

# Poisson Regression of Primary Care Access

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# Primary Care Access and Insured Rate

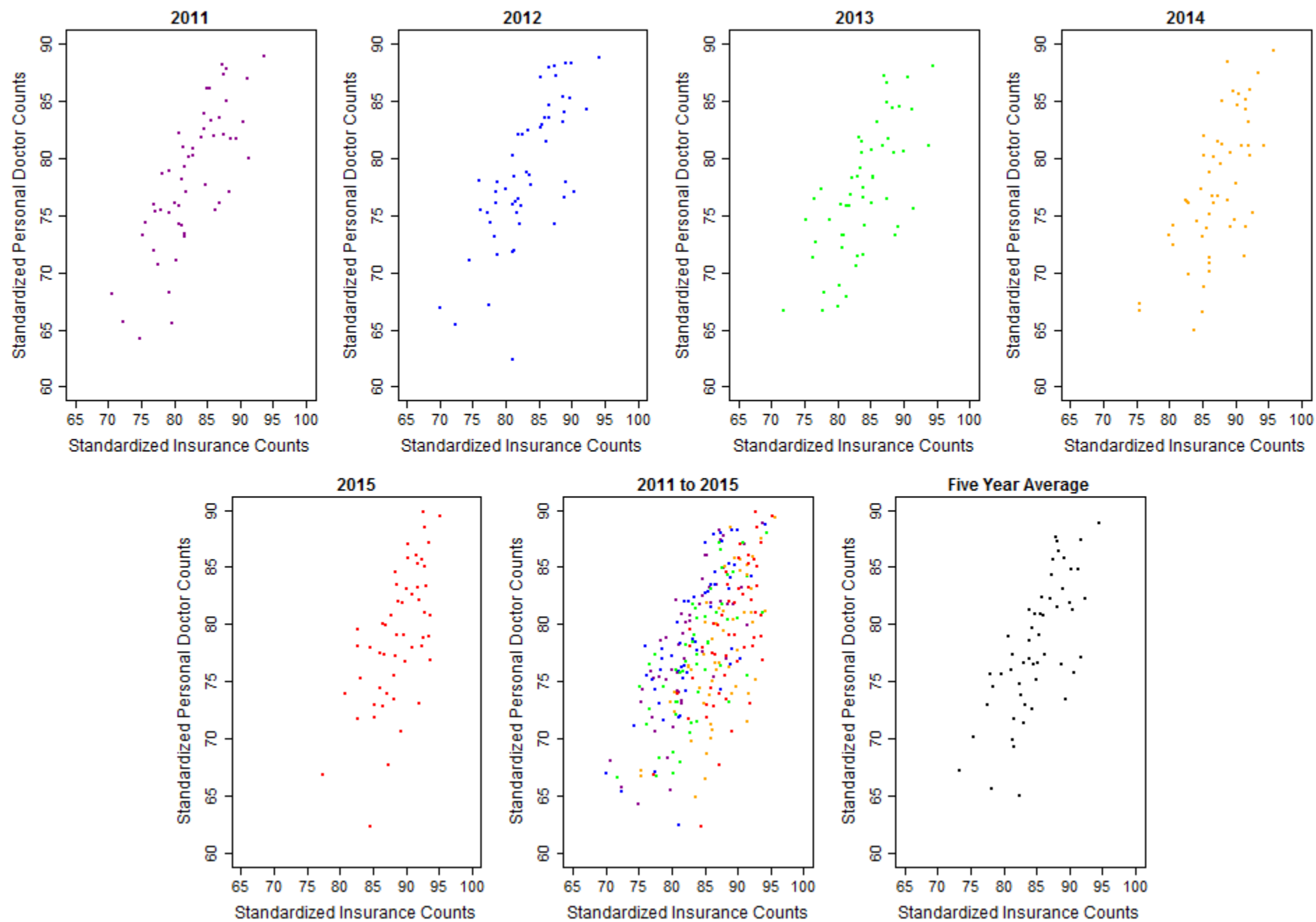
- Improved primary care access is strongly associated improved overall health outcomes and lower healthcare system costs
- The uninsured rate has dropped from around 18% in 2013 to 9% in 2016
- Are higher insured rates correlated with better primary care access?
- Relationship between number of individuals with a personal doctor and insured rate

# Personal Doctor Rate ~ Insured Rate

- Use at statewide data
- Regress count of individuals with a personal doctor on count of individuals with insurance
- Standardize counts to rates per 100 individuals (percentage)
- Use data from 2011 to 2015 Behavioral Risk Factor Surveillance System (BRFSS) annual surveys
- Total of six models:
  - 1 model for each year
  - 1 model for five year averages

