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Drivers of the Flood Insurance Protection Gap: A Socio-economic Analysis of German Residential Buildings in High-risk Regions

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Abstract: This paper aims to understand how socioeconomic factors influence the residential insurance protection gap in identified high-risk areas. By adapting Steinhausen et al.'s (2022) estimates of expected annual damages, we evaluate these gaps at NUTS 3 level and subsequently analyze them using a cross-sectional approach. We find that rising GDP per capita and urbanization contribute to widening this gap while higher education levels diminish it, emphasizing the influence of socioeconomic disparities and regional factors on the gap. Policy recommendations for high-risk regions include construction bans, mandatory local insurance policies, and education campaigns to enhance flood awareness and reduce financial vulnerability.

Keywords: Climate Insurance, Insurance Protection Gap, Flood risk, Residential Buildings

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1. Introduction

Disaster risks are intensifying across Europe, both in terms of severity and frequency (Coronese et al. 2019). The Intergovernmental Panel on Climate Change (IPCC) has developed a framework that disaggregates disaster risk into three essential components: hazard, vulnerability, and exposure. This approach enables a comprehensive financial assessment of risks, which holds significant importance within the domain of climate insurance. This type of insurance plays a central role in enhancing societal resilience against natural disasters (Jarzabkowski et al. 2019).

A widely discussed concept highlighting the relationship between disaster risk and insurance is the climate insurance protection gap (IPG). In our methodology, we adopt Tesselaar et al.`s (2022) definition of this concept as the flood risk level that remains uninsured. However, it is commonly defined as the ratio of insured to total losses. IPGs are crucial in climate insurance literature because they reveal financial vulnerabilities to natural hazards. Globally, the extent of the IPG varies significantly across regions and disaster types (Rousová et al. 2023). In Europe, the climate IPG remains considerable, with only about 25% of disaster-related damages covered by insurance (ECB and EIOPA 2023). Flooding is the most destructive natural disaster contributing to Europe's climate IPG, driven by its increasing severity and frequency (Paprotny, Terefenko, and Śledziowski 2024). While all types of floods cause substantial economic and social damage, fluvial floods are identified as the most catastrophic.

The German Insurance Association (GDV) has analyzed the number of addresses exposed to significant flood risks, emphasizing the need for tailored policies that enhance the resilience of residential properties. However, despite the public availability of high-risk zone data, policymakers have largely ignored these recommendations, evoking widespread public criticism. This response caused public incomprehension, given that the last major flood caused over €32 billion in economic losses and devastated numerous communities in 2021 (Mohr et al. 2023).

The discourse on flooding in high-risk areas also reveals a notable lack of empirical research. Only a limited number of studies have analyzed high-risk zones, and even fewer have examined the residential flood IPG in this context. This gap in the literature provides an opportunity to investigate the residential IPG and its underlying determinants, particularly socioeconomic factors influencing flood risk and insurance decisions. Focusing on these high-risk areas offers valuable insights into the drivers of the IPG, which are essential for creating and executing targeted, better-informed public policies to reduce disparities and strengthen resilience in vulnerable regions. This thesis analyzes the forces that may drive the IPG exclusively for residential buildings in high-risk regions throughout Germany, thereby addressing the research question:

"How do socio-economic factors drive the residential fluvial flood insurance protection gap in German high-risk regions?"

This paper finds that large IPGs exist alongside the Rhine and that key socioeconomic factors, including GDP per capita, urbanization, and education, are critical drivers of the IPG. Rising GDP per capita and urbanization levels are associated with a widening IPG due to asset concentration and increased exposure. In contrast, higher levels of education help narrow the gap due to their proven impact on income and possibly fostering risk awareness, financial literacy and encouraging insurance uptake. These findings present a novelty since no other contribution used a data-driven approach to analyze this gap in Germany. Further, they align with existing research, such as Booth (1991), Dottori et al. (2020), and Steinhausen et al. (2022), on the relationship between urbanization and flood risk, as well as Tesselaar et al. (2020) on economic barriers to insurance and regional inequalities. The study also highlights that flood risk is partially endogenous, shaped by human decisions, such as urban planning and institutional legacies like past mandatory insurance in Baden-Württemberg, which significantly improved coverage.

This paper is structured as follows: Section 2 introduces the concepts of climate insurance and the IPG through a review of existing literature. Section 3 outlines the data and methods of collection. Section 4 details the methodology employed in this research. Section 5 presents and discusses the key findings and limitations. Finally, the concluding section provides recommendations. Supplementary tables are included in the appendix.

2. Literature Overview

Since the 1970s, climate insurance research has progressed steadily, but its boom started in the 21st century. Lin et al. (2023) highlight that this field was partly driven by the IPCC, which has emphasized the potential of climate insurance as a tool to reduce economic losses since its first assessment in 1990 (Collier, Elliott, and Lehtonen 2021). Hydrological events, particularly floods, dominate European climate insurance research due to their significant and growing impact (Lin et al. 2023; Paprotny, Terefenko, and Śledziowski 2024). From 1980 to 2023, floods accounted for nearly half of the €738 billion in economic losses from climate-related to (European Environment Agency 2024).

Floods are classified into three categories: fluvial, pluvial, and coastal. Among these, fluvial floods are prone to intensification in both physical impact and economic consequences due to rising global temperatures (Dottori et al. 2020).

Although the economic impacts of natural hazards are well-documented, adaptation strategies and disaster risk management often remain insufficiently explored. A key concept illustrating the context is the climate protection gap, which Holzheu and Turner (2018, 8) defined as "the uninsured portion of losses resulting from an event, namely the difference between total economic and insured losses." Other contributions simplify the definition as the difference between total economic and insured losses (Climate Resilience Dialog 2024).

Closely related to this is the climate IPG, which the Geneva Association (2016) defines as the difference between the economically optimal level of insurance coverage and actual insurance purchase. Given the challenge of quantifying the ideal level of insurance, most studies use the uninsured portion of economic losses as a proxy. Others, such as Tesselaar et al. (2022), frame the IPG as the degree of flood risk not covered by insurance. These terms are frequently used interchangeably because of their similarities.

European nations display notable differences in climate IPGs (Rousová et al. 2023; ECB and EIOPA 2023). Countries like Norway, Denmark, and the Netherlands achieve the highest proportions of insured economic losses, whereas several Eastern European nations lag behind, with insurance rates below 5%. Furthermore, the IPGs vary by hazard type: 28% of damages from hydrological events, such as floods, are insured; in comparison, only 7% for climatological events like droughts and heatwaves are covered (Rousová et al. 2023).

