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Measuring Downside Exposure in Europe's Real Estate Market: A House Price-at-Risk Approach using Quantiles via Moments

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This work project introduces a House Price-at-Risk (HaR) model by applying the Quantiles via Moments approach, developed by Machado and Santos Silva (2019), for the first time. Through quantile regressions, it is demonstrated that models incorporating combinations of the quarterly house price growth, a financial stress indicator, a domestic systematic risk indicator, real personal disposable income, the price-income ratio and residential gross fixed capital formation prove to be reliable predictors of house price developments for one, two and three years ahead. Inserting data for Germany into the optimal models shows substantial downside risk in the German housing market.

Keywords: House Price-at-Risk, Quantile Regression, Quantiles via Moments, Housing Market, Macroprudential Analysis

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I. Introduction

Housing plays a special role in modern economies as it inherits a double role: On the one hand it satisfies a fundamental basic need and therefore is recognized as a human right in many countries. On the other, it serves as a speculative asset and is a common investment object not just for professional and institutional investors but also for individuals seeking to build personal wealth. This dual nature creates both opportunities and challenges in modern economies and calls for strict monitoring.

In line with its function as an investment object, real estate remains a constant economic driver. In recent decades, the real estate sector has contributed significantly to the European Union's (EU) economy, accounting for between 20% to 25% of its GDP. On average, approximately 11% of the EU's gross domestic product (GDP) is linked to residential investment alone (Rodrigues et al. 2022).

The speculative asset function also leads to real estate being an important driver of household wealth. The share of housing wealth in households' total assets in the Euro Area (EA) accounted for 56% in 2020, with significant differences between countries. While the indicator reached more than 75% in Spain ahead of the Great Recession, it remained constant for Germany around the value of 55% (de Bondt et al. 2020). Given its substantial share of household wealth, fluctuations in house prices can trigger wealth effects that influence demand, and, consequently, overall economic growth (Friedman 1957, Modigliani and Brumberg 1954).

Furthermore, housing serves as a collateral and has been identified to be connected to financial crises, which in a second step can spread to the real economy. This so-called financial accelerator works through the interaction between the borrowers' net worth and their borrowing conditions. When house prices decline, the reduced value of real estate weakens the collateral backing loans, increasing default risks. In response, banks tighten credit conditions, which negatively affects consumption and investment. As economic conditions deteriorate, borrower balance sheets worsen further, leading to even more credit tightening and therefore creating a feedback loop (Bernanke, Gertler und Gilchrist 1999).

This phenomenon directly impacts banks and financial institutions, which may hold devalued assets and face increasing non-performing loans. As more borrowers default and asset values decline, the financial sector becomes vulnerable, risking liquidity crises or insolvencies. In fact, two-thirds of the nearly 50 systemic banking crises in recent decades have followed real estate boom-bust cycles, with the 2007–08 global financial crisis serving as a prime example (International Monetary Fund 2019).

In addition, real estate prices have been connected to current account imbalances, where capital inflows increase the price of houses due to their inherent characteristic as a non-tradable good (André 2010). This leaves small open economies vulnerable to reverting capital flows that can in a next step start house price crisis and spread to further sectors in the economy as described before.

In the aftermath of the global financial crisis, a time marked by the sovereign debt crisis, real house prices in the EA saw a decline. This was followed by a rapid increase during the Covid-19 pandemic. Since 2022, house prices in most EA countries have begun to decline again, although they remain elevated compared to pre-pandemic levels. Adrian et al. (2020) identify monetary policy support and increased demand for new housing as the main drivers for the house price rise during the COVID-19 period. He warns that prolonged periods of rapid price growth can fuel expectations of continued price rises, leading to excessive risk-taking and increased market vulnerability.

The recent decline in house prices can be linked to rising interest rates implemented by the European Central Bank (ECB) in response to post-pandemic inflation: Higher interest rates result in reduced demand for new loans, while the ability of households with existing mortgages to manage debt payments is declining. Although house prices in most EA countries continued to decline through 2023, the pace has slowed. Nonetheless, overvaluation estimates remain high, with an EA median overvaluation of 8% as of the second quarter of 2023 (ECB 2023).

Given the economic and social significance of housing, combined with its potential for overvaluation and its role in triggering financial crises, closely monitoring the real estate market and its risks is essential. While traditional research tends to focus on the conditional mean using standard OLS regression analysis, this study adopts a quantile regression (QR) approach, which offers a more nuanced view by examining conditional quantiles. QR, introduced by Koenker and Basset (1978), has become a crucial tool in econometrics, with applications ranging from the study of foreign direct investment (FDI) and economic growth (Grima and Görg 2005, Chunying 2011) to analyses of wealth and income inequality (Mata and Machado 2005, Chernozhukov and Hansen 2004).

Seminal contributions by Adrian et al. (2019) established the use of QRs in a Value-at-Risk (VaR) setting, a tool especially used in finance.[1] Adrian et al.'s so-called Growth-at-Risk (GaR) methodology discovered heterogeneity in the impact of macro-financial variables on GDP growth. Further authors found similar results for different variables such as monetary policy shocks (Beutel et al. 2022), macroprudential policy (Aikman et al. 2019) or foreign financial conditions (Lloyd et al. 2024).

Departing from the GaR framework, further at-Risk models have been introduced. Most importantly for this work project, Adrian et al. (2020) studied the effects of variables such as exuberance measures, financial conditions and credit growth on the quantiles of real house prices for a panel of advanced and a panel of developing economies. They found that the

[1] VaR is a risk management tool used to estimate the maximum potential loss of an investment or portfolio over a certain time span, with a given confidence level. It helps firms assess the level of financial risk they are exposed to and make informed decisions about risk limits. VaR is commonly used by banks and investment firms to ensure that they hold enough capital to cover potential losses.

effects of these variables were stronger in the lower quantiles of house prices, increasing downside risk. Furthermore, it was shown that House Price-at-Risk (HaR) can be used as an indicator for financial crises, supporting earlier theoretical work.

In the following, HaR models with a focus on panel data have been introduced for example by the European Central Bank (2023) and the Deutsche Bundesbank (Hafemann 2023). Models by the Banco de España (Gergely and Rodríguez-Moreno 2022) and the IMF (Alter and Mahoney 2020), instead focus on single entities. These models find the supply of housing, price-income ratios, number of people employed and mortgage rates, among others, to cause the left tail of the distribution of real house prices to shift.

So far, the HaR literature has used an approach introduced by Canay (2011) when it came to estimating coefficients in a panel setting with fixed effects. The approach assumes the individual-specific effects to be constant across quantiles. This undermines the core objective of QRs, which is to allow for varying effects across different quantiles of the outcome distribution, as Santos Silva (2019) points out.[2]

Taking these findings into consideration, this work project will focus on a panel of six European economies to reassess the downside risk of house prices using most recent data. The analysis will contribute to the existing literature by using Machado and Santos Silva's (2019) Quantiles via Moments approach in a panel HaR setting with fixed effects. Furthermore, data will be employed to analyze heterogeneity in the effect of covariates on the dependent variable. Third, historical data will be used to disentangle the strength of explanatory variables in past crises, such as the sovereign debt crisis or the Covid-19 pandemic. Lastly, a robustness test is applied by comparing a traditional single entity QR to previous results.

[2] For further details on the Methodology see section below.

II. Data

Figure 1 illustrates the development of real house prices for the six European economies under analysis, as well as their median, from 1998 Q1 to 2024 Q1.[3] In the period leading up to 2007, house prices showed varying trends across countries. After 2007, during the time of the Great Recession and the European debt crisis, prices decreased in all countries except Germany and France. For instance, house prices in Portugal fell by approximately 30% from 2005 to 2014. Notably, Spain and Italy are the only countries where prices did not return to pre-crisis levels. The median line clearly highlights the turmoil following 2007, the COVID-19 surge in prices, and the post-COVID-19 price drop. While house prices have recently been stable in Spain, they have dropped in Germany, Italy, the Netherlands, and France. Portugal is the only country where prices have been consistently rising since 2014.

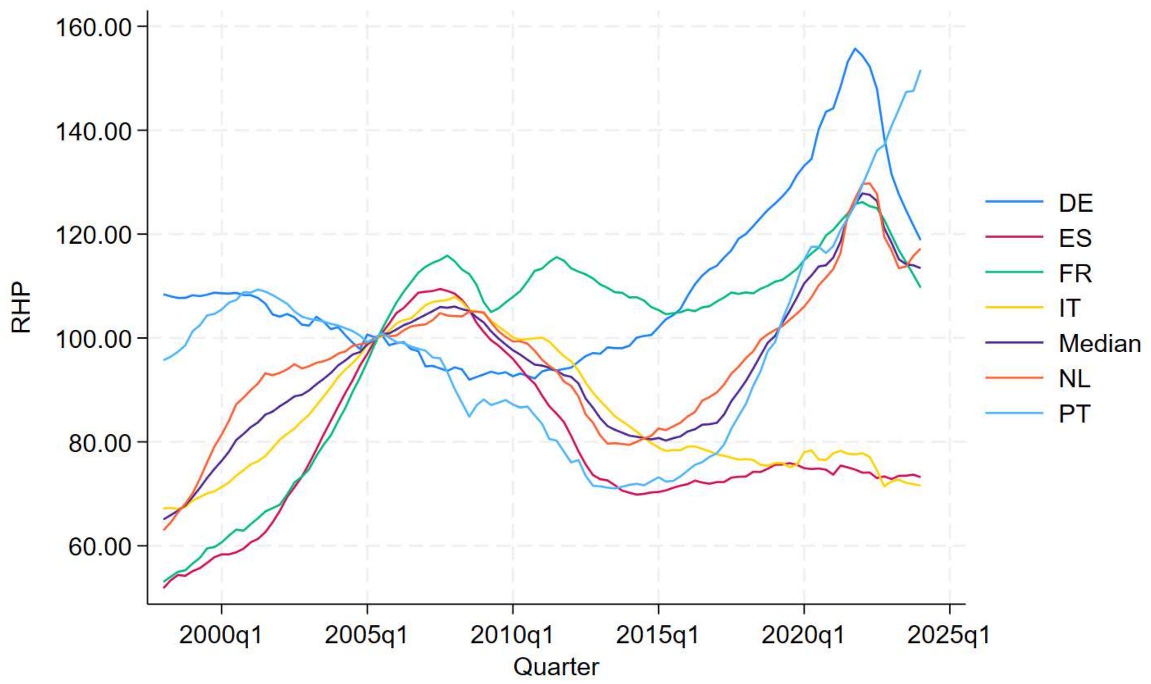

Figure 1: Real House Price Index for Germany (DE), Spain (ES), France (FR), Italy (IT), Netherlands (NL) and Portugal (PT) (Base=2005).

