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Assessment of Predictive Modeling for Identifying Fraud within the Medicare Program

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Abstract

Health care fraud is a major policy concern. In this paper, we report the results of applying fraud and abuse analytical detection technology with a predictive algorithm developed for use in the Medicare program to identify and extrapolate the extent of fraud and abuse in terms of prevalence and expenditure in 2009. Using Medicare claims representing 20% of all beneficiaries and 100% of beneficiaries for a 3% sample of all providers in the nation, we estimate $18.1 billion of financial benefit for Medicare in the Part B physician program alone that could be potentially saved by implementing fraud and abuse payment prevention technologies without the need to access detailed medical records. When the Part A inpatient services are included, the estimated fraud and abuse prevention impact rises to nearly $20.7 billion. A separate retrospective recovery financial benefit is estimated at $17.5 billion. Implementation of this system, and the associated technology, can begin immediately in order to start realizing these savings.

Key Words: health insurance, Medicare, fraud, health economics, physician payment

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Introduction

Health care fraud is a major policy concern. The extent of Medicare fraud suggested in congressional testimony by Harvard Professor Malcolm K. Sparrow could amount to hundreds of billions of lost dollars per year[1]. The Federal Bureau of Investigation (FBI) estimates that fraudulent billings to public and private healthcare programs are 3-10% of total health spending, or $75–$250 billion in fiscal year 2009.[2, 3, 4] As part of the Patient Protection and Affordable Care Act (PPACA), language was included to focus resources on healthcare fraud and abuse prevention. This effort was buttressed with passage of the 2010 Small Business Act (H.R. 5297), which commits Medicare to a five-year time table for applying predictive analytics to prevent improper payments rather than the current "pay and chase" strategy.[*]

The use of advanced analytics to identify and prevent a fraudulent transaction was pioneered by the financial services industry over twenty years ago to combat credit card fraud, which was, at that time, accelerating through the use of electronic payment technologies. The

[*] See legislative language in HR 5297 sec 4241: http://www.gpo.gov/fdsys/pkg/BILLS-111hr5297eas/pdf/BILLS-111hr5297eas.pdf

impact of implementing fraud prevention analytics for the credit card industry was a 50% reduction in fraud within five years of market usage.[5] The application of financial services predictive analytics to health insurance claims is appropriate due to the similarities in transaction payment systems. For example, credit card and health insurance claims systems each rely on a combination of debits and credits for accounting. Both industries also use standard code sets to record the purchaser and vendor (e.g., the medical provider and payer for health care) associated with a transaction. The primary innovations offered through the use of analytics are algorithms that identify aberrant behavior that is typically associated with fraud or abuse. At their best, analytics can be used in real time to stop (or at least delay) a potentially fraudulent transaction until verification is confirmed before payment to a vendor or a provider.

The purpose of this study is to estimate the potential savings to the Medicare program if fraud prevention predictive analytics were applied to Medicare fee-for-service claims data, as prescribed in HR 5297, on a pre-payment basis. To conduct this study, we used a set of algorithms designed to assess and score health insurance claims transactions using technology invented by scientists who were also members of the team that co-developed the financial services industry real-time fraud prevention analytic tools created in 1993 and still in use today. Application of the fraud predictive analytics algorithm created a probability score for each Medicare claim or the line item detail associated with the claim, and these claims were aggregated to identify patterns of estimated fraud or abuse for a national population and geographic segments along with an estimate of potentially preventable and recoverable reimbursements. Four research questions drove this investigation.

1. At a national level, what are the estimated potential savings from using a fraud and abuse detection algorithm for Medicare services?

2. Are there significant variations in estimated potential savings from using a fraud and abuse detection algorithm by medical specialty and place of service?
3. What is the accuracy of the algorithm? How much fraud and abuse predicted can be validated and thus counted on as preventable or recoverable reimbursements?

We begin by describing the background on the financial services industry and its application to the health care industry. Next, the fraud scoring analytics and the validation methodology using clinical audits will be reviewed. This will be followed by a description of the claims data used for the national estimation. The results of the national estimation are then presented and followed with a discussion of the key findings and limitations of the study. We conclude with a summary of policy implications of our results and suggestions for next steps for fraud analytics investigation and policy.

1. Background

In the late 1980s, financial services firms were at a crossroads in identifying and preventing fraud. Key stakeholders were inclined to look at their solutions with a retrospective approach and only within their own credit portfolio. Further, tools and technology were immature, so credit card issuers would typically pay merchants for the products and services up front, and investigate fraud after the fact - a process otherwise known as "pay and chase". Fraud mitigation, then, was a manual process based on a small number of fraud cases detected in prior experience. This process was highly ad hoc, retrospective, and maintained only by hard coding decision rules into a credit-card issuer's processing system. The state of financial services fraud detection in the 1980s is almost identical to that of health care fraud detection in 2010 when HR5297 was passed.

