Multivariate Time Series

A Multivariate Time Series Analysis of Climate Risk and Insurance Prices

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1 Introduction

In the coming decades, regions globally are expected to face severe climatic and ecological hazards due to ongoing global warming. These risks include flooding in coastal and other low-lying areas, biodiversity loss in terrestrial, freshwater, and marine ecosystems, significant reductions in regional food production and water availability, and heightened landslide activity in many mountainous regions. The damages associated with these phenomena are projected to intensify with each incremental rise in the global temperature. Impacts are expected to be more pronounced at 1.5°C above pre-industrial levels than at present and even more severe at 2°C (IPCC 2023).

Amid faltering de-carbonisation efforts, financial sectors — particularly insurance and reinsurance policies — are becoming central tools for mitigating adverse climate impacts on economies and livelihoods. Examples include agricultural micro-insurance and risk-sharing approaches in emerging economies with limited insurance markets, as well as increased public and private insurance uptake in developed countries (Collier et al. 2021). Policy frameworks incorporating weather and health insurance, contingent finance, and reserve funds can further mitigate the vulnerability and exposure of human systems to adverse climatic impacts (IPCC 2023).

This study examines the interplay between experienced and perceived climate risks and their impact on insurance market dynamics, with a specific focus on the United States. We analyse two pathways through which climate risks influence insurance prices: (1) an informational pathway, wherein individuals' perceptions of climate risk alter expectations and decision-making, thereby increasing insurance demand and prices; and (2) a direct pathway, where experienced climatic conditions materially impact individuals and their economic activities, increasing the costs involved with insuring against a rising number of billion-dollar disasters (Carleton and Hsiang 2016).

To analyse the relationship between perceived risk, realised disaster costs, and insurance prices, we utilise the *Climate Physical Risk Index* (PRI), a novel media-based index, alongside data on Consumer Price Indices (CPI) of urban tenants and household insurance. By further combining these datasets with inflation-adjusted climate disaster costs, this report aims to evaluate both direct and indirect effects of climate risks on the insurance sector. As a robustness check, we also incorporate the Producer Price Index (PPI) by Industry for premiums on homeowners' insurance to analyse the impacts of climate risks on the insurer side of the insurance market.

2 Literature Review:

Direct and Indirect Climate Risks To analyse the impacts of climate change on insurance markets, we differentiate between two pathways: an informational pathway that alters individuals' expectations about climatic conditions and thus influences their behaviour, and a direct pathway that changes the climatic conditions individuals experience (Carleton and Hsiang 2016). Regarding direct pathways, empirical evidence points to a sharp rise in insurance payouts following climate-related disasters. For example, in 2018 alone disasters in the United States and the Caribbean resulted in record insured losses of $144 billion and total economic damages of $337 billion—far exceeding the 10-year averages of $58 billion and $190 billion, respectively (Collier et al. 2021).

Insurance Markets and Climate Risk Regarding informational pathways, Boomhower et al. (2024) empirically identifies a winner's curse in the insurance market for climate risks, underscoring the critical role of information in actuarial pricing such risks. Their findings reveal significant heterogeneity in pricing behaviour among firms. Specifically, firms with less granular climate-related risk data tend to charge higher premiums but face greater expected losses due to mispricing or are forced to exit the market entirely. Similarly, Charpentier (2008) highlights the role of information in shaping households' insurance decisions. Climate-related damages can drive premiums higher, leaving households with short-term horizons and insufficient information underinsured. They also emphasise the uncertainty surrounding extreme weather events, which exacerbates unpredictability in pricing and decision-making. Doherty (1997) further argue that well-functioning insurance markets are critical for promoting incentive-compatible and preventative decision-making. However, mispricing can distort investment behaviour, such as encouraging housing development in areas overexposed to climate risks.

Expected Channels Based on the economic theory of climate impacts on insurance markets, we hypothesise that both extreme weather events and uncertainty about the gravity, frequency, and consequences of future events will positively influence individuals' insurance uptake, thereby increasing insurance prices in the U.S.. Simultaneously, we argue that increased costs related to prior climate disasters increase the need for insurance companies to enrol in re-insurance, hence driving the costs of insurance for houses and properties furthermore. Hence, we anticipate an increase in urban household insurance CPI following recent weather events and their estimated costs as individuals aim to mitigate future risks. Regarding globally perceived risk, we expect a more stable response of insurance CPI to general climate uncertainty.

3 Methodology

This section describes data sources, preliminary descriptive evidence, and the underlying methodology of the multivariate longitudinal analysis of climate risk, disaster costs, and consumer prices for insurance.

3.1 Data Sources

The data sets used in the analysis are presented in Table **??**. The U.S. CPI of urban tenants' and housing insurance and the U.S. PPI for houseowner's premiums are provided by the FRED database at a monthly level. Data on U.S. inflation-adjusted disaster costs were taken from the National Center for Environmental Information (NCEI). Finally, the daily Climate Physical Risk Index (PRI) was provided by Bua et al. (2024) at a daily level. The index is a global text-search-driven indicator based on Reuters News articles that spikes on days that experience an unexpected discussion on climate physical risk in the media. Such a discussion can encompass a broad range of relevant topics including acute and chronic climate hazards, as well as adaptation and mitigation policies (Bua et al. 2024). We combined the different sources by aggregating the PRI at the monthly level using the arithmetic mean and filtering the data to contain only observations from January 2005, the start date of the aggregated PRI measure, to December 2018, to avoid any unwanted effects associated with the COVID-19 pandemic and due to the most recent cost stemming from December 2018.