[3] The economies are Germany (DE), Spain (ES), France (FR), Italy (IT), Netherlands (NL) and Portugal (PT). Base year: 2005.

Figure 2 shows the unconditional distribution of yearly real house price changes in the pooled dataset. The data appears to be approximately normally distributed but contains some outliers. The median annual real house price growth is 1.46%, while the unconditional 5th quantile (P5) lies at -8.1%. The 5th quantile is typically used in at-Risk models to measure downside risk within a distribution of possible outcomes.

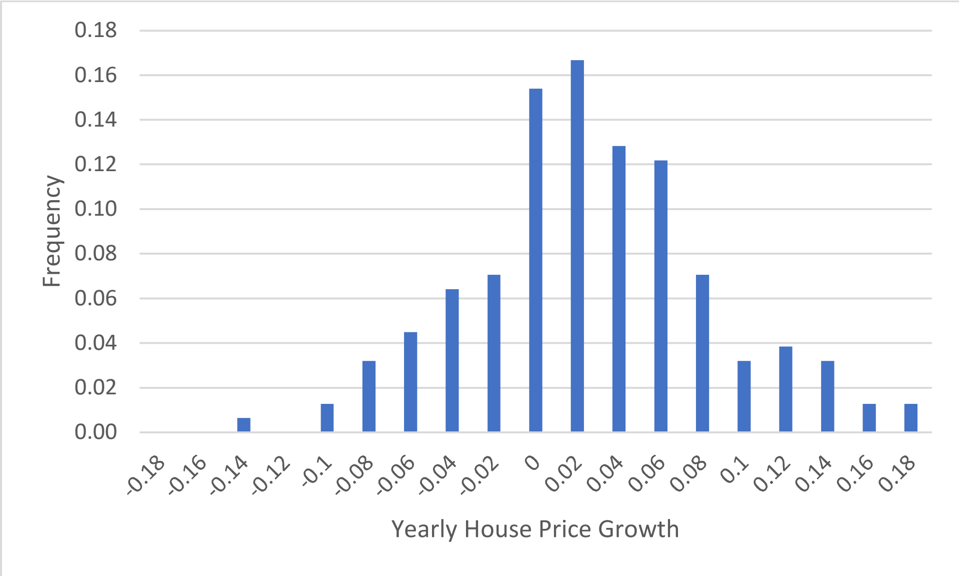

Figure 2: Frequency distribution of yearly real house price growth (pooled data).

House prices are primarily driven by the forces of demand and supply, so this analysis incorporates variables that reflect the dynamics on both sides of the real estate market. On the demand side, real personal disposable income (RPDI) and number of people employed (emp) are included, as they capture households' purchasing power and capacity to invest in property. Additionally, the EMU convergence criterion bond yields (IR) are used as a proxy for mortgage rates, as borrowing costs significantly affect housing demand by influencing loan affordability[4]. On the supply side, gross fixed capital formation for dwellings (GFCF) will serve as a proxy, as it reflects investment in new housing and overall housing stock availability.

[4] Findings of Sirmans et al. (2013) confirm the relationship between mortgage rates and bond yields.

Following the approach of Lang (2023), a country-level index of financial stress (CLIFS) accounting for broader financial conditions that may impact housing markets is also incorporated. To assess financial stability and market risk, two vulnerability indicators are used: household debt as a percentage of GDP (Debt) and Lang's (2019) domestic cyclical systemic risk indicator (d-SRI). The d-SRI includes six metrics related to credit, real estate, financial markets and external imbalances.

To capture broader economic confidence, the economic sentiment indicator (ESI) is used, while the price-income ratio (PI) serves as a crucial measure of housing affordability and potential overvaluation. Together, these variables form a comprehensive framework for understanding the multifaceted drivers of house prices.

Table A1 in Appendix A provides further information about the variables as well as their source. In addition, Figures A1- A5 in Appendix B display the time series of the different variables for the countries under analysis as well as the median time series. Figures A6- A23 in Appendix B depict the relationship between each of the explanatory variables, after accounting for stationarity, and the first difference of the natural logarithm of the quarterly real house price index[5] one year ahead and three years ahead, as well as the 10^{th} (P10), 50^{th} (P50) and 95^{th} (P95) percentile regressions, using pooled quantile regressions.

III. Methodology

Quantiles via Moments approach

This work project will analyze the relationship between real house prices and economic factors, financial stress indicators and vulnerability measures using a panel quantile regression approach.

[5] This is approximately the quarterly change in real house prices.

QRs can be seen as a generalization of the standard OLS method and follow the form,

$$Q_{y_{t+h}}(\tau \mid X_t) = X_t'\beta_{\tau,h}. \tag{1}$$

In this equation, the left side represents the conditional quantile of the dependent variable. y_{t+h} is the change in real house prices h-quarters ahead, and τ is the corresponding quantile. X_t is a vector of explanatory variables (including a constant), and $\beta_{\tau,h}$ denotes the impact on the quantile dependent variable of changes in the covariates.

While OLS attempts to minimize the residual sum of squares, the QR objective function minimizes the weighted sum of absolute residuals, i.e.,

$$\hat{\beta}_{\tau,h} = arg \min_{\beta_{\tau,h}} \sum_{t=1}^{\tau} \rho_\tau\left(y_{t+h} - X_t'\beta_{\tau,h}\right), \tag{2}$$

where ρ_τ is a check function that penalizes the residuals depending on their sign, that is,

$$\rho_\tau(u) = \begin{cases} \tau u, & u \geq 0 \\ (\tau - 1)u, & u < 0 \end{cases}. \tag{3}$$

QR offers several advantages over OLS: i) QR has the monotone equivariance property, meaning that it remains consistent even if the dependent variable undergoes a monotonic transformation. ii) QR does not rely on the homoscedasticity assumption (constant variance of errors), allowing it to model heteroscedasticity naturally, whereas OLS can provide inefficient estimates in the presence of non-constant variance, and iii) QR is insensitive to outliers (Busch et al. 2022).

When it comes to panel QR, the conditional quantiles of the real house price growth distribution at a given horizon will be modelled following Machado and Santos Silva's (2020) Quantiles via Moments approach. It is a robust technique for estimating panel quantile regression models with fixed effects, since it accounts for both location shifts and distributional shifts across quantiles. The conditional quantiles are estimated for a location-scale model and have the following form:

$$Q_{Y_{i,t+h}}(\tau|X_{it}) = \left(\alpha_{ih} + \delta_i q(\tau)\right) + X_{it}'\left(\beta_h + \gamma q(\tau)\right).$$

(4)

Here, $Y_{i,t+h}$ is the first difference of the log of the quarterly real house price index for country i at time t+h. The scalar coefficient $\alpha_{ih}(\tau) \equiv \alpha_{ih} + \delta_i q(\tau)$ is the individual-specific intercept (fixed effect), which varies by quantile and therefore can be called the distributional effect at τ. Compared to the common fixed effect in panel QRs, it is not just a location shift[6]. $\left(\beta_h + \gamma q(\tau)\right)$ represents the effect of covariates on the outcome variable, where $\gamma q(\tau)$ captures the scale effect of the quantile. This means that the effect of the covariates on the dependent variable can change with the quantile.

Estimation is performed using two fixed effects regressions and computing a univariate quantile: The algorithm for estimating the quantile regression model with fixed effects begins by de-meaning $Y_{i,t+h}$ and X_{it} to remove individual-specific effects, followed by regressing de-meaned $Y_{i,t+h}$ on X_{it} to obtain $\hat{\beta}_h$, capturing the effect of X_{it} on $Y_{i,t+h}$. The individual fixed effects $\hat{a}_{ih}$ are estimated by averaging the residuals of the previous regression. This is followed by the calculation of the residuals $\hat{R}_{it}$, considering $\hat{\beta}_h$and $\hat{\alpha}_{ih}$:

$$\hat{R}_{it} = Y_{i,t+h} - \hat{a}_{ih} - X_{it}'\,\hat{\beta}_h$$

(5)

The third step regresses the demeaned absolute residuals $|\hat{R}_{it}|$ on demeand X_{it} to estimate $\hat{\gamma}$, which represents how X affects the outcome variable depending on the quantile. Then, $\hat{\delta}_i$ is computed by averaging the difference between absolute residuals and the scale factor $X_{it}'\,\hat{\gamma}$. Finally, the quantile-specific function $q(\tau)$ is estimated by solving a minimization problem using the check function $\rho(\tau)$ yielding the quantile-specific distributional effect q,

[6] For comparison, see Canay (2011).

completing the model. While the estimator is biased for fixed T, simulation results indicate that this bias is negligible when n/T<10 (Machado und Santos Silva 2019).[7]

Forecast evaluation

To identify key drivers of House price-at-Risk, the out-of-sample predictive power of independent variables as well as combinations of the best performers is evaluated. For comparison, the tick loss is applied as an indicator for model fit, a tool commonly used in at-Risk models (Lang et al. 2023, Brownless and Souza 2021, Carriero et al. 2021). First, the panel is balanced, only keeping data after 1997 Q4. In the next step baseline panel quantile regression models with fixed effects are estimated, applying the Quantiles via Moments approach. The forecast horizons are set at 4, 8, and 12 quarters ahead, using the correspondingly lagged values of the first difference of the log of the real house prices index (RHP) as predictors. These models are estimated at the 5th percentile (τ =0.05) to capture downside risk. The forecasts are generated recursively, starting from 2008 Q1 through 2023 Q1.[8] For each iteration, the model was re-estimated by adding one additional quarter of data, ensuring that the forecasts were always based on the most recent information. The predicted values are then compared to the realized values of RHP to compute residuals. Subsequently, the out-of-sample tick loss is calculated, i.e.,

$$TL_{h,\tau} = \left(\tau - 1\left(\widehat{\epsilon_{h,\tau}} < 0\right)\right) \widehat{\epsilon_{h,\tau}}, \tag{6}$$

where $1(.)$ denotes the indicator function, and $\widehat{\epsilon_{h,\tau}}$ represents the forecast error between the quantile regression model forecast h-periods ahead and the realized value. In the case of τ = 0.05, the tick loss function penalizes under-predictions less than over-predictions. The

[7] This is known as the incidental parameter problem: There exists no transformation that gets rid of the incidental parameters. This work project uses T>96 and n=6 and therefore can neglect the bias.
[8] For h=8 and h=12 the last period is 2022 Q1 and 2021 Q1, respectively.

tick loss is averaged across the recursive forecasts to assess model performance. Lower values indicate better model performance.