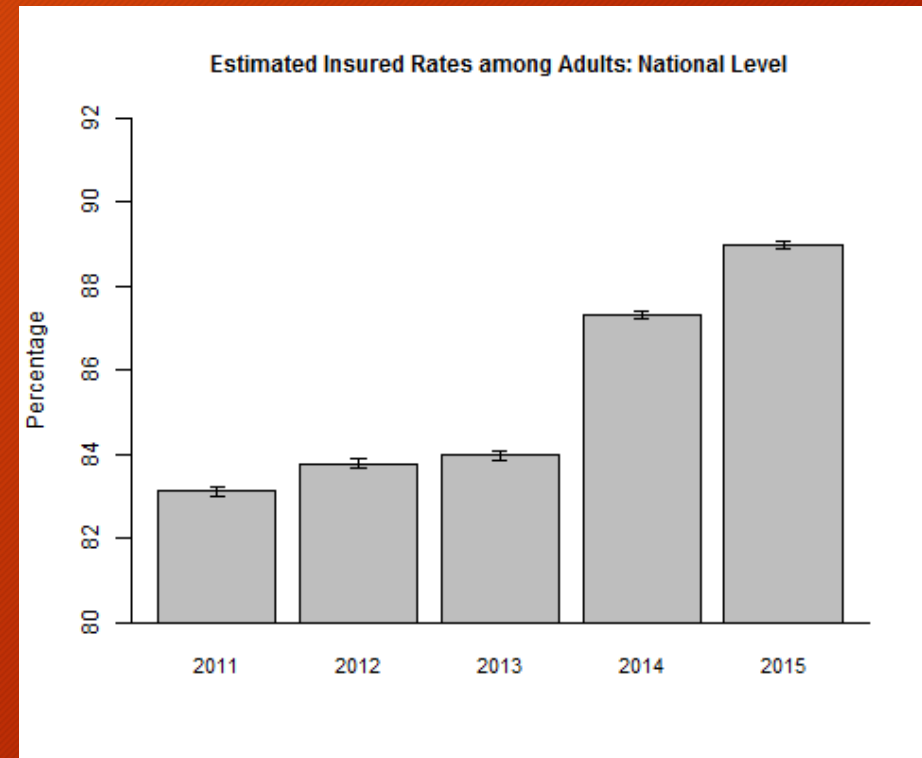


## Personal Doctor Counts v.s. Insurance Counts

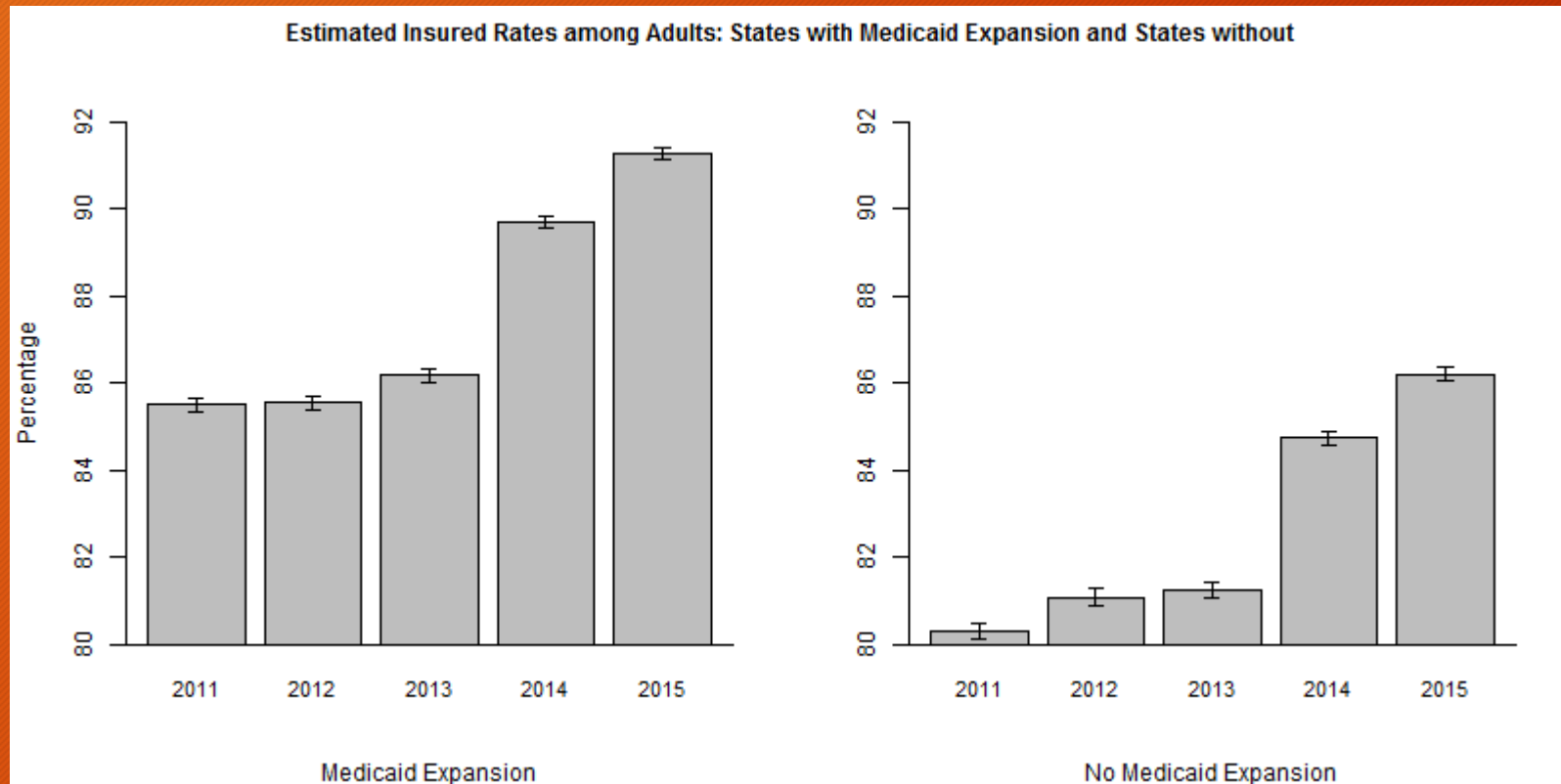


# Change in Insured Rates

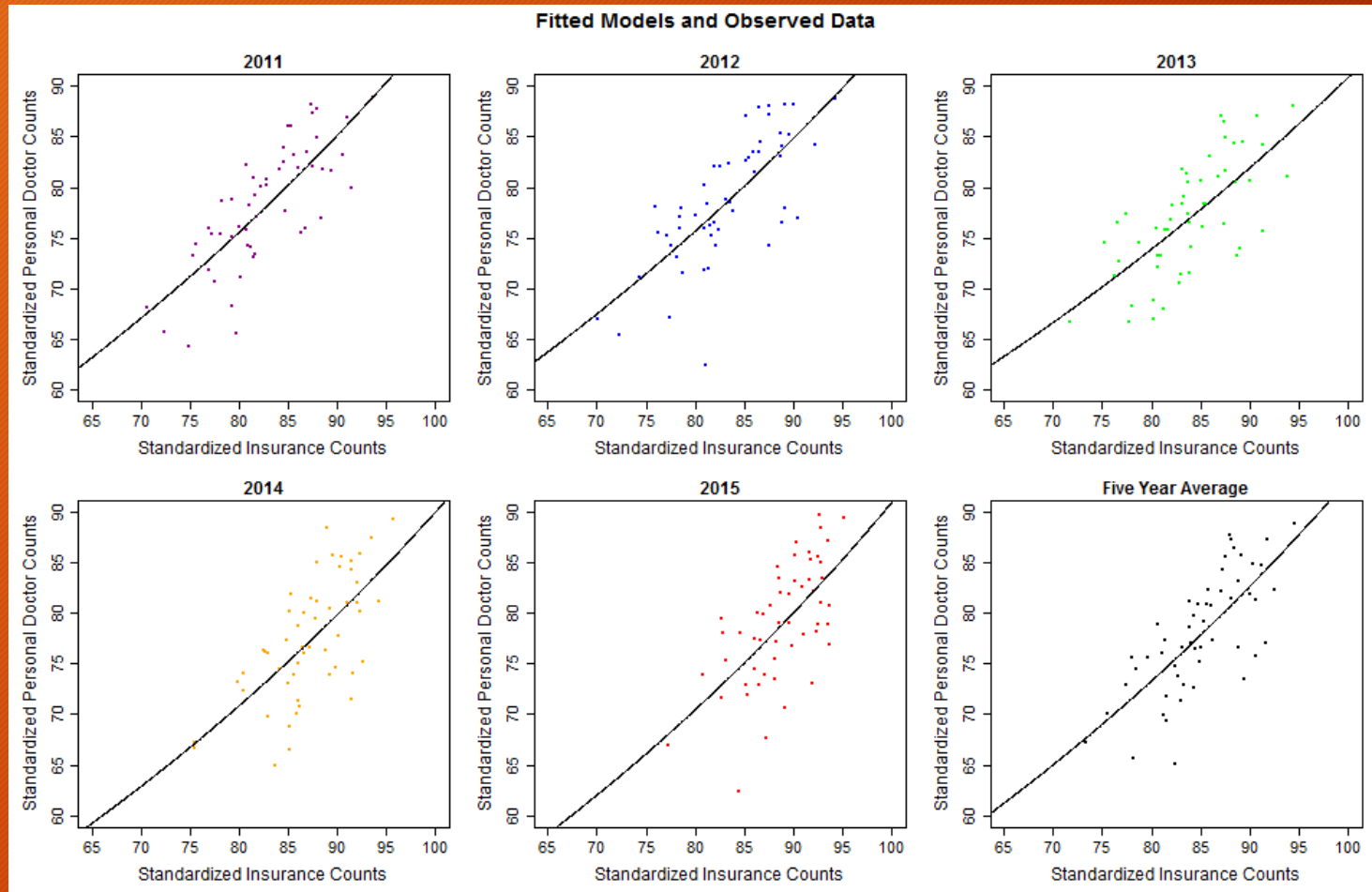
- Insured rates increase from 2011 through 2012
- Noticeable jump from 2013 to 2014
  - Period of time when most of the ACA reforms went into effect