Variable	Observation Period	Type	N	Mean	St.Dev.
CPI of Urban Tenants and Housing Insurance	1997-2024	Monthly	325	130.02	18.61
PPI of Homeowner's Insurance Premiums	1998-2024	Monthly	319	174.19	40.06
Physical Climate Risk Index (PRI)	2005-2023	Monthly	319	-0.000128	0.0077
Disaster Costs ($ Billion)	1980-2018	Monthly	171	9466.93	20179.00

Table 1: Summary Statistics

Disaster-Related Costs and Major Extreme Weather Events As can be seen in Figure 1a, our data selection includes several multiple billion-dollar U.S. weather disasters that are often quoted in the literature. Such key peaks in costs are for example: **2005:** Total damages amounted to $220 billion, driven by four hurricanes, including Hurricane Katrina, which caused $165 billion in damages and claimed 1,833 lives. **2008:** The U.S. saw three hurricanes, five severe storms, a drought, wildfires, and flooding. **October 2012:** Hurricane Sandy resulted in $72 billion in damages. **Summer 2017:** Hurricanes Irma, Maria, and Harvey collectively caused over $280 billion in damages within two months. Note that we cannot see the same sharp rises for climatic events in the CPI nor the PPI as these shocks likely need more time to affect yearly-set insurance prices.

However, looking at the PRI (Figure 1d), we can see large spikes following the events in 2006 and 2008, potentially indicating an impact on perceived climate risk in the media. Similarly, the spike in the year 2012 could likely be a result of the aftermath of Hurricane Sandy.

3.2 Multivariate Time Series Analysis

To study the relationship between disaster-related costs, perceived climate risks, and insurance prices, we performed the statistical procedure as described below. All analyses were implemented using SAS, with commented code on our GitHub as well as in the provided ZIP file to ensure reproducibility.[1]

Testing for Unit Root Behaviour and Non-Cointegration As a preliminary step, we first visually inspected each univariate time series to identify any apparent trends, seasonality, or structural breaks. After the visual inspection of potential non-stationarity, unit root behaviour was tested explicitly with a variety of tests - including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Ng-Perron (NPP), and the Kwiatkowski-Phillips-Schmidt-Shin tests. In the case that these tests detected an I(1) process, the respective time series was transformed into a log growth rate defined as the first difference of the logarithms of each variable. Integrated Durbin-Watson tests were used to determine the existence of autocorrelation within the residuals. Lastly, potential Co-integration of identified I(1) processes was tested using both the Engle-Granger (Engle and Granger 1987) and the Johansen approach.

Model Selection Based on the results of the co-integration tests, we select either a Vector Autoregressive VAR(p) model potentially including a Moving Average term (as a VARMA(p,q) model) if the studied time series show no sign of cointegration or a Vector Error Correcting Model (VECM) if cointegration is the case. The optimal lag sizes for the AR/MA orders were selected using the Hannan-Quinn Criterion (HQC).

Granger Causality and IRF Analysis Granger causality tests were employed to identify whether climate variables Granger-cause the CPI or the PPI. The tests involved evaluating the null hypothesis that the variables in Group 1 are influenced only by themselves and not by Group 2 (Group 2 does not Granger cause Group 1), with a 5% significance threshold for rejection. We have tested the following hypotheses:

1. The disaster-related costs do not Granger-cause the insurance CPI or the Climate Risk Index.
2. The disaster-related costs do not Granger-cause both the Physical Climate Risk Index and the CPI.
3. The Physical Climate Risk Index does not Granger-cause the insurance CPI.
4. The CPI does not Granger-cause the Physical Climate Risk Index.

[1] githhub.com

As the final analysis step, we then performed an Impulse-Response Analysis to investigate the dynamic response of the CPI to shocks in climate costs and perceived climate risk on insurance prices. This provided insights into both the magnitude and persistence of interactions among variables.

Additional Robustness Checks The robustness of our findings was confirmed via two additional checks. First, by examining the residual autocorrelation of the estimated VARMA or VAR model. Second, by applying the above-defined steps to the Producer Price Index of Housing Premiums. The idea behind this being that if insurance prices increase due to higher demand following specific disasters, the impulse response to changes in disaster costs or spikes in the PRI should affect the CPI only. If on the other hand, insurance prices increase due to changes in insurance companies' cost functions - for example due to a higher need for re-insurance - we would need to find an effect in the PPI as well.

4 Results

The following presents the preliminary test results and main results of the conducted IRF analysis as well as additional robustness checks regarding economic plausibility and model correctness.