In the following, the lagged RHP is combined with lagged variables of the variable list, one at the time. Again, panel quantile regressions with fixed effects are estimated for the horizons under analysis, recursively using most recent information. For each model the tick loss is calculated and averaged over the available data. Moreover, the tick loss improvement is calculated as the main indicator for model selection, i.e. the percentage improvement in average tick loss of the combined model compared to the baseline model with the same forecast horizon. The best performing single variables for each forecast horizon are further combined and tick loss improvements are calculated for these combinations to find the best performing model including RHP and two variables from the variable list.

After choosing the best models for the three different forecast horizons ranging from 4-12 quarters ahead, the results of the quantile regressions will be analyzed. In a first step the estimated coefficients of the optimal factors will be projected for different quantiles to detect heterogeneity.

Moreover, this work project will disentangle the effects of the best performers on P5 of RHP over time and place a special focus on the most recent forecasts for RHP 1, 2, and 3 years ahead. In addition, forecasts are summarized for different percentiles and horizons for overview purposes.

Covering percentiles from 1 to 99, a probability distribution function (pdf) is created for the predictions using data from the first quarter of 2024 with a forecast horizon of one year. To account for the asymmetry in the data, a skew-normal distribution is used to fit the predictions.

The skew-normal distribution, established by Azzalini (1985), provides a way to model asymmetric data while maintaining many properties of the normal distribution. It is defined by the following expression:

$$f(y; \lambda, \delta, \alpha) = \frac{2\theta(z)\Phi(\alpha z)}{\delta}, \quad y \in \mathbb{R}, \qquad \alpha, \lambda \in R, \qquad and\ \delta \in \mathbb{R}^+, \tag{7}$$

with $z = \frac{y-\lambda}{\delta}$, θ denoting the pdf, and Φ the cumulative distribution function. Lastly, a robustness test will be employed by calculating a single entity quantile regression and comparing the results.

IV. Results

Model selection

Table 1 reports the results for the average tick loss of the three baseline models for forecast horizons h= 4, 8, and 12. The autoregressive model using RHP with 4 lags performs best. As the forecast horizon increases to 8 and 12 quarters, the forecast accuracy decreases. This matches the expectation about economic forecasting models that uncertainty increases with longer-term predictions. Overall, the tick loss values are small, indicating good baseline model performance for all time horizons when it comes to forecasting downside risk of RHP. As stated before, under-predictions are penalized less than over-predictions. The low average values of the average tick loss suggest that the baseline models' forecast of the 5th percentile of RHP mostly underestimate the realized quarterly house price growth.

Table 1: Average tick loss for baseline models (regressing RHP on lagged values of itself).

Horizon (h)	Average Tick Loss
4	0.0054
8	0.0059
12	0.0061

A total of 39 unique models were estimated to find the best performing model for each forecast horizon. Table 2 shows the performance of the indicators that were added to the baseline model. The single indicators CLIFS, d-SRI, and Debt are improving the performance of the baseline model with a forecast horizon of 4 quarters, while PI's performance is just marginally worse. From combining the baseline model with pairs of two, the tick loss improvement suggests that the best model for h=4 is a model composed of RHP, CLIFS and d-SRI. This model improves the tick loss by 4.78%. Past price growth (RHP) inherently reflects the overall shifts in the housing market, implicitly capturing the effects of numerous variables, including mortgage rates, which, albeit relevant, are not directly included in the model as variables. Additionally, as previously mentioned, housing represents a substantial part of household wealth. Consequently, an increase in housing prices increases household wealth, potentially influencing the demand for similar assets. Financial stress (CLIFS) influences the availability of loans and therefore can alter the demand for real estate, especially in the short term. Since the number of non-performing loans increases in times of financial stress, it might also affect the supply of real estate. This is especially true during times of fire sales. Furthermore, the buildup of systematic risk (d-SRI) can change house prices with a time lag by influencing demand in a similar fashion.

When it comes to h=8 only adding GFCF, or RPDI improves the tick loss of the baseline model, while the performance of PI is only marginally worse again. GFCF outperforms the other indicators by far, improving the tick loss by 29.99% compared to the baseline. A combination of RHP, GFCF and RPDI as well as RHP, GFCF and PI improves the tick loss by 31.92% and 31.57%, respectively. Therefore, a model that is composed of RHP, GFCF and RPDI is the best performer for h=8. Since it takes time until investment in real estate (GFCF) materializes, it makes sense that GFCF only enters the optimal model for the horizon of two years ahead. RPDI entering the optimal model with h=8 might be explained by time lags in decision making of households. Furthermore, frictions when searching for a house to buy and searching for a fitting financing solution might explain the time lag of RPDI.

In the case of h=12, GFCF, Debt and PI can increase the forecast accuracy for the 5th percentile of RHP, when added to the baseline model. RPDI's performance comes very close to the one of the baseline, and therefore it will be considered as well. Combining the baseline model with the best single performer GFCF and either Debt, PI or RPDI, the model including RHP, GFCF and PI turns out to be the best performer with a tick loss improvement of 2.13%. The price-income ratio (PI) inherits information about possible overvaluation. Overvaluations are usually followed by substantial price declines, and therefore connected to the P5 of house prices. The time lag of three years seems reasonable.

Table 2: Tick loss improvement in % after adding variables to baseline models.

Variable (+RHP)	Tick loss improvement (%) h=4	Tick loss improvement (%) h=8	Tick loss improvement (%) h=12
CLIFS	1.59	-5.96	-43.07
GFCF	-191.40	29.99	2.08
ESI	-100.03	-648.52	-2150.50
dSRI	1.61	-1.41	-7.15
IR	-2.22	-6.04	-4.33
Debt	1.24	-1.02	1.72
emp	-1.64	-1.67	-1.64
PI	-0.75	-0.93	0.28
RPDI	-1.30	0.16	-0.73
CLIFS +dSRI	4.78		
CLIFS + Debt	2.32		
CLIFS + PI	1.69		
Debt + dSRI	1.12		
Debt + PI	0.47		0.62
PI + dSRI	1.51		
GFCF +PI		31.57	2.13
GFCF + RPDI		31.92	0.23
GFCF + Debt			-12.20

In conclusion the best model for h=4 is composed of RHP, CLIFS and d_SRI, and the best models for h=8 and h=12 are RHP, GFCF and RPDI and RHP, GFCF and PI, respectively.

Predictions

After finding the three best models for the different forecast horizons, this work project will now focus on the predictions for tail risk in the short and medium run. Figure 3 reports the covariates' betas for different conditional quantiles of RHP, as well as 95% confidence intervals for the optimal model with h=4. Interestingly, CLIFS inherits some heterogeneity along the quantiles of RHP, while dSRI does not. The effect of CLIFS on low quantiles of RHP one year ahead is negative but it turns positive for upper quantiles: If price growth is already low, an increase in financial stress decreases house prices while financial stress increases house prices if they are already showing high growth rates. Therefore, financial stress can act as a crisis accelerator in a housing market that is already under pressure. To address financial stress, policymakers have a wide toolkit at their disposal, ranging from classical monetary policy and fiscal stimulus to macroprudential measures such as countercyclical capital buffers for banks. A possible explanation for the homogeneity of dSRI and RHP could be data availability. Furthermore, only the betas for RHP are statistically significant at the 95% confidence level.

