Functional Job Analysis for Ohio's Public Children Services Agencies

Analyses on Behalf of
Public Children Services Association of Ohio (PCSAO)

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December 2014

Executive Summary

PCSAO aimed to develop a tool to assist counties in projecting how much caseworker effort would be needed to handle caseloads, taking into account relevant caseload characteristics. The reasoning was that different types of cases require more or less effort, so the tool would help counties know if their average caseloads were appropriate. It was also hoped that the tool would help counties improve caseload planning by categorizing cases into those requiring high effort, moderate effort, and low effort.

To help develop this tool, PCASO sponsored an analysis of SACWIS data. The most important analyses reported here are from 18 counties that agreed to log caseworker effort for three months. Key findings are as follows:

- Children's protective services practice varies widely by county, including screen-out rates and the use of traditional versus alternative response.

- Without taking case characteristics into account, there is wide variation across counties in how much caseworker time is devoted to the median intake case that has been screened-in, ranging from a low of 30 minutes to a high of 120 minutes (caseworker time is defined as time spent in direct contact with the client system, and excludes supervision, recording keeping, etc.).

- There is more uniformity among counties in terms of how concentrated caseworker effort is in just a small percentage of cases. For example, 25% of documented caseworker time spent in direct contact with clients was devoted to a small percentage of cases that ranged across counties only from 3% to 7% of all intake cases that were screened-in.

- There was also wide variation (70 minutes to 449 minutes) across counties in how much caseworker effort was devoted during a month to the median ongoing case.

- Analysis revealed that there was not much systematic variation between case characteristics and the amount of time a case requires, and certainly what weak relations as were found would not be of any value in caseload management. This finding applies to both intake cases and ongoing cases.

The report concludes that caseloads constitute a dynamical system, and that caseload management requires something more dynamical than a static scoring system. Analogies are made to load management practices in emergency rooms and in policing.

Objective

This is a report on analyses undertaken on behalf of PCSAO to improve an existing tool for managing caseloads at the county level. It was expected that there would be systematic differences in the time required to handle cases as a function of such factors as the number of locations, the number of alleged child victims, and so forth.

Data

All results presented in this report are based on SACWIS data for intake cases and ongoing cases that were active during the study period (August 1, 2013 and October 31, 2013). Detailed intake data were missing for cases that represented screened-out reports of child abuse or neglect (CAN), but the existence of these intake cases could be inferred from other available data. Of the ongoing cases active during the study period, intake information was available for only those cases where the initial report was made on or after May 1, 2013.

Only four counties in Ohio routinely use the SACWIS activity log to enter information about casework activity. During the study period, 14 additional counties agreed to log casework activity, for a total of 18 counties. Caseworkers were instructed to log only those activities that involved direct contact with clients. The logging included entering data on how many minutes were consumed by the logged activity.

Two appendices to this report provide descriptions of the analyses (Appendix I) and the results of the analyses (Appendix II). Readers who have questions about the analyses should find answers to their questions in the two appendices. The following material does refer to specific tables and graphs in case the reader wishes to learn more but in general the report assumes that the typical reader will not need to consult either appendix.

Overview of Intake Cases and Ongoing Case Spells

The purpose of this section is to highlight some differences among all 88 counties that are not related to activity logging.

There are about 22,000 new intake cases a month (Table 1), of which 52% are screened out, meaning that they do not proceed to the stage of assessment and investigation (AI). In any given month, there will be roughly 35,000 intake cases active, including those continued from a previous month, those opened and closed during the month, and those opened and continued to a new month. Some intake cases will be opened for several months, but that is unusual.

Of course new intake cases are highly concentrated in the major metropolitan counties, as is the state's population. And of course the sampling errors inherent in picking just three months from a much longer period of operations demands prudence in interpreting differences among the smaller counties. Nevertheless, it is striking how much the rate at which intake cases are screened-out varies. Just among those counties that reported 2,000 or more intakes during the study period, the screen-out rate varied from a low of 39% in Lucas County to a high of 63% in Summit County. While it was not within the scope of the project to investigate these rate differences, the finding does indicate that children's protective services practice varies widely by county.

As shown in Table 2, approximately 7,500 new cases of abuse are substantiated each month statewide (i.e., the AI resulted in a finding that an allegation of CAN was substantiated or indicated). While there are far fewer new ongoing cases per month than there are new intakes, ongoing cases may continue for years. Thus, there are typically more ongoing cases active at any time than there are intakes (roughly 42,500 ongoing versus 35,000 intakes).

Overview of Case Logging Efforts: Intake Cases

The analyses presented in this section, and in all subsequent ones, are based on the 18 counties that logged case activities in August, September, and October 2013.

Effort logging generally took place only for intakes that were screened in. The rates at which cases had activities logged is probably a little higher than the numbers shown (Table 3); some of what appears to be non-response might have been an intake that was in progress for only a few days at the beginning or end of the study period.

Even though 82% of intakes that were screened-in had activities logged, we cannot be certain that 82% of effort was logged. An intake might have contributed to the 82% if only a fraction of direct contacts with the client were recorded. Analytically, however, there is no alternative to assuming that we have a record of all contacts for any case for which any contacts were logged.

The median time spent for each intake case that had been screened in varied widely across counties (Table 4). Some of these county differences is simply sampling error; we might expect many differences in the smaller counties had a different three-month period been chosen. But even looking only at counties with 500 or more intake-case-months, the difference between Clermont and Lake (37 minutes versus 91 minutes) is striking.

It was possible to discern one kind of regularity in the data, and that is that in every county a very small percentage of the cases (3% to 7%) consumed a disproportionate share (25%) of caseworker effort. This in turn implies that a large percentage of cases collectively receive little effort in a given month. (Using Athens County as an example, 75% of logged effort was devoted to 35% of cases; therefore, 65% of cases received just 25% of caseworker effort.)

The variability among counties in terms of effort *concentration* was much smaller than the variability in *amount* of effort, suggesting a dynamic regularity in the data which will be remarked upon again in this report.

Overview of Case Logging Efforts: Ongoing Cases (Tables 4 and 5)

The median ongoing case in most counties consumed more caseworker time than did the median intake case, but there were some exceptions. Cuyahoga stands out for its low median time on ongoing cases (70 minutes). But aside from the relative amount of direct contact for intake and ongoing cases, it is obvious that the variability among counties in the medians is striking.

A concentration analysis showed that 5-8% of cases consume one-quarter of the effort associated with on-going cases (Cuyahoga being notable for a mere 3% of cases taking 25% of effect).And again, roughly two-thirds of cases are managed in any particular month with merely 25% of logged caseworker time.

Survival Analysis of Intake Effort

This section, and the next two, summarize analyses designed to determine how much of the variability in logged case activity could be explained by case characteristics. A total of 18 case characteristics were available for intake cases, including such things as the number of locations involved in the case, the type of case (e.g., sexual abuse), prior history, and the county in which the case was active. There were more characteristics available for ongoing cases, including such things as the neglect risk score, which is completed as part of the AI.

The only way to perform these analysis for ongoing cases, which might have begun well before the start of the logging period and continued long after, was to analyze how case characteristics varied with effort in any given month, But for intake cases only, it was also possible to do a survival analysis. This technique represents the best tool for determining what case characteristics affect time to completion of AI. It could not be done for ongoing cases because survival analysis requires you to have data beginning with the start of the case.

As shown in Table 7, survival analyses were performed for intake cases for each of two quite different measures of caseworker effort: elapsed calendar time and cumulative logged time. There was less of a relationship between these two measures ($r = .35$) than expected. As one example, consider the two largest counties. Whereas Cuyahoga and Franklin both complete the median intake case in about 39 days, Cuyahoga workers documented 28% more logged activity for the median intake case (390 minutes versus 205 minutes).

