Index Hedge Performance: Bootstrap Study of Hurricane Fran

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Abstract

Index-based catastrophe derivatives are an important development in insurance risk securitization because they provide a means of standardizing risk. This is critically important in generating the liquidity investors want and the capacity hedgers need. However, insurers are concerned that their unique loss experience may not correlate highly enough with existing catastrophe indices and that unexpected variation in hedge performance, i.e. basis risk, may be so large as to render these instruments ineffective as risk management tools.

This study examines index-based hedge performance using the Guy Carpenter Catastrophe Index (GCCI). Based on 16 companies' actual exposure and loss data for Hurricane Fran in North Carolina, the performances of ZIP-based and statewide hedges are quantitatively compared by generating a series of hedge statistics using a bootstrap approach. It is found that a ZIP-based hedge is significantly more efficient than a comparable statewide hedge.

1. INTRODUCTION

Index-based catastrophe derivatives are of primary importance to the development of insurance risk securitization because they provide the standardization necessary to generate liquidity, expedite negotiations, reduce transaction costs, and provide price transparency. These advantages are critically important to both investors and hedgers. However, since index-based contracts are based on many insurers' loss experience, hedgers are naturally concerned that their unique loss experience may not track a catastrophe index in the precise way they expect.

Unexpected variation in the hedge performance of index-based derivatives (basis risk) is directly related to the degree of correlation between an insurer's loss experience and the catastrophe index embedded in the hedge security. If the correlation is high, the hedger can rely on the derivative to produce recoveries as planned. As correlation diminishes, the hedge becomes more speculative and loses its effectiveness as a risk management tool. Despite their many advantages, index-based catastrophe derivatives are unlikely to gain widespread acceptance until hedgers can confidently measure and minimize potential basis risk.

Since index-based catastrophe derivatives were introduced by the Chicago Board of Trade in 1992, index-based hedge performance has drawn the attention of a number of researchers. D'Arcy & France [1992] and Hoyt & Williams [1995] measured correlation between homeowner insurers' underwriting profit margins and natural catastrophe losses for the largest nine insurers. Harrington, Mann & Niehaus [1995] examined basis risk associated with both national catastrophe contracts and national contracts based on individual lines of insurance. Major [1996] studied index-based hedges at ZIP code and state levels. Weber & Belonsky [1996] examined the correlation between regional index values and insurer loss experience for national insurance companies and smaller, regional insurers. Harrington, Mann & Niehaus [1997] examined the effectiveness of index-based hedges using statewide loss ratios of different lines of insurance. Major [1998a, 1998b] addressed the issue of basis risk management and provided a brief but informative review on the research and development in this area.

Although a significant amount of work has been performed to quantify potential basis risk, researchers have been stymied by the lack of high quality, detailed data available to them. The Guy Carpenter Catastrophe Index (GCCI) attempts to remove this difficulty by reporting detailed information about insured exposures and losses for most residential ZIP codes in the United

States. Given that the GCCI quantifies loss experience at a ZIP code level, homeowner insurers can use it to customize a hedge to their precise geographic exposure patterns.

Since insurance companies' exposures are not evenly distributed within a state, one would expect that homeowner insurers could experience less basis risk with a ZIP code level hedge than a statewide hedge. But how significant is this difference?

This question was first addressed by Major [1996], who quantitatively compared the performance of ZIP-based and statewide hedges. Using a model of insurer market penetration and a model of process risk, Major simulated the performance of ZIP-based and statewide hedges and reported a series of conditional and unconditional hedge statistics. Based on this work, he determined that a ZIP-based hedge would be much more effective than a statewide hedge. Major's work was hailed by both the insurance and investment communities but left some uncertainty about the significance of these findings due to the complexity of his underlying models.

This paper examines these same issues but without the use of any supporting models. Instead, this research relies on the actual exposure and loss data of 16 insurance companies and the GCCI for Hurricane Fran in North Carolina. This Paper documents how the bootstrap resampling approach was used to generate hedge statistics conditional on Hurricane Fran to compare the effectiveness of ZIP-based and statewide hedges.

The paper is organized as follows. Section two and section three provide the background information on the GCCI and Hurricane Fran data, respectively. Section four describes the methodology used in this study, and section five discusses the results of this investigation. Section six summarizes this work and places it in a risk management context.