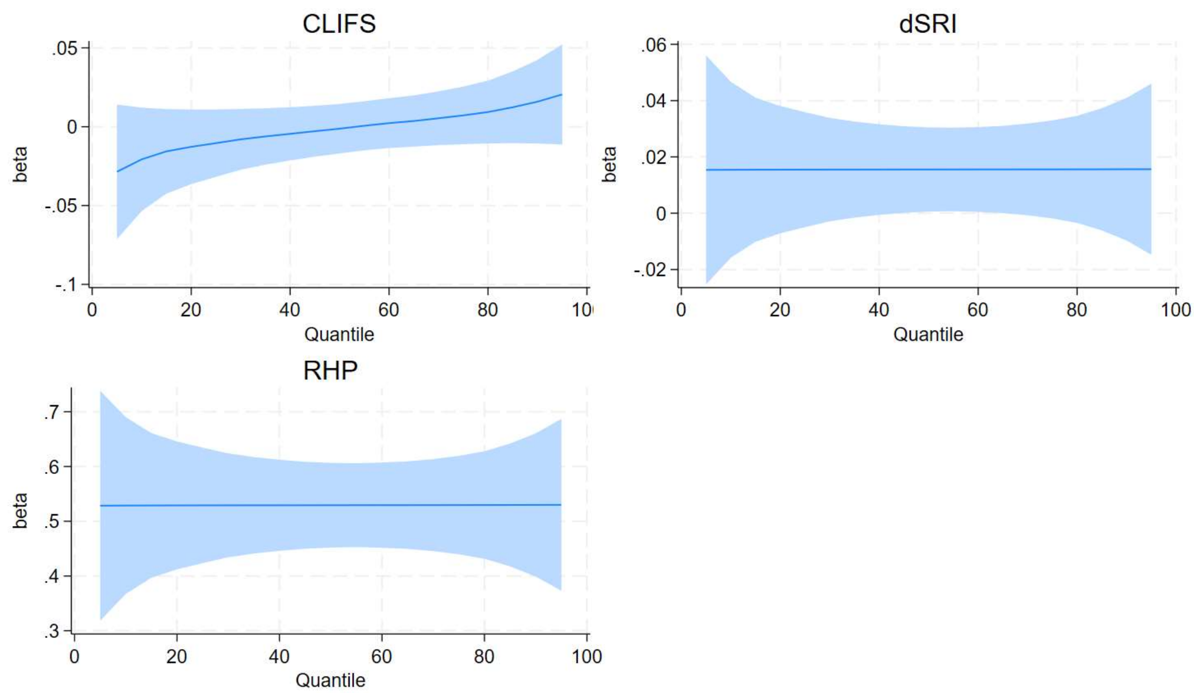

Figure 3: Betas for covariates depending on quantile for model with h=4.

Analyzing the betas for the medium run model (h=8) the picture looks different: All three coefficients of the explanatory variables show some level of heterogeneity across quantiles of house price growth, as depicted in Figure 4. For example, current RHP impacts lower quantiles of RHP two years ahead to a lower extent than it influences upper quantiles. Furthermore, just the coefficient of RPDI is not statistically significant. The significance of GFCF goes hand in hand with the previously analyzed tick loss improvement. For h=8, GFCF is outperforming all other single covariates by 29 percentage points.

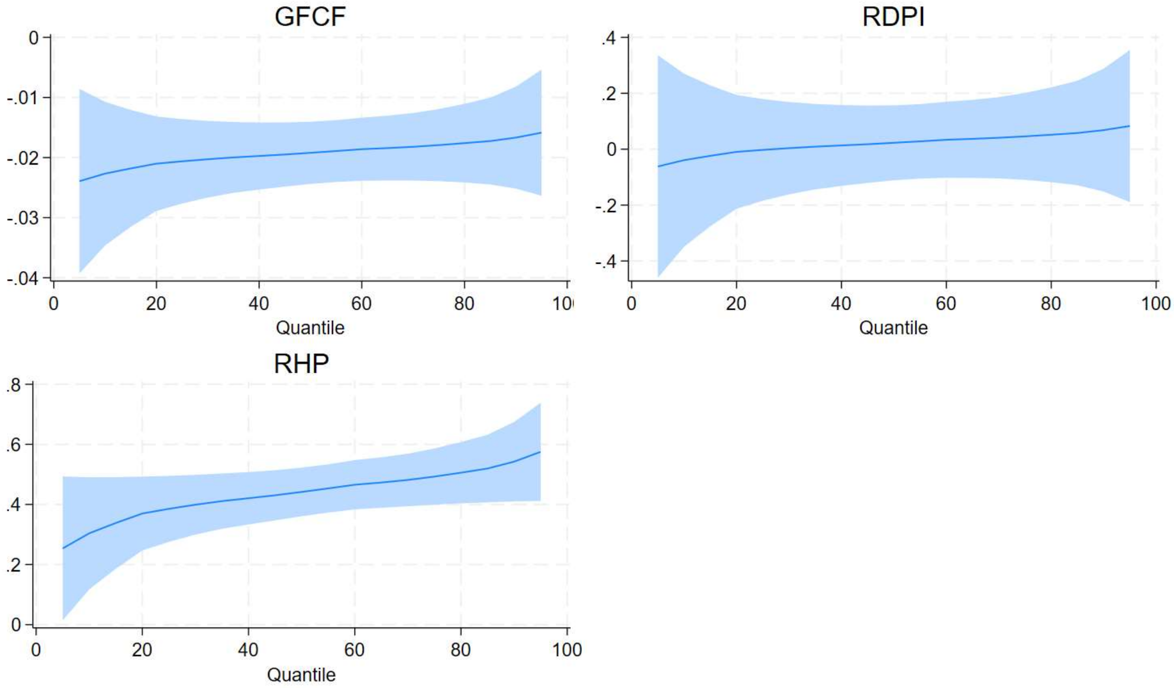

Figure 4: Betas for covariates depending on quantile for model with h=8.

The results for investment in real estate in the medium term support the theory that it takes time until investment influences house prices. Furthermore, an increase in housing supply decreases house prices, especially if prices are already low. These findings have important implications for economic policy. The negative relationship between GFCF and future house price growth could be due to overbuilding or excess supply in the housing market, leading to downward pressure on prices. Policymakers need to consider the lagged effects of investment in the housing market and the potential for supply-demand imbalances. By monitoring GFCF levels, regulators can assess the risk of future price corrections and implement policies to mitigate overinvestment, such as adjusting land-use regulations or providing guidance on lending practices for real estate development. A similar plot for the optimal factors for h=12 can be found in Appendix B (see Figure A24).

Historic Decomposition

In the next step this work project turns towards the decomposition of the predicted HaR. Figure 5 unravels the influence of the optimal factors for the best performing model with a forecast horizon of h=4, applied to Germany. For the period after 1997 Q4, CLIFS and RHP play the most prominent role for the predicted P5 of house price growth. For example, the escalation of house price risk during and after the financial crisis 2008/ 2009 was mainly influenced by worsening financial conditions (CLIFS). The prominent role of financial conditions during the financial crisis indicates spillover effects, and therefore suggests allowing for preemptive measures such as tightening lending standards. Interestingly, after 2015, the predicted 5th percentile of quarterly house price growth was above zero until 2022 Q1 and therefore mainly explained by past house price growth (RHP). As mentioned above, past RHP already inherits certain information and influences household wealth.

The period from 2022 Q1 until the most recent forecast in 2024 Q1 shows an escalation in house price risk that is unprecedented in the sample. The main contributor is past real house price growth, but also financial conditions and overall market risk can explain the development. More recently HaR at h=4 has eased in Germany but still stays elevated.

The recent escalation in house price risk suggests that vigilance is needed to prevent potential negative outcomes when it comes to the real estate market, which could have broader macroeconomic implications. This is especially relevant, since Germany is already experiencing a period of economic stagnation (Boysen-Hogrefe et al. 2024). By closely monitoring the contributing factors identified in the model, policymakers can design targeted interventions to stabilize the housing market and safeguard economic growth.

Figure 5: Effects of optimal factors for HaR in Germany with h=4.

Again, the work project switches to the medium term and analyzes the historical decomposition of the optimal factors for h=8, which is portrayed in Figure 6. The whole period after 1997 Q4 is dominated by the development of GFCF, while RHP plays a minor role and RPDI is almost nonexistent. This underscores the importance of investment dynamics in the housing market over longer horizons. Furthermore, HaR at P5 does not seem to be varying a lot. These findings point towards poor model performance which contradicts previous findings regarding the tick loss and significance of GFCF. The apparent poor model performance and limited variation in HaR suggest that additional factors may need to be considered for medium-term forecasts. This highlights the need for continuous refinement of risk monitoring tools to ensure they capture the relevant dynamics affecting the housing market. A similar figure for h=12 can be found in Appendix B (see Figure A25).

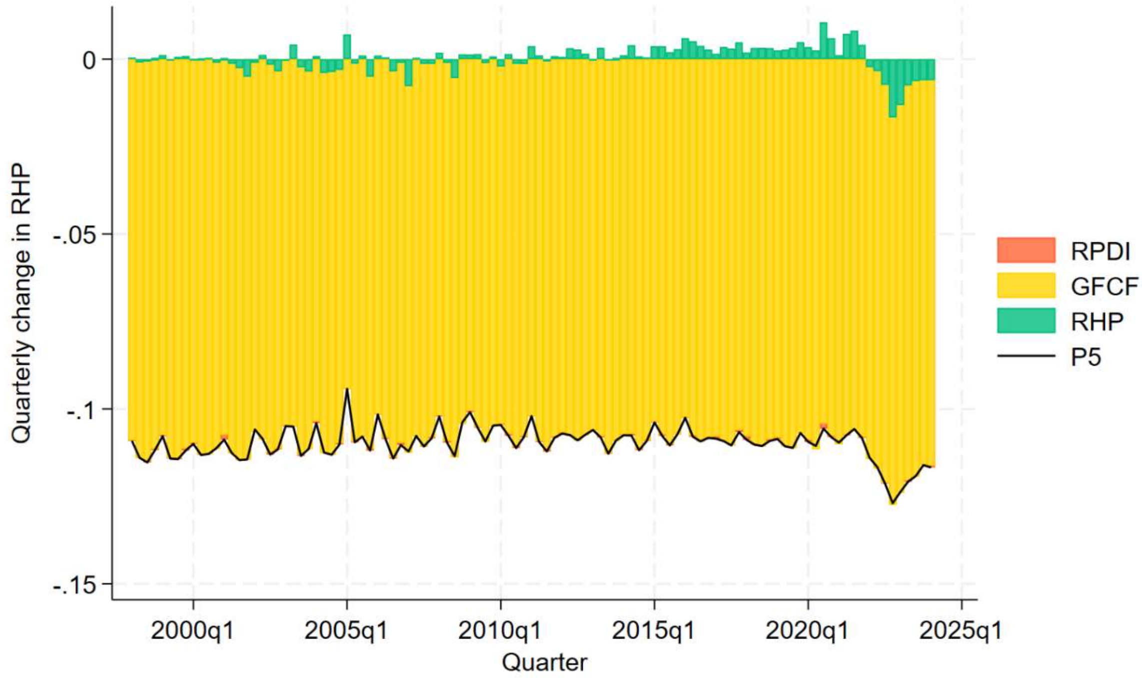

Figure 6: Effects of optimal factors for HaR in Germany with h=8.