4.1 Main Results: The impact of climate risks on Consumer Insurance Prices

Preliminary Test Results As observable in Figure 1, except for the aggregated PRI time series in Figure 1d, the remaining variables exhibit either strong trends - as in the case of the CPI and the PPI in figures 1b and 1c - or time-varying variance as in the case of the disaster-related costs in figure 1a. Hence, figures 2a and 2b for climate risk measures and 3a and 3b for insurance market indicators present selected test statistics for unit root behaviour - using the Augmented Dickey-Fuller Test as well as the (Ng-) Phillip Perron - and against stationarity - as in the case of the KPSS test. Based on these tests, one cannot reject the null hypothesis of a unit root for the CPI and PPI. Similarly, the KPSS test rejects its null hypothesis that the respective time series are stationary for all but the costs times series and PRI when testing with a trend. We model CPI, PPI, (and costs as a robustness check) as I(1) processes. Nevertheless, using both the bivariate Engle-Granger approach and the multivariate Johansen procedure, we cannot find significant evidence for cointegration among CPI or PPI with costs. [2]

VAR Estimation Results Based on the non-cointegration of the investigated I(1) variables, a Vector Autoregressive Model was selected to model the relationship between climate costs, risks, and insurance prices. Figure 4 shows the implemented grid search regarding the AR/MA combination that minimises the HQ Information

[2]Due to limited space we decided to omit these test statistics in the appendix. Naturally, every test described in the report is observable in the SAS file.

Criterium. Note that the represented maximum lag size of eight was chosen based on a comparison of different maximum values and the respective optimal AR-MA tuple. Indeed, the selection of a VARMA(p,q) model was relatively invariant concerning higher and lower maximum lag orders than 8, and the HQC of -1.8 was optimal in all settings. Hence, we have implemented a VARMA(1,1) model to analyse the relationship between climate costs, risk, and insurance price indices.

Granger Causality Tests Figure 5 provides results for potential Granger causality between the three studied variables. Noteworthy, all null hypotheses as described above remain unrejected except for the null that the CPI Granger-causes the PRI. While Granger-causality is strictly just a correlation and the observed finding could likely be a statistical artifact driven by noisy data, we argue that it could also be related to the nature of the PRI as news about increasing insurance prices due to climate risks could enter the risk index and thus result in a positive correlation among both time series.

IRF Modelling Figure 7 to 10 provide the graphs for four selected IRF functions. First the IRF of Costs, CPI, and PRI to a shock in CPI. Figure 8 and 9 show the same variables in response to a shock in Costs, and PRI respectively. Figure 10 shows the reaction of Costs, PPI, and PRI to a shock in PPI as our robustness check. In line with the findings on Granger causality, we can see in Figure 7 a significant impact of consumer price shocks on perceived climate risks that realises itself after roughly 12 months. However, no other cross-impacts we observable for the main variables of this study. Furthermore, Figure 9 shows some short-term persistence of impulses in the PRI but this lasts for no longer than two lags.

4.2 Robustness Checks

To validate the robustness of our findings, we conducted an additional analysis incorporating the Producer Price Index (PPI) of housing insurance premiums. This was done to evaluate whether the observed relationships between climate costs, perceived risks, and insurance prices extend to the producer side of the insurance market. By comparing the results using PPI with those derived from CPI, we aim to indicate whether or not our conclusions are statistical artifacts of consumer-side dynamics alone.

Testing for Cointegration We examined whether PPI is cointegrated with costs to ensure the validity of the VAR model's specification. The results as provided in the SAS code indicated no evidence of cointegration, reaffirming that a VAR framework is appropriate. Substituting PPI for CPI in the VAR model produced results largely consistent with those obtained using CPI. Specifically, disaster costs remained autoregressive of order one (AR(1)), while the Physical Risk Index (PRI) exhibited autoregressive behaviour of order two (AR(2), see Figure 6). Some significant higher-order lags for CPI predicting PRI were identified (e.g., at lags 6 and

12). However, these are likely attributable to seasonality or data artifacts rather than substantive economic relationships.

Granger Causality The Granger causality tests further support this conclusion. Unlike CPI, PPI does not appear to Granger-cause PRI, suggesting that any previously observed relation between CPI and PRI is likely statistical noise rather than indicative of an economic relationship. However, one speculative economic interpretation remains: substantial changes in CPI might prompt households to attribute rising insurance costs to increased climate risks, potentially influencing the PRI with a lagged effect. Nevertheless, given the lack of significant coefficients in the immediate or short-term lags, establishing a direct causal link remains challenging. The IRF confirms that shocks to disaster costs nor PRI do not significantly affect PPI (Figure 10). This is in contradiction with our Ex-Ante expectations, but may ultimately be due to the limitations outlined below.

5 Discussion and Limitations

The following limitations constrain the interpretation and generalisability of the presented results.

Data Quality and Scope The CPI data used in this analysis captures a composite measure of urban tenants' and household insurance, potentially including non-climate-related components. This generality reduces the precision with which the data reflects weather-related insurance pricing. Similarly, the PPI data potentially encompasses a range of producer-side costs, such as labour and operational expenses, which are unrelated to climate risks. Additionally, imperfections in competition within the insurance market may obscure the effects of disaster costs on producer pricing (Boomhower et al. 2024). The aggregation of the Physical Risk Index (PRI) from daily to monthly observations introduces further limitations. While necessary for alignment with our other data, this process smooths short-term spikes in media coverage of climate risks, diminishing the granularity of the analysis and the magnitude of spikes and may result in an underestimation of the effect climate risk perceptions/media coverage can have on the insurance market.