Early financial services fraud detection methods could not measure how much fraud was prevented or even if a new test strategy or treatment was more or less effective than the previous strategy. It was easy for perpetrators to go undetected—if a perpetrator *was* identified, it was usually after numerous fraudulent transactions. Perpetrators often discarded stolen credit cards and moved their scheme on to another issuer. Similar to medical providers or insurers, banks acting as credit-card issuers did not share information, operating instead within the silo of their own business and their own market.[6] To move forward, the financial services industry had to undergo a change of culture and practice supported by new technology that bridged data silos with highly structured proprietary data systems and predictive analytical technology.

In 1993, a technology-based incentive to change fraud detection in financial services was introduced– the use of predictive models for identifying credit card fraud. Predictive modeling had historically been used in the financial services industry for underwriting credit and loans, and it had been an accepted and proven method for decades.[7] (The predictive-modeling technology is analogous in the U.S. health insurance industry to risk adjustment of medical claims data to determine future premiums or provider reimbursement).

Predictive modeling is an integral part of learning processes to indicate fraud or abuse detection. In this context, predictive modeling is an analytical process used to create a statistical model of future behavior. A predictive model is made up of a number of predictors, which are variable factors that are likely to influence the behavior of someone considering committing fraud in the future. In predictive modeling, data is collected for the relevant predictors, a statistical model is formulated, predictions are made and the model is validated (or revised) as additional information becomes available. A scoring "engine" evaluates transactions at the time of processing and before payment. If the transaction appears to be "high-risk" or "out of the ordinary" the transaction is flagged for further attention and the scoring models provide a reason the transaction was flagged.

Health care industry proponents of predictive modeling believe it is both an effective means to reduce fraud and abuse and an efficient method to target high-risk segments, such as specialty group or geography, or educational tools and messages to influence provider behavior. In the following sections we describe the impact of a financial services approach to health insurance fraud detection.

2. Model

The predictive modeling analytical technology used to estimate fraud or abuse for this study is mathematical application of non-parametric statistics to generate estimates probability of fraud scores. A non-parametric approach allows one to model independent the probability of fraud and abuse within dimensions of claims, provider and beneficiary fraud. A dimension is simply defined as the variables from insurance data that can be constructed using information from the submitted claim, the beneficiaries' attributes and care and the provider's preferences and treatment patterns that are consistently demonstrated in their billing behavior. Specifically, each dimension is a predictive model in itself, with further models created and segmented by additional dimensions, including provider specialty and geography. Each non-parametric sub-model provides a probabilistic score, which summarizes the likelihood that one or more of the dimensions has procedure, claim, and provider or beneficiary characteristics with unusual, abnormal or fraudulent behavior. These probability estimates are then used to compare the relative performance, or risk, among different geographies and across multiple provider specialties or even industry segments.

The first step in utilizing the predictive model score for the national assessment is the calculation of a proprietary non-parametric statistic that measures dispersion for predictive variables. The non-parametric measurement estimates the deviation from normal peer behavior in a way that focuses on a single side of the characteristic's data distribution. It evaluates healthcare claims, providers and beneficiary data to determine if behavior is "typical" of other participants in their peer group or if they are "abnormal".[†] We chose this approach because our approach limits inaccuracies.[‡]

The model is designed to focus primarily on extreme values at the "high" or "unfavorable" end of the variable distributions in the model. The methodology then converts the score into a probability estimate to determine a threshold value where a claim, provider or beneficiary behavior causes a claim to go from a condition that is considered normal to a new and different condition of an uncommon or rare phenomenon, which is labeled as either potential fraud or abuse.

The score is defined as the value that represents the overall probability that one or more of the claim, provider or beneficiary characteristics, as measured on a scale of zero to one, is likely fraud or abuse. At a pre-determined value on the scale between zero (0) and one (1), the likelihood of being an aberrant claim, patient or provider is so great that the observation is labeled as "potential fraud or abuse".

Any value above this critical threshold value is considered to be unusual or not typical. This critical value is defined as the threshold value (T-V) statistic. The T-V statistic is the numeric score above which it is unlikely that a claim, provider or beneficiary is exhibiting a

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[†] A peer group is defined as a group of members of the same dimension, including but not limited to healthcare claims or procedures, providers or of the beneficiary. For example, a peer group for providers might be their medical specialty, such as pediatrics or radiology.

[‡] Non-parametric techniques do not rely on data belonging to any probability distribution. Non-parametric statistical techniques also do not assume that the structure of a model is fixed.

"normal" behavior pattern. Therefore, if the critical value score is, .95 (95%) for example, and the claim, provider or beneficiary score is higher than that critical value, it means that one or more of the claim's, provider's or beneficiary's characteristics have abnormal or unusual behavior values.

In summary, each provider was given a probability score in the final calculation. The score values range from zero to one hundred, with higher values indicating higher payment risk and lower values indicating lower payment risk. Therefore, the highest-score values have a high probability of fraud or abuse. These probability estimates can then be used to compare the relative performance, or risk, among different geographies and across multiple provider specialties.

3. Data

The data used for the application, validation and national estimate of Medicare fraud are Medicare Part A and Part B claims for calendar years 2007 through 2009 as well as supporting files related to beneficiary and provider attributes.