Seventeen case characteristics (see Appendix II) were correlated with elapsed calendar time and total logged time. None of these predictors correlated higher than $r = .10$ with effort. In contrast, the eighteenth predictor, county, correlated .29 with effort. County differences swamped the effects of case characteristics.

Regression Analysis of Logged Effort: Intake Cases (Table 8)

This section discusses a different way of determining what case characteristics might correlate with effort. Unlike the survival analysis discussed above, the method being presented now could be used for both intake cases and ongoing cases. This section presents the results for intake cases and the next section presents the results for ongoing cases.

The total amount of time devoted to a given case (intake or ongoing) in a given month was computed. If a case was active in only one month, it contributed one observation to the analysis, but if it opened, for example, in July 2013 and did not end until December 2013, then it would have contributed three observations to the analysis, one for each of the three month during which logging was performed.

As described in more detail in Appendix II, even using all 17 case characteristics in one model failed to result in a useful model. For example, the correlation between logged time/month and all of these case characteristics (except county) was only .12. As was the case with the survival analysis, county was as useful a predictor of how much time a case took as all of the case characteristics put together.

One additional model was run that included the case characteristics and county as predictors. Even after controlling for all of the case characteristics studied, county differences were striking. Or in other words: caseload differences do not explain county differences. This finding is important because it means that no tool for suggesting appropriate caseload sizes would be useful statewide.

How much time a given intake case consumed in caseworker activity in one month, say August, was weakly negatively correlated with effort on that case in another month, say, September. This weak negative correlation is consistent with intake cases being time-sensitive: All counties regard it was important to perform the AI in a timely fashion, so the more accomplished in one month, the less is left to do in the next.

Regression Analysis of Logged Effort: Ongoing Cases (Table 9)

This section describes analyses done using case characteristics to predict how much time will be devoted to an ongoing case during any month that the case is open. The analysis is conceptually similar to that described for intake cases in the previous section. One differences, though, was that it was only possible to study the effects of one variable at a time, for reasons explained in Appendix I).

As before, county differences are marked (r = .37). With two exceptions, none of the other case characteristics correlated with effort. The first exception was neglect risk (r = .16). There was a dose response such that higher levels of neglect risk were associated with higher logged effort. The second was the Is Child Safe indicator (r = .24). When the child victim was determined not to be safe (which occurred in approximately one-third of cases), logged activity was more than twice that of cases where the child victim was currently safe.

This seems like a large difference, and one that would be useful in caseload planning. However, when the amount of variability within these two subsets of cases is factored in, the so-called statistical effect (Cohen's d) for the indicator is just .53, a moderate effect. Still, there is this: If managers want one simple way to help balance the work associated with ongoing cases, they can try to distribute children who are not safe evenly among caseloads. The problem? With the average ongoing caseload in the neighborhood of 12-15 cases, and with there being so much variability among cases, stratifying caseloads by this factor will not make much difference. (A simulation was performed that compared these unsafe children being evenly distributed to workers versus being randomly assigned to workers. The improvement associated with matched caseloads on Is Child Safe was very modest.)

The correlation between months for how much time was devoted to a case was in the range of r =.40 to .45, regardless of what two months were being correlated: August and September, August and October, or September and October. This is different from the finding for intake cases, for which there was a weak negative correlation. This difference occurred because intake cases have a much shorter duration than do ongoing cases. It was also interesting because of the stability of the correlation. Generally correlations dampen as the time between observations increases. The findings are consistent with the idea that situations requiring intensive effort by the caseworker have a more or less constant probability of popping up. (This is admittedly a rather bold conclusion based on just three months of data.)

County Models for Intake Cases and Ongoing Cases (Table 10 and Figure 1)

Because county differences in practice seem to be so salient, models were run separately for each of the counties to predict the mean number of minutes/intake case/month. In other words, if the above results suggest that no state-wide model is possible, might it be the case that county-specific models are possible?

There is a statistical phenomenon known as over-fitting. If you use a large number of predictors to build a model for a small number of cases, you will get apparently good results that are the result of chance. All of this is explained in Appendix I. The upshot is that for only the largest counties would such models be possible, and among this very small group of larger counties for which the county-specific models might be appropriate, it was found that case characteristics are not useful in predicting logged caseworker effort.

Comparing Each County to State-Wide Quartile Ranges

To assist participating counties in comparing themselves to all others, Table 11 in Appendix II shows what percentage of intake cases handled by each county falls into each of the four quartiles defined by results for all 18 counties that logged activities during the study period. For example, Clermont handled 44% of its intakes in the amount of time (0-36 minutes) that all 18 counties as a whole devoted to only 25% of their cases. Given their sizes, it is not surprising that these four percentages are reasonably close to 25% in each of the quartiles for the largest counties in the table. Figure 2 in Appendix 11 suggests that there may be some reason to believe that larger counties devote more caseworker time to intake than do the average smaller counties.

Table 12 (also in Appendix II) is to ongoing cases what Table 11 was to intake cases, but with some interesting twists. First, Cuyahoga and Franklin have quite different profiles. Cuyahoga is nearly three times more likely to have an ongoing case fall into the lower quartile compared to Franklin, which in turn is more than twice as likely to have cases in the upper quartile. Second, whereas larger counties seem to spend more time on intakes, Figure 3 suggests they spend less time on ongoing cases.

Overall Conclusions

This research was undertaken with the idea that fixed characteristics of cases would be associated with caseworker effort in predictable ways. There was little evidence to support this view.

There are obviously marked county differences in practices. And while it is certainly true that some case characteristics are correlated with effort in expected ways (e.g., neglect risk), these differences occur against a tremendous amount of background variability that largely obscures the ability to detect these correlations or, more importantly, exploit them for the purpose of managing caseloads.

One possibility is that there are one or more variables not represented in SACWIS that moderate the correlations between case characteristics and caseworker activity. One example, hypothetical, is obviousness of the abuse or neglect, which might play a large role in AI. Another example might be the degree to which the caseworker has the cooperation of the members of the client system. A third example might be something like what Jared Diamond called the Anna Karenina principle. To paraphrase his idea, "All easy cases are alike; all difficult cases are difficult in their own way."

Over the course of the research, another explanation emerged for why some cases are more time-consuming than others. While not inconsistent with any of these three possibilities, it is simpler. This is a dynamical systems view of caseload management which suggests that a supervisor or an agency has a fixed supply of staff that must be deployed against a variable demand. It is hard to know in advance how difficult a case might be. And case demands probably vary over time; indeed, no matter hard or easy a given case might be, it will probably demand more effort during a month when the six-month review is due than in the month before or the month after. Workers and supervisors are constantly juggling cases to ensure that the highest priority needs at the moment receive at least a minimum of the required effort. This is easy during periods when a worker's caseload or an agency's caseload is down a bit, either in size or complexity, and much hard during taxing periods.

There are systems that are analogous. Policing and emergency medicine come to mind. If this dynamical systems view is correct, how we train supervisors and supervise workers can be adapted to incorporate lessons learned from these other systems.

About the Author

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Appendix I
Documentation of Tables

Background

ODJFS provided an extract of SACWIS data in early April 2014. The extract consisted of selected variables from about 50 SACWIS tables.

Information was made available for all new intakes from May 1, 2013 through December 31, 2013 with the following exception: while screened-out information and referral intakes (I&R) were included in the extract, information on screened-out reports of child abuse and neglect (CAN) were not. However, it was possible to infer the existence of those screened-out reports from case-agency link information.

Information was also made available on all cases that were in on-going status anytime between May 1, 2013 and December 31, 2013.

Unless otherwise note, the period of time for which data are presented, and which is sometimes referred to as the *study period* was August 1, 2013 to October 31, 2013. It was during this period that 14 counties attempted to log all of their case activities (in addition, four counties who have a practice of always logging their activities were among the 18 counties that are mentioned in many of the tables).