2. BACKGROUND ON THE GCCI

The Guy Carpenter Catastrophe Index (GCCI) measures the average homeowner insurance company's damage rate in a given area from atmospheric events such as hurricanes, tornadoes, hail, windstorms and winter freezes. It is an unweighted average of each sample company's paid losses divided by its insured coverage A value within a given ZIP code or collection of ZIP codes.

First published in August 1997 by IndexCo, LLC[1], the GCCI is the reference basis for option contracts traded on the Bermuda Commodities Exchange[2]. Several features distinguish the GCCI from other catastrophe indices. The GCCI:

- Is reported for most residential ZIP codes in the United States as well as for states and regions;
- Expresses the industry's loss in the form of a loss-to-value ratio or damage rate, rather than as a dollar amount; and
- Is computed using millions of actual insurance and paid loss records gathered from a predefined group of mainstream insurers using a standardized and transparent methodology.

This paper compares the effectiveness of a GCCI-based state level hedge with a ZIP code level hedge, customized to each insurer's geographic distribution of insured home exposures.

3. HURRICANE FRAN DATA

Hurricane Fran made landfall east of Cape Fear, North Carolina, at about 8 P.M. September 5, 1996. Although Fran was not a large hurricane, it produced a significant amount of insured damage. Property Claims Services estimated that total insured losses from Fran were $1.6 billion dollars (Parthasarathi [1996]). IndexCo estimated that there were approximately $664 million of homeowners insured damage, $618 million of which resulted from damage in North Carolina (Thomas and Cao [1998]).

To gather data for this study, IndexCo and the Insurance Services Office, Inc.[3] collected tens of millions of homeowner premium and loss records to determine individual company loss experience and to calculate the GCCI values for Hurricane Fran. The procedures used to calculate the GCCI are described in detail in the Index Manual with one primary difference. Exposure information was gathered by taking the average amounts of insurance in-force for each company during September of 1996, rather than March 1997, in accordance with the normal GCCI calculation. While not following the GCCI methodology precisely, this information

[1] IndexCo is an affiliate of Guy Carpenter & Company, Inc.
[2] For the detailed methodology of the GCCI see IndexCo [1998].

provides a good representation of the insurance in-force during Hurricane Fran. This study used all losses relating to Fran paid through December 31, 1997, reflecting essentially full development of Fran's losses.

IndexCo also had access to individual company information that made-up over 90% of the insurance in-force used to calculate the GCCI for Fran in North Carolina. These individual companies' actual insurance and loss experience, together with the GCCI for ZIP codes in North Carolina and for the state as a whole, provide a basis for the following bootstrap analysis of index-based hedge performance.

4. METHODOLOGY

1. Hedge Statistics

Assume L is a company's loss experience to be hedged and H is the index-linked hedge instrument. In order to quantify hedge performance, certain hedge statistics need to be examined.

One of the most often used statistics is $\rho(L,H)$, the correlation coefficient between L and H characterizing the degree of linear correlation between the loss experience and hedge instrument. Hedgers usually seek high correlation between their underlying experience and the hedge instrument. Under this consideration, a hedger would like $\rho(L,H) = 1$, providing a perfect hedge.

One way of describing hedge effectiveness is in terms of how much it can reduce the volatility of the underlying experience. Under this consideration, the optimal hedge ratio α_{opt} is defined such that the variance of the loss net of recovery is minimized, i.e.

$$\alpha_{opt} = \arg\ \min \operatorname{var}(L - \alpha \cdot H).$$

In fact, the optimal hedge ratio can be calculated by

$$\alpha_{opt} = \rho(L,H) \cdot \sqrt{\frac{\operatorname{var}(L)}{\operatorname{var}(H)}}$$

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[3] The authors would like to thank Fred Lloyd and Gena Shangold of the Insurance Services Office for their

The optimal hedge ratio can be considered as the number of the contracts to be chosen to minimize the volatility.

In this study, the volatility of an index-based hedge with hedge ratio α is measured by

$$\xi(\alpha, H) = \frac{\sqrt{\mathrm{var}(L - \alpha \cdot H)}}{\mathrm{E}(L)}.$$

This definition characterizes the hedge volatility by the ratio of the standard deviation of the company's loss value net of hedge recovery to the expectation of the loss without any hedge.

