RECOVERY VIRGINIA ALLOCATION MODEL

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INTRODUCTION

Given my background and experience in researching the public health impact of the opioid epidemic and available data revealing the scope of the epidemic, Sanford Heisler Sharp, LLP, The Cicala Law Firm PLLC and Kaufman & Canoles, P.C. have asked me to generate an allocation model that may be used to allocate funds among Virginia counties and independent cities in the event of a distribution of funds resulting from settlement of claims arising out of the opioid epidemic. This memorandum explains and includes the Recovery Virginia Allocation Model that I have prepared for this purpose.

ALLOCATION PROCEDURE

1. <u>Summary Overview</u>

I have reviewed numerous data sets involving the impact of the opioid epidemic on Virginia localities. I have reviewed both data sets that are generated by national sources (such as the Centers for Disease Control (CDC) and Drug Enforcement Administration (DEA)) and data sets generated by the Virginia Department of Health. While no single data set is conclusive, collectively several of the data sets can be combined to paint an objective picture of the impact of the opioid epidemic and can be used to differentiate among and allocate to Virginia localities.

Upon consideration of the available data, and as a first step in preparing the final allocation, I have developed a proprietary allocation method that I refer to in this Memorandum as the "Ruhm Allocation Model."

2. <u>Ruhm Allocation Model</u>

The Ruhm Allocation Model consists of three components: 1) Virginia opioid-related emergency department visits; 2) opioid-related deaths, as adjusted by the Ruhm Adjustment which accounts for known under-reporting of opioid deaths; and 3) opioid shipments (Morphine Milligram Equivalents (MMEs)) to localities. These three components are calculated for counties/cities relative to the Virginia (not national) total, and they are weighted equally in the final allocation formula.

Correlations between these three components are fairly high but not perfect (ranging from 0.70 to 0.95), which suggests that each provides useful and somewhat distinct information.

Factor 1: Opioid-Related Emergency Department (ED) Visits

The Virginia Department of Health tracks data on emergency department visits for unintentional opioid overdoses. I used this data to construct the first factor. My model uses the four years, 2015-2018, for which complete information is available. Data for independent cities and their adjacent counties are often combined in the Department of Health data.[1] In these cases, I allocated the city and county numbers proportionately based on 2018 populations.

Factor 2: Opioid-Related Overdose Deaths

The CDC maintains the Wonder Multiple Cause of Death database (MCOD), which includes data on opioid-related overdose deaths. My Allocation Model uses adjusted MCOD data from 2006-2016 to calculate the number of drug overdose deaths involving opioids for any given locality and the locality's share of the state total.

As noted, my Model uses adjusted data. The adjustment is necessary because the MCOD data relies on cause of death information from death certificates. These certificates are known to understate the involvement of opioids (and other drugs) because in a significant fraction of cases the drugs involved in the deaths are not specified. For this reason, my Model employs the "Ruhm Adjustment," which I developed in a series of publications, to adjust for lack of reporting in these non-specified cases. The opioid overdose death figures used are the MCOD totals after the Ruhm Adjustment is applied. [2]

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[1] This occurs because geographic location is assigned based on the patient's residential zip code, and zip codes often span independent cities and the counties adjoining them.

[2] The CDC suppresses its public data when there are fewer than 10 opioid deaths in a given locality. I have access to and was able to use restricted data and avoid this data suppression. However, I am not permitted to share the suppressed data points, or any information on cell sizes involving less than 10 deaths. This restriction did

Factor 3: Opioid Shipments

The final component is the amount of prescribed opioids, measured in MMEs, for 12 types opioid medications. The data are drawn from the Automation of Reports and Consolidated Orders System (ARCOS), which is a DEA database compiled from the mandatory opioid reporting required of opioid manufacturers and distributors. The use of MMEs, as opposed to merely the number of pills shipped, accounts for differences in prescription strength. My Model relies on ARCOS data from 2006-2014.

Unlike some other models, my Model does not adjust total MMEs by reference to any other factor, such as overdose deaths. I believe the use of additional multipliers results in double-counting, which I have attempted to avoid.