# Medicaid Expansion Adoption

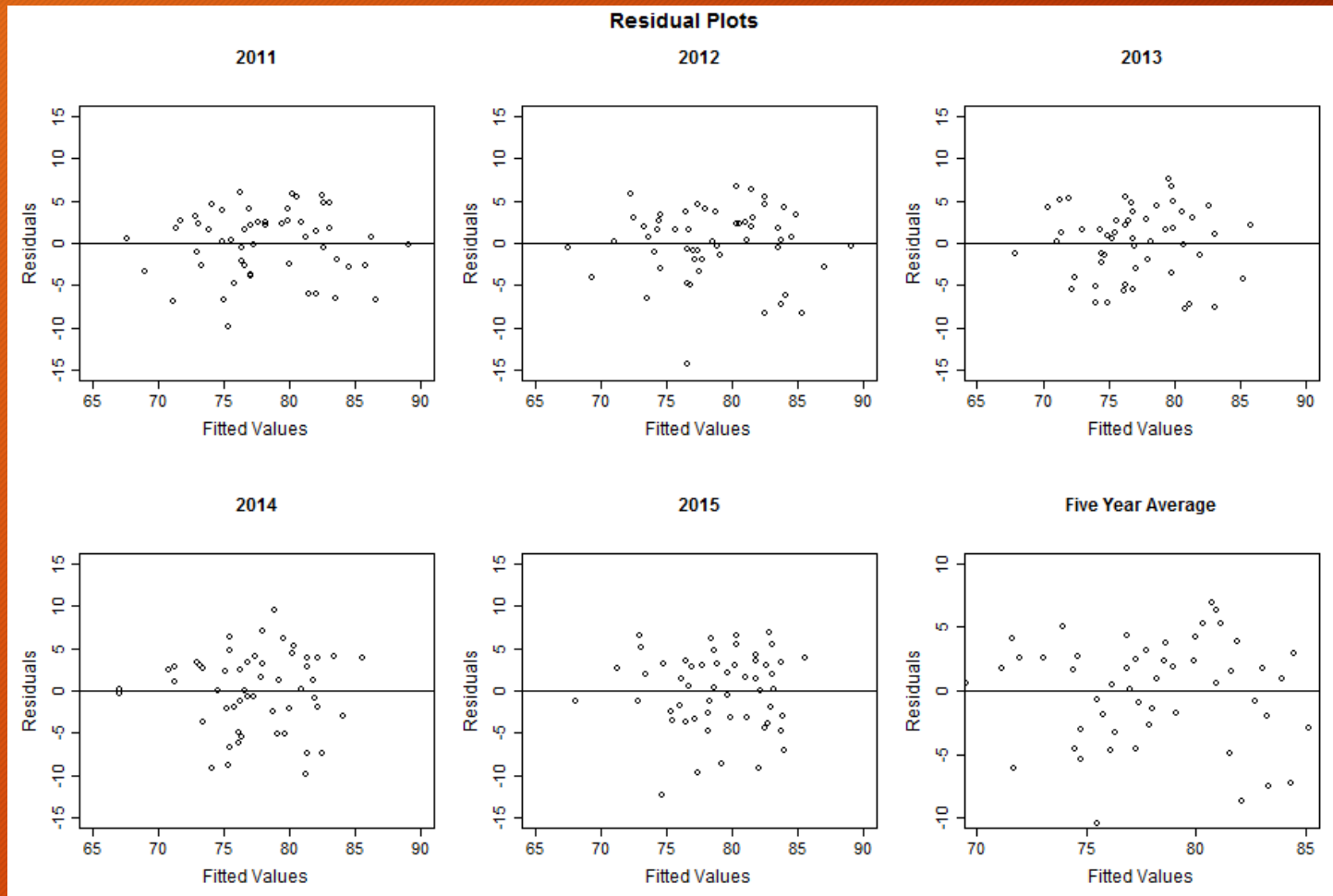


# Fitted Models





# Residual Plots





# Global Lack-of-Fit Tests

- Null Hypothesis:
  - Model fits the data
- Alternative Hypothesis:
  - Model does not fit the data (lack-of-fit)

*#Function takes fitted values and observed values as arguments*

```
Pearson.Global.Fit <- function(fitval, obsval, df = 51){  
  
  TS <- sum( (obsval - fitval)^2 / fitval )  
  p <- pchisq(TS, df, lower.tail = FALSE)  
  
  out <- data.frame(c(TS, p))  
  out <- t(out)  
  colnames(out) <- c("Test-Statistic", "P-value")  
  
  out  
}
```

$$X^2 = \sum_{i=1}^n \frac{(y_i - \widehat{\mu}_i)^2}{\widehat{\mu}_i} \sim \chi_{n-p}^2$$

$n$  = number of observations  
 $p$  = number of model parameters

*#Function takes fitted values and observed values as arguments*

```
LR.Global.Fit <- function(fitval, obsval, df = 51){  
  
  TS <- 2*sum( (obsval) * log( (obsval)/(fitval) ) )  
  p <- pchisq(TS, df, lower.tail = FALSE)  
  
  out <- data.frame(c(TS, p))  
  out <- t(out)  
  colnames(out) <- c("Test-Statistic", "P-value")  
  
  out  
}
```

$$G^2 = 2 \sum_{i=1}^n y_i \ln \frac{y_i}{\widehat{\mu}_i} \sim \chi_{n-p}^2$$

$n$  = number of observations  
 $p$  = number of model parameters

# Global Fit Tests - continued

**Table 6:** Pearson goodness-of-fit test-statistics and p-values for each model

	Test-Statistic	P-value
2011	9.911	1
2012	11.55	1
2013	11.06	1
2014	13.61	1
2015	13.37	1
Five Year Average	10.58	1