In particular, when $\alpha=0$, $\xi(0,H)$ is the "unhedged volatility", the coefficient of variance of L. When $\alpha=\alpha_{opt}$, $\xi(\alpha_{opt},H)$ is the "attained volatility". Attained volatility can be used as a measurement of basis risk because it quantifies the amount of volatility that remains after a hedge has been employed.

Hedge efficiency can also be measured by the percentage of volatility reduction produced by a hedge. This measure is defined as

$$\eta(\alpha_{opt}, H) = \frac{\xi(0,H) - \xi(\alpha_{opt}, H)}{\xi(0,H)} = 1 - \sqrt{\frac{\mathrm{var}(L - \alpha_{opt} \cdot H)}{\mathrm{var}(L)}}\ .$$

This definition is equivalent to the measurement of hedging effectiveness defined by Ederington [1979], except it uses standard deviation instead of variance.

For a given company, let L be the company's total loss value caused by Hurricane Fran in North Carolina. Assume AOI_z is the company's exposure (amount of insurance in force) at ZIP code z; G_z is the GCCI value (loss to value ratio) at ZIP code z; and G_{NC} is the GCCI value for state of North Carolina. The ZIP-based hedge instrument is:

$$H_{ZIP} = \sum_{z} G_z \cdot AOI_z$$

The statewide hedge instrument is:

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assistance in gathering the loss data for this study.

$$H_{ST} = G_{NC} \cdot \sum_{Z} AOI_{Z}$$

The hedge statistics for ZIP-based or statewide hedges can be obtained by taking $H=H_{ZIP}$ or $H=H_{ST}$, respectively.

2. Bootstrap Resampling

The bootstrap resampling procedure is a statistical method of generating subsets of data on the basis of random sampling with replacements. The concept of bootstrap resampling was first introduced by Efron [1979] on the consideration of the empirical distribution generated by a random sample of size *n* from an unknown distribution *F*. The bootstrap method is generally used to obtain an empirical distribution of certain estimators or statistics without distributional assumptions or analytic formulas. In our case, the bootstrap approach was used to estimate hedge statistics that describe certain aspects of the joint distribution of individual insurer's loss experience and the GCCI-linked hedge instrument.

The bootstrap resampling procedure of estimating hedge statistics for a given insurance company is as follows.

Step 1. Data Set-up

For each ZIP code, the company's exposure, loss, and GCCI value composed a vector of observation. Since there were 346 ZIP codes in North Carolina[4], the raw data to be bootstrapped consisted of 346 such vectors of observation.

Step 2. Resampling

The bootstrapped sample was obtained by randomly sampling with replacement from the raw data with a sample size of M. In this study, M was chosen to be 346, the same as the sample size of raw data. The company's total loss (L), ZIP-based hedge recovery (H_{ZIP}), and statewide hedge recovery (H_{ST}) were calculated based on the bootstrapped sample.

Step 3. Estimating hedge statistics

Repeating Step 2 five hundred times generated bootstrap replications of the company's total loss experience before and after consideration of customized ZIP-based and statewide hedges. i.e.

[4] Some data units were collections of ZIP codes with low population density. We will refer to these collections as ZIP codes, too.

$L^{(m)}$, $H_{ZIP}{}^{(m)}$, $H_{ST}{}^{(m)}$. $m=1, \ldots, 500$. Hedge statistics conditional on Hurricane Fran were estimated based on these replications.

5. RESULT AND DISCUSSION

The bootstrap resampling procedure was conducted for each of the 16 companies to obtain the hedge statistics for both ZIP-based and statewide hedges. Table 1 lists the correlation coefficient and the optimal hedge ratio. Table 2 lists the attained volatility and the percentage of volatility reduction. Figure 1 shows the correlation coefficients between each company's loss experience and its associated ZIP-based and statewide index-linked hedge instruments. Figure 2 shows the optimal ratios for both ZIP-based and statewide hedges. Figure 3 compares the percentages of volatility reduced by the ZIP-based and statewide hedges.