Empirical evidence on IPG impacts is scarce but suggests severe economic consequences. Rousová et al. (2023) find that disasters causing damages equal to 1% of GDP reduce GDP growth by 0.2 percentage points in regions with high uninsured losses, underscoring the need to address IPGs to enhance economic resilience.

Policymakers must understand the key determinants of the residential flood IPG, which is driven by flood risk and insurance coverage (EIOPA 2024). The IPCC defines flood risk as the likelihood of future harmful climate-related effects, which risks arise from the interaction of physical hazards, vulnerabilities, and exposure. Cardora et al. (2012) explain that disaster risk stems from the interplay of social and environmental factors. They identify three key factors: hazard, the potential occurrence of damaging events; exposure refers to the presence of people or assets in hazardous areas; and vulnerability, the susceptibility of exposed elements to negative impacts.

Flood insurance among Europe varies between voluntary, semi-voluntary, and mandatory systems. In Germany, flood insurance is optional and available as an add-on through the "Elementarversicherung," which covers 54% of households, although there are regional disparities (GDV 2024b). Nguyen et al. (2024) emphasize the role of the GDV's flood hazard zoning system (ZÜRS), established in 2000, in shaping insurance coverage. Further, they note that the former GDR's inclusion of flood damage in household insurance contrasts with today's lower penetration rates. Meanwhile, the authors also state that Baden-Württemberg, with 94% insurance coverage, benefited from compulsory building insurance until 1994. Andor et al. (2017) argue that earlier mandatory policies may influence current attitudes through status quo bias, fostering either a sense of security or reliance on government compensation.

Broader drivers, such as climate change and socio-economic developments, also impact flood risk and insurance coverage. Climate change compounds flood risk by raising the frequency and intensity of extreme events, such as 100-year floods. Coronese et al. (2019) record rising economic impacts, while Gagliardi, Arévalo, and Pamies (2022) caution that even if global warming is restricted to 1.5 degrees, Europe's economic losses may double by 2050 and could increase threefold by 2100. Additionally, the rising frequency of extreme flooding intensifies the IPG by diminishing both the affordability and accessibility of insurance, especially in high-risk areas. For instance, Tesselaar et al. (2020) demonstrate that insurers frequently react to increased risk by elevating premiums in flood-prone areas, thus rendering coverage less accessible to low-income households.

Socio-economic factors also play a critical role in shaping the IPG. Urbanization contributes significantly to flood risk by shifting natural landscapes to artificial ones, disrupting the movement and storage of rainwater (Booth 1991). This risk is compounded by continued development in high-risk flood zones, a persistent issue in many countries, including Germany (Rentschler et al. 2023). According to the GDV (2023), over 270,000 residential buildings are located in high-risk areas, and approximately 1,360 buildings are added each year. Thus, inappropriate land-use management policies significantly contribute to the extent of the damages associated with flooding events.

Further, urbanization correlates positively with GDP per capita (OECD 2020). GDP per capita has been scarcely discussed in connection with the IPG. This economic activity indicator is also utilized to broadly measure average living standards or economic well-being, but is not without shortcomings like its inability to display inequalities (OECD 2012). However, together with urbanization these factors contribute to more residential properties and increased flood exposure. Moreover, higher GDP per capita has been linked to increased property values, although the findings were barely significant (Brausewetter, Thomsen, and Trunzer 2022).

Conversely, flood risk can also suppress property prices in high-risk areas. Hirsch and Hahn (2018) found that properties within flood zones in Regensburg were significantly devalued. However, their study is limited to one city and a four-year observation period, including a major 2013 flood. Aus dem Moore et al. (2022) observed that property prices in flood-prone regions were unaffected by the 2021 floods, whereas van Assen (2024) notes that flood-induced prices are most pronounced immediately after an event but diminish over time.

Further, affordability remains a significant obstacle, restricting coverage for economically vulnerable households (Holzheu and Turner 2018). In combination with rising flood risk, regions with high-income inequality could display declining insurance coverage, particularly for low-income households (Tesselaar et al. 2020). Moreover, education and age influence flood insurance adoption, as both positively correlate with higher uptake rates (Atreya, Ferreira, and Michel-Kerjan 2015). Additionally, risk perception is crucial since experiences after disasters frequently boost the uptake of flood insurance. For instance, Pitterle (2022) noted an increase in insurance demand after the German 2021 floods spurred by increased media attention and personal encounters with flooding. Nevertheless, this surge in adoption tends to be short-lived, with rates typically reverting to levels seen before the disaster (Gallagher 2014).

On the other hand, factors inherent to voluntary insurance systems actively discourage uptake. The "charity hazard" phenomenon, where households expect government compensation after disasters, reduces demand for private insurance (Tesselaar et al. 2022).

These factors highlight the complex interaction between climate change, socio-economic issues, and institutions in shaping the IPG. Understanding these drivers is crucial for developing targeted interventions to enhance resilience in high-risk areas.

Germany's flood-prone and high-risk areas are increasingly well-documented (GDV 2024a). Major river basins, including the Elbe, Upper Danube, Rhine, Weser, and Ems, drive fluvial flooding. Analysis of 1951–2002 data shows a significant rise in flood frequency across most regions, with rare, statistically insignificant declines, highlighting growing flood risks (Petrow, Zimmer, and Merz 2009). Despite their importance for targeted flood protection policies, socio-economic disparities in Germany’s high-risk flood areas remain unexplored regarding the residential flood IPG. Most analyses rely on national data, neglecting crucial regional disparities in the IPG.

3. Data

This study's data covers the highest-risk NUTS 3 regions in Germany's chosen federal states, sourced from GDV (2024a) and relies on estimations from Steinhausen et al. (2022). The GDV commissioned a study from VdS Schadenverhütung GmbH to analyze the number of Germany's approximately 22.4 million addresses situated in flood-prone zones and published the results for the top five districts most exposed per federal state. Two types of flood prone zones were considered. First, areas that are likely to incur a 1-in-100 flood event and secondly, areas that are located in flood hazard zones with frequently incurring floods. Most of the addresses investigated in the study fall into the former zones, while only a fraction falls into the latter. Still, the GDV considers these regions as high-risk due to their apparent exposure and vulnerability. However, some districts were excluded, as certain federal states had only 3 or 4 severely exposed districts. To further cultivate the sample, additional high-risk regions, identified by Steinhausen et al. (2022) with expected annual damage of €2.5 million were compiled. Additionally, some outliers with exorbitant high EADs were also excluded. However, districts included under the GDV but with EADs exceeding €2.5 million remain categorized under the GDV.