**Table 7:** Likelihood ratio goodness-of-fit test-statistics and p-values for each model

	Test-Statistic	P-value
2011	10.01	1
2012	11.78	1
2013	11.12	1
2014	13.73	1
2015	13.56	1
Five Year Average	10.7	1

# Comparative Fit Test: Deviance

- Null Hypothesis:
  - Null model fits the data just as well as fitted model
- Alternative Hypothesis:
  - Alternative model fits data better than null model

$$TS = \text{Deviance}_{\text{null}} - \text{Deviance}_{\text{fitted}} \sim \chi_1^2$$

**Table 8:** Comparative fit test-statistics and p-values for each model

	Test-Statistic	P-value
2011	14.66	0.0001289
2012	14.14	0.0001694
2013	10.14	0.001453
2014	10.81	0.001009
2015	9.551	0.001999
Five Year Average	12.1	0.0005035



# Predictive Power

- None of the confidence intervals include 0

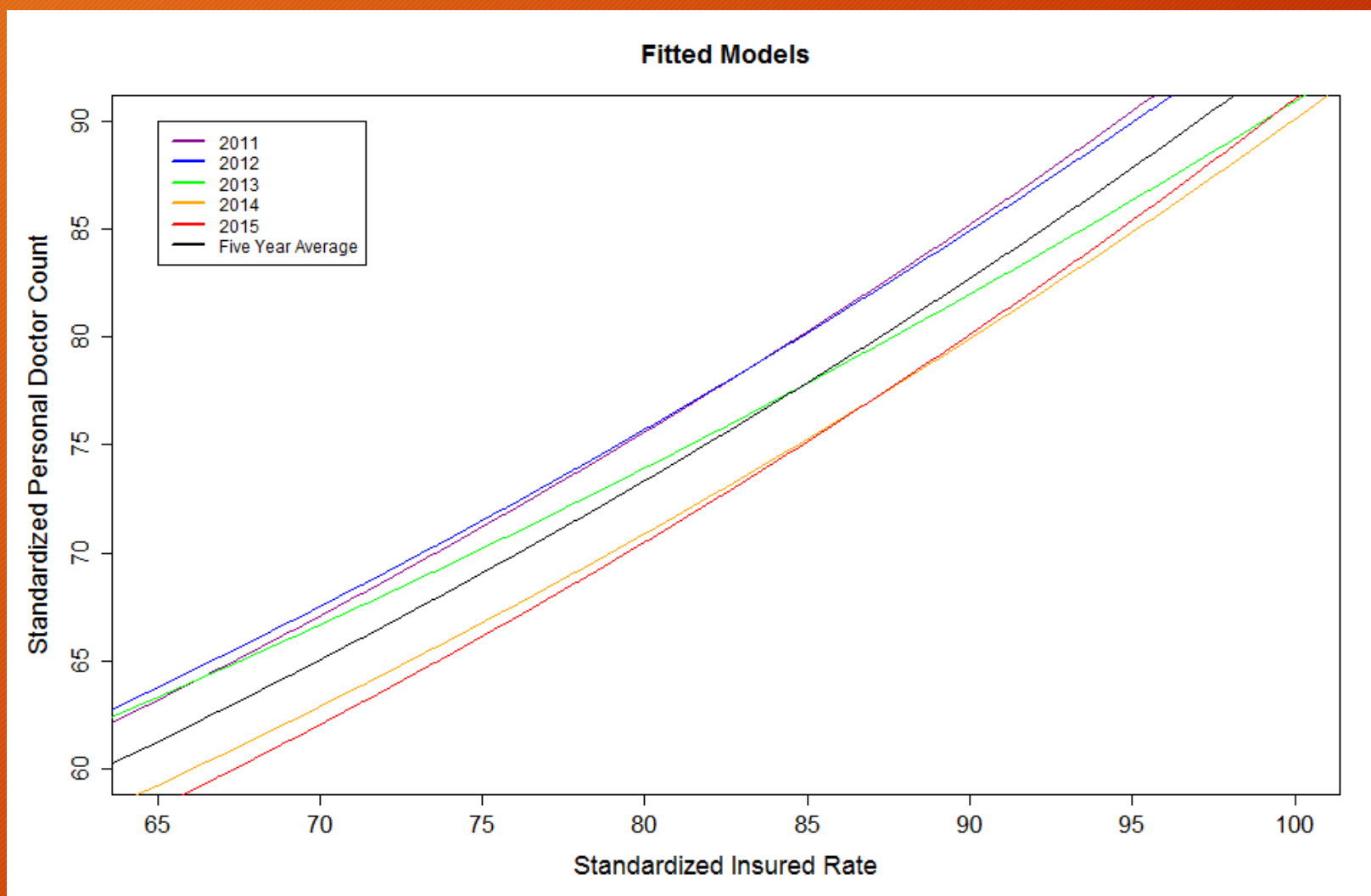
$$\hat{\gamma} = \frac{C - D}{C + D}$$

$$\widehat{SE}[\gamma] = \sqrt{\frac{n(1 - \hat{\gamma}^2)}{C + D}}$$

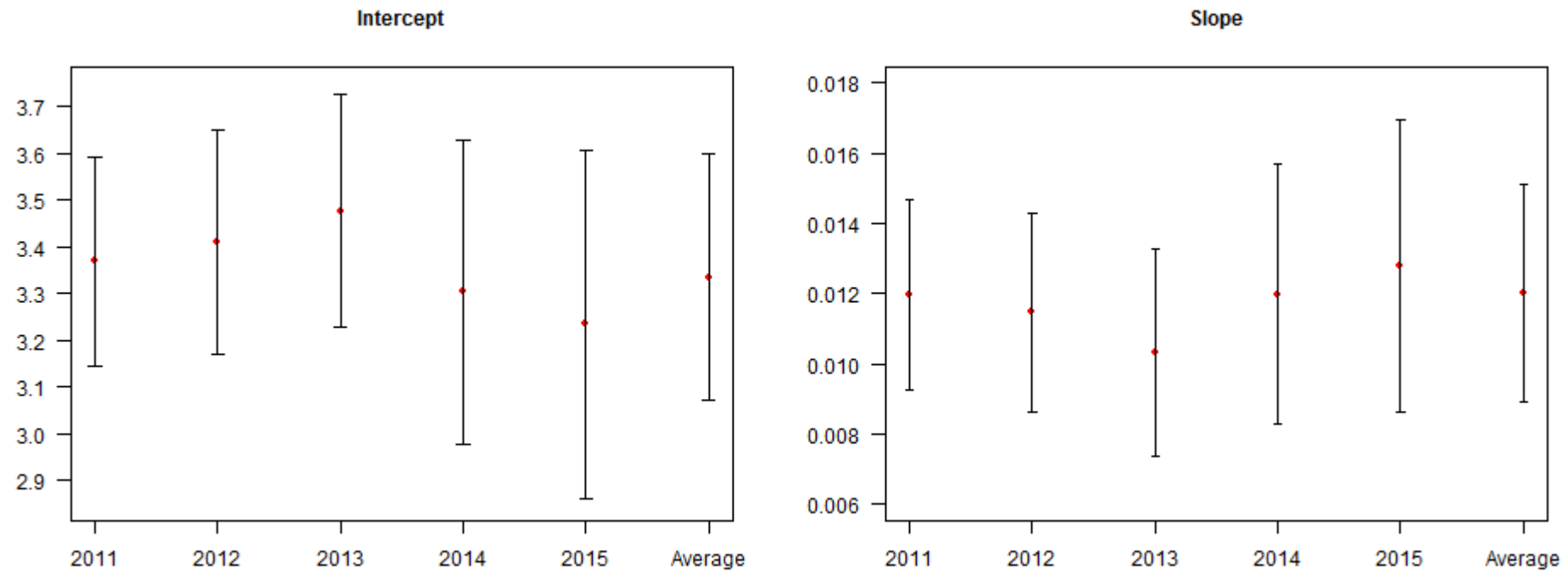
where  $n$  = total number of observations

**Table 11:** Estimated gamma values and 95% confidence intervals for each model.

	Lower Bound	Point Estimate	Upper Bound
2011	0.2455	0.5631	0.8808
2012	0.2364	0.5559	0.8754
2013	0.1787	0.5094	0.8402
2014	0.1328	0.4717	0.8106
2015	0.1415	0.479	0.8164
Five Year Average	0.22	0.5428	0.8656

