

# Loss Cost Components and Industrial Structure

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## Abstract

**Motivation.** Concomitant with the 2007-2009 recession, the U.S. economy experienced profound changes in industrial structure that led to widely varying growth rates of employment by industry. Whereas some of these changes may be temporary, others are likely to be permanent or keep progressing. Among the sectors exhibiting the most significant shifts in employment levels are manufacturing, health care, and construction. Quantifying the impact of the changes to the industrial structure on loss cost components is important for understanding trends in NCCI aggregate ratemaking.

**Method.** A statistical model is employed to measure the impact of the rates of employment growth by industry and the change in the rate of private nonfarm employment growth on the growth rates of frequency and the indemnity and medical severities. Frequency is defined as the ratio of the lost-time claim count (developed to ultimate) to on-leveled and wage-adjusted premium. Severity is defined as the ratio of (on-leveled, developed-to-ultimate, and wage-adjusted) losses to the number of lost-time claims (developed to ultimate). In a sensitivity analysis, ridge regression is applied to control for possible multicollinearity.

**Results.** The industries whose changes in the rates of employment growth are most pertinent to variations in the rate of frequency growth are health care and construction (but not manufacturing). The industrial structure is of little import to the growth rate of indemnity severity, but of consequence for the growth rate of medical severity. Further, the evidence regarding the effect on the growth rate of frequency of changes in the rate of employment growth agrees with the findings on the impact of job flows previously documented in Schmid [6].

**Availability.** The model was implemented in R (<http://cran.r-project.org/>) using the sampling platform JAGS (Just Another Gibbs Sampler, <http://www-ice.iarc.fr/~martyn/software/jags/>). JAGS was linked to R by means of the R package rjags (<http://cran.r-project.org/web/packages/rjags/index.html>).

**Keywords.** Aggregate Ratemaking, Industrial Structure, Loss Cost Components, Ridge Regression

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## 1. INTRODUCTION

Concomitant with the 2007-2009 economic recession, the U.S. economy experienced profound changes in industrial structure that led to widely varying growth rates of employment by industry. Whereas some of these changes may be temporary, others are likely to be permanent or keep progressing. Among the sectors exhibiting the most significant shifts in employment levels are manufacturing, health care, and construction. Quantifying the impact of the changes to the industrial structure on loss cost components is important for understanding trends in NCCI aggregate ratemaking.

The impact of changes in the industrial structure on loss cost components is quantified at the state level using a Bayesian statistical model. The model relates the logarithmic rates of frequency growth on the logarithmic rates of employment growth by industry and on the first difference in the logarithmic rate of total private nonfarm employment growth. This analysis is then repeated for the

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rates of indemnity and medical severity growth. In a sensitivity analysis, ridge regression is applied to these three loss cost components to control for possible multicollinearity among the covariates.

In keeping with NCCI trend selection methodology in aggregate ratemaking, frequency is defined as the ratio of the lost-time claim count (developed to ultimate) to on-leveled and wage-adjusted premium. Severity is defined as the ratio of (on-leveled, developed-to-ultimate, and wage-adjusted) losses to the number of lost-time claims (developed to ultimate). With frequency and severity defined in this way, the loss ratio equals the product of frequency and the pertinent severity. Because frequency and the severities share the claim count as an influence, albeit in opposite ways (as claim count is the numerator of frequency and the denominator of the severities), some of the economic forces bearing on frequency have the opposite effect on the severities. Although these opposing effects do not necessarily offset each other entirely, economic conditions oftentimes affect the loss ratio much less than they affect frequency and the pertinent severity.

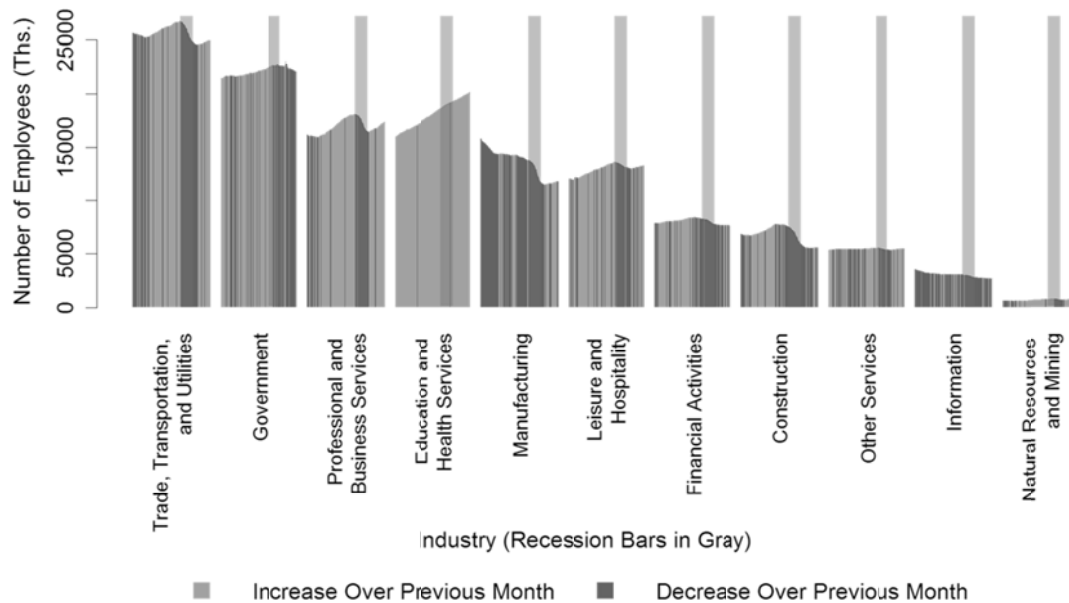
The aggregate ratemaking data employed in the analysis are on a paid basis; state funds are included where applicable. There are 37 states in the data set, 35 of which are on policy years, the remaining two are on accident years. The model makes use of employment forecasts (by industry and private nonfarm) from a professional forecasting firm in generating forecasts for the loss cost components. These forecasts for the loss cost components extend through Policy (or, where applicable, Accident) Year 2015.

The model shows that construction, among all industries, exerts the most influence on loss cost components during the studied time period. This influence is most manifest in the time window of the recession (which lasted from December 2007 to June 2009) and its immediate aftermath (Policy Year 2009 and Accident Year 2010). The four states that experienced the steepest decline in construction employment in the United States between 2007 and 2009 (based on annual numbers) are Nevada (56 percent), Arizona (51 percent), Florida (44 percent), and Idaho (40 percent), all of which are included in the data set. By comparison, the overall percentage decline in construction employment in the United States during the same time period amounted to only 28 percent.

Chart 1 presents industry histograms that display monthly numbers of nonfarm employees broken down by Bureau of Labor Statistics (BLS) sectors and supersectors. The histograms start in November 2001, which marks the trough in employment following the 2001 recession. The light gray bars indicate increases in employment relative to the respective previous month; similarly, the dark gray bars indicate decreases in employment relative to the previous month.

