	0.22	0.01
lee.county	0.00	0.00	0.01
lexington.city	0.12	0.06	0.02
loudoun.county	0.69	0.36	0.38
louisa.county	0.04	0.02	0.03
lunenburg.county	0.08	0.04	0.01
lynchburg.city	0.00	0.00	0.08
madison.county	0.08	0.04	0.01
manassas.city	0.36	0.19	0.44
manassas.park.city	0.21	0.11	0.44
martinsville.city	0.04	0.02	0.04
mathews.county	0.17	0.09	0.01
mecklenburg.county	0.00	0.00	0.02
middlesex.county	0.18	0.09	0.01
montgomery.county	0.19	0.10	0.06
nelson.county	0.09	0.05	0.01
new.kent.county	0.30	0.15	0.01
newport.news.city	0.11	0.06	0.13
norfolk.city	0.00	0.00	0.18
northampton.county	0.06	0.03	0.01
northumberland.county	0.19	0.10	0.01
norton.city	0.42	0.22	0.03
nottoway.county	0.15	0.08	0.01
orange.county	0.00	0.00	0.02
page.county	0.00	0.00	0.01
patrick.county	0.28	0.14	0.01
petersburg.city	0.17	0.09	0.06
pittsylvania.county	0.11	0.06	0.07
poquoson.city	0.16	0.09	0.07
portsmouth.city	0.25	0.13	0.07
powhatan.county	0.57	0.30	0.02
prince.edward.county	0.11	0.06	0.01
prince.george.county	0.23	0.12	0.05
prince.william.county	0.34	0.18	0.44
pulaski.county	0.28	0.14	0.02
radford.city	0.27	0.14	0.06
rappahannock.county	0.21	0.11	0.01
richmond.city	0.23	0.12	0.18
richmond.county	0.19	0.10	0.00
roanoke.city	0.11	0.06	0.09
roanoke.county	0.22	0.11	0.08
rockbridge.county	0.00	0.00	0.02
rockingham.county	0.19	0.10	0.08
russell.county	0.17	0.09	0.02
salem.city	0.23	0.12	0.09
scott.county	0.29	0.15	0.01
shenandoah.county	0.00	0.00	0.03
smyth.county	0.16	0.08	0.02
southampton.county	0.15	0.08	0.02
spotsylvania.county	0.43	0.22	0.13
stafford.county	0.16	0.08	0.11
staunton.city	0.17	0.09	0.08
suffolk.city	0.21	0.11	0.07
surry.county	0.15	0.08	0.00
sussex.county	0.19	0.10	0.01
tazewell.county	0.00	0.00	0.03
virginia.beach.city	0.00	0.00	0.42
warren.county	0.32	0.17	0.03
washington.county	0.15	0.08	0.05
waynesboro.city	0.18	0.09	0.08
westmoreland.county	0.11	0.06	0.01

williamsburg.city	0.05	0.03	0.09
winchester.city	0.21	0.11	0.08
wise.county	0.37	0.19	0.03
wythe.county	0.26	0.13	0.02
york.county	0.00	0.00	0.07

Based on simulation of 5 years, using 3 closest municipalities, and the 75th percentile savings level with individual aggregate savings of 24.6 and pooled savings of 13.0 (52.9% reduction in pooled savings relative to individual savings)