Moreover, Bremen, Hamburg, and Berlin were excluded due to their unique administrative characteristics, resulting in a final sample size of 92 NUTS 3 regions. Figure 1 below provides a geographical overview of these high-risk areas.

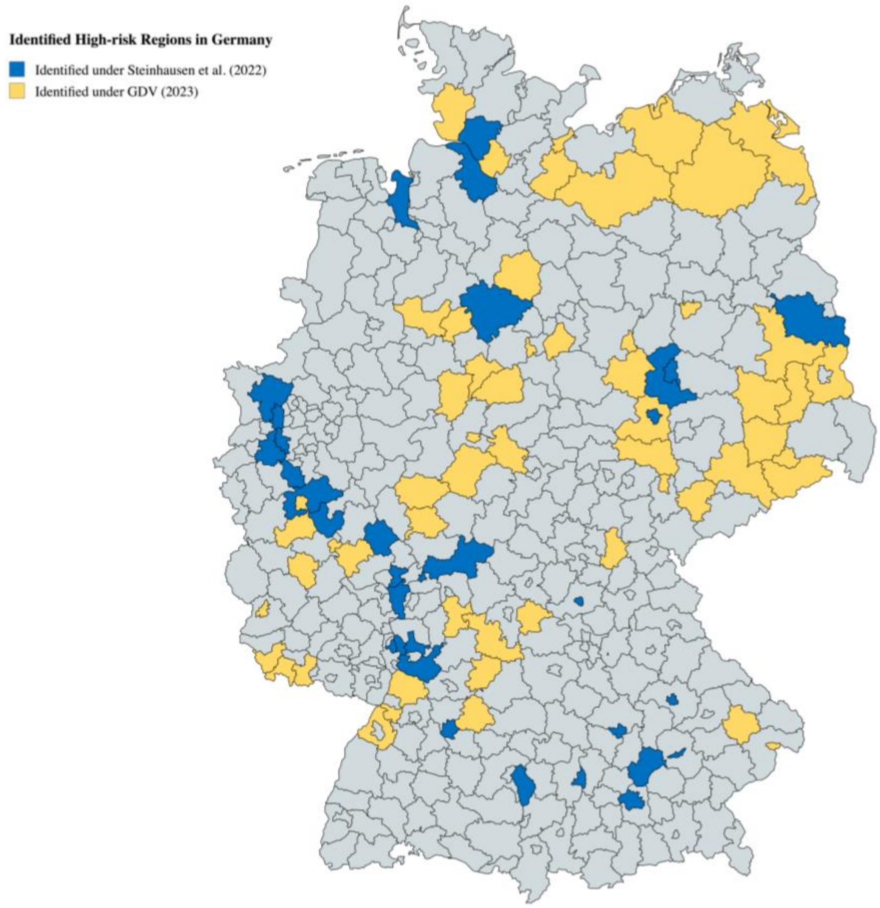

Figure 1. Geographical overview of high-risk flood areas divided by source. Created with MapChart, https://www.mapchart.net/

Among Germany's 401 NUTS 3 regions, 92 are classified as high-risk, with 68.5% being rural. Bavaria has the highest number of high-risk regions (13), while Saarland has the fewest (4). However, Saarland exhibits the highest proportion of high-risk districts relative to its total districts (83.3%), whereas Bavaria has the lowest proportion (13.5%). Comparing this geographical overview to German flood maps reveals that along the Rhine and Elbe, most of the regions are located. Further, the distribution of rural and urban districts differs significantly between high-risk regions identified by the GDV (2024a) and Steinhausen et al. (2022). The former highlights rural districts more due to differing definitions of high-risk zones.

For this thesis, data selection and retrieval are central to explaining which socio-economic factors drive the IPG in the highlighted high-risk districts. The dependent variable, residential flood IPG, is approximated using residential EADs and the insurance penetration rate for extended natural hazard insurance. The former is retrieved from an academic source that published its data for further use, while the latter were obtained from the GDV´s website. As mentioned earlier, the EADs were calculated using estimates from Steinhausen et al. (2022), which examines factors influencing future fluvial flood risk, especially regarding European residential buildings. To our knowledge, it is the sole public open data source for EADs at the NUTS 3 level.

The authors analyze EAD by assessing key flood risk drivers, including flood hazard characteristics, exposure data, and various vulnerability factors. Their methodology aligns with prior research, such as that by Tesselaar et al. (2020), but innovates by quantifying flood drivers in greater detail and integrating private precautions using the multi-variable flood loss model BN-FLEMOps. The model uses data from 1980 to 2010, centered around 1990, as a baseline to evaluate changes in flood risk. By integrating damages across various flood return periods, the authors provide a comprehensive measure of flood damages.

The public-available data set is split into various files shaped by assumptions influencing EAD calculations. EADs are computed for 2025, 2050, and 2080 under multiple scenarios that assess climate change impacts (RCP 4.5 and RCP 8.5), exposure, and their combined effects. EADs are also calculated for the 25th, 50th, and 75th quantiles to illustrate potential damages. This paper emphasizes the 50th quantile for 2025, reflecting median EAD values for that year under the representative concentration pathway (RCP) 4.5.

As most data is only available for the year 2022, this paper adjusts the EADs for 2025 based on inflation rates, assuming all other factors remain constant. This assumption is supported by data indicating minimal growth in economic and demographic indicators in recent years. Furthermore, this paper uses EAD values that isolate climate change's impact while holding exposure levels constant. Figure 2 in the appendix illustrates the EAD distribution across high-risk regions.

Among the ten regions with the greatest EAD, eight are urban districts. The rural district of Groß Gerau (Hesse) exhibits the highest EAD value at €13,453 thousand, followed by the urban district of Mannheim (Baden-Württemberg) at €12,520 thousand, and the city district of Cologne (Nordrhine-Westpfalia) with €10,154 thousand. Damages remain the highest alongside the Rhine. At the federal level Rhineland-Palatinate exhibits the highest EADs, while Saxony reports the highest average EADs among high-risk regions in eastern Germany.

As expected, the EADs are seemingly linked to the share of urban areas. This finding implies that urban areas are at greater risk of significant flood damage compared to rural areas.