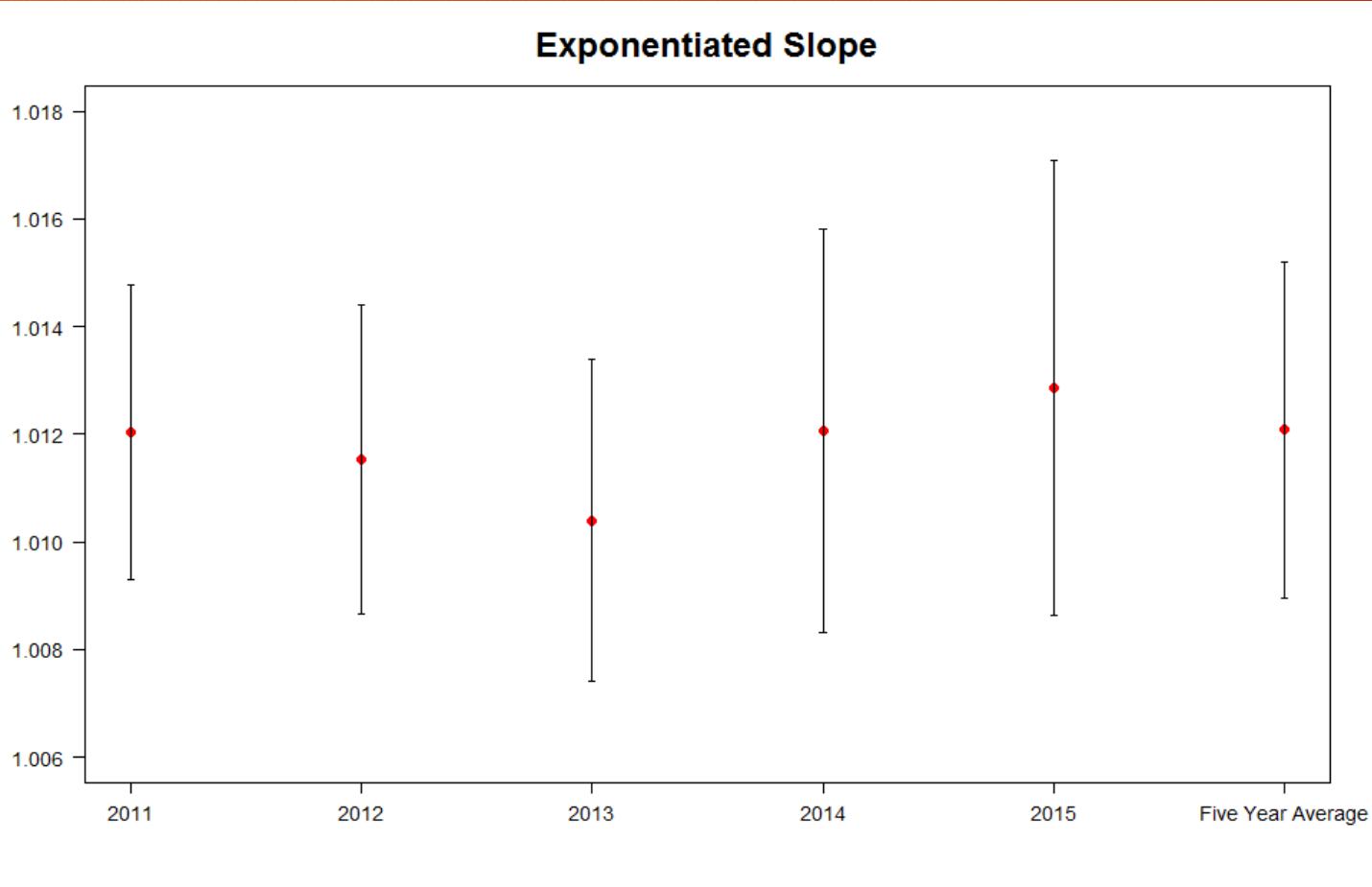


### 95% Confidence Intervals for Model Parameters





- Using the five year average model we expect that for a 1 percentage increase in the insured rate that the percentage of individuals with a personal doctor should increase by 1.012 fold.
- While this may seem like a small change, it can be quite large at the state level.



	Lower Bound	Point Estimate	Upper Bound
2011	1.009	1.012	1.015
2012	1.009	1.012	1.014
2013	1.007	1.01	1.013
2014	1.008	1.012	1.016
2015	1.009	1.013	1.017
Five Year Average	1.009	1.012	1.015

# Interpreting a Poisson Model

$$p(y) = \frac{\lambda^y e^{-\lambda}}{y!} \quad \text{Where } \lambda = V[Y] = E[Y]$$

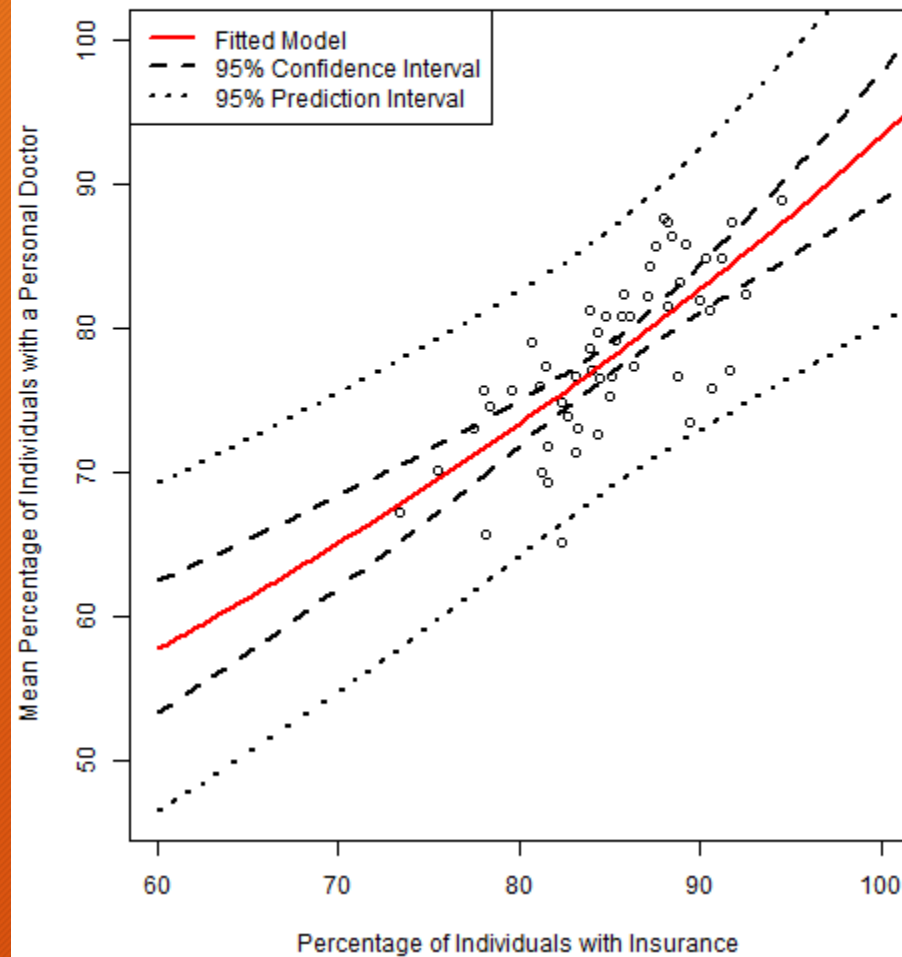
$$\ln(\lambda) = \beta_0 + \beta_1 X_1$$