Table 1

This table presents information about new intakes only. Data are available for every county in the state. The following points are made regarding the state as a whole, but should clarify the meaning of each column of data for any particular county.

N = 11,434 intakes from before August 1, 2013 were still in the process of being handled as of August 1st. A total of 67,313 new intakes came in during August, September, and October of that year. As of October 31, 2013, there were 13,900 intakes whose final disposition was still to be determined because work on the intake case was continuing. Intakes that were categorized as Family in Need of Services (FINS) had no readily available disposition date because these types of cases are not closed via Assessment and Investigation (AI). A somewhat arbitrary closure date was therefore used for all FINS cases, which was the intake date + 60 days.

Of all the 78,747 intakes that were active during the study period, 52% were screened-out I&R intakes or screened-out CAN intakes.

A small number of intakes (1,610) were of an indeterminate type as of October 31, 2013.

Of the remaining 35,865 intakes that were screened-in, most were CAN reports that received a traditional response (TR) and most of the remaining intakes were CAN reports that received an alternative response (AR). Not every county used AR during the study period, which explains the many zeros (represented by dashes) in that column. Screened-in intake cases that were not CAN reports were either dependency reports or FINS reports.

Table 2

Table 2 is similar to Table 1 in presenting data for all counties over three months in 2013. The definitions of old cases and continued cases is the same as in Table 1. But unlike Table 1, Table 2 presents data only for CAN intake reports that (a) received TR and had AI findings of substantiated or indicated, or (b) received AR and were opened. To emphasize this last point, in order to be part of Table 2, a case had to be in on-going status sometime during the study period (TR and AR cases have different codes for this, but they amount to the same thing).

A *case spell* refers to a case during a particular period of time that it was open. In a period as short of three months, there were not many cases with multiple spells, but there were some. A case continued from July might have been closed in early August and then a new allegation could have arrived in September, been investigated, and caused the case to be re-opened in October. This would represent one case with two spells, and it is important to note that this and all other tables with case information treat these two spells as separate occurrences.

Examination will reveal that many more cases were continued from July 2013 into the study period as compared to intakes (Table 1) and that many more cases were continued from the end of the study period into November 2013. The explanation for this is simple: Screened-out intakes are typically resolved in a few days and many intakes that are screened-in are resolved in a month or two. In contrast, on-going cases can run for years.

The following point illustrates how Table 1 and Table 2 are consistent. Table 1 shows that there were approximately 29,000 screened-in CAN reports (8,254 AR + 20,538 TR). Table 2 shows that there were 22,347 new case spells during the study period. This explanation glosses over the fact that a new case spell in August might have had a July intake and, at the other end of the study period that a new intake might not have resulted in a new spell until November. In spite of this, there is clearly a difference between the number of screened-in intakes and the number of new spells. This difference reflects the fact that a screened-in intake may have resulted in a finding that the allegation was neither substantiated nor indicated. In such situations, the case never progresses to on-going status. (There were a small number of substantiated/indicated cases that never progressed to on-going status. It is not known why.)

Table 3

This and all subsequent tables involve only the 18 counties that logged case activity. Workers were instructed to log only those hours spent in direct client contact. Workers could log activities in a variety of ways. There were some problems with these data. For example, sometimes the amount of time logged seemed excessive; amounts beyond 12 hours/worker/24-day period were scaled back. As another example, some logging entries related to form-filings were generated automatically, and these were set to 5 minutes. As another, workers made a variety of errors in use of the drop-down menus, sometimes claiming they provided AR service in a county that did not use Alternative Response, or claiming AI work after the assessment and investigation were completed. These two specific examples were both treated as valid case activity that was simply miscoded. And then finally, even though there were several ways a worker could indicate the duration of time being logged, all of the entries were sometimes blank. In these cases, missing value imputation was used to assign a random amount of time from the empirical distribution of all times recorded for that activity. Since the average imputed log entry involved quite brief time values, it is unlikely that these imputed values exerted undue influence over results presented in this and subsequent tables.

In Table 3, an *active intake case* is an intake that was in progress, if only for a day, between August 1, 2013 and October 31, 2013. Screened-out (SO) and screened-in (SI) intakes are as defined with respect to earlier tables. UNK intakes are those few for which screening status was unknown. The table demonstrates that few (2% statewide) SO intakes had any time logged, but that 82% of screened-in intakes active during the study period had at least one logged activity. There is no way to determine, for a particular case, what percentage of actual effort was logged. The apparent finding that FINS intake cases were less likely to be logged is probably illusory. For the other kinds of screened-in intakes, a specific end date was known but FINS intakes had assumed end dates, as described earlier. So a portion of these FINS cases apparently active during the study period could well be intakes that for all practical purposes were completed in June or July of 2013.

Table 4

This table introduces the idea of an *intake case month*. Consider the example of Athens County. Table 3 shows that Athens had 182 screened-in intakes during the study period. Table 4 presents logged active about screened-in cases only. But Table 4 shows that Athens had 254 case months. Why is there a difference between 182 and 254?

First, Table 4 presents data for only those screened-in intake cases for which any logging was done, so instead of being based on 182 cases, it is based on only 82% (from Table 3 for Athens) x 182 or 149 intake cases.

Second, Table 3 is about discrete intake cases, whereas Table 4 is about intake case-months, the definition of which is any intake that was active in a given month. So if an intake case was initiated and disposed of in the space of one calendar month, then it contributes one intake case-month to Table 4. But if it spread across two months or three months, then it contributed two or three case months to Table 4. Take 254 (case months for Athens) and dividing by 149 reveals that the average screened-in intake in Athens County was active in 1.7 calendar months.

Table 4 includes the average number of minutes a given logged intake case received per month during the study period, and the percentiles for that logged activity. The zeros probably are less a cause for concern than one might imagine. If a case came in on the last day of the month, it might have had zero logged activity that month.

The last set of columns in Table 4 provide a concentration analysis that may be interpreted as follows (based on the example of Athens County). On average, across the three months, 25% of the logged activity in any given month is devoted to a mere 6% of the logged intakes active in that month. Another 25% of the effort is explained by the next 11% of the cases (because 6% + 11% = 17%). Another 25% of the effort is explained by the next 18% of the cases (because 17% + 18% = 35%). Remarkably, then, 65% of the intake cases in Athens County active in any one month received about 25% of the logged activity.

The bottom row of Table 4 includes a statistic known as the *coefficient of variation*. This is rarely used, but it is useful here. The statistic known as the standard deviation (SD) has the same metric as the measure being examined. This means that the SD in height of a sample measured in inches is much different from the SD in height of the same sample measured in meters. In other words, two standard deviations can't be compared if the two metrics are different. This is the problem solved by the coefficient of variation, which is equal to the standard deviation in a measure divided by the mean, thus cancelling the units of measure, The coefficient of variation can be used to compare variation in two quantities that are measured in different ways or where the two measures have very different means.

Table 5

This table is just like Table 3, but for case spells, not intake cases.

Table 6

This table is just like Table 4, but for case spells, not intake cases.

Table 7

A survival analyses analysis was performed for 9,149 intake cases beginning August 1, 2013 to October 31, 2013. The analysis was restricted to CAN reports known to have been screened-in, and further restricted to cases from the 18 logging counties that had any logged activity.