Secondly, the insurance penetration rates for residential buildings against natural hazards are crucial for evaluating the extent of flood insurance coverage in different regions of Germany. The data in this paper provided by the GDV (2024a) captures the extent to which German homes are insured under the „Elementarversicherung“ for natural hazards through the elementary scheme, covering risks such as floods, severe rainfall, and earthquakes. Unlike standard home insurance, which typically covers storms and hail, these hazards are included in the extended natural hazard insurance scheme. The GDV excludes contracts for severe heavy rainfall, which aids this paper in ensuring a more targeted focus on general flood risk under the "Elementarversicherung" scheme. This approach aligns with the objective of analyzing flood insurance penetration, as floods, alongside storms and hail, are among the main causes of natural hazard damages in Germany (Kreibich et al. 2014). The study targets high-risk flood areas to enhance analysis, making findings more relevant for assessing regional flood insurance coverage and establishing a foundation for exploring insurance market trends and flood risk management.

Furthermore, the data utilized for model estimation was gathered from the Historical Analysis of Natural Hazards in Europe (HANZE) database (Paprotny 2024), which records fluvial, pluvial, and compound flood events across 42 European nations between 1870 to 2020. For the analyzed NUTS 3 regions, fluvial flood data from 1950 onward is used to calculate the annual averages.

Data for the regional apartments and houses price index on NUTS 3 level was sourced from the RWI-GEO-REDX dataset, which provided by the RWI Research data center (RWI 2024). This dataset relies on the RWI-GEO-RED dataset, which comprehends detailed property characteristics for the years between 2008 - 2023 such as prices, living area, and amenities among others. Based on this data, the RWI-GEO-REDX uses hedonic regressions to calculate three distinct price indices. Most relevant for this paper are the regional price indices, which reflects relative price differences across regions compared to the national average at a given time. As price indices are calculated on the grid level, they are aggregated by weighting the share of observations in each grid relative to the total observations in the district or municipality[1]. This dataset is available through the public and scientific use file. This paper

[1] For more information on the estimation of the price index, please see the data description by Thiel (2024).

relies on the scientific use file, allowing for fewer than 50 observations per region and year compared to the public use file.

Data for the remaining variables for the year 2022 like income inequality at NUTS 2 level of GDP per capita, the share of the urban area and the share of high school absolvents at NUTS 3 level have been retrieved from EUROSTAT and the German official federal statistic office DESTATIS.

Table 1 below summarizes the variables used for the model. The average adjusted EAD was €2,703 thousand, with large variations across the sample The average insurance coverage was approximately 50%, ranging from 28% to 95%. Table 2 (appendix) compares the high-risk identified by the GDV (2024a) and Steinhausen et al. (2022).

Table 1. Variables and Descriptive Statistics used in the Analysis in 2022

Variable	Obs	Mean	Std. Dev.	Min	Max
Adj_EAD	92	2702656.1	2622601	30411.411	12558913
Coverage	92	.499	.157	.28	.95
GDPPC	92	45432.196	18899.076	23830	140365
Inc_Inequality	92	4.16	.5	3.3	5.3
PriceIndex	92	20.963	59.38	-48.41	296.677
Urban	92	17.622	13.535	4.4	58.6
EDUC	92	32.002	7.482	17.6	51.1
FREQ	92	1.303	.589	.543	3.243
GDV	92	.63	.485	0	1
Flood	92	.043	.205	0	1
BW	92	.087	.283	0	1

4. Methodology

The literature review outlined key factors influencing the IPG, while the data section detailed the data collection. This section describes the methodology for calculating the IPG, along with the empirical strategy and methods of estimation.

4.1 Calculation of the insurance gap

Several methods are available to estimate the IPG. The simplest method is to express the IPG as the ratio of insured losses to total economic losses. However, this approach is often impractical due to data limitations, especially at regional levels, such as NUTS 3 in Germany.

Of the 80 recorded flood events documented in the Risk Data Hub provided by the Disaster Risk Management Knowledge Center (DRMKC), only a fraction has been harmonized for flood damages at the NUTS 3 level. Alternatively, the IPG can be modeled using expected damages as a foundation (Tesselaar et al. 2022). Specifically, EAD has become central to flood IPG modeling, incorporating flood return periods and exceedance probability[2] to estimate potential (Arnbjerg-Nielsen and Fleischer 2009; Olsen et al. 2015). In this context, the overall IPG is calculated using proxies for insured losses and expresses the amount of flood risk that is not insured.

Building on Tesselaar et al. (2022, 6), who proxied the IPG by "multiplying the EAD per capita with the uninsured population, which is the inverse of the penetration rate multiplied by the exposed population", this research focuses explicitly on residential flood protection gap. Thus, the model used in this paper defines the IPG as follows:

$$IPG_i = EAD_i \times (1 - PR_i)$$

where IPG_i represents the insurance protection gap for residential buildings at NUTS 3 region i, for the year 2022, EAD_i denotes the expected annual damages for the NUTS 3 region i, and PR_i is the NUTS 3 region i elementary insurance penetration rate. While Tesselaar et al. (2022) estimated the protection gap based on EAD per capita, this paper adopts a broader approach by estimating the protection gap using solely EAD at the NUTS 3 level.

4.2 Econometric model

To empirically analyze the IPG for residential buildings, this study employs a cross-sectional regression model focusing on the most flood-exposed regions within 13 German federal states. The following equation is estimated:

[2] The likelihood of surpassing a specific value within a set future timeframe. This probability helps forecast extreme occurrences like floods (Kunreuther 2002; Lambert et al. 1994).

$$ln(IPG_i) = \beta_0 + \beta_1 \ln(GDPPC_i) + \beta_2 \ln\,(PriceIndex_i) + \beta_3 Inc\_Equality_i + \beta_4 EDUC_i + \beta_5 Urban_i + \beta_6 BW_i + \beta_7 \ln(FREQ_i) + \beta_8 FLOOD_i + \beta_9 GDV_i + \epsilon_i \quad (1)$$

The dependent variable is the logarithm of the residential flood insurance protection gap, where i represents the ith NUTS 3 region. The variable $\ln(GDPPC_i)$ is the logarithm of GDP per capita for the NUTS 3 region in 2022. The variable $PriceIndex_i$ is a price index taken from the RWI-GEO-REDX dataset for the NUTS 3 region in 2022. The variable $Inc\_Equality_i$ measures the income quintile share ratio, comparing the income of the wealthiest 20% of the population within a NUTS2 region to that of the poorest 20% in 2022. The $EDUC_i$ variable represents the share of high school absolvents per NUTS 3 region, while the variable $Urban_i$ estimates the urban area to total land area per NUTS 3 region in 2022. The dummy BW_i identifies all regions in Baden-Württemberg, reflecting the state's especially high insurance uptake. To capture the varying levels of risk across high-risk zones, $FREQ_i$ is used to measure the annual frequency of floods of the last 70 years per NUTS 3 region. This proxy reflects how frequent damages drive higher premiums, discouraging insurance uptake and contributing to the IPG. Further, the dummy $FLOOD_i$ was constructed to account for the 2021 floods in Germany. Lastly, the dummy variable GDV_i distinguishes high-risk regions identified by the GDV from those classified by Steinhausen et al. (2022).