To refine and validate the predictive model for Medicare fraud or abuse, multiple years of an entire state's population of Medicare data were utilized for the original development. These data represent 100% of the fee-for-service claims for Medicare beneficiaries living in a large Midwest state from 2009 and 2010. A Medicare Administrative Contractor (MAC) provided these data for the purpose of validating the predictive model used for this paper's analysis. Critical data elements used for analysis were beneficiary IDs and provider IDs, the date(s) of service, beneficiary and provider location (i.e. zip codes), total allowed charge amount and diagnostic and procedure codes. Additional data provided were Medicare claims contractor provider identification files with detailed provider practice information that could be augmented with additional data to verify addresses and the validity of a current provider practice.

The data used for the state analysis was an extract of medical practice records completed by the MAC following security and HIPAA compliance procedures outlined in the Data Use Agreement. The data used for the national estimates were requested under a different government contract and delivered through the Medicare claims contractor procurement process.

A 5% random sample of beneficiaries participating in the Medicare fee-for-service program was obtained for dates of service in 2007 through 2009. These files included all sample information required for the application and validation of the predictive modeling technology. We were provided with 100% of all claims for the given beneficiaries randomly sampled for inclusion in the study population.[§]

An additional random sample was requested for national estimation of fraud or abuse prevalence and cost. For the second sample, we identified a 3% random sample of providers and extracted all of their claims.[**] We also obtained all of the claims of the beneficiaries seen by the random 3% sample of providers. This intersection provided us with a sample of claims data for nearly 20% of all beneficiaries in the Medicare program from 2007 to 2009.

4. Application and Validation of Predictive Modeling for Health Insurance Fraud Detection

A team of independent health insurance investigators was engaged to conduct four separate validation reviews of sampled, scored providers, claims and procedures. All claims reviewed had passed existing policy rules, fraud edits and audits in place during 2009. Detailed reviews consisted of nurses and claims specialists performing reviews of the model output and

[§] This represented 5% of the total beneficiaries in that state and in the 2007-2009 calendar year period.
[**] For the predictive models to work ideally a 100% provider-level data along with 100% beneficiary-level data would be used.

reason codes, along with detailed claims and procedure history reviews.[††] A medical director supported the investigative professionals. Statistical analysis and summaries, based upon one year of claims and procedure history, were created to quantify and support investigations. The reviewers were blind to the score assigned for three reviews from independent reviewers to ensure an unbiased validation process.

Three reviews were performed iteratively to validate and recalibrate the model. Specifically, the objectives of these reviews were to:

- Validate whether the model was acceptably ranking providers as low, medium, high-risk or extreme-risk for the follow-on validation review
- Assess the predictive value of specific model variables and adjust, eliminate or add to the variables in order to improve model performance prior to the validation review
- Validate CMS claim payment reason code descriptions from the model to provide guidance to claim investigations and explain high-scoring behavior.

Review one included random selections from high and low scoring providers needing feedback from the medical investigative team. The feedback process identified opportunities for improvement in the model through the addition, modification, or elimination of variables and other statistical modifications. The feedback process also provided confirmation of the model's ability to rank order the need for further review or investigation.

Based on feedback from Review 1, the models were updated and refined. Review two was sampled from the updated model in a similar random manner as review one. This review

[††] Model attributes responsible for a high-scoring provider are designated as model score reason codes. The top reasons for the calculated score are presented to investigators to aid in their review process.

was to evaluate the updated model and provide final feedback prior to the financial evaluation phase of the validation.

The evaluation process for both reviews was as follows: The medical investigative team was provided the appropriate list of providers, all their claims and procedures submitted during the time period evaluated, data analysis summaries and key model attributes and reason codes responsible for the model score. The team returned each master record of their evaluation with a recommendation of whether or not the provider, their claims or procedures merited further, more detailed investigation. This detailed investigation tag included whether or not the analyst believed there was enough evidence to pursue further recoupment action.

The third review was a random selection of providers who scored between 95 and 100. The objective was to estimate the amount of actionable fraud and abuse for this population. This review involved estimating both the financial impact of preventing payment on aberrant claims as well as a recovery estimated for past behaviors. To qualify as actionable, findings had to be quantifiable and significant in terms of claims payment expenditure to warrant action without medical review. Validated findings were then used to quantify the prevention and recovery financial benefit.[‡‡] Final results were summarized and extrapolated to the entire population for the state being reviewed.

The fourth review was intended to simulate the process that would be used in a live environment for queuing and evaluation of suspect providers. This allowed for a focused review of potential behavior that could have immediate return on investment and could be used to provide evidence to support intended actions for investigators such as systematic denial, education, or consent settlement in a constrained resource environment.

[‡‡] Even though the definition of fraud or abuse is used in this document, no legal or judicial proceedings were pursued against any provider.

Providers sampled in the fourth review had the following additional characteristics:

- High Risk Probability Scores of 95 – 100
- "High Dollar" Amount Paid on an Annual Basis (i.e. > $500,000)
- Highly-defendable findings, based upon score and reason descriptions, with or without medical review
- Pattern of abuse that was actionable both retrospectively as well as preventable – that is, the provider was continuing the same pattern of fraud or abuse in the next year

5. National Potential Fraud and Abuse Estimate

The predictive analytical algorithms and methodology tested for the large Midwest state were subsequently refined on a national sample and applied to our two national random samples of claims data. Care was taken to ensure that model and assessment variables used during the validation could be used on national basis. Because it was a 5% random sample of beneficiaries, we generated a national financial impact estimate by weighting the results by a factor of 20. For the other sample of providers where we had all of the provider's beneficiary claims, we generated a national estimate of prevalence by weighting the estimated results by a factor of 10. Additional analysis was performed on the provider sample to ensure accurate performance for the same providers throughout the entire time period.