Predictors considered individually included:

a. TR vs. AR
b. Type of case (5 levels, such as sexual abuse, neglect, etc.)
c. Number of participants (recoded to 3 or fewer vs. 4-5 vs. 6 or more)
d. Number of alleged perpetrators (recoded to 1 vs. 2 or more)
e. Number of alleged perpetrators in the home (recoded to 0 vs. 1 or more)
f. Number of alleged child victims (recoded to 1 vs. 2 or more)
g. Number of alleged child victims about whom there were previous allegations (recoded to 0 vs. 1 or more)
h. Number of locations (recoded to 1 vs. 2 or more)
i. Number of characteristics noted (examples being things like domestic violence, positive toxicology, etc.; the reason these variables, which appear to be promising predictors of case complexity, were not used individually is because they appear to have not been used at all by many workers)
j. Each of eight complicating factors relevant to CAN allegations (e.g., single head of household, substance abuse, mental or emotional problems of the child, etc.)
k. County

Factors that individually made a significant contribution to the model were included in an overall model.

The model was estimated twice, once to model elapsed calendar time and once to model total amount of logged activity. In either case, the observation was considered censored if the AI results were not known by October 31, 2013. It was interesting to note that the correlation between these two measures of time was only 0.34, meaning that only about 10% of the variance in logged activity could be explained by elapsed calendar time. Or, more informally, how much activity a case requires does not have all that much to do with how many days pass before the disposition is known.

The specific results summarized in Table 7 are for the percentiles in elapsed days (or logged minutes) by county. The results are shown by county because county was by far the strongest predictor in the model. For an example of how to interpret the table, note that 50% of intakes studied from Athens County consumed between 235 and 611 minutes of logged activity, with another 25% requiring less time than 235 minutes and 25% requiring more time than 611 minutes.

Why are county differences the only results shown in Table 7? Because there were no meaningful correlations between intake case activity in a given month and any of the other predictors.

Table 8

While survival analyses would ordinarily be considered the preferred technique for modeling how long cases take to handle, there were two practical reasons why survival analyses were of limited value in this context.

First, intake data was not available for any intakes that occurred prior to May 1, 2013. As a result, for many of the case spells active during the study period, crucially important data that would have been associated with intake records was missing. But at the same time, it was important to do an analysis for intakes that would parallel the only possible analysis that could be done for case spells.

Second, caseworkers and supervisors tend to think much more in terms of current caseloads, as in “how many intakes (or cases) am I currently handling?” So models were also developed, using exactly the same predictors mentioned in regard to Table 7, to predict how much time an intake would take during a given month.

Table 8 shows the mean number of minutes a given intake requires in a given month, as measured by logged activity. At first blush, these numbers seem quite different from those presented in Table 7. For example, Table 7 showed that there were 96 intake cases in Athens County but Table 8 shows 224 intake-months. Recall from Table 4 that an intake-month is defined as any case active in any given month, so one intake can contribute more than one intake-month. This has practical appeal. A worker’s caseload is not just how many new cases she has in a month, it is all of the cases she has in a month, both new and old. (The reason intake-months in Table 8 do not match intake-months in Table 4 is that Table 8 is restricted to CAN intakes.)

The Adjusted Minutes/Month is an important column but one that is difficult to grasp. One possible explanation for the county-differences found in this study is that the counties all have very different caseloads. Unfortunately, the long list of predictor variables used in the models (see the notes for Table 7) are all correlated with one another. But if we imagine that every cell in this table with 36 dimensions (the number of *degrees of freedom* in the model) all had exactly the same number of cases, then we can ask the question: What would county differences look like if they all had exactly the same number of sexual abuse cases without medical neglect and with two locations and two perpetrators, etc. etc. etc.? And the answer is provided by the so-called *adjusted* minutes/month. Applying the coefficient of variation to these numbers, it is obvious that differences in case characteristics across counties have very little to do with observed county differences.

Why are county differences the only results shown in Table 8? Because there were no meaningful correlations between intake case activity in a given month and any of the other predictors.

Table 9

This table is similar to Table 8 except that it concerns efforts to predict how much logged time an ongoing case took in a given month. But there were a few important differences.

First, three additional predictors were used: the abuse risk score, the neglect risk score, and the indicator of whether or not the alleged child victim was currently safe. All of these pieces of information would be known at the time the case was transitioning from AI to ongoing status, and could therefore be part of the decision-making about what caseworker would be given a case.

Second, because there was no intake-related data for any ongoing case for which the intake was conducted prior to May 1, 2013, it was not possible to run an integrated model with multiple predictors in it; cases with missing predictors would have been dropped from the analysis. Instead, models were developed for each predictor noted in the description of Table 7 and the new predictors (e.g., neglect risk).

Third, a consequence of not being able to run one integrated model was that it was not possible to adjust county mean minutes of logged activity for the effects of all the other variables, so there is no “adjusted” column in Table 9.

Table 10 and Figure 1

In order to see if the predictors of intake caseload activity were useful within counties, the same model summarized in Table 8 was run separately for each county. And superficially it appears that this multitude of predictors can generate some useful predictions for logged intake activity at the level of individual counties. For example, the correlation between these predictors and logged intake time in Sandusky County is 0.40.

Unfortunately, as shown in Figure 1, there is a very strong relationship between how many intakes a county does and how well this model works, illustrating nicely what statisticians mean by over-fitting. Using close to 40 degrees of freedom to build a model of only 133 observations capitalizes too much on chance. (Indeed, 19 variables that were nothing more than randomly generated numbers would perfectly explain 20 other randomly selected values.)

The upshot of this analysis was that only Cuyahoga County appears to have any basis for predicting intake activity from case characteristics, and even there the model only explains about 4% of the variance, far too little to be of any practical importance.

Another way of saying this is that Table 10 is essentially lacking in any value, and is included only to indicate that county specific models of intake time were considered and were found to be of no value.

Similarly, although there is no table for it, I ran models attempting to predict logged activity on ongoing cases. Among the four largest counties (Cuyahoga, Franklin, Lucas, and Stark) there was nothing remotely worthy of reporting.

Table 11 and Figure 2

Table 11 displays how each county's effort on intake case activities are distributed across the quartiles of the distribution of intake effort across all 18 counties that logged activities during the study period. Given the relative sizes of Cuyahoga and Franklin counties, it is not surprising that their distributions are close to 25% in each of the state quartiles. What is more noteworthy is how different from an even 25%/quartile distribution is displayed by some of the smaller counties.

Figure 2 demonstrates that while there is a good deal of variability among the smaller counties, some portion of which is simply sampling error, there appears to be a modest positive correlation between county intake caseload size and logged time on intakes.

Table 12 and Figure 3

Table 12 and Figure 3 are for case spells exactly what Table 11 and Figure 2 are for intakes. Here, however, it is interesting to note that Cuyahoga and Franklin, which still play the biggest roles in determining the state-wide quartiles, have different profiles, with Cuyahoga having many fewer cases in the upper quartile and Franklin having many more in the bottom quartile. And unlike Figure 2, which suggested larger counties spend more time on intake, Figure 3 suggests that larger counties spend less time on ongoing cases.

It must be noted, however, that the influence of these two large counties in both Figures 2 and 3 is so very substantial, to the point that the results should be treated with caution.