Spatial and Contextual Granularity An additional limitation arises from the nationwide aggregation of CPI, PPI, and PRI data. Climate events, by their nature, are spatially localised, with impacts on insurance pricing often restricted to affected or nearby regions. For instance, insurers may adjust premiums only in areas directly impacted by specific disasters. The use of national-level aggregates risks overlooking these localised adjustments, potentially underestimating significant effects in the analysis. The PRI index for example may inadequately capture regional variations in disaster perception, further limiting its explanatory power in our models.

Causal Interpretation The findings presented in this report are observational and rely on econometric methods to infer relationships among variables. While VAR and Granger causality analyses provide insights into temporal dynamics, they do not establish causal relationships in a strict sense. For example, the observed correlation between CPI and PRI may result from reverse causality or omitted variables, such as unobserved regional factors influencing both perceptions and pricing.

Broader Market Dynamics Our analysis does not account for broader market dynamics, such as regulatory interventions, subsidies, or shifts in competition within the insurance sector. These factors may independently influence insurance pricing, complicating the attribution of observed changes solely to climate risks. Furthermore, the analysis spans 2005 – 2019, due to our data limitation, excluding the volatile period during the COVID-19 pandemic and the recent, increasingly frequent, disasters / extreme weather events.

6 Conclusion

This report has analysed the relationship between extreme weather events' costs, perceived climate risk, and consumer prices for urban housing and tenant insurance. Providing a multi-step analysis of each univariate time series and a consequent VAR(1) estimation and IRF analysis between the variables, we find no impulse response of consumer insurance prices to heightened climate risk or realised disaster damage. We can find some speculative evidence for the impact of higher CPI levels on perceived physical risks. However, this could likely be due to statistical noise rather than causality. An additional robustness finds no significant impact of disaster costs or perceived risk on Producer Prices regarding insurance premiums.

References

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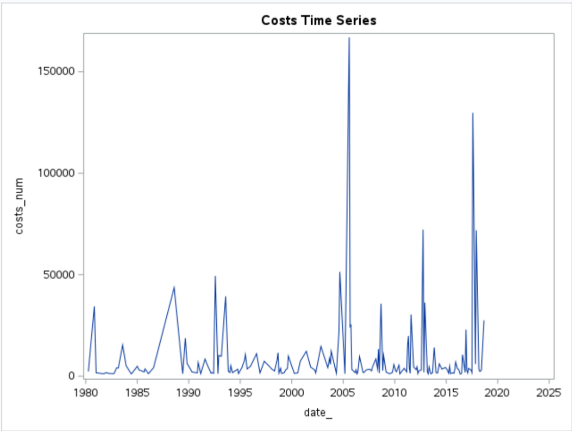
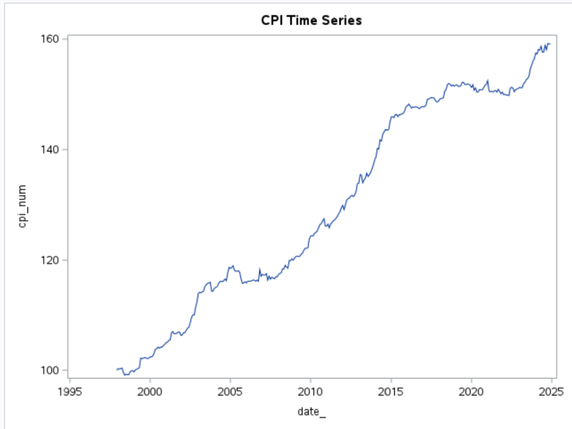
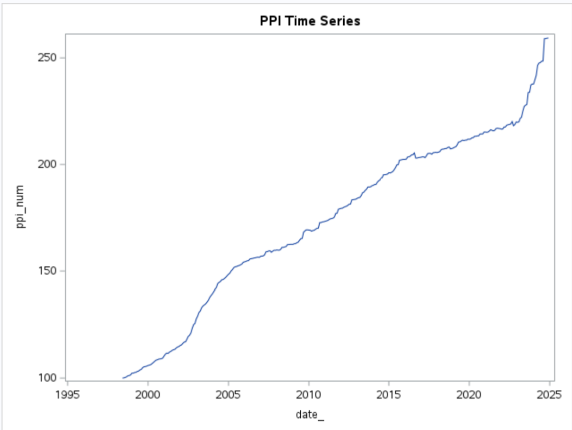
7 Appendix



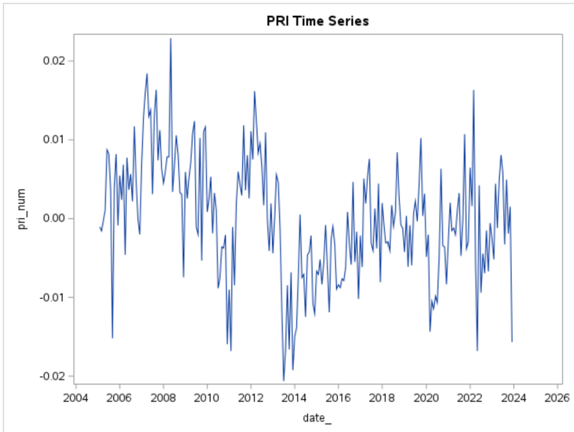
(a) Costs Plot



(b) CPI Plot



(c) PPI Plot



(d) PRI Plot

Figure 1: Univariate Time Series - Overview

Abhängige Variable	costs_num

Costs Time Series

Die Prozedur AUTOREG

Gewöhnliche Kleinste-Quadrate-Schätzwerte			
SSE	6.52679E10	DFE	168
MSE	388499230	RMSE	19710
SBC	3826.17665	AIC	3823.04675
MAE	8457.35072	AICC	3823.0707
MAPE	158.667059	HQC	3824.31692
Durbin-Watson	1.6288	Summe R-Quadrat	0.0000