4.3 Methods of estimation

First, this paper estimates equation (1) using a cross-sectional regression without accounting for heteroscedasticity, as both Beusch-Pargan and White's tests showed no evidence of its presence. Subsequently, standard errors are clustered to account for the possibility of correlated errors within regions. Clustering addresses intra-regional dependencies that might lead to underestimated standard errors and overconfidence in the coefficients. The errors are clustered by NUTS 2 region, allowing localized interpretation of the results. However, clustering resulted in 29 clusters with sizes ranging from 1 to 8 observations with an average of 3.2. Thus, traditional clustering might still result in biased estimates. In order to become more confident in the estimates of our model, this paper employs the wild bootstrap method. The wild bootstrap, introduced by (Wu 1986), adjusts heteroscedasticity by creating bootstrap samples that reflect the distribution of residuals. This is achieved by multiplying each residual by a random variable with a mean of zero and a variance of one. Unlike traditional methods, which may yield inaccurate standard errors and confidence intervals when clusters are small or unevenly sized, the wild cluster bootstrap is more robust in these cases. Research by MacKinnon and Webb (2017) demonstrates that this method provides more reliable inference in settings with unbalanced clusters. Therefore, equation (1) is estimated using the wild cluster bootstrap method with Rademacher weights available in STATA. This symmetric distribution is easy to implement, making it a popular option in practice.

We rely on the variance inflation factors (VIF) to assess if multicollinearity is a concern. The literature displays large dissents about the threshold that signals multicollinearity. While Johnston, Jones, and Manley (2018) defined the most conservative cut-off at an estimate of 2.5, other literature proposes higher thresholds of 5 or even 10 (Vittinghoff et al. 2005; James et al. 2023). Table 3 (appendix) shows the results of the VIF calculation. The highest VIF is PriceIndex with 3.4; thus, although some variables exhibit moderate collinearity, no apparent problem with multicollinearity exists.

5. Results and Discussion

After detailing the methodology, this section presents and discusses the results of the calculated IPG and the cross-sectional regression analysis.

5.1 Insurance Protection Gap

This paper estimates the regional IPG of the German high-risk districts, representing the expected annual flood damages of residential buildings not covered by elementary insurance. Figure 3 below illustrates the estimated IPG for the 92 identified districts in 2022.

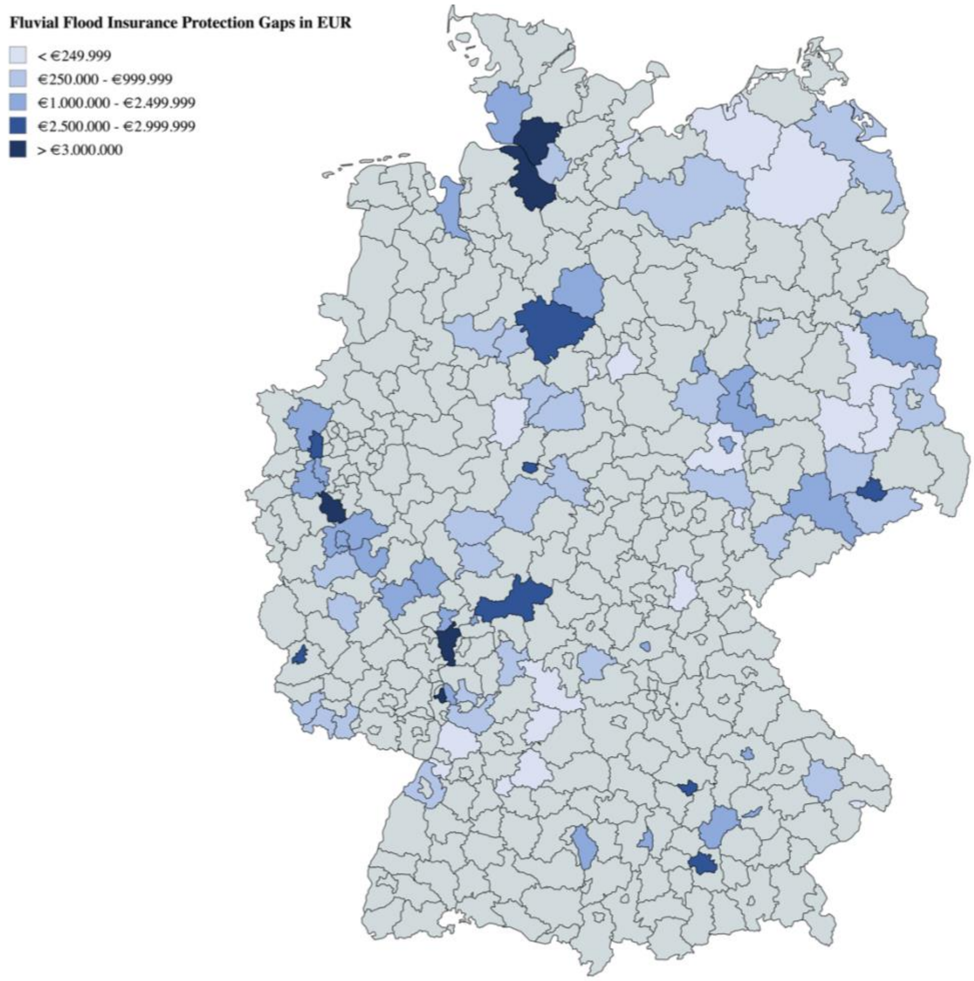

Figure 3. Distribution of the residential fluvial flood insurance protection gaps in 2022. Created with MapChart, https://www.mapchart.net

Few regions have IPGs exceeding €2,500 thousand, with the highest values found in three rural districts: Groß-Gerau (Hesse) at €5,400 thousand, Steinburg (Schleswig-Holstein) at €4,334 thousand, and the Stade (Lower-Saxony) at €3,940 thousand, respectively. Both of the latter are located alongside the Elbe, exhibiting low insurance coverage of only 33%. A majority of regions, including Groß-Gerau, are located in proximity to the Rhine River or its extensions. As seen in Table 4 (appendix), the estimates for the IPG significantly differ based on the categorization of high-risk regions. The overall IPG average across all regions is €1,248.