Appendix II
Tables and Figures

Table 1
Intake Cases by County

		New Intakes Aug to Oct 2013					All Intakes Active Aug to Oct 2013 (Old + Total)							
							Screened Out			Screened In				
County	Old	Total	Aug	Sep	Oct	Contin-ued	N	%	Unk	Total	CAN AR	CAN TR	DEP	FINS
State	11,434	67,313	21,615	22,091	23,607	13,900	41,272	52	1,610	35,865	8,254	20,538	1,852	5,221
Adams	18	229	70	93	66	25	128	52	8	111	-	68	20	23
Allen	95	961	300	302	359	117	693	66	6	357	75	213	25	44
Ashland	62	288	84	93	111	62	174	50	8	168	-	143	14	11
Ashtabula	70	720	232	244	244	91	448	57	12	330	98	160	23	49
Athens	54	535	185	186	164	52	406	69	1	182	85	69	15	13
Auglaize	36	161	57	55	49	32	84	43	1	112	34	48	-	30
Belmont	84	362	120	107	135	122	192	43	7	247	79	48	-	120
Brown	61	210	60	53	97	56	85	31	3	183	24	66	5	88
Butler	245	1,740	578	562	600	264	1,029	52	38	918	155	655	33	75
Carroll	29	141	44	45	52	12	99	58	1	70	33	28	-	9
Champaign	52	315	112	99	104	43	243	66	5	119	66	33	6	14
Clark	94	945	327	285	333	78	731	70	12	296	78	144	8	66
Clermont	130	1,549	514	493	542	154	1,090	65	51	538	-	458	36	44
Clinton	59	401	139	150	112	54	282	61	10	168	47	71	-	50
Columbiana	109	657	210	220	227	115	441	58	9	316	156	84	5	71
Coshocton	37	201	66	66	69	41	102	43	-	136	78	32	3	23
Crawford	52	256	84	82	90	60	153	50	17	138	-	116	3	19
Cuyahoga	1,947	10,023	3,316	3,305	3,402	2,288	5,878	49	294	5,798	-	4,978	416	404
Darke	25	209	59	76	74	27	168	72	-	66	-	11	1	54
Defiance	9	208	65	62	81	23	176	81	-	41	26	15	-	-
Delaware	84	535	187	155	193	86	370	60	4	245	86	117	6	36
Erie	69	453	151	147	155	78	313	60	6	203	85	87	7	24
Fairfield	130	1,006	332	329	345	179	668	59	11	457	231	159	24	43
Fayette	35	207	55	79	73	51	118	49	7	117	32	46	15	24
Franklin	1,408	8,049	2,514	2,676	2,859	1,588	4,544	48	143	4,770	1,820	1,955	183	812
Fulton	52	245	106	76	63	58	114	38	1	182	63	73	4	42
Gallia	21	73	16	22	35	30	23	24	6	65	-	62	-	3
Geauga	65	349	118	101	130	109	181	44	15	218	39	73	33	73
Greene	104	762	246	246	270	113	468	54	3	395	-	343	18	34
Guernsey	44	470	142	130	198	61	327	64	9	178	83	70	8	17
Hamilton	1,155	3,865	1,244	1,344	1,277	1,922	2,003	40	225	2,792	462	1,995	198	137
Hancock	41	392	130	118	144	47	297	69	5	131	38	79	3	11
Hardin	10	230	85	69	76	24	152	63	-	88	3	75	2	8

Table 1
Intake Cases by County

		New Intakes Aug to Oct 2013					All Intakes Active Aug to Oct 2013 (Old + Total)								
							Screened Out			Screened In					
County	Old	Total	Aug	Sep	Oct	Contin-ued	N	%	Unk	Total	CAN AR	CAN TR	DEP	FINS
State	11,434	67,313	21,615	22,091	23,607	13,900	41,272	52	1,610	35,865	8,254	20,538	1,852	5,221
Harrison	12	98	24	35	39	19	69	63	1	40	12	25	2	1
Henry	34	181	60	55	66	40	126	59	2	87	22	49	1	15
Highland	85	227	79	73	75	127	134	43	88	90	-	45	1	44
Hocking	51	215	74	70	71	65	121	45	2	143	91	27	16	9
Holmes	6	104	26	42	36	15	76	69	-	34	8	22	1	3
Huron	51	446	167	136	143	46	336	68	1	160	76	46	6	32
Jackson	35	135	57	39	39	28	72	42	2	96	6	52	2	36
Jefferson	55	515	183	153	179	73	445	78	15	110	41	37	11	21
Knox	91	528	180	170	178	116	360	58	9	250	-	226	4	20
Lake	119	1,160	333	391	436	139	862	67	5	412	60	244	52	56
Lawrence	158	333	122	112	99	110	105	21	4	382	-	100	-	282
Licking	72	737	242	239	256	135	449	56	17	343	115	199	-	29
Logan	35	345	117	96	132	46	229	60	4	147	54	71	2	20
Lorain	191	1,194	349	407	438	238	547	39	14	824	-	739	3	82
Lucas	496	2,682	815	928	939	626	1,232	39	39	1,907	980	636	-	291
Madison	30	256	76	84	96	47	146	51	5	135	81	37	1	16
Mahoning	145	1,162	368	379	415	142	768	59	18	521	255	153	26	87
Marion	59	522	164	194	164	62	360	62	14	207	75	108	2	22
Medina	67	454	144	135	175	103	329	63	1	191	76	71	9	35
Meigs	38	93	36	36	21	84	26	20	44	61	8	46	4	3
Mercer	35	136	42	54	40	38	73	43	10	88	41	40	1	6
Miami	40	451	111	169	171	52	332	68	2	157	72	57	7	21
Monroe	17	111	43	32	36	16	63	49	1	64	47	16	1	-
Montgomery	447	3,245	976	1,080	1,189	468	2,114	57	56	1,522	84	1,075	142	221
Morgan	13	63	18	21	24	22	36	47	5	35	10	5	-	20
Morrow	27	192	58	65	69	20	145	66	2	72	-	49	-	23
Muskingum	113	563	184	174	205	88	358	53	24	294	-	210	6	78
Noble	10	73	16	30	27	10	52	63	-	31	17	9	-	5
Ottawa	24	152	43	62	47	52	100	57	18	58	31	20	-	7
Paulding	8	106	31	35	40	13	80	70	2	32	15	16	1	-
Perry	45	218	61	69	88	69	143	54	32	88	-	71	-	17
Pickaway	17	133	42	44	47	23	90	60	2	58	20	22	4	12
Pike	34	199	68	65	66	37	132	57	4	97	3	32	1	61

Table 1
Intake Cases by County

		New Intakes Aug to Oct 2013					All Intakes Active Aug to Oct 2013 (Old + Total)							
							Screened Out			Screened In				
County	Old	Total	Aug	Sep	Oct	Contin-ued	N	%	Unk	Total	CAN AR	CAN TR	DEP	FINS
State	11,434	67,313	21,615	22,091	23,607	13,900	41,272	52	1,610	35,865	8,254	20,538	1,852	5,221
Portage	169	986	339	301	346	215	663	57	7	485	137	266	37	45
Preble	66	189	69	55	65	78	115	45	7	133	75	46	5	7
Putnam	15	115	33	40	42	11	88	68	-	42	24	10	-	8
Richland	287	1,182	362	374	446	346	552	38	22	895	288	346	62	199
Ross	139	402	131	120	151	199	228	42	112	201	31	142	13	15
Sandusky	30	455	141	149	165	36	367	76	-	118	54	39	15	10
Scioto	54	343	96	130	117	50	225	57	3	169	56	54	1	58
Seneca	44	461	129	147	185	59	334	66	-	171	79	61	-	31
Shelby	17	371	134	113	124	29	296	76	2	90	-	74	1	15
Stark	433	1,771	581	560	630	420	936	42	27	1,241	414	647	29	151
Summit	359	2,743	869	894	980	433	1,944	63	7	1,151	219	648	147	137
Trumbull	190	1,147	382	399	366	208	658	49	9	670	283	109	46	232
Tuscarawas	42	480	160	137	183	44	361	69	3	158	41	88	4	25
Union	52	298	103	102	93	61	186	53	1	163	60	65	12	26
Van Wert	26	152	47	54	51	13	121	68	1	56	-	47	1	8
Vinton	29	87	25	27	35	50	45	39	23	48	-	33	1	14
Warren	44	537	179	167	191	53	354	61	5	222	-	138	27	57
Washington	76	344	112	100	132	99	221	53	11	188	94	42	3	49
Wayne	102	715	217	226	272	123	426	52	3	388	-	332	25	31
Williams	31	201	70	67	64	32	138	59	5	89	24	60	1	4
Wood	75	461	149	161	151	100	256	48	1	279	99	134	1	45
Wyandot	8	97	30	24	43	10	68	65	-	37	-	28	1	8