Probability Density Function

The analysis will now focus on the probability density function of the forecasts using the most recent data. Figure 7 depicts the probability density function for Germany with a forecast horizon h=4, using data from 2024 Q1. The conditional 5th percentile lies at -1.44% quarterly real house price growth and the conditional median lies at -1.36%. Annualizing these values, using the simple approximation of

$$yearly\ growth\ = 4\ \times\ quarterly\ growth, \tag{8}$$

helps to compare the conditional to the unconditional distribution. The conditional 5th percentile of yearly real house price growth in Germany lies at -5.76%, while the conditional median lies at -5.44%. This compares to an unconditional P5 of -8.1% and median of 1.46% for the whole panel. One should keep in mind that model selection was solely based on the tail risk of RHP and therefore forecasts for the median could possibly be enhanced by applying an alternative model. Still, these findings underline the current pressure on the German real estate market. For policymakers, this serves as a critical warning sign of potential stress in the housing market, which could have adverse effects on household wealth, consumption, and financial sector stability.

Figure 7 also unravels how the optimal factors contribute to the current outlook. Lagged real house price growth plays the most prominent role when determining HaR 4 quarters ahead, while CLIFS and dSRI contribute similar, but smaller shares. Once again, one needs to consider that current RHP already inhibits various factors that influence house prices. Similar figures for h=8 and h=12 can be found in Appendix B (see Figure A26 and Figure A27) .

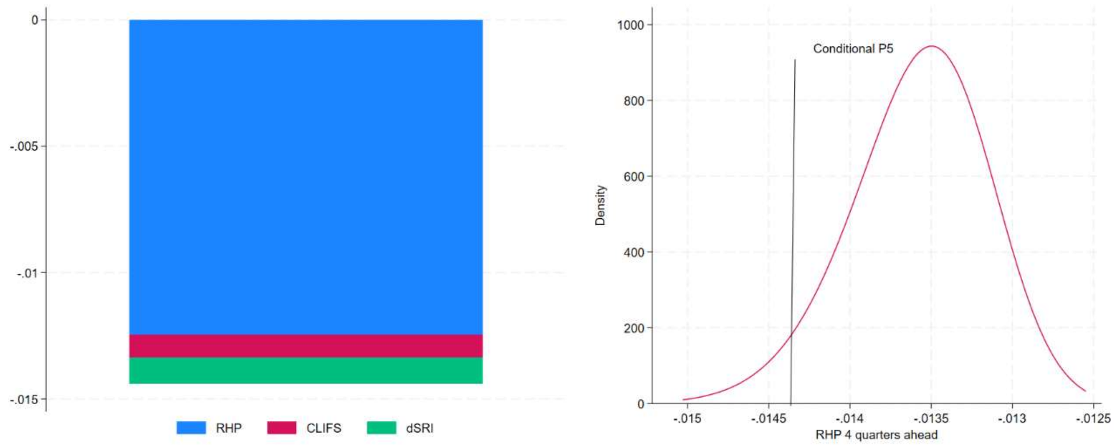

Figure 7: Decomposition and pdf for DE with h=4 using data Q1 2024.

For a better overview of the forecast for Germany, Figure 8 depicts the predictions for all three forecast horizons as well as the 5^{th}, 50^{th} and 95^{th} percentile. It becomes evident that predictions look unfavorable across all percentiles and periods. Interestingly the forecast becomes more negative with the forecast horizon. While the values of P5, P50, and P95 are close when it comes to the 1 year ahead forecast, the spreads opens further with increasing forecast horizons. The widening spread in the forecasted percentiles over longer horizons indicates increasing uncertainty and potential volatility in the housing market.

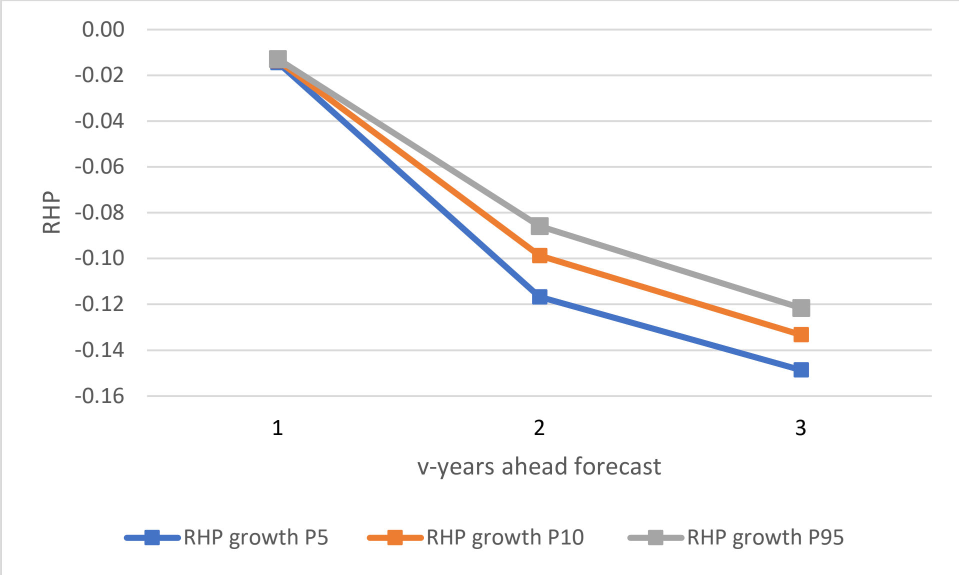

Figure 8: v-years ahead forecast for Germany.

V. Robustness

While Machado and Santos Silva's approach allows for country-specific fixed effects to vary by quantile, these fixed effects remain time-invariant. Already by filtering out the fixed effects, some information that could contribute to predicting future house prices is inevitably lost. Moreover, if the fixed effects do change over time, these changes will influence the coefficients and bias them. A relevant example includes institutional shifts within the economies studied, such as those brought on by deepening European integration.

To address this limitation, this work project employs a second model: a traditional single entity quantile regression applied to Germany, using the optimal factors from the panel model with h=4. To employ as much data as available, the model uses data from 1983 Q1 to 2023 Q1. Here, the quarterly conditional P5 is -2.16%, translating to an annual conditional P5 of -8.64%. This value is approximately 3 percentage points below the conditional P5 of the fixed effects model and 0.5 percentage points below the unconditional quantile of the panel dataset. For Germany alone, the unconditional P5 based on post-1983 Q1 data stands at -4.98%. This robustness test confirms that risk in the German housing market remains high. Potential losses could be even higher than forecasted by the model using panel data. Figure A28 in Appendix

B reports the decomposition and pdf for the single entity model employing data from Q1 2024. Besides the constant, d-SRI and current RHP play the most prominent role for current risk buildup.

VI. Conclusion

Due to its dual nature as a basic need and an investment object, housing calls for strict monitoring. Furthermore, real estate is an important driver of household wealth and serves as a collateral for loans. Wealth effects can alter output via demand and depressed collateral values can trigger financial crisis. By closely monitoring and accurately forecasting house prices, the build-up of risk can be detected early on, and policies can be implemented to mitigate such risks.

Utilizing a panel approach, such as the one developed by Machado and Santos Silva (2019), enables the use of more data points compared to traditional quantile regression, which often focuses on a single entity. Especially when analyzing downside risk, which usually focuses on the 5th percentile, the availability of data can be a serious challenge. In the case of P5 only 5% of data points for house prices are used in the calculation of the coefficients. Given that macro time-series in certain countries are only available from the 1990s onwards, this data limitation can hinder accurate forecasting. In fact, research by Lang et al. (2023) suggests that the out-of-sample predictive power can be improved by using panel data compared to a model using only data from a single entity.

So far authors have used the approach by Canay (2011) when estimating at-Risk models with panel data. Nevertheless, the approach developed by Machado and Santos Silva (2019) offers one significant advantage over Canay's method: While Canay assumes fixed effects to be the same for every quantile, Machado and Santos Silva's algorithm allows the fixed effects to vary with the quantile.

Still, this panel approach does not come without limitations. While it allows the covariate coefficients and fixed effects to vary with the quantiles, it assumes that the country fixed effects are time-invariant. This assumption may not hold for the six European economies examined, which likely experienced some integration from 1998 to 2024. It is very likely that the development towards greater integration has changed the institutional setting for some of the countries. Furthermore, events like the Spanish real estate crisis between 2008 and 2014 triggered policy changes and therefore might have changed the institutional landscape even further. Since country fixed effects are asumed to reflect institutional settings, presuming stability in these fixed effects despite changing institutional contexts could bias covariate coefficients.

Further complications arise from exogenous factors. Real estate markets in countries like Portugal and Spain are more heavily influenced by tourism and foreign investment than others, yet a panel model typically includes only the best common explanatory factors. This may omit country-specific variables that could improve predictions of the dependent variable in certain nations.

Considering all factors mentioned, it becomes clear that a panel model for assessing downside risk across six European economies can meaningfully extend risk assessment beyond single-entity models. In cases where data availability is limited, especially for smaller EA economies, a panel approach can offer valuable insights for quantifying downside risk. However, caution is necessary when interpreting the results, as potential pitfalls could influence the reliability of such assessments.