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**Chart 1:** Change in Industrial Structure Following the 2001 Post-Recession Low in Employment

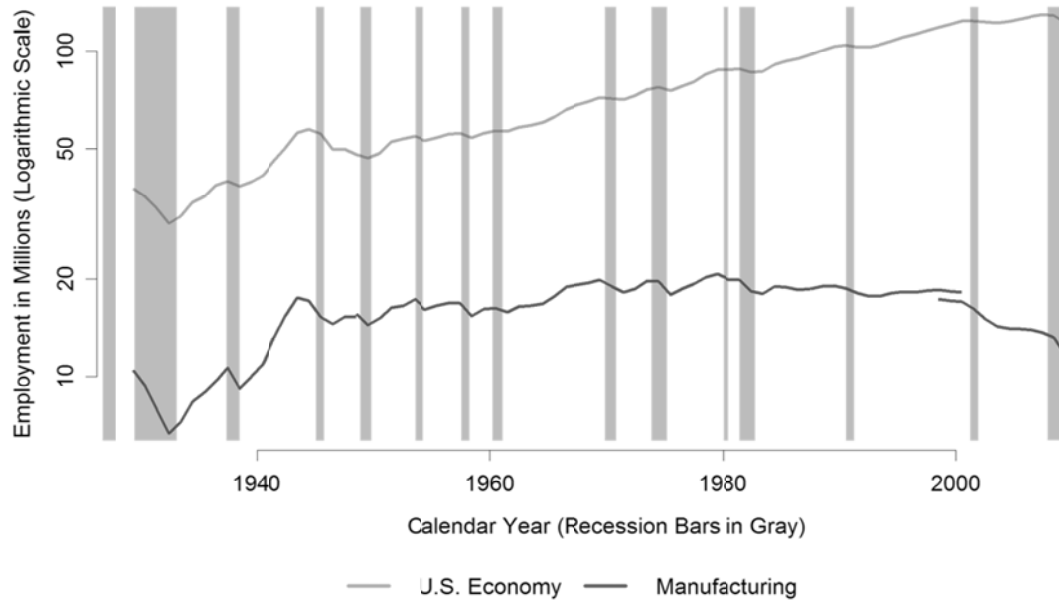


Note: Nonfarm Employment, seasonally adjusted, monthly observations, November 2001 through September 2011. Source: FRED, <https://research.stlouisfed.org/fred2>; U.S. Bureau of Labor Statistics (BLS), <http://www.bls.gov>.

Most noticeable are the comparatively steep percentage declines in employment in the manufacturing and construction sectors during and immediately following the latest recession (which is indicated by the gray rectangles). At the same time, the employment increases in the supersector Education and Health Services showed little signs of slowing during the latest recession. Note that the public school system is included in the government sector; more than 80 percent of the employees in the supersector Education and Health Services fall into the category Health Care and Social Assistance (or, health care, for short), the remainder comprising Educational Services.

Although manufacturing employment started recovering in 2010, this recovery may fail to restore the pre-recession level of employment. Such has been the experience since the double-dip recession of the early 1980s. As Chart 2 shows, over the past 30 years, manufacturing has never reached the pre-recession level during the subsequent economic recovery.

**Chart 2:** Manufacturing Employment



Note: Employment is from National Income and Product Account (NIPA) Tables 6.5 (A [1929-1948], B [1948-1987], C [1987-2000], and D [1998-2009]) and measured in numbers of full-time equivalent employees. The break in the manufacturing series indicates the switch from SIC (Standard Industrial Classification) to NAICS (North America Industry Classification System). Frequency of observation: annual; latest available data point: 2010. Source: Bureau of Economic Analysis (BEA), <http://www.bea.gov>.

## 1.1 Research Context

Understanding loss cost trends and forecasting these trends is challenging. First, the data series are comparatively short and, second, these series exhibit a high degree of volatility.

There are two types of models that have been developed for the purpose of eliciting loss cost trends. First, there are models that estimate the trend rate of growth of the loss cost component under the assumption of stationarity on time intervals between structural breaks. Among these models are the Exponential Trend model traditionally considered in NCCI aggregate ratemaking. Another class of models employs covariates in forecasting trends in lost cost components. The shortness of the time series and their high volatilities pose a particular problem for such structural models. In small samples, only the most extreme contributions of covariates are able to breach the

threshold of statistical significance; see Gelman and Weakliem [2]. This is because the shorter the sample, the higher the standard error of the estimated regression coefficient, all else being equal. Specifically, the risk associated with regression on small samples is that the correlation between the dependent variable and the covariate is a random outcome, which does not repeat itself in systematic ways in the future. As a result, the covariate may adversely affect the quality of the forecast. All else being equal, the more covariates are tested during the model building process, the higher is the probability that a covariate will be included based on random correlation.

Among models that employ covariates for the purpose of forecasting loss cost trends are the model discussed here and the model developed by Brooks [1]. The covariate in the Brooks model that has the most explanatory power is the ratio of cumulative injury claims to total indemnity claims. This raises another problem of structural models, which is the availability of forecasts for the covariates.

## **1.2 Objective**

The objective is to quantify the effect of changes in the industrial structure on the lost cost components in NCCI aggregate ratemaking. This quantification is primarily for the purpose of improving the understanding of loss cost trends during the aftermath of the 2007–2009 economic recession. It is not the objective of the model to deliver trend estimates that feed directly into the trend selection in aggregate ratemaking; this is because this model is geared toward an economic situation that is likely to be transitory. The degree of change in the industrial structure may not perpetuate itself at the current pace, which would deprive the model of its value added. Likewise, had this model been developed prior to the latest recession, it may have been dismissed due to a lack of explanatory power.

## **1.3 Outline**

What follows in Section 2 is a description of the model. Section 3 then discusses the data and presents the estimated effects. Section 4 concludes.

## **2. THE MODEL**

In three independent regressions, the logarithmic growth rates of frequency and the severities are related to the logarithmic rates of employment growth by industry and the first difference in the logarithmic rate of growth of private nonfarm employment. For every state, the conditional mean

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of the logarithmic rate of growth of the respective loss cost component is assumed to be normally distributed. All data are state-level observations.

The states are estimated simultaneously in a pooled time-series cross-section framework. All states share the same regression coefficients (of the employment growth by industry and the change in the rate of private nonfarm employment growth); this is to reduce the risk of mistaking noise for a signal in a situation where the time series are short and volatile, as discussed. The variance of the normal distribution of the conditional mean is allowed to vary by state, thus resulting in a discrete scale mixture of normal distributions as the likelihood of the Bayesian model.

In addition to the growth rates of employment by industry, the first difference in the rate of private nonfarm employment growth is the only other covariate. The inclusion of this covariate in the regression model is motivated by the study by Schmid [6] on job flows. In this study, it was shown that the rate of frequency growth is affected by changes in the rates of job creation and job destruction. Because forecasts for job creation and destruction are not available, only the net job flows effect (that is, net job creation as it manifests itself in employment growth) is included in the model.