Phillips-Perron-Unit-Root-Test					
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau
Nullmittelwe	2	-124.6225	<.0001	-9.9272	<.0001
Einfacher Mi	2	-136.4000	0.0013	-10.6773	<.0001
Trend	2	-136.6541	0.0005	-10.6582	<.0001

Augmented Dickey-Fuller-Unit-Root-Tests							
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Nullmittelwert	0	-124.7199	<.0001	-9.9288	<.0001		
Einfacher Mittelwert	0	-136.8980	<.0001	-10.6835	<.0001	57.0689	<.0010
Trend	0	-137.1464	<.0001	-10.6645	<.0001	56.8696	<.0010

Ng und Perron Einheitswurzeltest					
Typ	Optimales Lag	Langfristige Varianz	Methode	Statistik	P-Wert
Einfacher Mi	8	75117781.3	MZalpha	-15.3457	0.0090
	8	75117781.3	MSB	0.1805	0.0109
	8	75117781.3	MZ	-2.7698	0.0050
	8	75117781.3	PT	1.6027	0.0070
	8	75117781.3	MPT	1.5973	0.0069
	8	75117781.3	DFGLS	-4.0873	<.0001
Trend	3	236003811	MZalpha	-50.6091	<.0001
	3	236003811	MSB	0.0993	<.0001
	3	236003811	MZ	-5.0267	0.0001
	3	236003811	PT	1.8041	<.0001
	3	236003811	MPT	1.8190	<.0001
	3	236003811	DFGLS	-5.3488	<.0001

KPSS-Test auf Stationarität			
Typ	Lags	Eta	Pr > Eta
Einfacher Mi	4	0.1139	0.5214
Trend	4	0.0874	0.2221

(a) Costs

Abhängige Variable	pri_num

Costs Time Series

Die Prozedur AUTOREG

Gewöhnliche Kleinste-Quadrate-Schätzwerte			
SSE	0.01083633	DFE	168
MSE	0.0000645	RMSE	0.00803
SBC	-1146.9215	AIC	-1150.0514
MAE	0.00648146	AICC	-1150.0275
MAPE	104.88898	HQC	-1148.7813
Durbin-Watson	0.7593	Summe R-Quadrat	0.0000

Phillips-Perron-Unit-Root-Test					
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau
Nullmittelwe	2	-57.1547	<.0001	-6.0466	<.0001
Einfacher Mi	2	-57.3908	0.0013	-6.0428	<.0001
Trend	2	-73.3572	0.0005	-7.0513	<.0001

Augmented Dickey-Fuller-Unit-Root-Tests							
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Nullmittelwert	0	-64.2352	<.0001	-6.3131	<.0001		
Einfacher Mittelwert	0	-64.4435	0.0013	-6.3088	<.0001	19.9025	<.0010
Trend	0	-78.0897	0.0005	-7.1966	<.0001	25.9430	<.0010

Ng und Perron Einheitswurzeltest					
Typ	Optimales Lag	Langfristige Varianz	Methode	Statistik	P-Wert
Einfacher Mi	5	0.0000	MZalpha	-4.1500	0.2020
	5	0.0000	MSB	0.3459	0.2630
	5	0.0000	MZ	-1.4356	0.1770
	5	0.0000	PT	6.7026	0.2100
	5	0.0000	MPT	5.9110	0.1932
	5	0.0000	DFGLS	-1.5611	0.1461
Trend	5	0.0000	MZalpha	-5.8202	0.5430
	5	0.0000	MSB	0.2909	0.5968
	5	0.0000	MZ	-1.6929	0.5059
	5	0.0000	PT	17.3200	0.5821
	5	0.0000	MPT	15.6390	0.5461
	5	0.0000	DFGLS	-1.9057	0.4027

KPSS-Test auf Stationarität			
Typ	Lags	Eta	Pr > Eta
Einfacher Mi	8	0.7233	0.0110
Trend	7	0.1295	0.0776

(b) PRI

Figure 2: Stationarity Tests - Costs and PRI

Abhängige Variable	cpi_num

Costs Time Series

Die Prozedur AUTOREG

Gewöhnliche Kleinste-Quadrate-Schätzwerte			
SSE	27160.185	DFE	168
MSE	161.66777	RMSE	12.71486
SBC	1343.18499	AIC	1340.05509
MAE	11.4514114	AICC	1340.07904
MAPE	8.69460748	HQC	1341.32526
Durbin-Watson	0.0020	Summe R-Quadrat	0.0000

Phillips-Perron-Unit-Root-Test					
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau
Nullmittelwe	2	0.2534	0.7425	4.8914	1.0000
Einfacher Mi	2	0.4916	0.9764	0.9042	0.9954
Trend	2	-7.2731	0.6346	-2.9707	0.1437

Augmented Dickey-Fuller-Unit-Root-Tests							
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Nullmittelwert	0	0.2534	0.7425	4.9101	0.9999		
Einfacher Mittelwert	0	0.4919	0.9764	0.9057	0.9954	12.0936	<.0010
Trend	0	-7.3855	0.6253	-2.9610	0.1465	5.6548	0.0861