Unsurprisingly, IPG values align closely with EADs. Districts with elevated EADs typically exhibit larger IPGs. However, unlike the EADs, the highest IPG were observed in rural districts alongside the Elbe and the Rhine. The top three districts are followed by urban districts like Ludwigshafen, Cologne and Dresden. Nonetheless, the variation across districts suggests that factors beyond flood risk, such as socio-economic conditions, risk perception, regional insurance practices, and historical insurance policies, significantly influence the IPG.

5.2 Regression Results

The table below reports the regression output of equation (1).

Table 5. Regression Output – Response Variable ln(IPG)

	(1) normal	(2) clustered	(3) wild cluster bootstrap
lnGDPPC	.824**	. 824**	. 824**
	(.421)	(.374)	
PriceIndex	-.005*	-.005**	-.005*
	(.003)	(.002)	
Inc_Inequality	-.071	-.071	-.071
	(.242)	(.226)	
Urban	.032***	.032***	.032**
	(.011)	(.009)	
EDUC	-.037**	-.037***	-.037**
	(.015)	(.011)	
BW	-1.687***	-1.687***	-1.687
	(.345)	(.508)	
lnFREQ	.590**	. 590**	. 590**
	(.251)	(.22)	
FLOOD	.465	.465**	.465
	(.491)	(.206)	
GDV	-1.18***	-1.22***	-1.22***
	(.249)	(.153)	
_cons	6.245	6.245	6.245
	(4.479)	(3.9)	
Observations	92	92	92
R-squared	.575	.575	.575

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

The empirical findings confirm that several predictors stand out as statistically significant. The logarithm of GDP per capita significantly impacts the IPG in high-risk regions and should be viewed as an elasticity. With a coefficient of 0.84 ($p < 0.05$) across all models, this indicates that a 1% increase in GDP per capita correlates with a 0.88% rise in the IPG. This suggests that more economically active high-risk districts have larger IPGs, likely due to the accumulation of assets and their exposure in high-risk areas. Similarly, urbanization is highly significant and positively correlates with the IPG. The coefficient of 0.032 ($p<0.05$) indicates that a percentage change in urbanization leads to a 3.3% rise in the IPG, all else equal.[3] This finding, suggests that urban high-risk regions often face higher flood risks due to higher population densities, impervious surfaces, and more residential buildings.

In contrast, the dummy variable for Baden-Württemberg shows a negative coefficient of -1.69, indicating that regions located in Baden-Württemberg, on average, have an 81.5% lower IPG than those in other regions. This finding is significant across two models and highlights the long-term effects of the state's past mandatory policies, which encourage better alignment between risk and coverage. Similarly, the dummy variable distinguishing high-risk areas highlighted by the GDV 2024 and Steinhausen et al. (2022) proved significant across all models, showing a coefficient of -1.18. This indicates that, on average, districts labeled as high-risk by the GDV exhibited 69.3% lower IPGs than those identified by Steinhausen et al. (2022). This result suggests that the high-risk regions defined under the GDV significantly differ from those of Steinhausen et al. (2022), with the former focusing on address-level exposure instead of projected losses and might do not deserve the classification as high-risk.

Other significant factors include education with a coefficient of -0.037 ($p<0.05$), suggesting that a 1% increase in high school graduation rates corresponds to a 3.6% reduce in the IPG, holding all other factors constant. Thus, regions with larger shares of high school graduates are linked to a significantly reduced IPG, indicating that more educated individuals in these high-risk areas have a greater awareness of flood risk and a deeper understanding of financial literacy. The price index, which reflects apartment and house prices in a region, is significant at 5% for one model and has a negative coefficient of -0.005, indicating that higher

[3] To interpret this coefficient, it must first be exponentiated, subtracted by one, and multiplied by 100. Further, a unit change translates to a percentage change since the variable is scaled from 1 to 100.

property values are associated with 0.5% lower IPG, likely due to wealthier homeowners investing in insurance or risk mitigation measures.

Historic flood frequency has a coefficient of 0.59, indicating that an increase of 1% raises the IPG by 0.59%, reflecting how repeated flooding drives higher premiums and discourages insurance uptake. Moreover, the 2021 flood dummy variable demonstrates a moderately significant and consistent relationship with the IPG at the 5% level in just two out of three specifications. The coefficient of 0.465 indicates that districts impacted by the 2021 flood had, on average, IPGs that were 57.8% larger than those in other areas, indicating that areas identified as high-risk in the sample are especially susceptible to flood hazards. This finding was significant in one model. Additionally, spikes in perceived risk might not correspond with coverage. Income inequality is not significant across any specification.

5.3 Discussion

The results highlight a complex interplay between socio-economic factors, flood risk exposure, and insurance behavior in shaping the IPG. GDP per capita might drive housing prices in urban centers (Brausewetter, Thomsen, and Trunzer 2022). Further, it could indicate asset accumulation, thus increasing exposure to flood risks. Therefore, if the coverage is not adequately aligned with the associated risks—exemplified by residential assets situated in high-risk areas—the IPG could widen. However, controlling for property price indices reveals that high-risk regions with higher property values tend to have lower IPGs. This suggests that higher property prices may reflect higher incomes, better risk management, stronger building standards, and informed insurance decisions. Thus, GDP per capita as a broad indication of average living standards do not uniformly increase the IPG, but in certain contexts, it can help align coverage with risk exposure. Additionally, GDP per capita is an imperfect proxy as it masks inequalities and limits its relevance for explaining IPGs. Thus, GDP per capita alone cannot capture the subtleties of the IPG and must be interpreted with caution.

Urban areas compound this complexity, as they face greater flood risks due to higher population densities, asset concentrations, and impervious surfaces that exacerbate runoff (Booth 1991). Consequently, urbanization emerges as a significant driver of flood risk in high-risk areas. Even high-risk urban areas may face overlooked vulnerabilities despite public recognition of their risks. These findings align with existing literature and underscore the need for policymakers to prioritize granular analyses within high-risk regions.