6. Results

National Medicare fraud and abuse estimates based on the predictive model are presented in Figures 2 through 8. Financial estimates are based upon probability scores of 95 and higher.

These results will yield a significant saving if used in a systematic prepayment fraud analytical technology assessing 100% of claims and providers.[§§]

The national, annual estimate for suspect, high scoring Part B providers reveals a potential financial benefit of $18.1 billion in allowed amount. The details of this estimate are presented in Figure 2.[***] There is an additional potential benefit of $5.4 billion in annual retrospective cost recovery (dating back three years from the start date of scoring). A three-year retrospective financial benefit is estimated to be approximately $16 billion.

Figure 3 shows a national estimate of Part B physician fraud or abuse in score range of 95 and higher. Large states that are extreme-risk include California, Texas, Florida and New York. By major census region, the South is high-risk, largely reflecting the strong influence of Florida. The region with the lowest risk of Medicare fraud includes the Western states, and in particular the interior western states of Idaho, Wyoming, Montana, Utah and Colorado.

Financial recovery and prevention benefit by type of service provider is presented in Figure 5. Both the percentage of claims and the financial impact are shown.[†††] The "place of service" with the greatest amount of potential financial benefit was the physician's office setting, where as much as 56% of 2009 total allowed amount reside, but over 70% of total dollars are at risk for all providers with scores of 95 or higher.

[§§] While not included as an estimate in this analysis, additional fraud or abuse prevention savings also exists in score ranges of 90-94.

[***] A sample calculation is below: Dollars at Risk = (Total Part B Allowed Amount in probability scores of 95-100) X (Accuracy Percentage); Net Recovery or Prevention Amount = (Dollars at Risk) X (Validation Recovery or Prevention Percentage) X (Sample Weighting Factor).

[†††] The greatest place of service was air ambulance, because of the distances traveled and extraordinary variation in claim payment totals. We don't consider our air and sea ambulance estimate to be reliable without further investigation.

Figure 6, examines the provider specialties associated with fraud or abuse with scores of 95 or greater. The specialties with greatest share of risky total expenditures are cardiology (12.31%), internal medicine (11.26%), diagnostic radiology (9.31%) and ophthalmology - cataracts (6.28%). Of course these are some of the largest specialties in volume, which is reflected in the third column in Figure 6. The share of total dollars at risk for all providers with scores of 95 or higher compared to overall specialty share of expenditures shows that internal medicine is much less of a concern. However several specialties have higher than total expenditure share amounts associated with fraud and abuse including cardiology, diagnostic radiology and ophthalmology – cataracts.

Turning our attention to Part A, the national estimate of inpatient preventable fraud is shown in Figure 7. This table segments a 2009 national annual estimate of all Part A inpatient services and presents the share of claims associated with scores of 95 or higher. Approximately $2.6 billion was identified as suspect associated with providers worthy of investigation.[‡‡‡] The Part A additional financial benefit is only $0.5 billion in annual retrospective cost recovery. A three-year retrospective financial benefit is estimated at approximately $1.5 billion for Part A inpatient services.

7. Discussion

This analysis represents the first national estimate of the extent of annual and retrospective preventable Medicare fraud or abuse. Prior estimates of fraud or abuse were based on assumptions, not detailed claims analysis coupled with objective examination and validation of patient data and provider practices. The primary contributions of this research are two fold. One, it demonstrates the efficacy of the fraud prevention technology as prescribed in the 2010

[‡‡‡] While not included as an estimate in this analysis, additional fraud or abuse prevention savings also exists in score ranges of 90-94.

law HR 8527 and it provides a national estimate of recoverable fraud. Secondly, it demonstrates that predictive modeling can be deployed and implemented quickly to both prevent and recover Medicare money spent on abusive provider practices, especially in Part B.

Answers to the four questions motivating this analysis constitute its key findings. In answer to the first question, we estimate that the national potential annual savings from using a fraud detection algorithm for Medicare Part B services is $18.1 billion dollars for providers worthy of investigation that do not require accessing detailed medical records[§§§]. It is estimated that there are possibly an equal amount of dollars that are recoverable if medical records are accessed. An additional $16 billion is estimated for a three-year retrospective recovery financial benefit. This means that, if implemented on a nationwide scale, it is estimated that this technology could potentially recover $34.1 billion in the first year and save $18.1 billion annually on an on-going basis. This estimate takes into account the accuracy of the predictive modeling based on the validation analysis but it does not include the incremental benefits that will result from the improvements and increased data accuracy and the "feedback loop" that will be part of a deployed system. These estimates do not include the incremental financial benefit from identified fraud and abuse in scores of 90-94. The estimates also do not account for the increased savings derived from the sentinel effect that always accompanies improved fraud and abuse prevention programs. Once high-risk providers know they are being monitored by sophisticated and accurate systems, it is expected that they will behave in a more compliant, "normal" or typical manner.