Ng und Perron Einheitswurzeltest					
Typ	Optimales Lag	Langfristige Varianz	Methode	Statistik	P-Wert
Einfacher Mi	7	1.1678	MZalpha	1.3166	0.9527
	7	1.1678	MSB	1.1211	0.9670
	7	1.1678	MZ	1.4760	0.9838
	7	1.1678	PT	104.4037	0.9698
	7	1.1678	MPT	91.7498	0.9739
	7	1.1678	DFGLS	1.0718	0.9560
Trend	0	0.2765	MZalpha	-1.3881	0.9600
	0	0.2765	MSB	0.5929	0.9948
	0	0.2765	MZ	-0.8230	0.9250
	0	0.2765	PT	74.5629	0.9911
	0	0.2765	MPT	64.4188	0.9890
	0	0.2765	DFGLS	-0.8839	0.9184

KPSS-Test auf Stationarität			
Typ	Lags	Eta	Pr > Eta
Einfacher Mi	9	1.7533	<.0001
Trend	8	0.2824	0.0021

(a) CPI

Abhängige Variable	ppi_num

Costs Time Series

Die Prozedur AUTOREG

Gewöhnliche Kleinste-Quadrate-Schätzwerte			
SSE	61415.7105	DFE	168
MSE	365.56971	RMSE	19.11988
SBC	1481.07438	AIC	1477.94448
MAE	17.0392143	AICC	1477.96843
MAPE	9.59858103	HQC	1479.21465
Durbin-Watson	0.0012	Summe R-Quadrat	0.0000

Phillips-Perron-Unit-Root-Test					
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau
Nullmittelwe	2	0.3221	0.7599	7.7741	1.0000
Einfacher Mi	2	-0.3507	0.9365	-0.9074	0.7841
Trend	2	-3.4845	0.9131	-1.0351	0.9355

Augmented Dickey-Fuller-Unit-Root-Tests							
Typ	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Nullmittelwert	0	0.3221	0.7599	8.0818	0.9999		
Einfacher Mittelwert	0	-0.3469	0.9368	-0.9214	0.7796	34.6833	<.0010
Trend	0	-3.0910	0.9318	-0.9515	0.9468	0.7854	0.9879

Ng und Perron Einheitswurzeltest					
Typ	Optimales Lag	Langfristige Varianz	Methode	Statistik	P-Wert
Einfacher Mi	5	1.1988	MZalpha	1.3627	0.9565
	5	1.1988	MSB	2.0613	0.9995
	5	1.1988	MZ	2.8090	0.9999
	5	1.1988	PT	356.1101	0.9992
	5	1.1988	MPT	296.2655	0.9992
	5	1.1988	DFGLS	2.1086	0.9976
Trend	0	0.3003	MZalpha	-3.5959	0.7749
	0	0.3003	MSB	0.3284	0.7353
	0	0.3003	MZ	-1.1808	0.8037
	0	0.3003	PT	22.7548	0.7313
	0	0.3003	MPT	22.9069	0.7619
	0	0.3003	DFGLS	-1.1911	0.8097

KPSS-Test auf Stationarität			
Typ	Lags	Eta	Pr > Eta
Einfacher Mi	9	1.7932	<.0001
Trend	8	0.2252	0.0082

(b) PPI

Figure 3: Stationarity Tests - CPI and PPI

Kleinstes Informationskriterium basierend auf HQC									
Lag	MA0	MA1	MA2	MA3	MA4	MA5	MA6	MA7	MA8
AR 0	-0.83744	-1.312411	-1.254554	-1.201331	-1.067385	-0.940263	-0.838823	-0.733327	-0.7191
AR 1	-1.250454	-1.795137	-1.701135	-1.619198	-1.520618	-1.37609	-1.232573	-1.104307	-0.982351
AR 2	-1.214404	-1.72951	-1.569751	-1.477381	-1.370559	-1.218744	-1.085924	-0.971612	-0.871229
AR 3	-1.041785	-1.635573	-1.464223	-1.331973	-1.230038	-1.077792	-0.93609	-0.806372	-0.773786
AR 4	-0.898583	-1.481229	-1.309235	-1.203782	-1.121051	-0.977942	-0.833721	-0.697966	-0.718883
AR 5	-0.782402	-1.383719	-1.215297	-1.093376	-0.997025	-0.844898	-0.717446	-0.583912	-0.583112
AR 6	-0.663032	-1.248532	-1.087018	-0.955496	-0.851016	-0.725298	-0.608942	-0.506961	-0.502565
AR 7	-0.518419	-1.149739	-1.005669	-0.837382	-0.738493	-0.617563	-0.502356	-0.49205	-0.457896
AR 8	-1.015	-1.109443	-0.958289	-0.801755	-0.709369	-0.580856	-0.497313	-0.511594	-0.41804

Figure 4: VARMA Coefficient Selection Based On HQC

Granger-Kausalität-Wald-Test			
Test	**DF**	**Chi-Quadrat**	**Pr > ChiSq**
1	12	3.92	0.9848
2	12	5.33	0.9462
3	24	15.49	0.9057
4	12	7.80	0.8005
5	12	24.27	0.0187