In this work project, data from six European economies was analyzed to evaluate downside risk in the German real estate market over the short and medium term. The findings reveal significant vulnerabilities in Germany's housing market. These results were also supported by a model based solely on German data, which, in fact, indicated an even lower 1 year ahead

P5 forecast. Coupled with Germany's economy already facing recession, these results signal a need for close monitoring and possible policy intervention. Regulatory and macroprudential policies to mitigate further build-up of risk could include tightening loan-to-value-ratios, debt-to-income limits, or the implementation of countercyclical capital buffers for banks. Additional measures could include interest rate adjustments, mandatory risk diversification policies for banks, and adjustments in the field of taxation. Furthermore, in case of the model forecasting RHP 2-years-ahead, where investment in real estate plays a major role, policies could aim at mitigating overinvestment. Possible measures include adjusting land-use regulations or providing guidance on lending practices for real estate development.

Lastly, the models used in this work project only included variables with uniform lag lengths. Although the inclusion of lags improves model accuracy, future research could enhance this approach by allowing variables to enter the model with different lags.

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VIII. Appendix A: Additional Tables

Table A1: Variables and Sources.

Variable	Source
Composite Leading Indicators of Financial Stress (CLIFS)	ECB
Household Debt to GDP (Debt)	Bank for International Settlements
Domestic Systematic Risk Indicator (d-SRI)	Jan-Pieter Lang, ECB
EMU convergence criterion bond yields	Eurostat
Economic Sentiment Indicator (ESI)	Eurostat
GFCF-Dwellings (GFCF)	Eurostat
People Employed (emp)	ECB
Price to Income ratio (PI)	OECD
Real Personal Disposable Income (RPDI)	Dallas FED
Real House Price (RHP)	Dallas FED

IX. Appendix B: Additional Figures

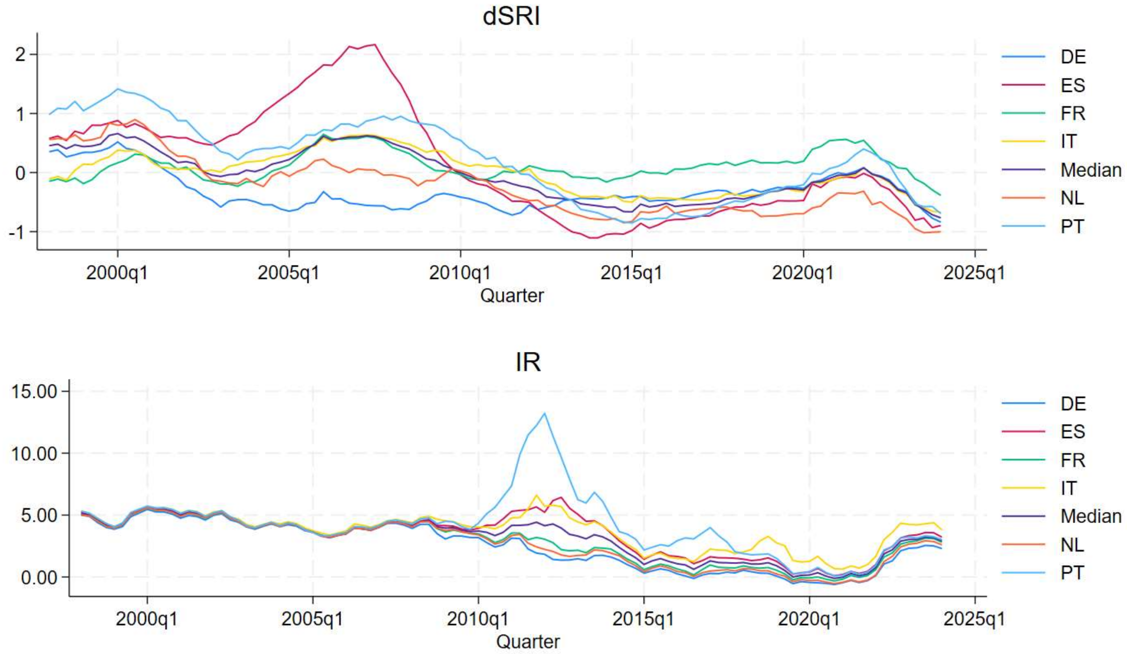

Figure A1: Domestic Systematic Risk Indicator (d-SRI) and Interest Rates (IR) time series.

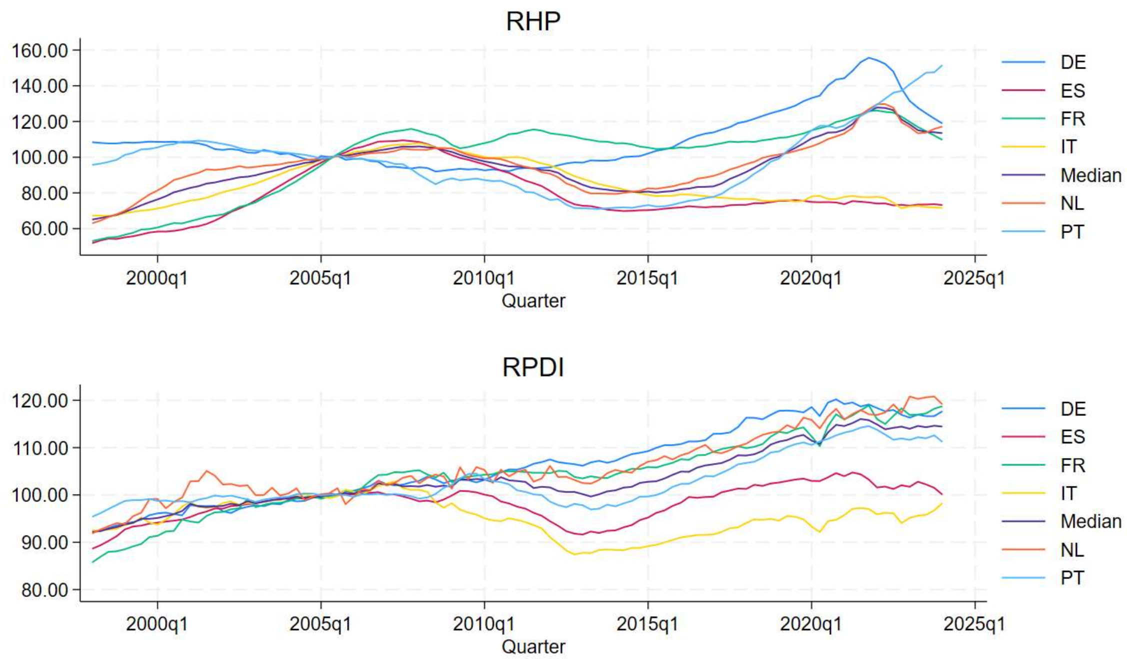

Figure A2: Real House Price (Base=2005) (RHP) and Real Personal Disposable Income (Base=2005) (RPDI) time series.

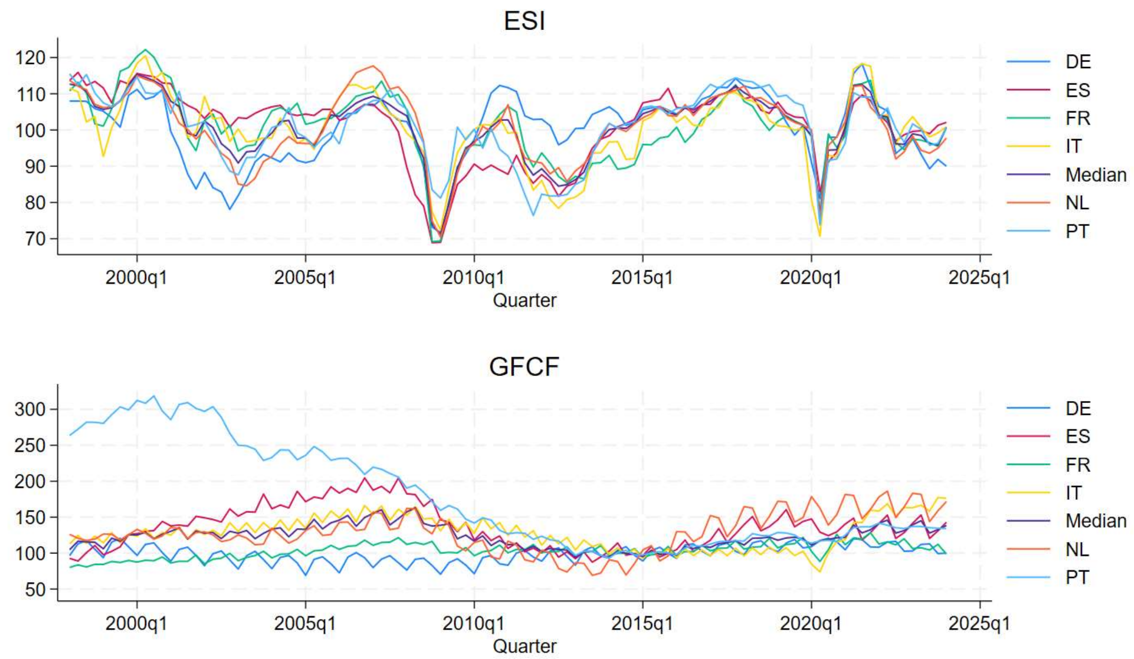

Figure A3: Economic Sentiment Indicator (ESI) and Gross Fixed Capital Formation in Dwellings (GFCF) time series.