In a sensitivity analysis, a ridge regression version of the model was estimated. Ridge regression was developed by Hoerl and Kennard [3][4] for the purpose of reducing the mean square error of estimated regression coefficients in the presence of nonorthogonality. Specifically, ridge regression is an approach to mitigate the adverse effects of multicollinearity, which arises from correlations among the set of covariates. Such multicollinearity may cause the estimated regression coefficients to be excessively large in magnitude or have the wrong sign.

The use of ridge regression is motivated by the possibility that the industry growth rates are highly correlated with each other, as they are subject to common shocks (associated with economic recessions and expansions). On the other hand, if the differences between the ridge estimates and the conventional estimates are small, this indicates that these correlations are mild and the estimated regression coefficients can be relied upon.

All covariates were centered, which implies that the intercept of the regression equation delivers the growth rate of the respective loss cost component in the steady state.

For the purpose of the ridge regression, all covariates were standardized, which means that they were not only centered but also normalized by their sample standard deviations. Following the

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estimation, the regression coefficients were transformed back to non-standardized (yet centered) coefficients for the purpose of making them comparable to the conventional estimates.

Ridge regression is straightforward to implement in Bayesian regression models, as documented in The BUGS Project [7]. After standardizing the covariates, the prior distributions for the covariates are assigned a common precision (which is the reciprocal value of the variance). In the model, a common precision is shared by the parameters measuring the impact of the employment growth by industry (but not by the parameter that quantifies the effect of the change in the rate of private nonfarm employment growth).

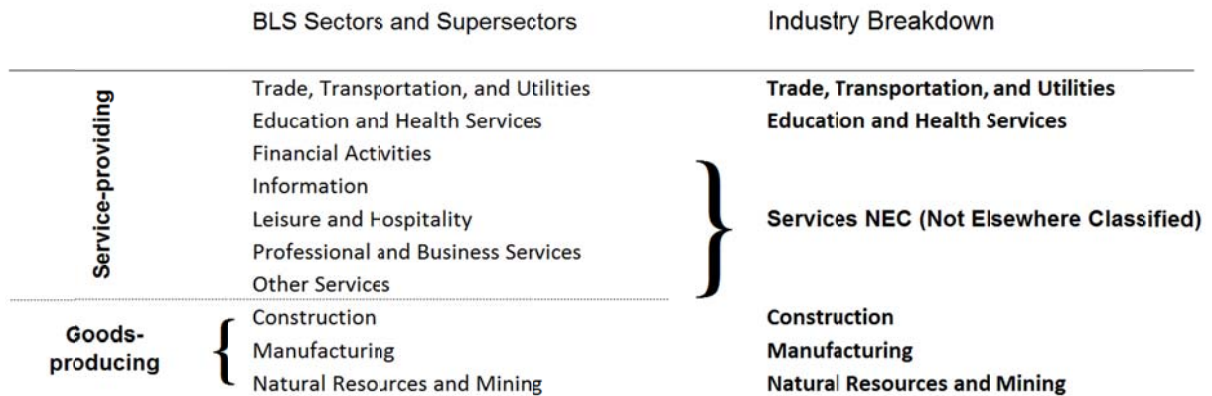
In order to align the time window of the covariates with policy years, the rate of employment growth by industry was measured Q2 (second quarter of the calendar year) over Q2. For instance, the rate of frequency growth in construction employment for Policy Year 2008 is calculated by comparing the employment level in Q2/2009 to the one in Q2/2008. For accident year data, the corresponding growth rate was measured Q4 over Q4. The same principle applies to the difference in the rate of growth of private nonfarm employment.

For the purpose of statistical modeling, the industries displayed in Chart 1 were aggregated. The resulting broader industry categorization reduces the number of covariates and thus the risk of fitting to noise. Further, the government sector was dropped because this sector is not pertinent to the analysis.

Chart 3 displays the industry aggregation. The services sectors were grouped into a single industry, except for Trade, Transportation, and Utilities and Education and Health Services. Trade, Transportation, and Utilities is a large sector and, unlike some other services sectors, its level of employment is highly susceptible to variations in economic activity. For this reason, the Trade, Transportation, and Utilities sector is treated as a stand-alone industry. Education and Health Services shows a trajectory of employment growth different from any other services industry (as shown in Chart 1) and hence deserves special attention. The three goods-producing sectors Construction, Manufacturing, and Natural Resources and Mining were also left disaggregated.

The model was implemented in R (<http://cran.r-project.org/>) using the sampling platform JAGS (Just Another Gibbs Sampler, <http://www-ice.iarc.fr/~martyn/software/jags/>). JAGS was linked to R by means of the R package rjags (<http://cran.r-project.org/web/packages/rjags/index.html>).

**Chart 3: Industry Aggregation**



### 3. FINDINGS

The data (expressed as growth rates) are from the 2010 NCCI ratemaking season and run from 1991 through 2008 for policy years, and from 1992 through 2009 for accident years. Employment data are on a quarterly basis and provided by a professional data provider and forecaster. Note that forecasts are subject to revision; the forecasts used in this study are as of July 6, 2011. From these quarterly observations, 12-month growth rates are calculated, as discussed. Historical employment observations run through Q1/2011; employment forecasts start in Q2/2011.

The measured quantitative effects for the influence of the industrial structure on loss cost components are presented in Table 1 (frequency growth), Table 2 (indemnity severity growth), and Table 3 (medical severity growth). The displayed regression coefficients have a straightforward interpretation. For instance, in Table 1, the regression coefficients measure the change of frequency growth in percentage points in response to a one-percentage point change in employment growth in the industry in question. As an example, let us start out in a situation where frequency declines at an annual rate of four percent and construction employment grows at an annual rate of one percent. Then, the construction sector shrinks, its growth rate dropping by seven percentage points to a negative six percent. If nothing else changed, frequency growth would increase by approximately one percentage point (a negative 0.07 multiplied by a negative 0.154) to a negative three percent from the original negative four percent.