Table 1: Correlation Coefficient and Optimal Hedge Ratio

	Correlation Coefficient		**Optimal Hedge Ratio**	
Company	**ZIP-based**	**Statewide**	**ZIP-based**	**Statewide**
1	0.992	0.693	0.737	1.452
2	0.979	0.377	1.300	0.942
3	0.973	0.527	1.168	0.994
4	0.972	0.481	1.105	1.235
5	0.965	0.370	0.824	0.518
6	0.965	0.193	1.019	0.298
7	0.963	0.792	1.249	2.702
8	0.955	0.476	1.027	1.434
9	0.945	0.225	0.967	0.285
10	0.923	0.413	0.692	0.565
11	0.921	0.100	1.054	0.038
12	0.902	0.417	0.829	0.742
13	0.899	0.146	0.846	0.062
14	0.883	0.438	1.138	1.223
15	0.872	0.243	1.126	0.186
16	0.623	0.524	0.703	1.029
Average	0.921	0.401	-----	-----

Table 2: Attained Volatility and Volatility Reduction

	Attained Volatility			Volatility Reduction	
Company	**No Hedge**	**ZIP-based**	**Statewide**	**ZIP-based**	**Statewide**
1	0.276	0.035	0.199	87.3%	27.9%
2	0.150	0.031	0.139	79.5%	7.4%
3	0.185	0.043	0.157	76.8%	15.0%
4	0.175	0.041	0.153	76.4%	12.4%
5	0.158	0.041	0.146	73.7%	7.1%
6	0.143	0.037	0.141	73.9%	1.9%
7	0.223	0.060	0.136	73.2%	39.0%
8	0.130	0.039	0.115	70.3%	12.1%
9	0.168	0.055	0.164	67.4%	2.6%
10	0.248	0.095	0.226	61.5%	8.9%
11	0.274	0.107	0.272	61.0%	0.5%
12	0.163	0.070	0.148	56.9%	9.1%
13	0.239	0.105	0.236	56.1%	1.1%
14	0.196	0.092	0.176	53.1%	10.1%
15	0.575	0.282	0.558	51.0%	3.0%
16	0.394	0.308	0.335	21.8%	14.8%
Average	0.231	0.090	0.206	65.0%	10.8%

The bootstrap analysis leads to the following conclusions.

- The correlation coefficient, conditional on Hurricane Fran, between individual company loss experience and ZIP-based index hedge instrument was significantly higher than that between the company loss experience and statewide index hedge instrument. Table 1 and Figure 1 show that the correlation coefficient for the ZIP-based index hedge instrument was as high as 0.992, with an average of 0.92. Company 16 in Table 1 is an outlier, having the lowest correlation coefficient of 0.62. It is worth noting that this company had less than 0.1% market share in North Carolina and less than 0.25% of the exposure and losses that made up the index. If we eliminate company 16, the average correlation coefficient would be 0.94 for the ZIP-based index hedge instrument. For the statewide index hedge instrument, the average correlation coefficient was approximately 0.40. It is expected that the unconditional correlation coefficients calculated across all possible storms will be higher for both ZIP-based and statewide index instruments. However, the difference between the unconditional correlation coefficients for ZIP-based and statewide index hedge instruments will still be significant.

- A large part of loss experience volatility could be reduced by using a ZIP-based index hedge, due to the high correlation of the customized Index with insurance company loss experience. Table 2 and Figure 3 show that on average about 65% of the volatility was reduced by using the optimal ZIP-based hedge while the optimal statewide hedge reduced only about 11% of the company loss volatility. This remarkable difference indicates that ZIP-based index hedge is much more efficient.

- As Table 1 and Figure 2 show, the optimal hedge ratio corresponding to ZIP-based hedge was close to 1.0 while the optimal ratio for statewide hedge had much higher variation. This result means the potential effectiveness of ZIP-based index hedge can be relatively easily achieved without a sophisticated hedge strategy. Considering the cost of the hedge and the fact that insurance companies often have multiple objectives, for example reducing expected losses as well as loss variation, having an optimal hedge ratio close to 1.0 is very helpful to companies.

6. SUMMARY

This study provides an empirical comparison of index-linked statewide and ZIP-based hedges. Using 16 insurance companies' exposure and loss data for Hurricane Fran in North Carolina, it is found that the ZIP-based hedge is significantly more effective than statewide hedge. Since a bootstrap approach is adopted that is purely data driven, the result is relatively robust, and suggests that insurers may find index-based catastrophe derivatives customized at ZIP code level to be highly effective hedging instruments.