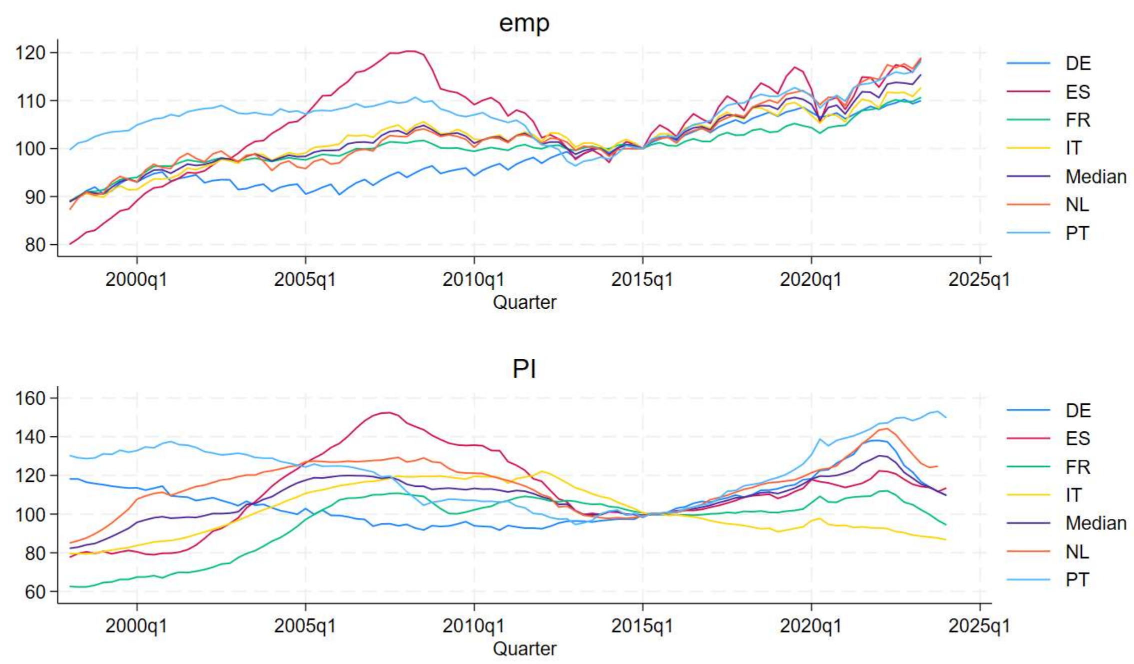

Figure A4: People Employed Index (Base= 2015) (emp) and Price to Income ratio (Base=2015) (PI) time series.

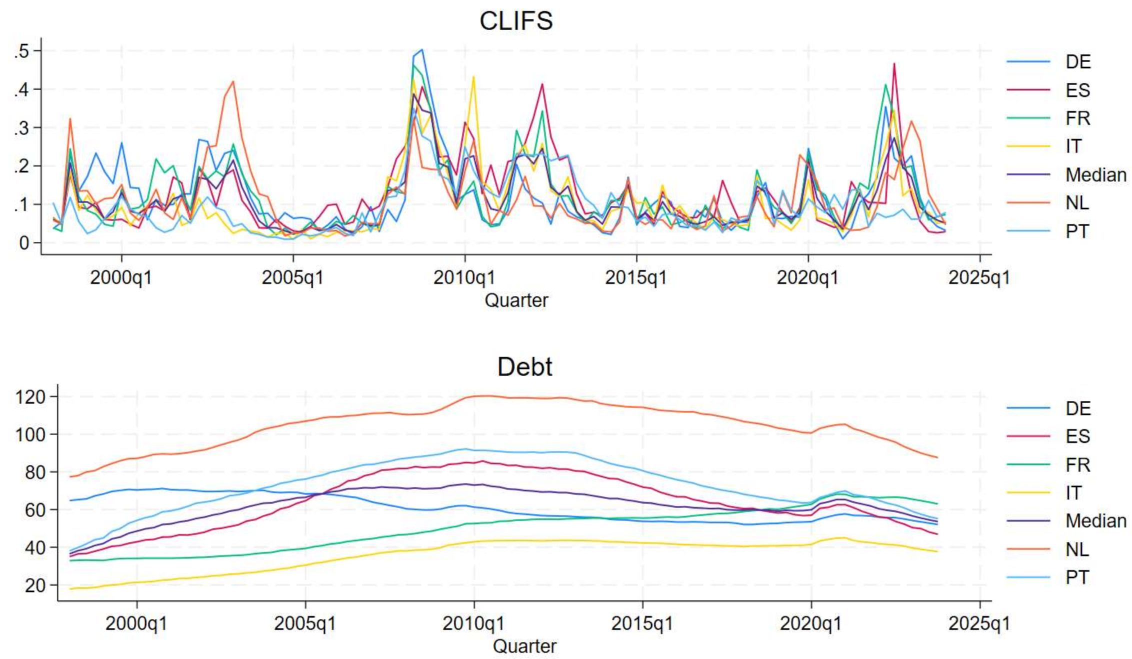

Figure A5: Country-Level Index of Financial Stress (CLIFS) and Household Debt to GDP (Debt) time series.

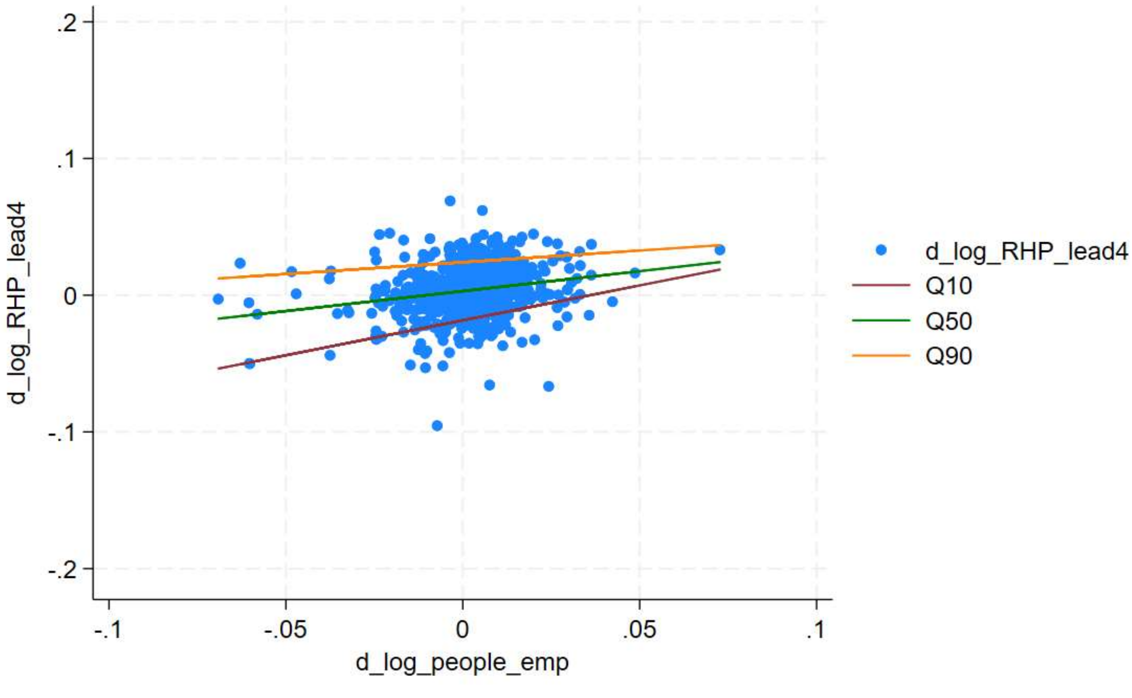

Figure A6: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of log people employed.

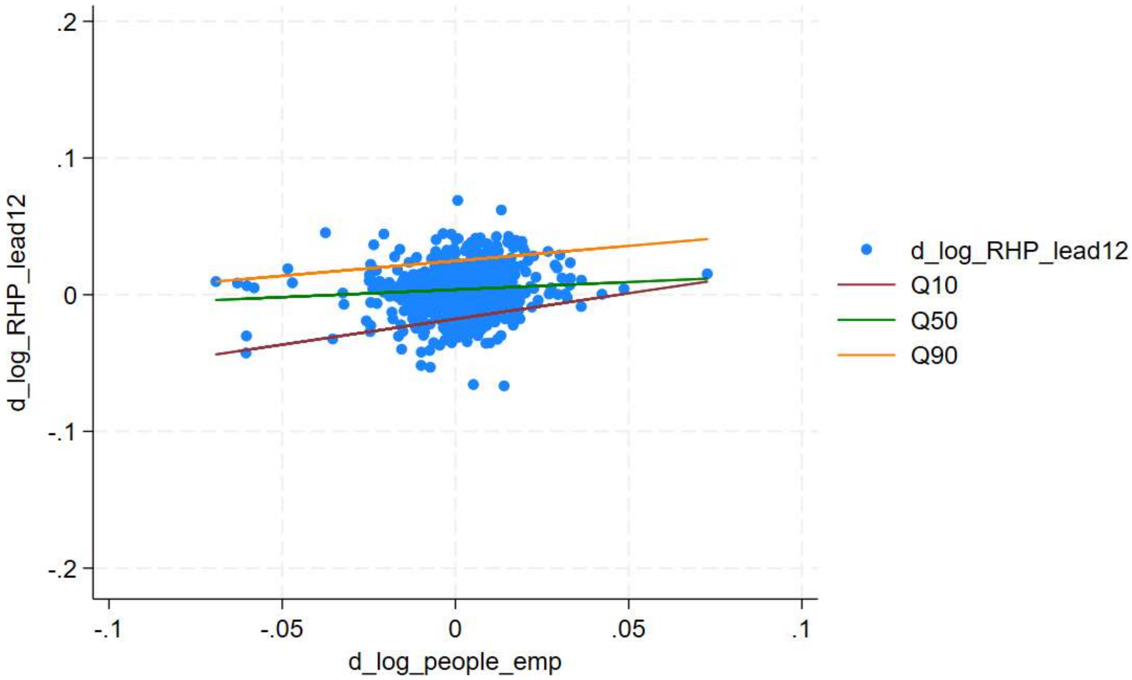

Figure A7: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of log people employed.