At the same time, the decrease in the growth rate of construction employment, if not offset by changes in employment growth in other industries, changes the rate of private nonfarm employment



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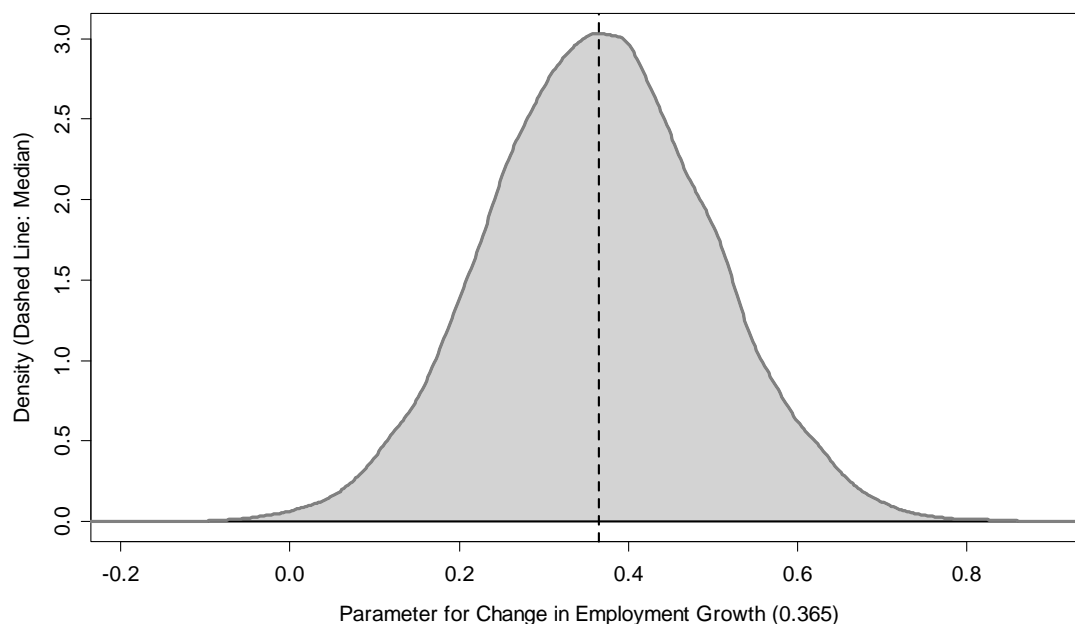
growth in the state. This implication points to the second effect, which is related to job flows. For the frequency growth regression, the posterior distribution of the coefficient that reflects the influence of changes to the rate of employment growth is displayed in Chart 4.

**Table 1:** Effect on Frequency Growth in Percentage Points in Response to a One-Percentage Point Change in Industry Employment Growth Change

	Discrete Scale Mixture of Normal Distributions		
	Standard Approach	Ridge Regression	Probability that Variable Has Explanatory Power (Percent)
	Estimated Coefficient	Estimated Coefficient	
Trade, Transportation, and Utilities	-0.132	-0.129	13.17
Education and Health Services	-0.430	-0.422	87.47
Services NEC	0.149	0.135	23.68
Construction	-0.154	-0.148	87.61
Manufacturing	0.125	0.125	23.69
Natural Resources and Mining	0.002	0.001	8.53

Note that the public school system is part of Government, not Education and Health Services. The bulk of jobs in Education and Health Services fall into the category Health Care and Social Assistance.

**Chart 4:** Effect of Change in Net Job Creation on Frequency Growth



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Chart 4 shows that a drop in the rate of private nonfarm employment growth, as typically associated with a slowdown in economic growth, causes the rate of frequency growth to decline. Specifically, economic recessions tend to accelerate the decline in frequency, whereas recoveries from recessions tend to slow down this decline or reverse it temporarily.

**Table 2:** Effect on Indemnity Severity Growth in Percentage Points in Response to a One-Percentage Point Change in Industry Employment Growth Change

Discrete Scale Mixture of Normal Distributions			
	Standard Approach	Ridge Regression	Probability That Variable Has Explanatory Power (Percent)
	Estimated Coefficient	Estimated Coefficient	
Trade, Transportation, and Utilities	0.120	0.104	4.73
Education and Health Services	0.035	0.027	1.91
Services NEC	-0.248	-0.229	4.48
Construction	0.058	0.054	2.43
Manufacturing	-0.022	-0.023	2.21
Natural Resources and Mining	-0.015	-0.013	2.13

Note that the public school system is part of Government, not Education and Health Services. The bulk of jobs in Education and Health Services fall into the category Health Care and Social Assistance.

**Table 3:** Effect on Medical Severity Growth in Percentage Points in Response to a One-Percentage Point Change in Industry Employment Growth Change

Discrete Scale Mixture of Normal Distributions			
	Standard Approach	Ridge Regression	Probability That Variable Has Explanatory Power (Percent)
	Estimated Coefficient	Estimated Coefficient	
Trade, Transportation, and Utilities	0.425	0.383	96.30
Education and Health Services	0.148	0.143	25.89
Services NEC	-0.508	-0.455	93.22
Construction	0.151	0.142	96.27
Manufacturing	-0.198	-0.191	91.07
Natural Resources and Mining	-0.072	-0.070	98.20

Note that the public school system is part of Government, not Education and Health Services. The bulk of jobs in Education and Health Services fall into the category Health Care and Social Assistance.

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To continue with the numerical example, if the mentioned hypothetical contraction of the construction sector reduced the rate of private nonfarm employment by three tenths of a percentage point, then this effect of a decline in the rate of job creation would accelerate the frequency decline by approximately 0.1 percentage points (a negative 0.003 multiplied by 0.365), thus bringing the total effect on frequency growth to about 0.9 percentage points. In summary, the rate of frequency decline would slow to 3.1 percent from the original four percent.

Tables 1 through 3 display the ridge regression results alongside the conventional regression outcomes. Because ridge regression shrinks the regression coefficients toward zero, these coefficients are smaller in absolute value than those generated by the conventional regression approach. The comparatively modest differences in magnitudes between the coefficients of the two approaches validate the conventional regression estimates.

Evidence of explanatory power of the covariates was established by means of the Generalized Linear Spike-and-Slab Stochastic Search Variable Selection approach developed by Pang and Gill [5]. By means of variable selection, it is possible to provide a probability that the null hypothesis is true (and, hence, a probability that the null hypothesis is false). For instance, in Table 1, the probability that variation in construction employment growth has power in explaining variation in frequency growth equals 87.61 percent. The only other industry with a high probability of having explanatory power is health care; the probability that variations in health care employment are relevant for variations in frequency growth equals 87.47 percent. Interestingly, the probability that variations in the growth rate of manufacturing employment contribute to variations in the growth rate of frequency runs at only 23.69 percent.

The reason that a decline in the growth rate of construction employment has a positive impact on frequency growth (that is, decelerates the decline in frequency) is that construction is a low-frequency industry in the context of NCCI aggregate ratemaking. This is because, for aggregate ratemaking purposes, frequency is defined as claim count normalized by premium, as opposed to claim count normalized by wages or the number of full-time equivalent employees.