Test 1: Gruppe 1 Variablen:	cpi_logfd
Gruppe 2 Variablen:	costs_num

Test 2: Gruppe 1 Variablen:	cpi_logfd
Gruppe 2 Variablen:	pri_num

Test 3: Gruppe 1 Variablen:	cpi_logfd pri_num
Gruppe 2 Variablen:	costs_num

Test 4: Gruppe 1 Variablen:	pri_num
Gruppe 2 Variablen:	costs_num

Test 5: Gruppe 1 Variablen:	pri_num
Gruppe 2 Variablen:	cpi_logfd

Figure 5: Granger Causality Tests With CPI

Schematische Darstellung der Parameterschätzer													
Variable/Lag	**C**	**AR1**	**AR2**	**AR3**	**AR4**	**AR5**	**AR6**	**AR7**	**AR8**	**AR9**	**AR10**	**AR11**	**AR12**
cpi_logfd	+	...	...	...	...	...	...	...	...	...	...	...	...
pri_num	.	.+.	.+.	...	...	...	-..	...	..-	...	...	...	-..
costs_num	.	..+	...	..+	...	...	...	...	...	...	...	...	...
+ ist > 2*Std.fehler, - ist < -2*Std.fehler, . ist zwischen, * ist N/A													

Figure 6: VARMA Significant Coefficients

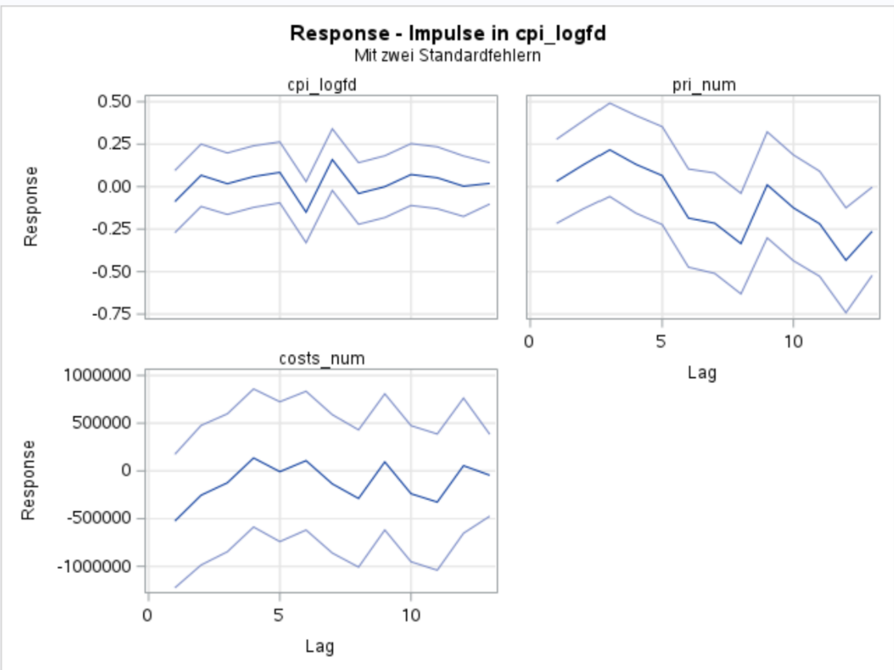


Figure 7: IRF - Shock in CPI

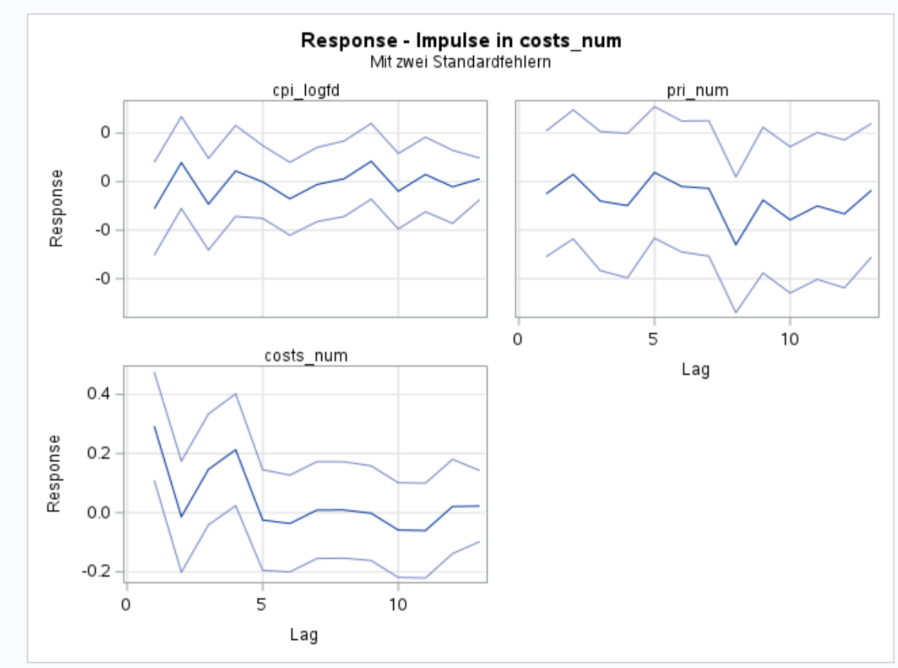


Figure 8: IRF - Shock in Costs

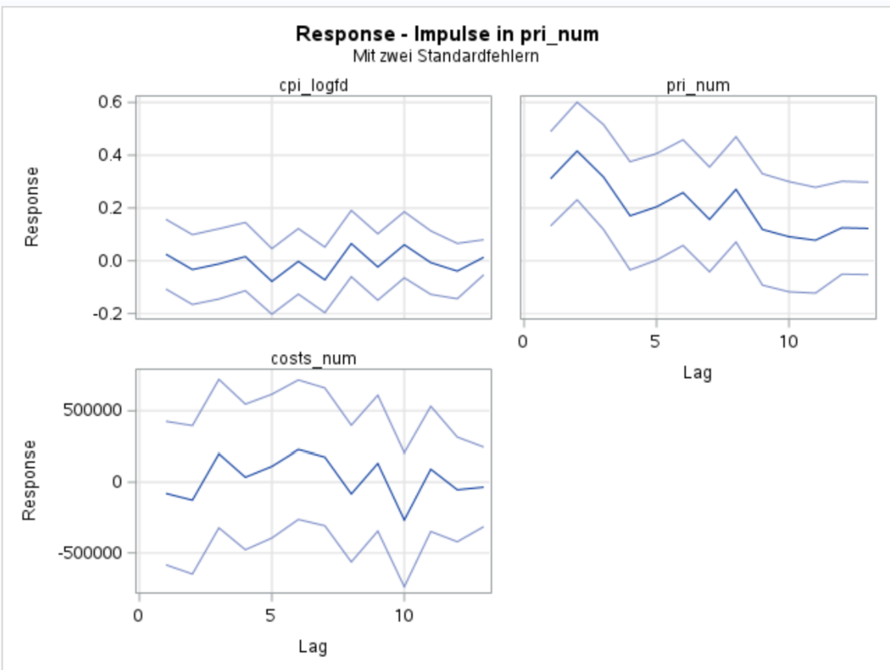


Figure 9: IRF - Shock in PRI

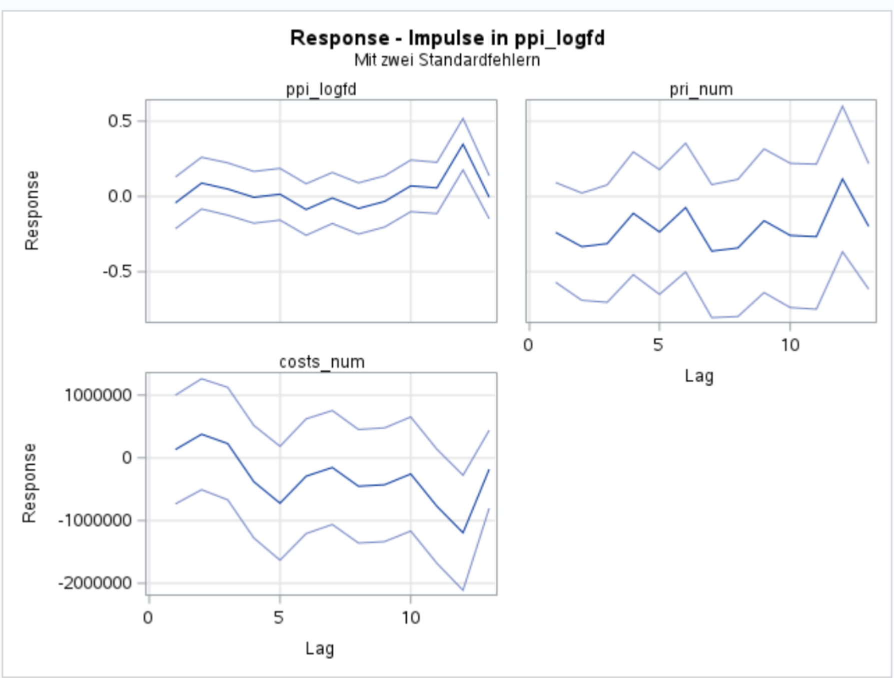