The second research question concerned a national estimate of the potential savings from using a fraud detection algorithm for Medicare Part A services. Our annual estimate from this analysis is significantly lower, with only $2.6 billion dollars considered worthy of investigation

[§§§] . A three-year retrospective financial benefit is also estimated at approximately $15 billion for Part B physicians and preventable. In fact, the data suggests that it is may be possible that Part A providers are under-billing in order to avoid costly and time-consuming audits. An additional $1.5 billion is estimated for a three-year retrospective recovery financial benefit. Our estimates infer the amount of actual preventable fraud is significantly less in Part A than Part B, even though the total amount billed is almost the same, but further analysis is suggested to validate this finding.

The third research question concerned the accuracy of the predictive fraud model algorithm. Based primarily on the validation exercise, it appears this model's accuracy is approximately 70%. While an accuracy rate of 70% may not be considered particularly high, it is consistent with the first generation of financial services fraud prevention analytics and the data inaccuracies previously discussed. We also identified a significant improvement opportunity by implementing a feedback loop and improving the accuracy of specialty group definitions. As demonstrated in the financial services industry, predictive models become considerably more accurate after they are in production. Even though financial services industry predictive models are far less complex and the data is significantly more "accurate" and reliable, the 70% accuracy rate of these first healthcare predictive models is significantly better than the earliest financial services industry fraud models. With improvements in data accuracy and reliability and a feedback loop that can correct and modify questionable information, it is anticipated that model performance will improve tremendously. For example, with the data and feedback loop enhancements and natural evolution through subsequent model versions it is estimated that future generations of these predictive models will attain a better than 90% accuracy rate.

The fourth research question concerned the ability to validate if the predictive analytical technology can satisfactorily evaluate all of the provider claims systematically in a manner that is consistent with medical review. By systematically scoring 100% of providers, claims and beneficiaries sampled for the validation under four separate reviews, we have shown during our assessment that performance is consistent across multiple validations.

8. Caveats

We highlight two caveats. First, although our average accuracy rating was only 70%, we were not able to use 100% of the claims data for the national estimates that would have improved the accuracy rate. Also, the accuracy rate will surely improve in subsequent iterations of the model as more fraud is validated, the data accuracy is improved, the feedback loop is implemented and the fraud analytics model improves to reduce the false positive rate.

We did not have sufficient access to data that would allow us to develop a true false positive and false negative rate. Our second best option was to assess the accuracy of our fraud predictions with a Medicare claims contractor providing an independent manual claims review and validation of our predictive score model. Beyond this, there are two ways to generate true false positive and false negative rates to enable more robust sensitivity and specificity metrics in the future. One way is to expand the scope of analysis to examine a subset of beneficiaries that have had all of their transactions independently verified with survey and chart abstraction. This is an expensive research design and outside the scope of this analysis. The second way is to record the responses of providers identified as abusive or fraudulent, through a feedback loop, after the predictive model technology used by CMS is implemented nationally. This second approach is, in fact, used successfully in the financial services industry.

9. Policy Implications

The major policy implications of this research are realized in the savings to the Medicare program—and which can be used to improve the fiscal outlook of the program or pay for increased coverage options associated with health reform. From a welfare loss perspective, any way to mitigate fraud or abuse will provide greater stability to the nation's largest single publicly financed program. This analysis suggests an automated process can be used to identify and prevent fraud or abuse that is likely to cost far less and be far more effective than the after the fact claim audit process now in place. In a classic economics study, Darby and Karni (1973)[8] concluded that fraud mitigation would not be optimal unless the technology deployed was not in fact more costly than the fraud itself. This analysis suggests the fraud mitigation technology, likely disruptive at first, will yield effective results as it did for the financial services industry almost two decades ago.

In summary, this analysis provides an estimate of the potential saving of predictive modeling applied to the Medicare program as prescribed by HR 8527. Within one to two more years the actual results of the legislation will be able to be tested as a natural experiment. Until then, this analysis provides a first benchmark for the potential of new game changing technology for fraud prevention that will help preserve the scarce resources allocated to Medicare for years to come.

Figure 1
Summary of Predictive Model Prevention Validation and Accuracy

2009 State Sample	Validation Population Metrics – Allowed Amount	
Physician Population Evaluated	38.6 Thousand	Total Providers
	$4.2 Billion	Annual Allowed Amount
	54.5 Million	Annual Claims
Providers with > $40,000 Annual Allowed Amount	16.5 Thousand (43% of Total)	Remaining Providers
	$3.8 Billion (90% of Total)	Annual Allowed Amount
Probability Scores of 95-100 Proportion of Actuals Predicted for Model	1,903 (5% of Total)	Providers with Annual Allowed Amount > $40,000
	$782 Million (18.7% of Total)	Total Allowed Amount at Risk
Prevention Financial Estimate of Prediction for Suspect Providers Worthy of Investigation <u>with</u> Financial Benefit	64%	Validation Accuracy Rate
	$517 Million (9.9% of Total)	Allowed Dollars At Risk
Fraud and Abuse Retrospective Cost Recovery Estimate	30%*	Provider Claims (all or part) That are Fraud or Abuse
	$155 Million (3.7% of Total)	