The interpretation of the regression coefficients in Table 2 (indemnity severity) and Table 3 (medical severity) is analogous to the reading of the regression coefficients in Table 1 (frequency) delivered above. It is noteworthy that all the regression coefficients switch signs when going from frequency (Table 1) to the severities (Tables 2 and 3). This confirms that the effects on frequency growth of changes in the rates of employment growth by industry are at least partially offset by effects on the severities. This offset originates primarily from the medical severity where all but one

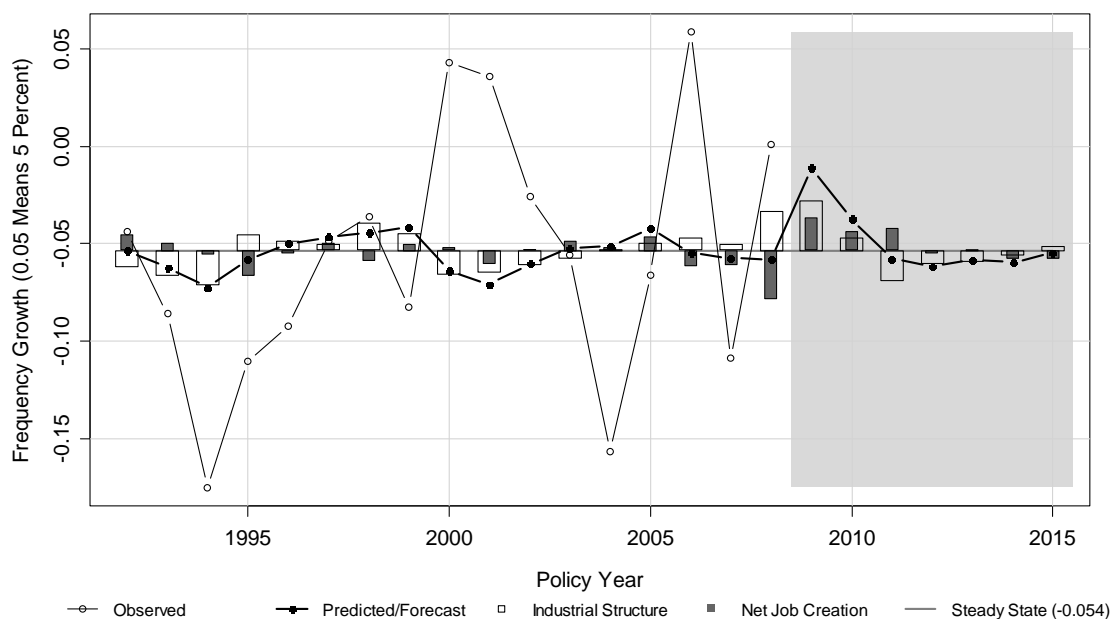
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regression coefficient exhibit high probabilities of having explanatory power. This is in stark contrast to the regression coefficients for indemnity severity, none of which musters more than a five-percent probability of being statistically relevant.

As discussed, the change in the rate of private nonfarm employment growth is the only covariate aside from the rates of employment growth by industry. The probability that changes in private nonfarm employment growth have statistical power to explain frequency growth equals 90.73 percent. This statistical evidence agrees with the role of jobs flows for the business cycle behavior of frequency discussed in Schmid [6]. The probabilities that changes in the rate of private nonfarm employment growth are relevant to the rates of indemnity growth equals 100 percent; the corresponding number for medical severity reads 32.57 percent.

Chart 5 summarizes for the first analyzed state the regression results for frequency growth. In this state, which is on policy years, the (percentage) decline in construction employment approximately equals the reading for the United States overall. The observed rates of frequency growth are plotted alongside the values predicted by the model. The gray box represents the future from the perspective of the 2010 ratemaking season. Within the gray box, the predicted values for the rate of frequency growth are forecasts. All displayed growth rates are logarithmic.

**Chart 5:** State No. 1: Job Losses in Construction Were Close to the National Average



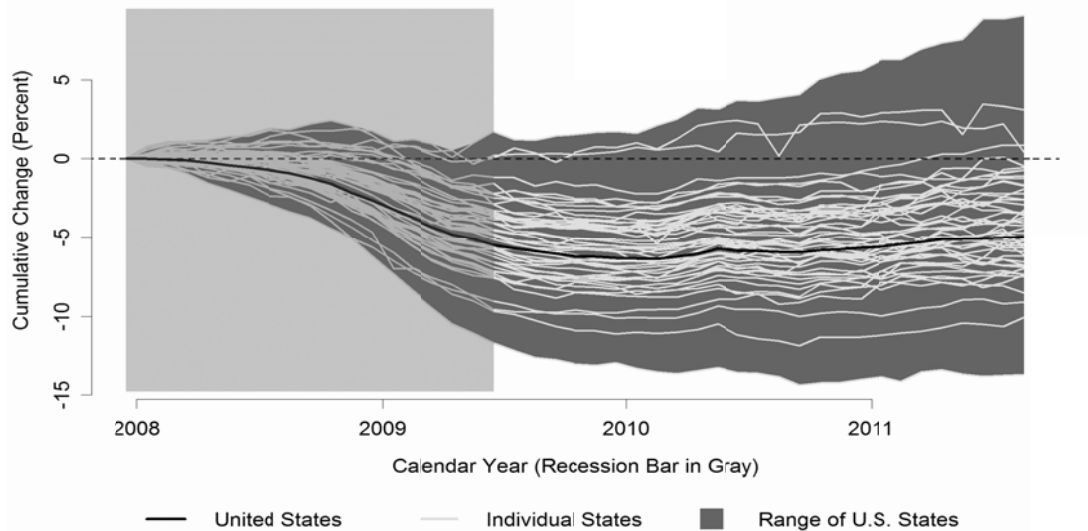
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The steady state rate of frequency growth of the state displayed in Chart 5 runs at a negative 5.4 percent and is represented by a horizontal line. By comparison, the equally weighed average of the steady state rates of frequency growth among the 37 states in the data set equals a negative 4.4 percent; the corresponding premium-weighted average comes to a negative 4.3 percent. (Premiums are as of Policy Year 2008 or Accident Year 2009, as applicable.)

In Chart 5, the transparent box represents the influence of changes in the industrial structure, as measured by variations in the rates of employment growth by industry; the solid gray box stands for the effect of variations in the change of the rate of private sector employment growth. Both boxes measure the influence relative to the steady state.

There is little action in the estimated effects prior to Policy Year 2008. Although the recession started in December 2007, most states did not experience meaningful declines in employment before mid-2008. The delayed response of employment to the recession is evident from Chart 6, which displays the cumulative employment growth since the onset of the recession for every U.S. state, the District of Columbia, and the United States. In this chart, the recession is represented by a gray box.