From a risk management perspective, it should be clear that while catastrophe index-based securities can be used to reduce underwriting volatility they do not behave exactly like reinsurance. Using an index of loss to determine settlement values creates a certain amount of basis risk for the hedger. Providing this risk is not too great, negotiation and settlement efficiencies provided by index-linked securities may outweigh the cost of this uncertainty.

Although this study does not take into account event size, it is important to note that Fran was not a large Hurricane. Other research (Harrington, Mann and Niehaus, [1997]) suggests that insurer loss experience may correlate better with an Index as the size of the catastrophe increases. If this is true, it implies that there may be significantly less basis risk in hedging the risk of larger events.

In the future, it is likely that insurers will supplement their existing reinsurance with index-linked contracts designed to protect against peak loss experience in areas where they have considerable amounts of insured property at risk. Therefore, Index-based catastrophe derivatives may prove to be a viable risk management tool, offering competitive and transparent pricing and providing significant new insurance capacity.

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Figure 1: Correlation Coefficients conditional On Hurricane Fran

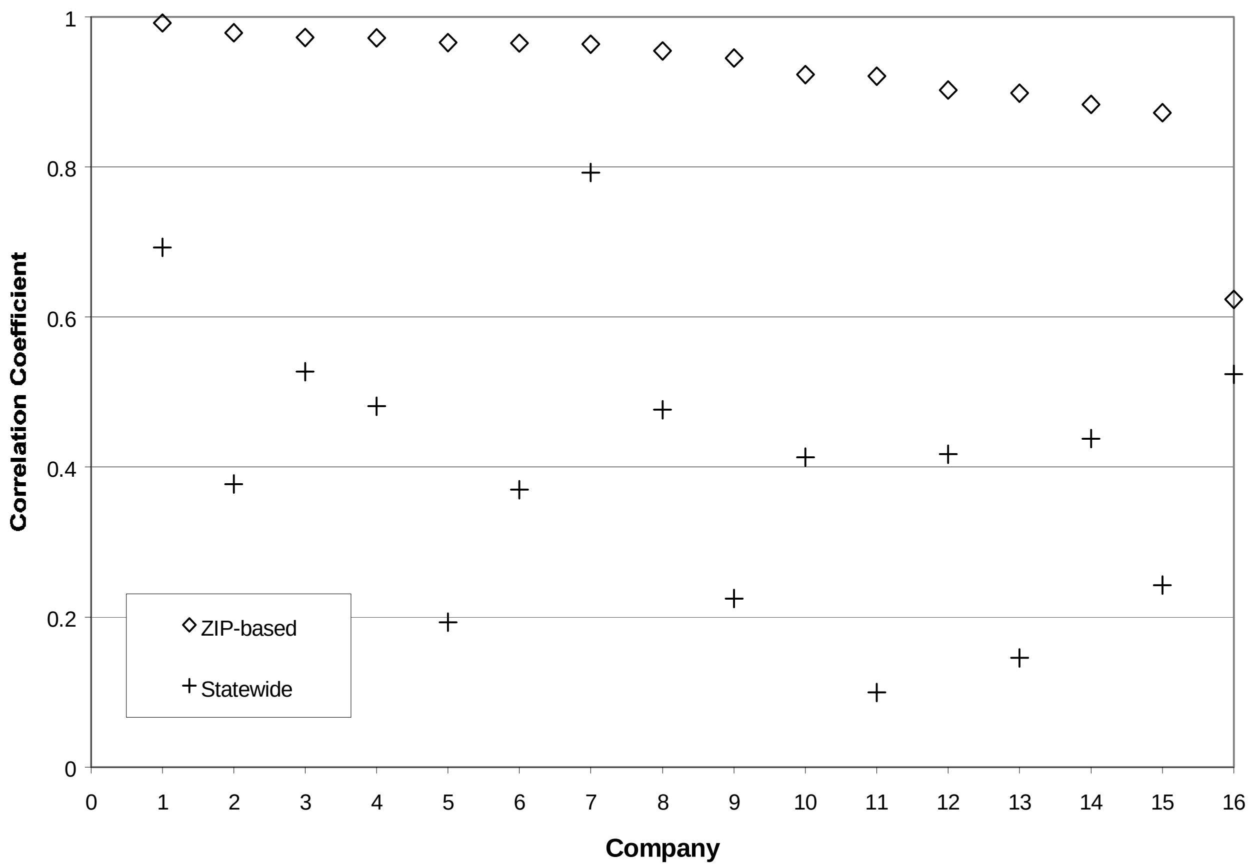

Figure 2: Optimal Hedge Ratio Conditional On Hurricane Fran

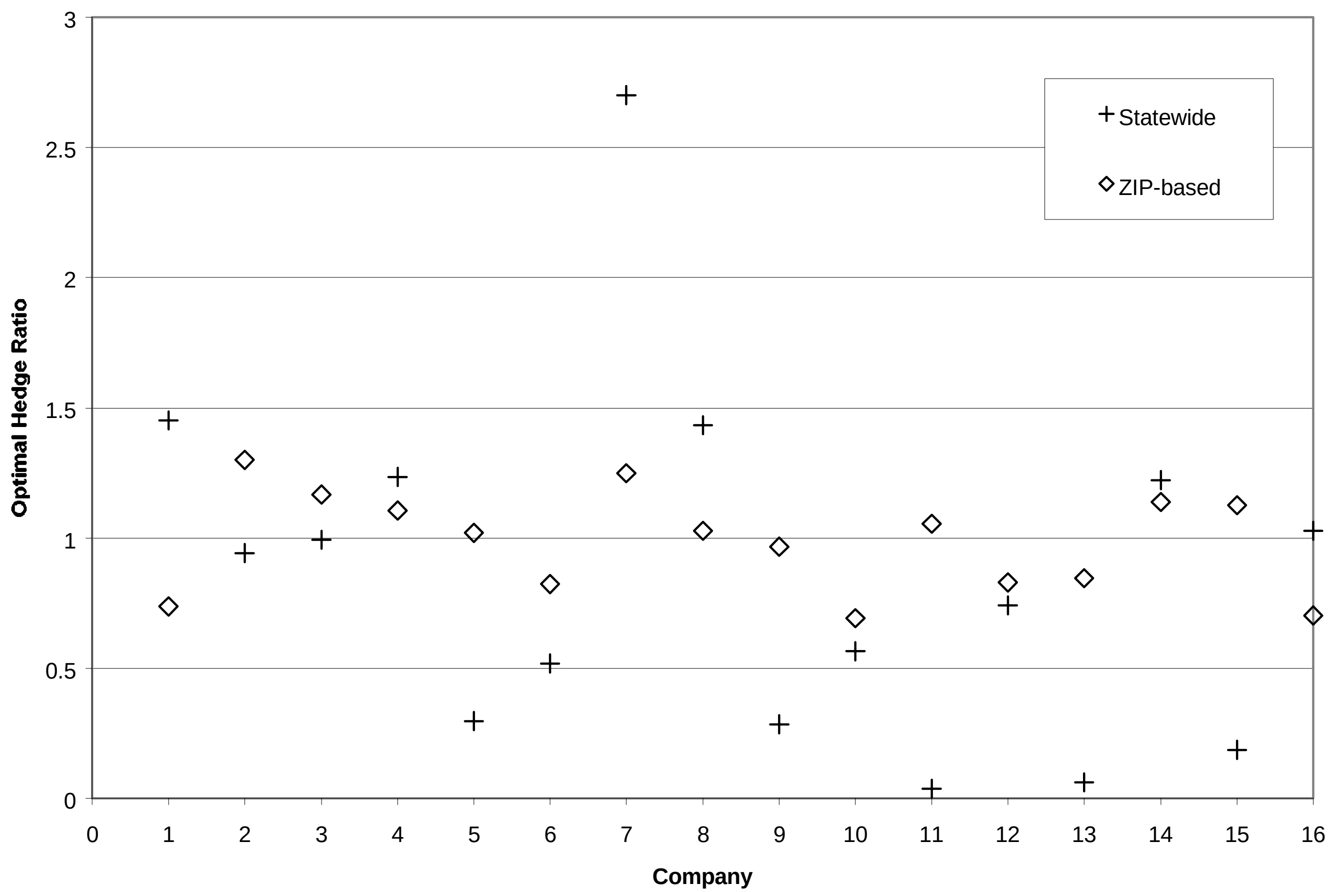

Figure 3: Percent of Reduced Volatility