Education significantly narrows the IPG since better-educated populations typically have higher incomes (Psacharopoulos and Patrinos 2018). They also might demonstrate greater risk awareness and higher insurance uptake (Atreya, Ferreira, and Michel-Kerjan 2015; Rufat, Robinson, and Botzen 2024). Further, more educated individuals might also have a deeper understanding of financial and insurance literacy. Still, as Lusardi (2019) notes, education does not guarantee financial literacy. The limited literature on disaster insurance literacy suggests an important gap: understanding how various forms of knowledge and experience shape insurance decisions could provide valuable insights for policies aimed at boosting uptake in high-risk areas.

The persistent significance of Baden-Württemberg´s high insurance coverage supports the role of historical mandates and institutional legacies fostering persistent insurance uptake (Andor, Osberghaus, and Simora 2020). Meanwhile, the frequency of flooding and the major flood events, such as those in 2021, underscore the necessity of precise identification of hazard risk zones. The strong alignment of IPG reductions with the GDV's hazard classifications further highlights the importance of accessible and transparent risk information.

Finally, the absence of a clear relationship between income inequality and the IPG may reflect the limitations of available measures. The S80/S20 ratio is limited to NUTS2 regions, focuses solely on extremes, and does not account for middle-income distributions, potentially overlooking critical nuances in insurance behavior (T. Drezner, Z. Drezner, and Hulliger 2014).

Alternate measures, such as the Gini coefficient, could provide a clearer understanding of the relationship between inequality and IPGs.

Collectively, GDP per capita, urbanization, education, institutional legacies, and hazard data all shape the IPG in distinct yet interrelated ways.

5.4 Tailored Policies Recommendations

This research highlights several measures to close the IPG in high-risk regions, which face increased risks due to limiting or prohibiting construction in these zones is essential, as further development increases flood risks and uninsured damages. Some measures have already been implemented, such as restricting credit for building in flood-prone zones. For instance, Rhineland-Palatinate now uses flood hazard maps to designate non-construction zones in areas impacted by the 2021 floods (Birkmann et al. 2023). Urban planning should prioritize resilience by promoting flood-resistant construction and integrating risk reduction into post-flood reconstruction. Coordinated land-use management offers a promising approach to mitigate flood risk.

Public awareness remains critical. Birkmann et al. (2023) revealed that 80% of households affected by the 2021 floods were unaware of their flood exposure. Targeted educational campaigns in areas could increase awareness of flood risks and the benefits of insurance. While tools such as flood hazard maps improve general risk awareness, they often fail to reach individuals with limited education or language barriers. Tailored guidance for these groups is essential. Policymakers could also consider mandating continuing education for insurance agents selling flood policies, ensuring that consumers receive accurate and informed advice.
This strategy has proven effective in Oregon, USA (Kousky and Netusil 2023).

Mandatory flood insurance could also help narrow the IPG. While nationwide mandates may face resistance in Germany, temporary requirements in specific high-risk regions could normalize insurance adoption and promote long-term coverage. For example, homeowners with house loans in high-risk areas could be required to secure flood insurance, mirroring practices in the United States. Such measures would enhance immediate recovery efforts while improving long-term financial preparedness against future risks.

Greater data granularity and standardized risk classifications are essential for developing targeted policy interventions in at-risk regions. Coupled with tailored education and regulations, these efforts can enhance IPG and boost resilience in flood-prone areas areas.

6. Limitations

This thesis outlines several limitations to consider when interpreting the findings. First, it relies on cross-sectional data, capturing only a single point in time. While efficient, such data cannot establish causality or account for temporal changes, limiting the analysis of dynamic shifts in the IPG and long-term effects of contributing factors (Wang and Cheng 2020).

Second, the focus on German high-risk NUTS 3 regions with a small sample size (92 observations and ten variables) restricts generalization. However, because the risks are often location-specific, these results can still be useful for informing better public policy decision-making. Further, regression modeling under these conditions can risk overfitting, as at least ten observations per variable are recommended. Additionally, the definition of high-risk regions might have to be adjusted for GDV regions due to the partly low EADS. Further, excluding low- and medium-risk regions limits the ability to assess the IPG across the full spectrum of flood risks.

Third, the EADs from Steinhausen et al. (2022) are modeled estimated based on assumptions that may not fully capture recent land-use changes or atypical flood patterns. While robust on average, these figures might underestimate damages from rare, high-impact events like the 2021 floods.

Fourth, although flooding dominates extended hazard insurance uptake in high-risk regions, other hazards, such as heavy rain or landslides, may also influence decisions. This complicates efforts to isolate the impact of floods. Moreover, district-level insurance penetration data cannot capture within-district variability, such as differences between urban and rural areas or among socio-economic groups, which likely affect the IPG.

Fifth, the cross-sectional design introduces endogeneity issues, including reverse causality and omitted variable bias. These challenges are compounded by the lack of data on insurance premiums and detailed hazard classifications, such as ZÜRS Geo zones, which strongly influence premiums and flood exposure. Furthermore, cultural attitudes, regional policies, and expectations of government assistance ("charity hazard") likely shape insurance behavior and flood risk, adding complexity and potential bias to the findings.

Lastly, using a regional price proxy index to control for housing market conditions may introduce measurement bias. The index, based on hedonic regression of advertised housing prices, does not capture final transaction prices and may fail to reflect latent flood risks. However, as noted before, it is not confirmed that latent flood risk is priced in housing prices. While real flood events, such as the 2021 disaster, caused temporary price shifts, evidence suggests that housing markets in affected regions recovered quickly, and flood risk in regions unaffected by inherent flooding remains largely unpriced (aus dem Moore et al. 2022). More research is needed to understand how housing prices reflect risks. For instance, research in the US provides helpful guidelines. Contributions like Varela (2023) reveal that white buyers with higher income are buying homes in high-income neighborhoods impacted by flooding, which balances out initial price declines. Meanwhile, Blackwell, Mothorpe, and Wright (2024) discovered that raising houses does not impact property values.

Despite these limitations, this study provides valuable insights into the determinants of the IPG in high-risk regions. Future research could enhance robustness and generalizability by incorporating more granular data at the local level and for risk classifications. This would expand geographic coverage and allow for the adoption of longitudinal designs. However, this is beyond the scope of this paper and should be left to future research.