**Chart 6:** Cumulative Change in Nonfarm Employment Since Onset of Recession

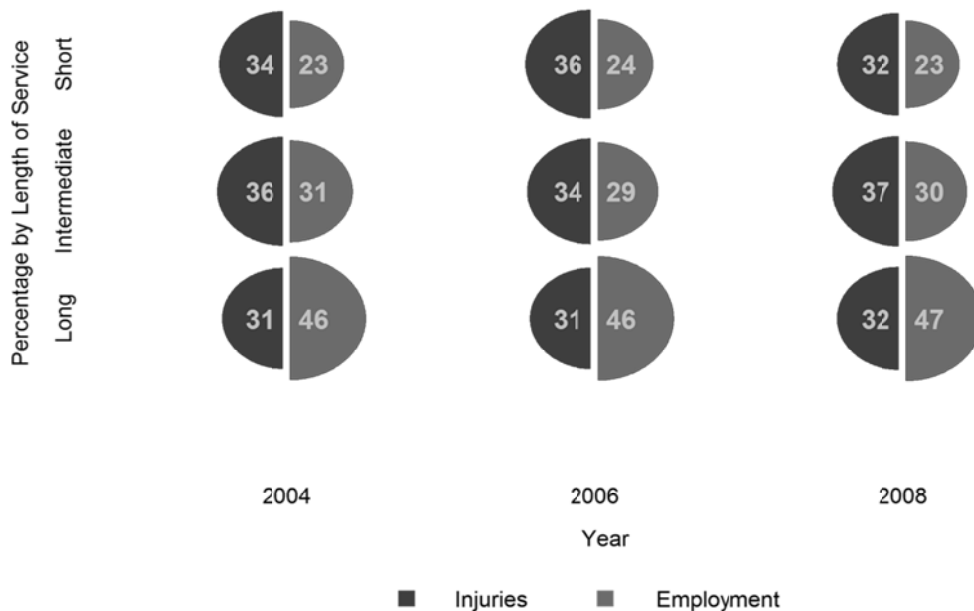


Note: Nonfarm Employment, seasonally adjusted. The set of individual states and the range of U.S. states include the District of Columbia. Frequency of observation: monthly; latest available data point for US: August 2011. Tick marks indicate beginning of year. Sources: U.S. Bureau of Labor Statistics (BLS), <http://www.bls.gov>; NBER, <http://www.nber.org/cycles.html>.

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As shown in Chart 5, in Policy Year 2009, the change in industrial structure contributed to an increase in frequency, which was more than offset by the influence originating from the slowdown in net job creation. As hiring moderates, the share of short-tenured workers on the payroll declines, which contributes to an acceleration of the frequency decline. This reasoning is supported by Chart 7, which states that about a quarter of workers are responsible for about one-third of all workplace injuries—these are the workers that have been with the current employer for one year or less.

**Chart 7: Workplace Injury Proportions by Job Tenure**



Note: Workplace injuries represent nonfatal injuries and illnesses involving days away from work. Short job tenure means 11 months or less (workplace injuries) or 12 months or less (employment). Intermediate length of service means one to five years and 13 months to four years, respectively. Long length of service means more than five years or five years or more, respectively. Percentages for workplace injuries do not account for a small “residual category.” Job tenure information for employment is available bi-annually (for January only). Percentages may not add to 100 due to rounding. Source: U.S. Bureau of Labor Statistics (BLS), <http://www.bls.gov>.

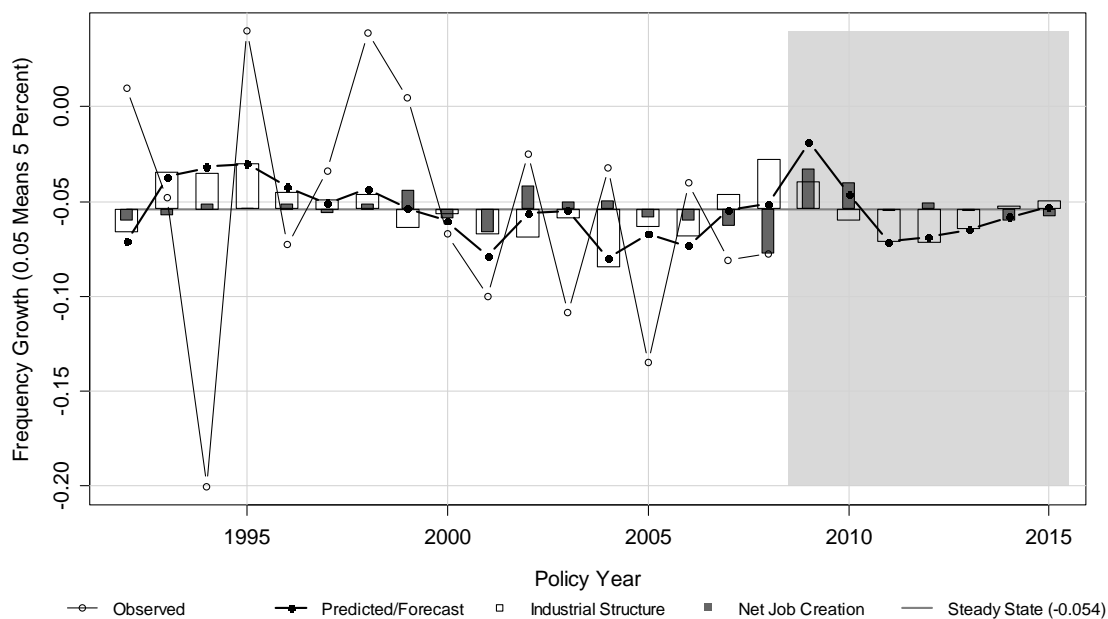
Chart 5 shows two effects on the rate of frequency growth that holds for nearly all of the 37 analyzed states. First, in Policy Year 2008 (or Accident Year 2009, where applicable), the industrial structure effect and the net job creation effect opposed each other; while the industrial structure

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effect contributed to an increase in the rate of frequency growth, the net job creation effect subtracted from it. Second, in Policy Year 2009 (or Accident Year 2010, where applicable), the two effects pointed in the same direction by contributing to an increase in frequency growth. The reason for the net job creation effect changing direction is that employment growth turned positive in many states in late 2009 and early 2010, as depicted in Chart 6.

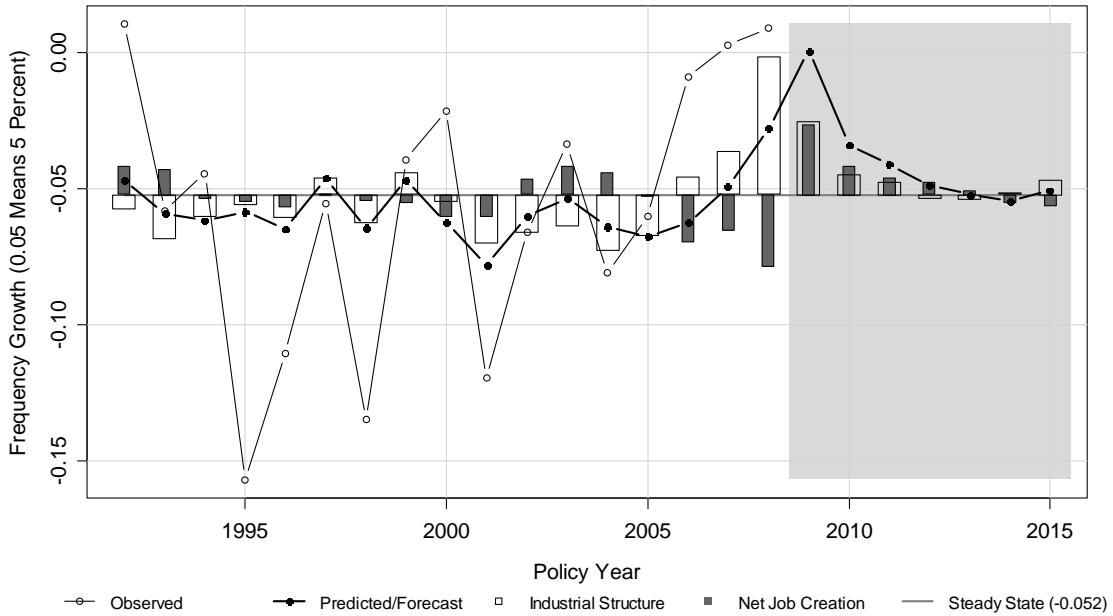
For further five states, the regression results for frequency growth are summarized in Charts 8 through 12. Similar to the state exhibited in Chart 5, the state displayed in Chart 8 experienced a (percentage) decline in construction employment that was about equal to the decline in the United States overall. Things are different in Charts 9 through 12, which represent states with sharply contracting construction sectors; note that states that experienced steep declines in construction employment were also subject to above-average (percentage) losses in private nonfarm employment. As is evident from Charts 9 through 12, both the industrial structure effect and the net job creation effect are more pronounced (when measured in changes of percentage points) than in the states shown in Charts 5 and 8. Taking the two effects together, frequency growth in Policy Year 2009 (Accident Year 2010) is forecast to be several percentage points higher (but not necessarily positive) for states with worse-than-average slumps in the housing market.