$$\ln(\lambda_{x+1}) - \ln(\lambda_x) = \beta_0 + \beta_1(X+1) - \beta_0 - \beta_1 X = \beta_1 = \ln\left(\frac{\lambda_{x+1}}{\lambda_x}\right)$$

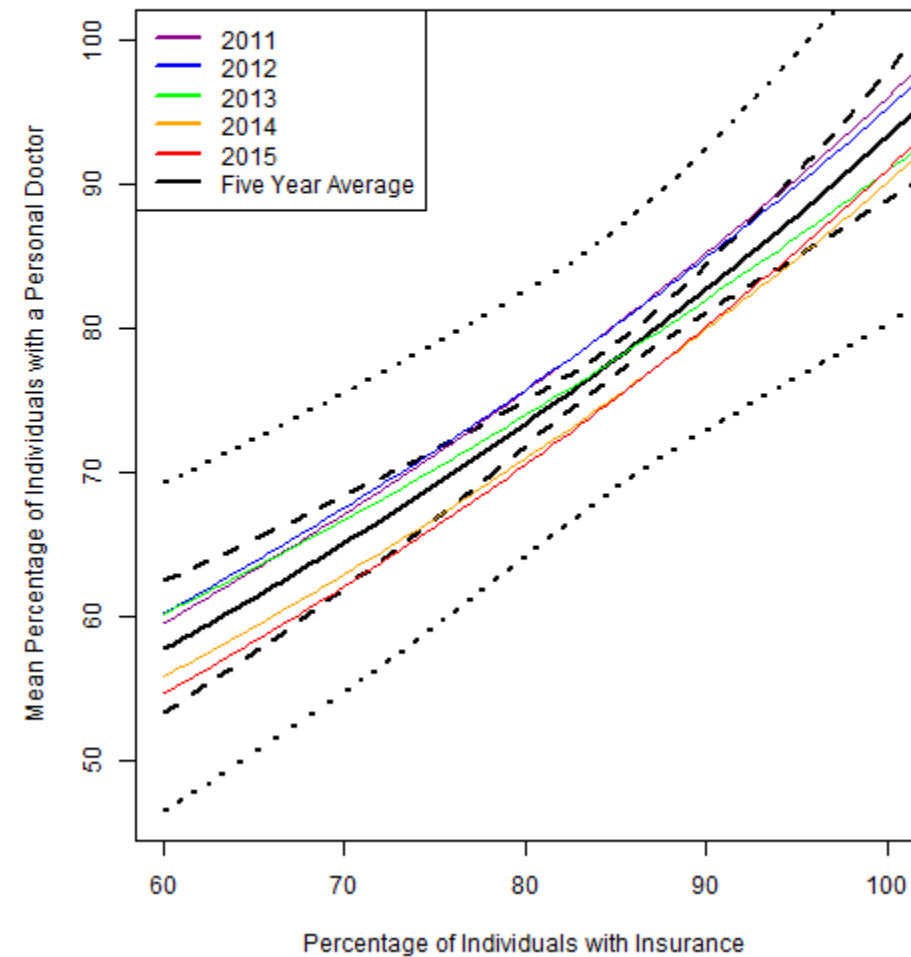
$$\frac{\lambda_{x+1}}{\lambda_x} = e^{\beta_1}$$

## 95% Confidence and Prediction Intervals for Five Year Average Model

With Observed Data



Individual Year Models Superimposed





# Conclusion

- Insured rates have significantly increased in recent years
- States that did not adopt the Medicaid expansion have significantly lower insured rates (~5%)
- Higher insured rates in states are correlated with increased proportion of individuals with a personal doctor
  - For a 1 percentage increase in insured rate we expect the percentage of adults with a personal doctor to increase by about 1.012 fold.
- Trend does not change significantly from year to year and can be expected to continue in a similar fashion
- Increase in percentage of individuals indicates an increase in primary care access
  - Improvement in health outcomes
  - Decrease in healthcare system costs