7. Conclusions

Flooding is one of the most devastating natural disasters in the European Union, with fluvial flooding posing significant risks in flood-prone regions. This study investigates how socio-economic factors, such as GDP per capita, urbanization, and income inequality, shape the residential fluvial IPG in German high-risk NUTS 3 districts. By controlling for housing price indices and flood exposure, including flood characteristics, the findings highlight persistent IPG dynamics, even in economically active areas, and emphasize the urgent need for targeted interventions. The IPG is more than a statistical metric; it reflects structural inequities and the tangible consequences of insufficient adaptation to climate hazards, measured in financial and human losses. Communities facing increasing climate risks require thoughtful policies to address rising inequality and declining insurance penetration, which some studies warn may reach a socio-economic tipping point (Tesselaar et al. 2020). However, this trajectory can be reversed with effective interventions, several of which are discussed in this paper. This thesis contributes to the limited literature on the residential flood IPG and provides a foundation for addressing its disparities. Nonetheless, much work remains. Future research should prioritize longitudinal analyses, integrate more granular hazard classifications, and explore innovative approaches to balance affordability with comprehensive coverage. As climate risks intensify, closing the protection gap is essential for mitigating losses and fostering security and equity. While the challenges are substantial, the opportunity to protect and empower communities is equally significant.

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9. Appendix

Figure 2: *Distribution of EADs in 2022*

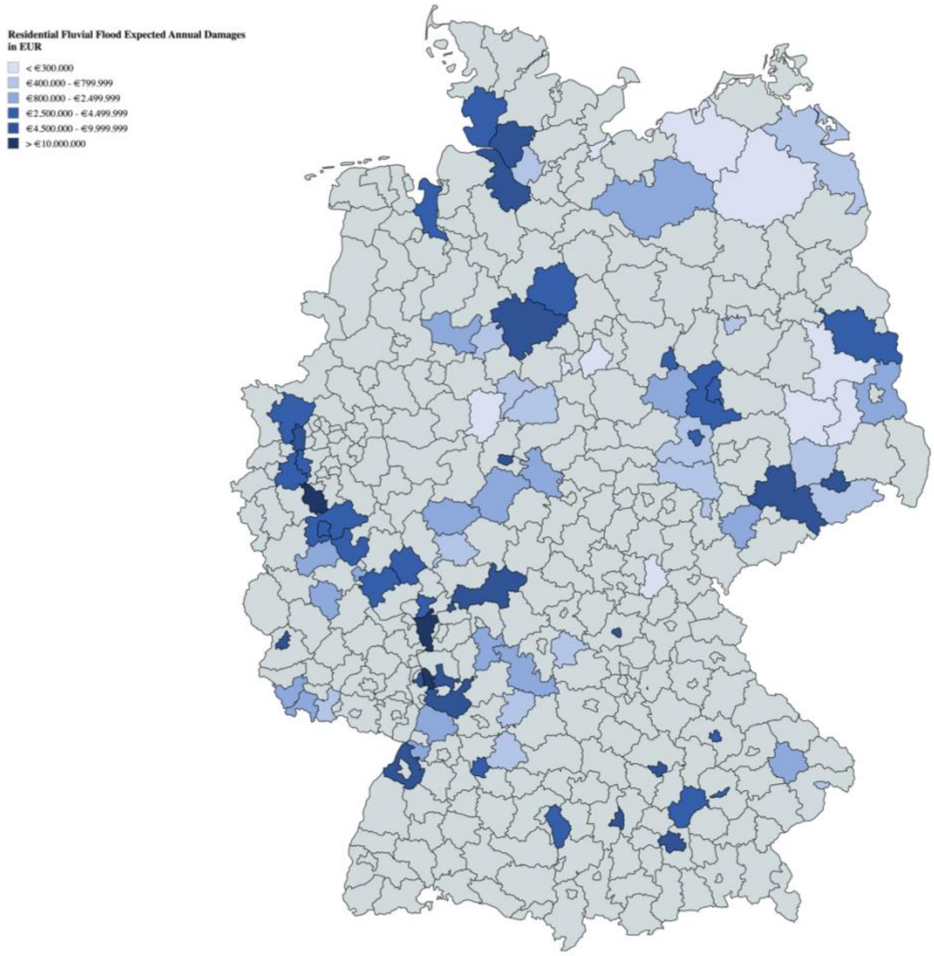

Figure 2. Created with MapChart, https://www.mapchart.net

Table 2: *Variables and descriptive statistics used in the analysis in 2022 divided by the GDV (2024a) and Steinhausen et al. (2022)*

Variable	Obs	Mean	Std. Dev.	Min	Max
		GDV			
Adj_EAD	58	1488555.5	1788367.4	30411.411	7539325.9
Coverage	58	.482	.158	.28	.95
GDPPC	58	39969.259	12177.463	23830	82085
Urban	58	13.31	10.265	4.4	48.1
EDUC	58	31.833	7.065	18.4	51.1
FloodDummy	58	.017	.131	0	1
PriceIndex	58	-2.516	36.029	-48.41	111.173
FREQ	58	1.186	.422	.543	2.543
BW	58	.086	.283	0	1
Inc_Inequality	58	3.957	.362	3.3	4.8
		Steinhausen			
Adj_EAD	34	4773768.8	2536180.6	2446886.5	12558913
Coverage	34	.528	.153	.3	.95
GDPPC	34	54751.324	24225.372	32082	140365
Urban	34	24.976	15.324	6.7	58.6
EDUC	34	32.291	8.246	17.6	50.7
Flood	34	.088	.288	0	1
PriceIndex	34	61.017	69.708	-30.37	296.677
FREQ	34	1.503	.765	.543	3.243
BW	34	.088	.288	0	1
Inc_Inequality	34	4.506	.518	3.5	5.3

Table 3: *Output of the VIF calculations*

	VIF	1/VIF
PriceIndex	3.397	.294
Urban	2.673	.374
lnGDPPC	2.429	.412
Inc_Inequality	1.809	.553
GDV	1.776	.563
EDUC	1.542	.649
lnFREQ	1.335	.749
Flood	1.23	.813
BW	1.157	.864
Mean VIF	1.928	.

Table 4: *Descriptive Statistics of the IPG 2022 divided by the GDV (2024a) and Steinhausen et al. (2022)*

Variable	Obs	Mean	Std. Dev.	Min	Max
		Total			
IPG	92	1248278.7	1215485.9	18246.847	5400332.7
		GDV			
IPG	58	716428.26	888875.74	18246.847	4333800.1
		Steinhausen			
IPG	34	2155553	1167944.1	149804.57	5400332.7