**Chart 8:** State No. 2: Job Losses in Construction Were Close to the National Average

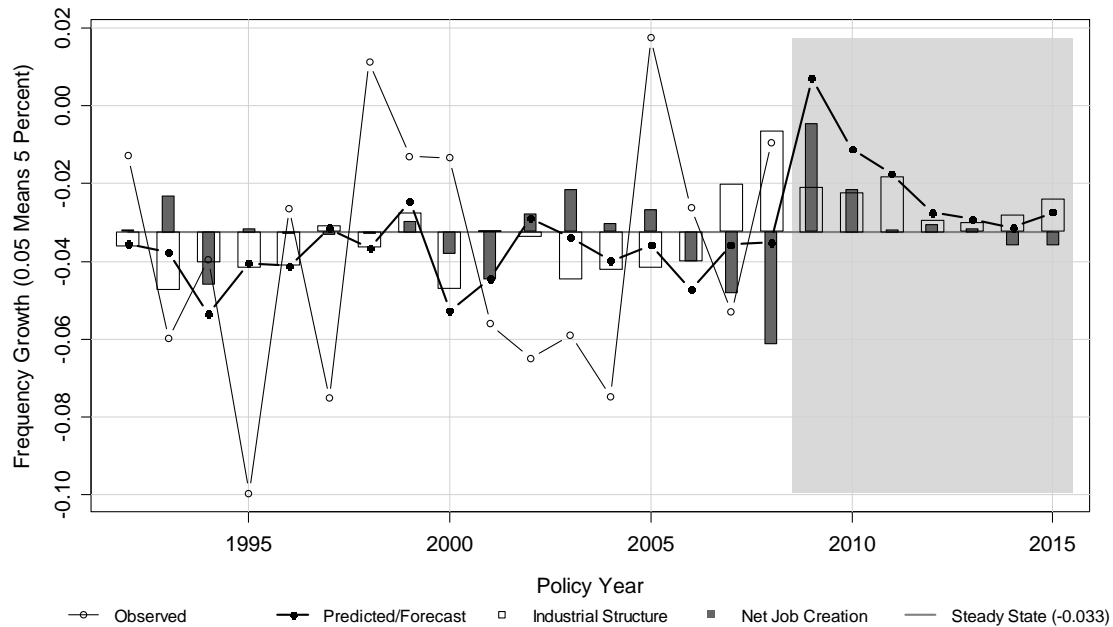


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**Chart 9: State No. 3: Job Losses in Construction Exceed the National Average**



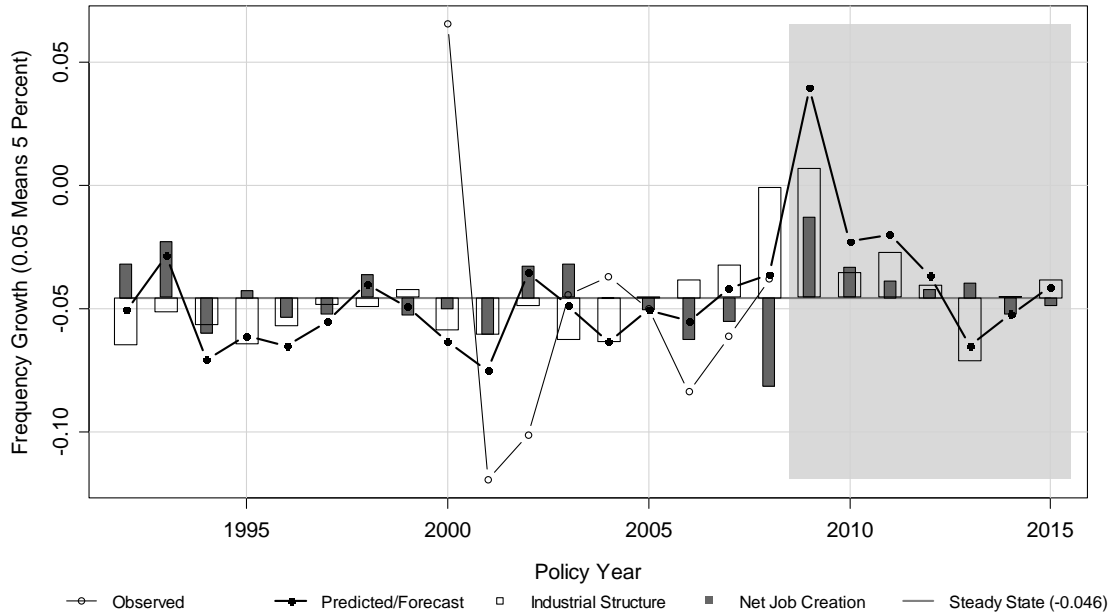
**Chart 10: State No. 4: Job Losses in Construction Exceed the National Average**