3. <u>PEC Allocation Model</u>

I am also aware that the Plaintiff's Executive Committee (PEC) of the National Prescription Opiates Multi-District Litigation (Opioid MDL), pending in federal court in Ohio, has prepared an allocation model for use in connection with a hypothetical national class settlement.

The PEC allocation formula consists of three components: 1) the number of persons with opioid use disorder; 2) the number of opioid-related overdose deaths; and 3) the amount of opioid drugs shipped to the locality. Each of these components is calculated by reference to a particular county's (and, in Virginia's case, independent city's) share of the national total. The PEC Model purports to weights the three components equally; however, as described below, the model uses certain adjustments that place greater weight on two of the factors and effectively reduce the weight attributed to a locality's MME shipment data.

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not impact my allocation model or my ability to publicly report the allocation shares for any given Virginia independent city or county.

Factor 1: Number of Persons with Opioid Use Disorder

Opioid Use Disorder, or OUD, is the clinical term for opioid addiction. The National Survey on Drug Use and Health (NSDUH) tracks the number of persons with OUD. The PEC Model takes the national OUD data for 2007-16 and assigns each county and independent city its share of that national total.[3]

Factor 2: Opioid-Related Overdose Deaths

The PEC Model also uses MCOD data from 2006-2016, adjusted by reference to the Ruhm Adjustment described above, to calculate the number of drug overdose deaths involving opioids for any given locality and the locality's share of the national total.

Factor 3: Opioid Drug Shipments

The PEC Model's third component is the amount of prescribed opioids, measured in morphine milligram equivalents (MMEs), shipped into a locality. The PEC Model uses ARCOS data for 2006-2014.

The PEC Model also further adjusts total MMEs. Specifically, the total number for any given locality is multiplied by the larger of the locality's ratio of OUD cases or opioid overdose deaths to the corresponding national total. As noted above, this additional multiplier effectively dilutes the impact of MMEs as an independent factor.

4. **<u>Blending Process</u>**

Because no single data set or approach can, standing alone, perfectly capture opioid impact on a given locality, I have determined

[3] The NSDUH only provides OUD data at the state level. Local (i.e., sub-state) OUD data is not publicly available. However, the NSDUH does report opioid "misuse" at the sub-state level ("misuse" is generally defined as using an opioid for a nonmedical purpose within the past 12 months). Thus, the PEC Model first determines a given locality's percentage of the total opioid misuse in a state (i.e., if the total state misuse is 10,000 and the locality misuse is 1,000, that locality would be assigned a 10% share). It then calculates local OUD estimates by assigning each locality its misuse percentage of the overall state OUD number (i.e., if a locality has a 10% misuse share, and the state has total OUD of 100,000, the PEC Model assigns 10,000 for the locality's OUD total).

that blending the Ruhm Allocation Model and the PEC Allocation Model provides an equitable method to allocate among Virginia localities.

Thus, as a final step in preparing the Recovery Virginia Allocation Model, I computed the Ruhm Allocation shares for each county and independent city in the Commonwealth. Then I applied the PEC Allocation to each Virginia county and independent city.[4] After completing these steps, each Virginia locality was assigned the average of the Ruhm Allocation and PEC Allocation shares.

Litigating Localities Factor

I have also developed a factor recognizing litigating localities. This factor works as follows: ten (10) percent of any given fund is set aside and only allocated among litigating counties and cities. Non-litigating localities only participate in ninety (90) percent of any given fund. The allocation shares for the ten percent fund are assigned to litigating localities using the same averaged result of a final allocation model.

I applied the Litigating Localities Factor to the blended model, which is to say that all Virginia counties and cities, both litigating and non-litigating, were deemed to receive their full allocated share of ninety (90) percent of any given settlement fund. For the remaining ten (10) percent, only litigating counties and cities were included, and each litigating locality received its allocated share, relative to the other litigating localities.

[4] Because the PEC allocation model was calculated on a national basis, to compute the Virginia sub-state allocations for that model I computed the total allocation share for all Virginia localities. The national allocation shares were then divided by the Virginia total, such that the Virginia shares summed to one.