Table 2
Case Spells by County

County	Old	New Case Spells Aug to Oct 2013 Total	Aug	Sep	Oct	Continued
State	34,336	22,347	7,243	7,318	7,786	35,873
Adams	124	88	28	31	29	135
Allen	341	244	73	76	95	378
Ashland	166	104	34	36	34	169
Ashtabula	204	255	84	91	80	239
Athens	138	117	44	42	31	138
Auglaize	53	72	29	23	20	51
Belmont	362	146	46	39	61	310
Brown	157	118	39	31	48	135
Butler	1,142	642	226	198	218	1,152
Carroll	61	38	12	16	10	44
Champaign	94	67	24	21	22	91
Clark	290	190	63	64	63	263
Clermont	408	393	149	126	118	462
Clinton	192	93	33	36	24	167
Columbiana	320	204	63	79	62	328
Coshocton	100	91	37	32	22	101
Crawford	158	88	30	26	32	193
Cuyahoga	5,050	2,975	950	991	1,034	5,175
Darke	77	41	13	11	17	78
Defiance	39	32	7	9	16	51
Delaware	153	140	54	36	50	150
Erie	308	125	40	42	43	300
Fairfield	417	291	91	96	104	499
Fayette	90	80	17	32	31	94
Franklin	5,001	2,947	938	963	1,046	5,136
Fulton	68	121	52	33	36	85
Gallia	336	47	9	18	20	340
Geauga	195	141	45	42	54	201
Greene	316	272	93	82	97	324
Guernsey	89	125	34	39	52	111
Hamilton	2,650	1,577	527	544	506	3,154
Hancock	99	86	32	21	33	119
Hardin	55	70	23	20	27	62
Harrison	50	26	5	10	11	52
Henry	103	42	14	12	16	77

Table 2
Case Spells by County

County	Old	New Case Spells Aug to Oct 2013 Total	Aug	Sep	Oct	Continued
State	34,336	22,347	7,243	7,318	7,786	35,873
Highland	286	57	17	18	22	326
Hocking	125	85	36	24	25	132
Holmes	193	22	5	10	7	137
Huron	132	106	44	26	36	121
Jackson	72	60	26	12	22	70
Jefferson	192	74	27	15	32	212
Knox	188	140	43	36	61	202
Lake	344	276	72	104	100	369
Lawrence	161	216	81	74	61	148
Licking	412	283	90	83	110	473
Logan	105	103	29	28	46	114
Lorain	491	614	176	200	238	557
Lucas	1,176	1,313	406	441	466	1,274
Madison	78	98	25	33	40	102
Mahoning	537	365	121	120	124	507
Marion	209	147	41	60	46	212
Medina	134	115	33	28	54	154
Meigs	228	54	20	20	14	259
Mercer	88	59	17	25	17	96
Miami	159	115	29	46	40	182
Monroe	44	44	24	8	12	39
Montgomery	1,730	1,027	305	356	366	1,785
Morgan	101	25	9	9	7	111
Morrow	64	44	11	16	17	58
Muskingum	268	175	53	57	65	230
Noble	16	19	8	4	7	19
Ottawa	104	48	15	18	15	118
Paulding	40	25	9	6	10	42
Perry	260	61	18	19	24	272
Pickaway	45	45	13	14	18	46
Pike	113	64	26	19	19	111
Portage	437	296	102	88	106	468
Preble	170	68	33	19	16	178
Putnam	89	27	12	9	6	98
Richland	770	507	133	173	201	810

Table 2
Case Spells by County

County	Old	New Case Spells Aug to Oct 2013				Continued
		Total	Aug	Sep	Oct	
State	34,336	22,347	7,243	7,318	7,786	35,873
Ross	495	149	54	46	49	534
Sandusky	86	79	25	25	29	88
Scioto	155	108	37	38	33	159
Seneca	109	109	29	43	37	150
Shelby	67	69	25	17	27	83
Stark	1,511	753	252	231	270	1,364
Summit	1,043	707	238	219	250	1,116
Trumbull	398	461	151	161	149	399
Tuscarawas	155	118	29	41	48	145
Union	105	80	30	30	20	110
Van Wert	54	30	7	11	12	42
Vinton	145	36	11	13	12	162
Warren	229	174	65	56	53	241
Washington	232	115	37	35	43	257
Wayne	318	225	88	76	61	332
Williams	115	60	23	22	15	117
Wood	139	182	64	61	57	159
Wyandot	13	27	11	7	9	19

Table 3

Number of Active Intakes Aug to Oct 2013 and % of Active Intakes with Logged Activities, by Type

County	Number of Active Intake Cases				% Logged by Outcome of Screening			% of SI Logged by Type			
	Total	SO	Unk	SI	SO	Unk	SI	TR	AR	DEP	FINS
All 18 Counties	35,963	18,189	641	17,133	2	85	82	83	94	81	59
Athens	589	406	1	182	1	100	82	83	91	80	31
Champaign	367	243	5	119	2	100	88	94	89	83	71
Clermont	1,679	1,090	51	538	2	96	84	86	-	89	61
Cuyahoga	11,970	5,878	294	5,798	3	83	76	79	-	72	52
Fayette	242	118	7	117	3	100	81	85	97	73	58
Franklin	9,457	4,544	143	4,770	2	91	84	86	92	93	60
Guernsey	514	327	9	178	2	100	85	86	94	100	35
Huron	497	336	1	160	1	100	88	93	95	83	66
Lake	1,279	862	5	412	2	100	88	90	97	98	59
Lucas	3,178	1,232	39	1,907	2	90	87	88	95	-	59
Madison	286	146	5	135	3	80	82	86	90	100	31
Miami	491	332	2	157	9	50	90	96	94	100	52
Muskingum	676	358	24	294	0	71	77	87	-	100	49
Ottawa	176	100	18	58	2	39	83	65	100	-	57
Sandusky	485	367	-	118	1	-	89	87	100	93	30
Stark	2,204	936	27	1,241	3	81	90	91	94	86	72
Trumbull	1,337	658	9	670	1	89	83	82	94	85	70
Wood	536	256	1	279	2	100	80	85	96	0	31

Table 4
Amount of Time Logged on Screened-In Intake Cases

County	Intake Case-Months	Minutes of Activity Per Month Per Intake						% Time (Column Heading) Devoted to % Intakes		
		Mean	Min	25th %ile	50th %ile	75th %ile	Max	25	50	75
Athens	254	168	0	45	102	230	1,241	6	17	35
Champaign	188	120	0	30	69	137	910	4	13	33
Clermont	861	73	0	15	37	81	1,235	3	12	31
Cuyahoga	7,902	164	0	25	83	202	5,323	4	12	29
Fayette	172	92	0	12	49	125	874	3	13	29
Franklin	6,726	163	0	30	86	189	3,291	4	12	30
Guernsey	250	157	0	45	99	180	950	6	16	38
Huron	223	109	0	20	60	117	1,060	4	12	32
Lake	583	152	0	35	91	200	1,715	5	16	35
Lucas	2,734	141	0	25	81	164	4,284	4	13	32
Madison	183	108	0	25	60	116	1,102	4	13	33
Miami	232	138	0	40	93	195	685	7	19	38
Muskingum	399	93	0	14	55	120	852	5	14	31
Ottawa	110	84	0	5	30	95	875	3	9	23
Sandusky	164	215	0	55	120	207	1,941	4	13	33
Stark	1,917	146	0	25	80	170	3,109	3	12	30
Trumbull	941	117	0	15	65	140	2,010	3	12	30
Wood	375	116	0	33	80	140	1,017	4	16	38
Coefficient of Variation		0.28		0.48	0.32	0.27		0.28	0.18	0.12