Figure 10: IRF - Shock in PPI

8 Data Appendix

Variable Label	Description
cpi_num	CPI for Tenants' and Household Insurance in U.S. City
ppi_num	PPI for Homeowner's Insurance Premiums
costs_num	Monthly Disaster Costs in $Billion
pri_num	Monthly Mean of Daily Climate Physical Risk Index
cpi_log	Logarithm of CPI for Tenants' and Household Insurance
ppi_log	Logarithm of PPI for Homeowner's Insurance Premiums
cpi_logfd	First difference of logarithm of CPI for Tenants' and Household Insurance
ppi_logfd	First difference of logarithm of PPI for Homeowner's Insurance Premiums

Table 2: SAS Variable Explanation

Data Set	Label
FRED Consumer Price Index (CPI) for All Urban Consumers Tenants' and Household Insurance in U.S. City Average	fred.stlouisfed.org
National Center for Environmental Information (NCEI) Historical Data on U.S. Natural Disasters 1980-2024, including Costs in CPI-Deflated Billion US$	www.ncei.noaa.gov
Climate Physical Risk Index (PRI)	www.policyuncertainty.com
FRED Producer Price Index by Industry Premiums for Property and Casualty Insurance Premiums for Homeowner's Insurance	fred.stlouisfed.org

Table 3: Explicit Data Sources