RESULTS

The Recovery Virginia Allocation Model is set forth in Table 1, below, and shows the allocation percentages for each county and independent city in Virginia. These percentages can be applied to any total settlement funds to be distributed to localities in Virginia and will yield the locality-specific dollar amounts.

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Table 1: Opioid Settlement Allocations to Counties and Independent Cities

Location	%	Location	%	Location	%
Accomack	0.348%	Franklin City	0.079%	Norton City	0.110%
Albemarle	0.863%	Frederick	1.277%	Nottoway	0.133%
Alexandria City	1.162%	Fredericksburg City	0.524%	Orange	0.638%
Alleghany	0.213%	Galax City	0.139%	Page	0.410%
Amelia	0.100%	Giles	0.409%	Patrick	0.329%
Amherst	0.299%	Gloucester	0.424%	Petersburg City	0.395%
Appomattox	0.133%	Goochland	0.225%	Pittsylvania	0.750%
Arlington	1.378%	Grayson	0.224%	Poquoson City	0.186%
Augusta	0.835%	Greene	0.178%	Portsmouth City	1.937%
Bath	0.037%	Greensville	0.124%	Powhatan	0.262%
Bedford	0.777%	Halifax	0.353%	Prince Edward	0.190%
Bland	0.147%	Hampton City	1.538%	Prince George	0.351%
Botetourt	0.362%	Hanover	1.079%	Prince William	3.556%
Bristol City	0.434%	Harrisonburg City	0.523%	Pulaski	1.061%
Brunswick	0.107%	Henrico	4.473%	Radford City	0.247%
Buchanan	0.929%	Henry	1.220%	Rappahannock	0.091%
Buckingham	0.127%	Highland	0.023%	Richmond	0.084%
Buena Vista City	0.078%	Hopewell City	0.344%	Richmond City	4.225%
Campbell	0.456%	Isle of Wight	0.356%	Roanoke	1.498%
Caroline	0.318%	James City	0.612%	Roanoke City	1.859%
Carroll	0.440%	King George	0.306%	Rockbridge	0.235%
Charles City	0.073%	King William	0.178%	Rockingham	0.614%
Charlotte	0.138%	King and Queen	0.072%	Russell	1.064%
Charlottesville City	0.463%	Lancaster	0.135%	Salem City	0.786%
Chesapeake City	2.912%	Lee	0.556%	Scott	0.421%
Chesterfield	4.088%	Lexington City	0.093%	Shenandoah	0.660%
Clarke	0.125%	Loudoun	2.567%	Smyth	0.592%
Colonial Heights City	0.283%	Louisa	0.449%	Southampton	0.137%
Covington City	0.100%	Lunenburg	0.088%	Spotsylvania	1.417%
Craig	0.070%	Lynchburg City	0.816%	Stafford	1.443%
Culpeper	0.790%	Madison	0.163%	Staunton City	0.440%
Cumberland	0.100%	Manassas City	0.452%	Suffolk City	0.710%
Danville City	0.637%	Manassas Park City	0.095%	Surry	0.058%
Dickenson	0.948%	Martinsville City	0.494%	Sussex	0.081%
Dinwiddie	0.196%	Mathews	0.088%	Tazewell	1.606%
Emporia City	0.050%	Mecklenburg	0.344%	Virginia Beach City	4.859%
Essex	0.101%	Middlesex	0.108%	Warren	0.766%
Fairfax	8.672%	Montgomery	1.205%	Washington	0.996%

Fairfax City	0.269%	Nelson	0.147%	Waynesboro City	0.363%
Falls Church City	0.102%	New Kent	0.156%	Westmoreland	0.223%
Fauquier	1.210%	Newport News City	2.047%	Williamsburg City	0.086%
Floyd	0.182%	Norfolk City	3.388%	Winchester City	0.649%
Fluvanna	0.194%	Northampton	0.122%	Wise	1.756%
Franklin	0.954%	Northumberland	0.129%	Wythe	0.642%
				York	0.561%