Table 5

Number of Active Cases Aug to Oct 2013 and % of Active Cases with Logged Activities, by Type

	Number of Active Cases				
County	Total	TR	AR	Unknown	% Logged
Athens	80	46	12	22	73
Champaign	30	17	8	5	83
Clermont	150	125	0	25	83
Cuyahoga	3,572	2,694	6	872	76
Fayette	39	27	1	11	72
Franklin	2,015	1,481	120	414	79
Guernsey	57	36	4	17	70
Huron	43	32	1	10	77
Lake	142	114	7	21	85
Lucas	564	395	52	117	79
Madison	28	15	8	5	82
Miami	61	21	23	17	72
Muskingum	135	113	0	22	84
Ottawa	9	7	0	2	78
Sandusky	60	29	10	21	65
Stark	230	155	14	61	73
Trumbull	178	104	32	42	76
Wood	49	35	0	14	71

Table 6
Amount of Time Logged on On-Going Cases

County	Case Spell-Months	Minutes of Activity Per Month Per Ongoing Case: Mean	Min	25th %ile	50th %ile	75th %ile	Max	% Time Devoted to % Cases: 25	50	75
Athens	142	752	0	125	449	1,170	4,127	7	18	33
Champaign	68	247	5	97	177	310	1,099	7	19	41
Clermont	317	342	0	107	285	483	2,042	8	22	43
Cuyahoga	6,915	152	0	30	70	175	4,396	3	11	28
Fayette	67	102	0	30	70	135	628	6	18	39
Franklin	4,173	300	0	102	200	385	4,432	6	18	39
Guernsey	90	319	0	120	215	450	1,366	8	20	40
Huron	81	240	0	60	145	245	2,151	5	14	32
Lake	323	278	0	105	160	315	2,230	5	15	39
Lucas	1,162	489	0	150	311	685	4,804	7	19	38
Madison	51	404	0	75	200	517	1,799	6	14	27
Miami	100	323	0	80	218	505	1,475	7	19	36
Muskingum	266	340	0	95	234	490	1,610	7	19	38
Ottawa	19	417	0	65	148	805	1,445	11	21	37
Sandusky	97	506	0	120	330	697	3,484	6	16	35
Stark	428	221	0	60	131	302	1,740	5	16	34
Trumbull	341	386	0	135	276	470	2,183	7	19	40
Wood	92	323	0	127	267	451	1,253	10	24	46
Coefficient of Variation		0.43		0.37	0.44	0.52		0.27	0.18	0.13

Table 7
Survival Analyses of How Long N=9,149 Intake Cases Take

County	N	Percentiles of Elapsed Days			Percentiles of Logged Mins.		
		25	50	75	25	50	75
Athens	96	28	40	54	235	345	611
Champaign	58	42	46	59	211	326	759
Clermont	348	20	31	49	70	120	218
Cuyahoga	2,894	26	38	62	220	390	711
Fayette	55	22	36	53	130	220	290
Franklin	2,559	29	40	45	192	305	563
Guernsey	115	27	34	43	160	300	530
Huron	83	24	30	44	115	183	327
Lake	214	30	41	45	190	314	515
Lucas	1,171	21	32	45	149	236	491
Madison	90	28	37	44	99	194	335
Miami	100	29	40	45	185	350	495
Muskingham	140	19	29	43	100	160	275
Ottawa	41	57	CNBD	CNBD	237	414	CNBD
Sandusky	66	23	30	44	151	247	615
Stark	679	36	44	48	185	320	603
Trumbell	277	16	29	42	110	181	345
Wood	163	30	43	45	135	220	340

CNBD - Could not be determined

Table 8
Observed and Predicted Differences in Mean Logged Time for Intake Cases

County	N	Minutes/ Month	Adjusted Minutes/ Month
Athens	224	85	126
Champaign	160	61	99
Clermont	739	35	59
Cuyahoga	6,978	62	104
Fayette	115	41	69
Franklin	5,501	78	122
Guernsey	228	91	134
Huron	172	56	94
Lake	447	83	121
Lucas	2,372	72	120
Madison	171	60	94
Miami	200	82	139
Muskingham	314	37	59
Ottawa	103	24	40
Sandusky	135	112	174
Stark	1,647	65	105
Trumbell	532	66	109
Wood	344	69	110
Coefficient of Variation		0.34	0.31

Table 9
County Differences in Mean Logged Time for Spell-Months

County	N	Minutes/ Month
Athens	142	340
Champaign	69	147
Clermont	321	210
Cuyahoga	7,023	62
Fayette	67	60
Franklin	4,243	169
Guernsey	90	180
Huron	83	89
Lake	327	163
Lucas	1,174	277
Madison	51	161
Miami	103	135
Muskingham	267	191
Ottawa	19	147
Sandusky	97	212
Stark	452	92
Trumbell	342	226
Wood	92	224

Table 10
Predictors of Logged Time for Intake-Months

County	Intake-Months	r
Athens	224	0.20
Champaign	160	0.39
Clermont	739	0.20
Cuyahoga	6,978	0.21
Fayette	115	0.38
Franklin	5,498	0.12
Guernsey	228	0.30
Huron	172	0.31
Lake	447	0.22
Lucas	2,370	0.17
Madison	171	0.22
Miami	200	0.34
Muskingham	314	0.26
Ottawa	103	0.30
Sandusky	135	0.40
Stark	1,645	0.15
Trumbell	532	0.19
Wood	344	0.21

Table 11
Percentage of Intakes by State-Wide Percentiles

County	Intake-Months	Percentage of Intake Months by State Quartiles			
		Lower (< 36)	Lower Middle (36-92)	Upper Middle (93-191)	Upper (>191)
Athens	214	14	27	28	31
Champaign	151	18	42	25	16
Clermont	686	44	33	16	8
Cuyahoga	6,355	24	24	23	29
Fayette	105	34	28	23	15
Franklin	5,328	23	24	26	26
Guernsey	225	20	25	33	22
Huron	164	27	34	26	14
Lake	435	22	26	25	27
Lucas	2,296	25	25	27	23
Madison	169	32	33	21	14
Miami	190	16	28	27	29
Muskingum	285	40	29	16	15
Ottawa	84	39	29	17	15
Sandusky	133	13	21	42	24
Stark	1,569	27	23	26	24
Trumbull	502	21	28	30	21
Wood	340	25	32	30	13

Table 12
Percentage of Case Spells by State-Wide Percentiles

		Percentage of Spell Months by State Quartiles			
County	Spell-Months	Lower (<61)	Lower Middle (61 - 140)	Upper Middle (141-320)	Upper (> 320)
Athens	138	7	17	20	57
Champaign	69	19	25	33	23
Clermont	317	11	21	24	44
Cuyahoga	6,652	45	24	18	13
Fayette	65	45	34	18	3
Franklin	4,161	13	23	32	31
Guernsey	89	17	16	30	37
Huron	77	23	22	35	19
Lake	321	9	35	32	24
Lucas	1,161	8	16	28	49
Madison	49	14	24	31	31
Miami	94	14	20	29	37
Muskingum	265	15	20	25	40
Ottawa	18	17	22	17	44
Sandusky	92	13	11	22	54
Stark	434	28	24	27	21
Trumbull	338	10	15	31	44
Wood	91	9	18	32	42

Figure 1 - Over-fitting is demonstrated in the strong relationship between R-squared and number of cases