2009 State Sample	Validation Population Metrics – Payment Amount	
Physician Population Evaluated	38.6 Thousand	Total Providers
	$3.3 Billion	Annual Medicare Dollars Paid
	54.5 Million	Annual Claims
Probability Scores of 95-100 Proportion of Actuals Predicted for Model	2,840 (7.4% of Total)	Number of Providers
	$627 Million (19.7% of Total)	Total Payment Dollars at Risk
Prevention Financial Estimate of Prediction for Suspect Providers Worthy of Investigation <u>with</u> Financial Benefit	64%	Validation Accuracy Rate
	$401 Million (9.6% of Total)	Payment Dollars At Risk

Fraud and Abuse Retrospective Cost Recovery Estimate	30%*	Provider Claims (all or part) That are Fraud or Abuse
	$120 Million (2.9% of Total)	

*** Note:** 15% Estimate without Medical Records
15% Estimate with Medical Records

Figure2
National Estimate of Part B Physician Fraud and Abuse Prevention

2009 Part B National Sample	Population Score Distribution			
Probability Scores	**Annual Allowed Amount (000,000)**	**Allowed Amount Percentage of Total**	**Annual Payment Amount (000,000)**	**Payment Amount Percentage of Total**
<=59	$6,644	5.9%	$4,986	5.8%
60-69	$10,323	9.1%	$7,775	9.0%
70-79	$18,856	16.7%	$14,260	16.5%
80-89	$30,838	27.3%	$23,564	27.3%
90-94	$17,976	15.9%	$13,836	16.0%
95-100	$28,266	25.0%	$21,787	25.3%
Total	$112,903	100%	$86,208	100%

2009 Part B National Sample	Validation Population Metrics	
Physician Population Evaluated	$112.9 Billion	Annual Allowed Amount
	$86.2 Billion	Annual Payment Amount
Probability Scores of 95-100 Proportion of Actuals Predicted for Model	$28.3 Billion (25.0% of Total)	Allowed Amount
	$21.8 Billion (25.3% of Total)	Payment Amount
Prevention Financial Estimate of Prediction for Suspect Providers Worthy of Investigation <u>with</u> Financial Benefit	64%	Validation Accuracy Rate

Financial Estimate of Prediction for Suspect Providers	$18.1 Billion (16.0% of Total)	Allowed Amount at Risk
	$13.9 Billion (16.2% of Total)	Payment Amount at Risk
Fraud and Abuse Retrospective Cost Recovery Estimate	30%*	Provider Claims (all or part) That are Fraud or Abuse
	$5.4 Billion (4.8% of Total)	Allowed Amount
	$4.2 Billion (4.9% of Total)	Payment Amount

*** Note:** 15% Estimate without Medical Records
15% Estimate with Medical Records

Figure 3

Medicare Part B Physician Geographical Risk Index for Probability Scores 95 and Greater