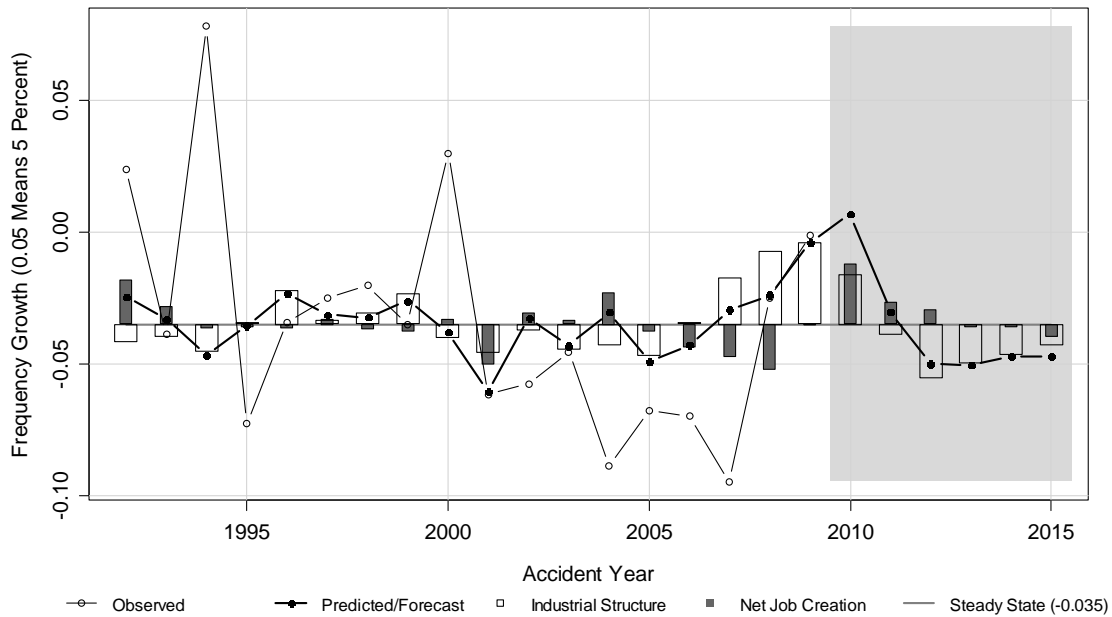


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**Chart 11:** State No. 5: Job Losses in Construction Exceed the National Average



**Chart 12:** State No. 6: Job Losses in Construction Exceed the National Average



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Chart 5 and Charts 8 through 12 show that the economic effects that emanate from the changes in the industrial structure effect and the net job creation are expected to taper off quickly after Policy Year 2009 (Accident Year 2010). Based on the forecasts for employment growth used in the model, the effects will have largely dissipated by Policy (Accident) Year 2015.

## **4. CONCLUSIONS**

The change in industrial structure concomitant with the 2007-2009 recession and its aftermath affects ratemaking loss cost components in important ways. This effect is largely due to the pre-recession expansion and subsequent contraction of the construction sector. Thus, the effect is most pronounced in states that experienced a steep downturn in the housing market.

There are offsetting effects on the part of the severities. Medical severity appears to be more responsive to changes in industrial structure than indemnity severity, although this finding should not be considered conclusive.

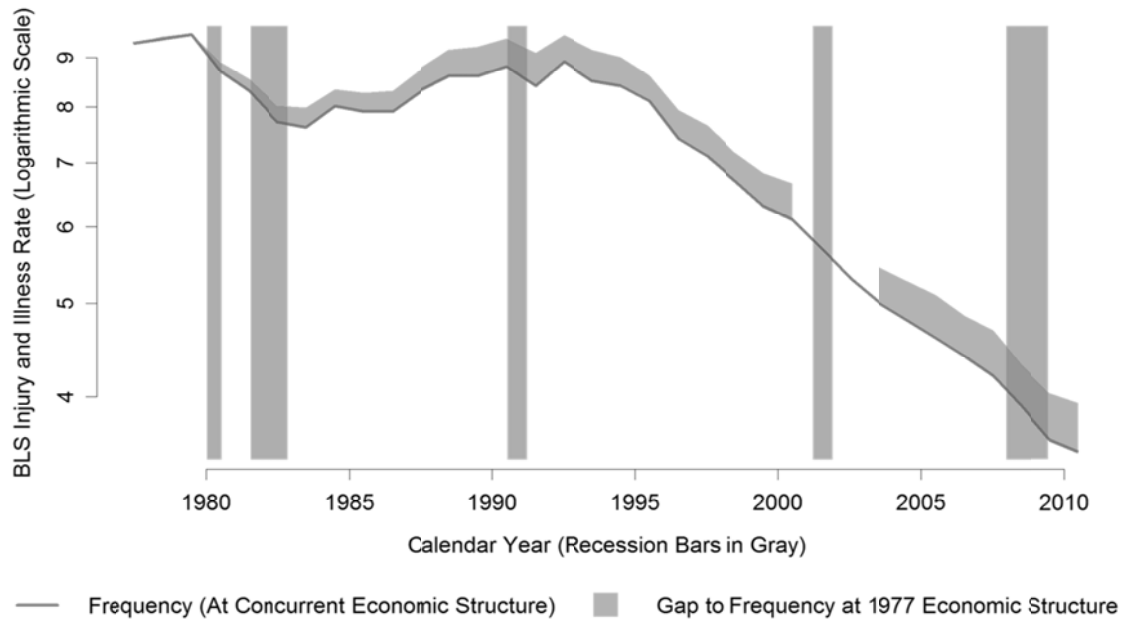
The model has not been validated using a holdout period. This is because, within the history of available aggregate ratemaking data, there have been no changes in the industrial structure of the economy comparable in magnitude.

The effect is likely to be transitory. In the model, the rates of frequency and severity growth revert to their steady states as the economy returns to its trend rate of growth. It is important to note that this return to the steady state is a model assumption, not a model outcome.

In fact, an important question raised by this analysis is how the recent changes in industrial structure may have altered the steady state of frequency growth. Although this question is beyond the scope of the analysis presented here, there is evidence that the role of the industrial structure in determining the rate of frequency decline in the steady state is rather small.

Chart 13 shows the BLS injury and illness rate for all private industry on an annual basis since 1977, the first year for which this data series is available. The edge of the gray shading reports the injury and illness rate that we would have observed had the industrial structure not changed in 1977. The chart shows that the bulk of the frequency decline happened within the industries, and only 7.5 percent of the frequency decline that was observed between 1977 and 2010 is due to the change in industrial structure. This finding motivated the assumption of an unaltered steady state in the presented statistical model.

**Chart 13:** BLS Injury and Illness Rate and Change in Industrial Structure



Note: Injury and Illnesses Cases per 100 Full-Time-Equivalent Workers, Total Recordable Cases, All Private Industry. Frequency of observation: annual; latest available data point: 2010. No data points are available for 2001 and 2002 due to changes in industry classification. Tick marks indicate beginning of year. The data points are mid-year. Sources: Bureau of Economic Analysis (BEA), <http://www.bea.gov>; U.S. Bureau of Labor Statistics (BLS), <http://www.bls.gov/iif>.

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### **Abbreviations and notations**

BEA, Bureau of Economic Analysis  
BLS, Bureau of Labor Statistics  
BTS, Bayesian Trend Selection  
BUGS, Bayesian Inference Using Gibbs Sampling  
FRED, Federal Reserve Economic Data  
JAGS, Just Another Gibbs Sampler  
MCMC, Markov-Chain Monte Carlo Simulation  
NAICS, North American Industrial Classification System  
NBER, National Bureau of Economic Research  
NCCI, National Council on Compensation Insurance  
NIPA, National Income and Product Accounts  
SIC, Standard Industrial Classification

### **Biography of the Author**

**Frank Schmid**, Dr. habil., was, at the time of writing, a Director and Senior Economist at the National Council on Compensation Insurance, Inc.