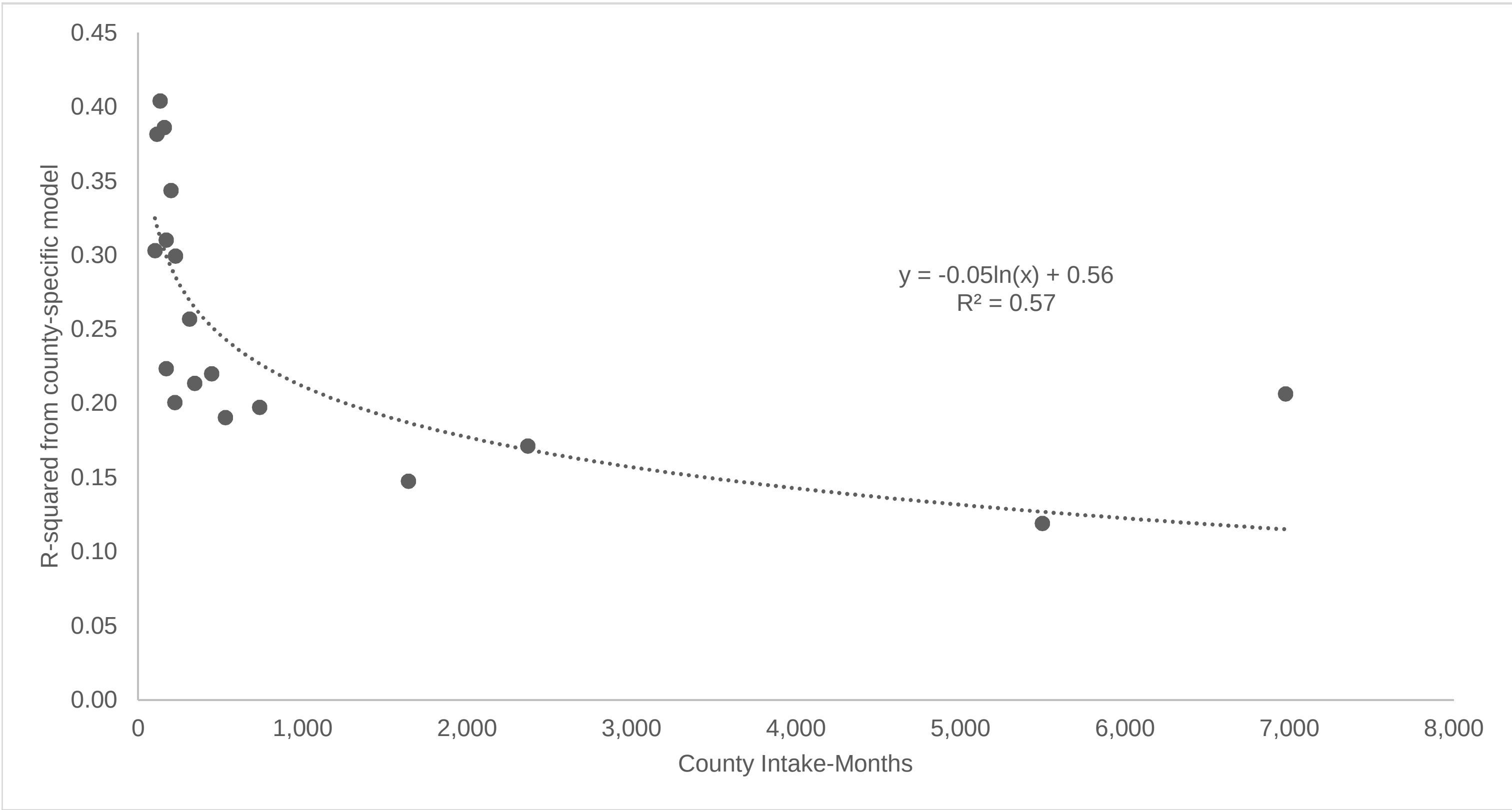

Figure 2 - The relationship between county intake-months and mean minutes/intake/month

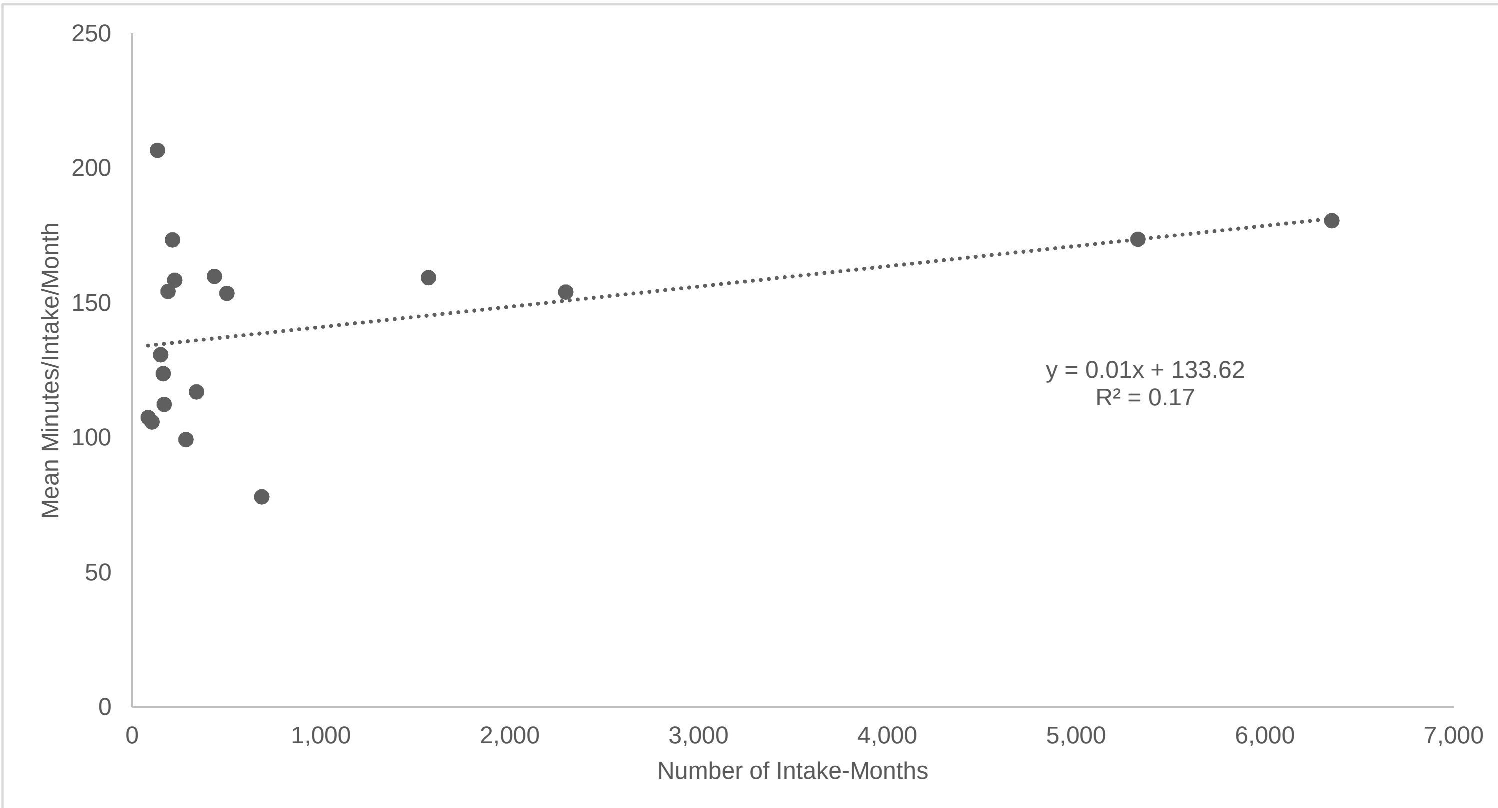

Figure 3 - The relationship between county spell-months and mean minutes/case/month