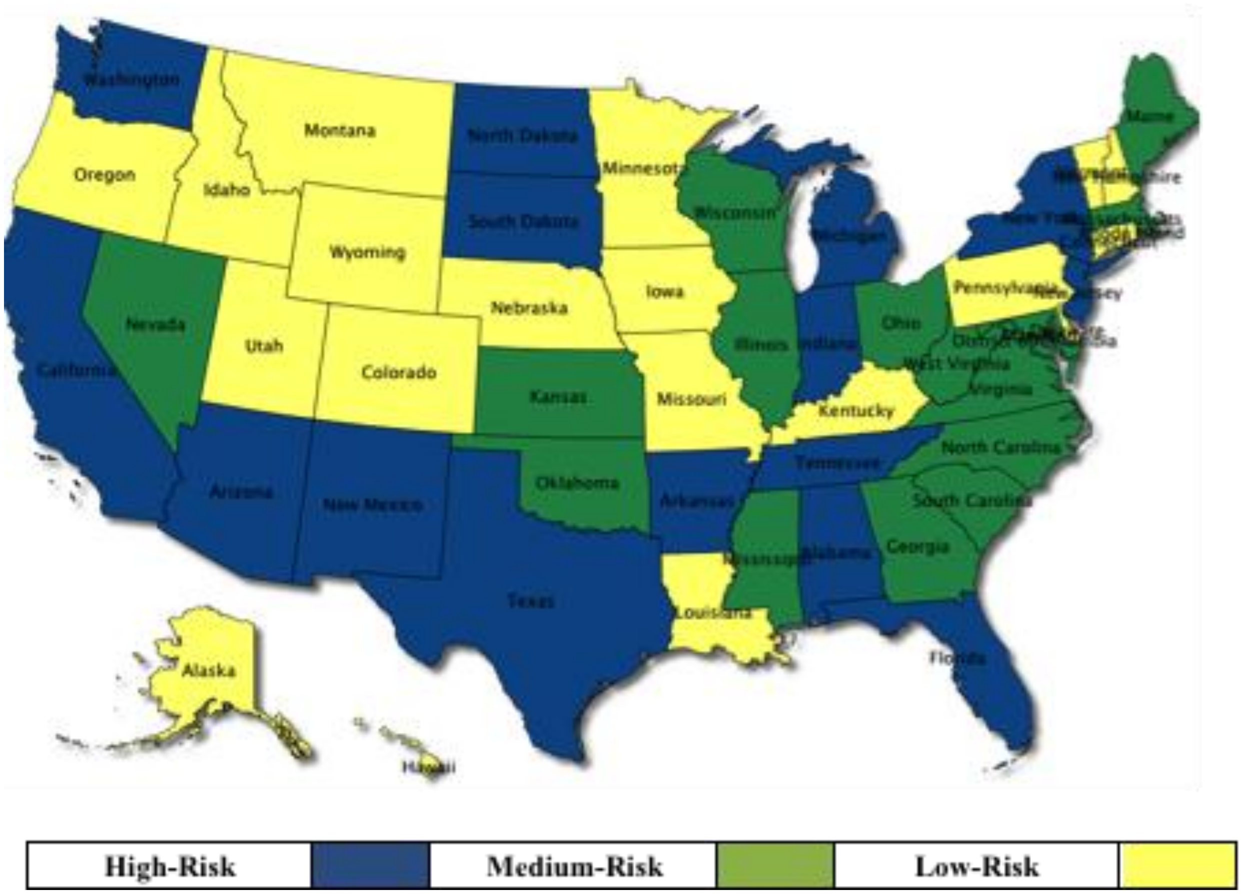
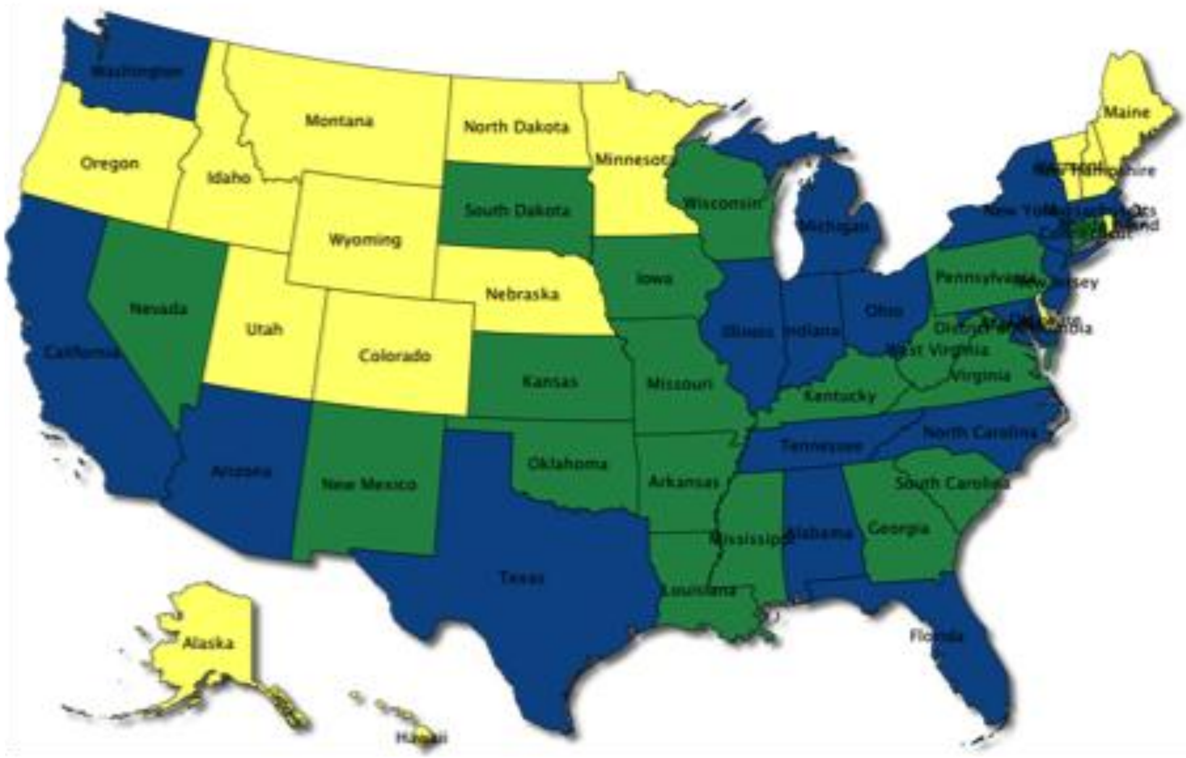


Figure 4
Medicare Part B Physician Geographical Financial Estimate of Allowed Amount for Prediction of Suspect Providers



High-Risk $250M-3B		Medium-Risk $100M-249M		Low-Risk <$100M	

2009 Part B National Sample	Probability Scores of 95 or Greater – Allowed Amount

Place of Services	Percent of Dollars Scoring 95-100	Share of Place of Service	Dollars at Risk (000,000)
Ambulance – Air or Water	0.64%	0.16%	$116.1
Ambulance – Land	2.88%	4.30%	$522.4
Ambulatory Surgical Center	1.97%	4.53%	$357.2
Comprehensive Inpatient Rehabilitation Facility	0.04%	0.14%	$7.6
Custodial Care Facility	0.13%	0.13%	22.9
Emergency Room Hospital	0.38%	3.18%	$69.2
End-Stage Renal Disease Treatment Facility	0.35%	0.62%	$62.9
Home	2.12%	0.90%	$384.6
Independent Laboratory	1.21%	1.22%	$220.1
Inpatient Hospital	13.31%	18.01%	$2,412
Inpatient Psychiatric Facility	0.15%	0.15%	$27.9
Intermediate Care Facility / Mentally Retarded	0.01%	0.02%	$2.2
Mass Immunizations Center	0.02%	0.07%	$3.6
Nursing Facility	1.02%	1.33%	$184.7
Office	70.02%	56.02%	$12,686
Outpatient Hospital	4.21%	7.21%	$762.0
Psychiatric Facility Partial Hospitalization	0.07%	0.03%	$13.1
Skilled Nursing Facility	0.74%	1.35%	$134.8
Other Categories	0.71%	0.65%	$129.5
Total	100%	100%	$18,100

Figure 5

National Estimate of Part B Physician Preventable Fraud and Abuse Assessment by Place of Service

Figure 6

Part B Physician National Estimate of High-Risk Specialty Code Expenditures

2009 Part B National Sample	Probability Scores of 95 or Greater – Allowed Amount		
Provider Specialty Group	**Percent of Dollars Scoring 95-100**	**Share of Specialty Group**	**Dollars at Risk (000,000)**
Ambulance Service Provider	3.48%	4.49%	$629.4
Anesthesiology	0.83%	1.32%	$150.0
Cardiac Surgery	0.53%	0.32%	$95.6
Cardiology	12.31%	8.41%	$2,226.7
Clinical Laboratory	1.26%	1.21%	$228.6
Dermatology	3.30%	2.82%	$597.2
Diagnostic Radiology	9.31%	5.03%	$1,684.5
Emergency Medicine	0.86%	2.44%	$155.8
Family Practice	4.26%	5.64%	$771.1
Gastroenterology	0.80%	1.62%	$145.5
General Practice	1.39%	0.74%	$252.2
General Surgery	3.68%	2.66%	$665.1
Hematology	1.05%	0.49%	$190.5
Hematology / Oncology	4.66%	5.83%	$842.5
Infectious Disease	0.77%	0.51%	$139.3
Internal Medicine	11.26%	11.38%	$2,037.6
Interventional Radiology	2.06%	1.66%	$373.3
Medical Oncology	1.86%	1.76%	$337.3
Nephrology	1.51%	2.05%	$272.5
Neurology	1.19%	1.52%	$216.0
Nurse – Medical Office	0.51%	0.48%	$93.1
Obstetrics / Gynecology	0.58%	0.53%	$105.5
Ophthalmology Cataracts	6.28%	4.77%	$1,136.9
Ophthalmology General	0.20%	0.13%	$36.9
Orthopedic Surgery	3.24%	3.41%	$586.6
Otolaryngology	0.68%	0.86%	$122.3
Physical Medicine & Rehabilitation	0.79%	1.10%	$143.4
Physical Therapist	2.07%	1.79%	$375.0
Podiatry	1.42%	1.81%	$256.6
Psychiatry	0.98%	1.25%	$178.1
Pulmonary Disease	0.89%	1.77%	$161.8
Radiation Oncology	1.72%	1.80%	$311.3
Rheumatology	1.26%	1.07%	$228.5
Thoracic Surgery	0.45%	0.33%	$82.2
Urology	3.47%	3.01%	$627.8
Vascular Surgery	0.72%	0.57%	$130.8
Remaining Specialty Codes	8.31%	13.33%	$1,504.1

Total	100%	100%	$18.100

Figure 7
National Estimate of Part A Medicare Inpatient Fraud and Abuse Prevention

2009 Part A National Sample	**Population Score Distribution – Paid Amount**	
Probability Scores	**Inpatient Annual Paid Dollars (000,000)**	**Percentage of Total**
<=59	$2,007	1.5%
60-69	$21,271	15.8%
70-79	$45,668	33.9%
80-89	$51,913	38.6%
90-94	$11,151	8.3%
95-100	$2,590	1.9%
Total	$134,602	100%

2009 National Sample	**Validation Population Metrics**	
Physician Population Evaluated	$134.6 Billion	Annual Inpatient Paid Dollars
Probability Scores of 95-100 Proportion of Actuals Predicted for Model	$2.6 Billion (1.9% of Total)	Total Paid Dollars at Risk
Prevention Financial Estimate of Prediction for Suspect Providers Worthy of Investigation <u>with</u> Financial Benefit	60%	Validation Accuracy Rate
	$1.8 Billion (1.2% of Total)	Paid Dollars at Risk
Fraud and Abuse Retrospective Cost Recovery Estimate	30%*	Claims (all or part) That are Fraud or Abuse
	$466 Million (0.4% of Total)	

*** Note:**	15% Estimate without Medical Records
	15% Estimate with Medical Records

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