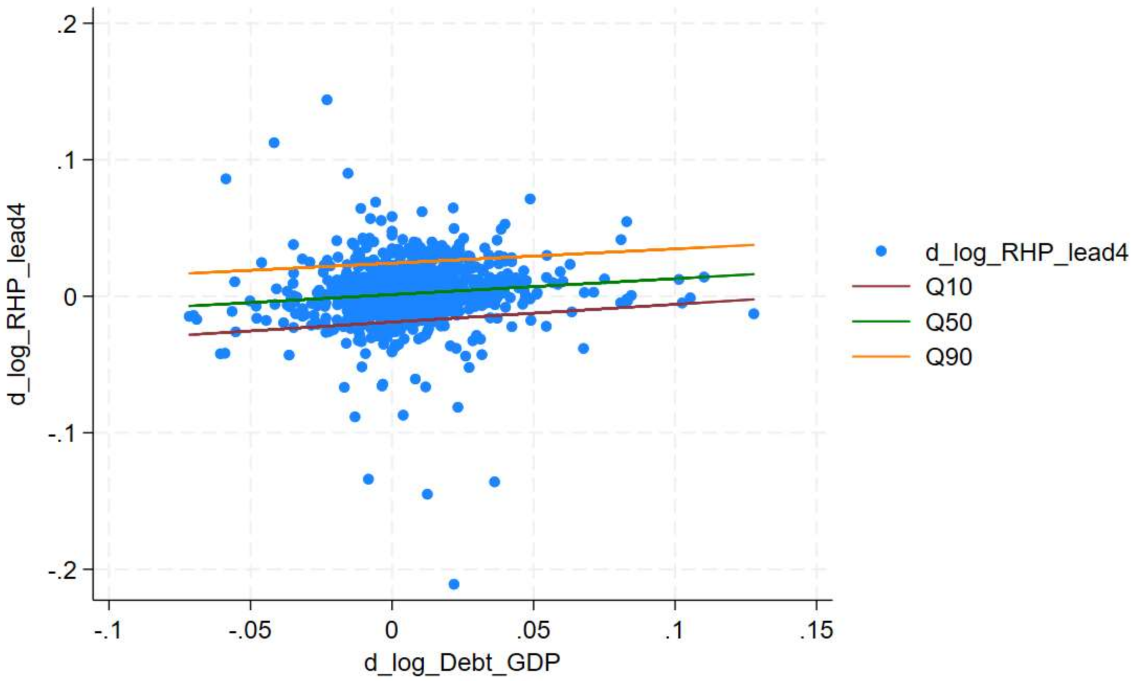

Figure A8: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of log of Debt to GDP.

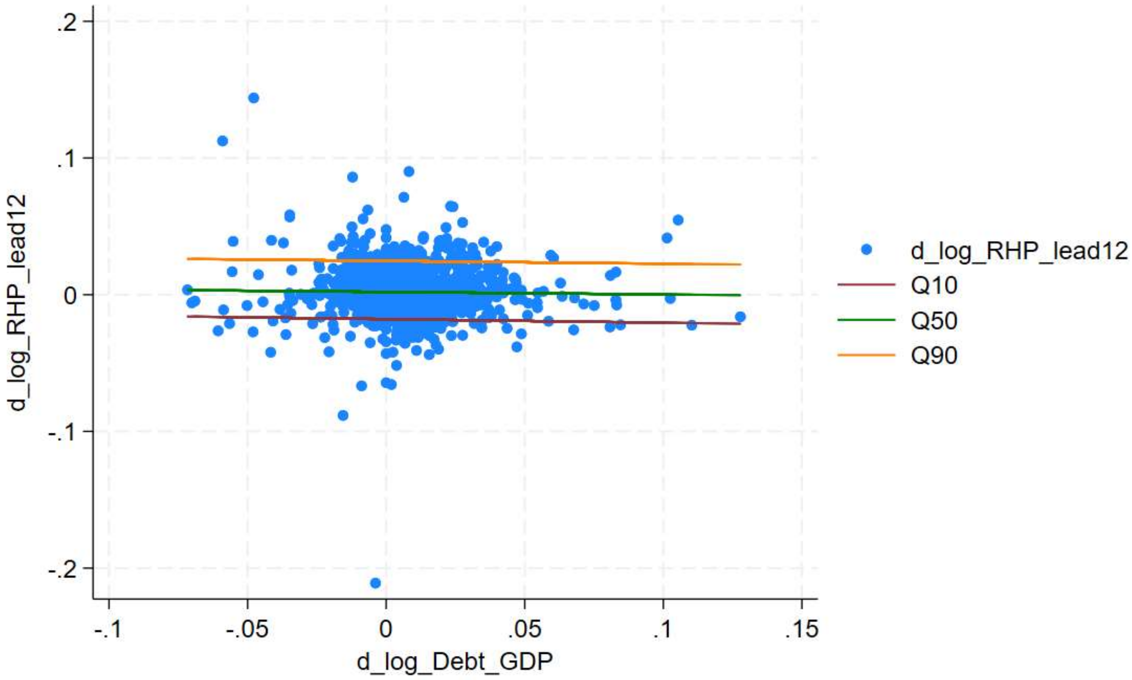

Figure A9: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of log of Debt to GDP.

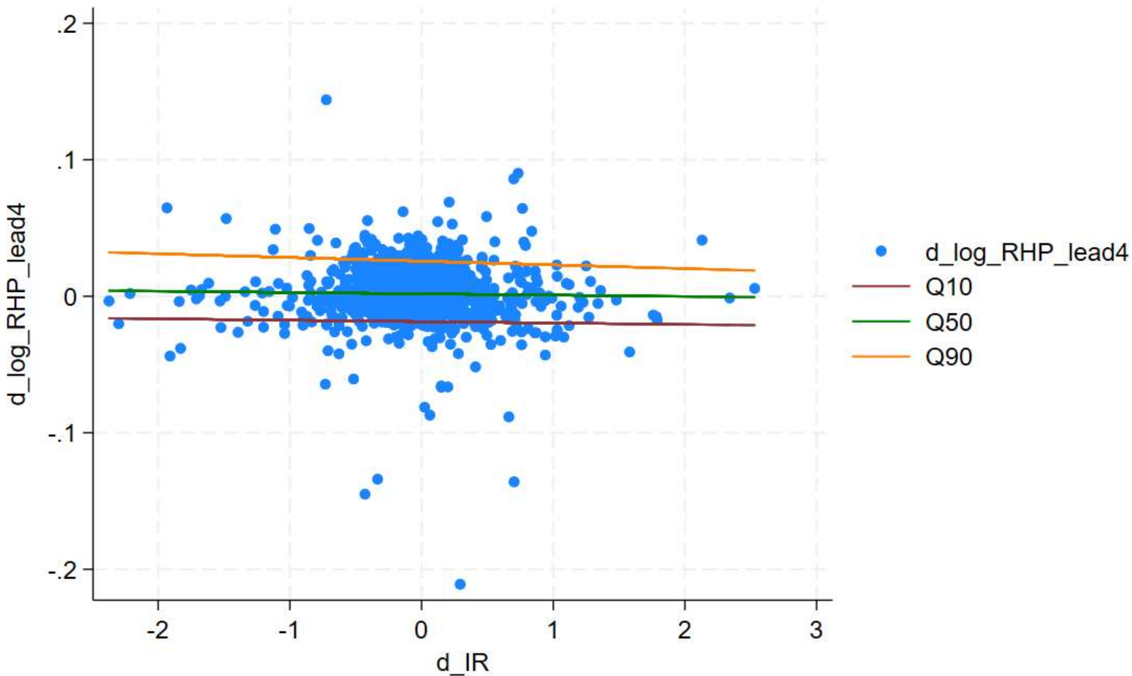

Figure A10: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of interest rates.

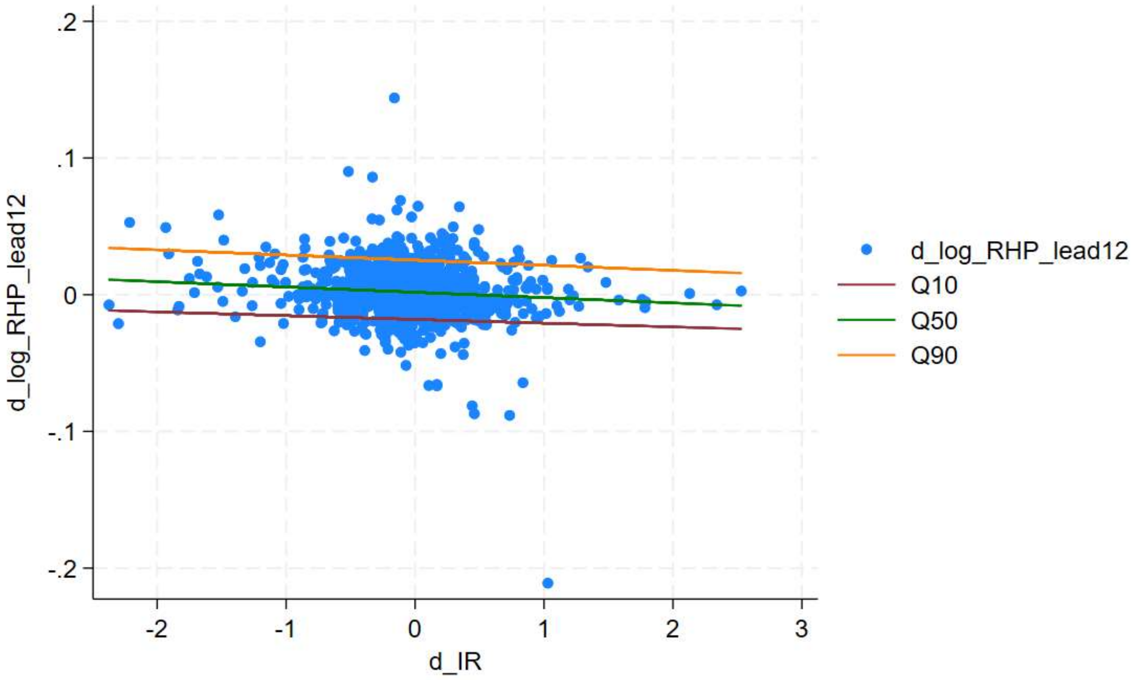

Figure A11: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of interest rates.

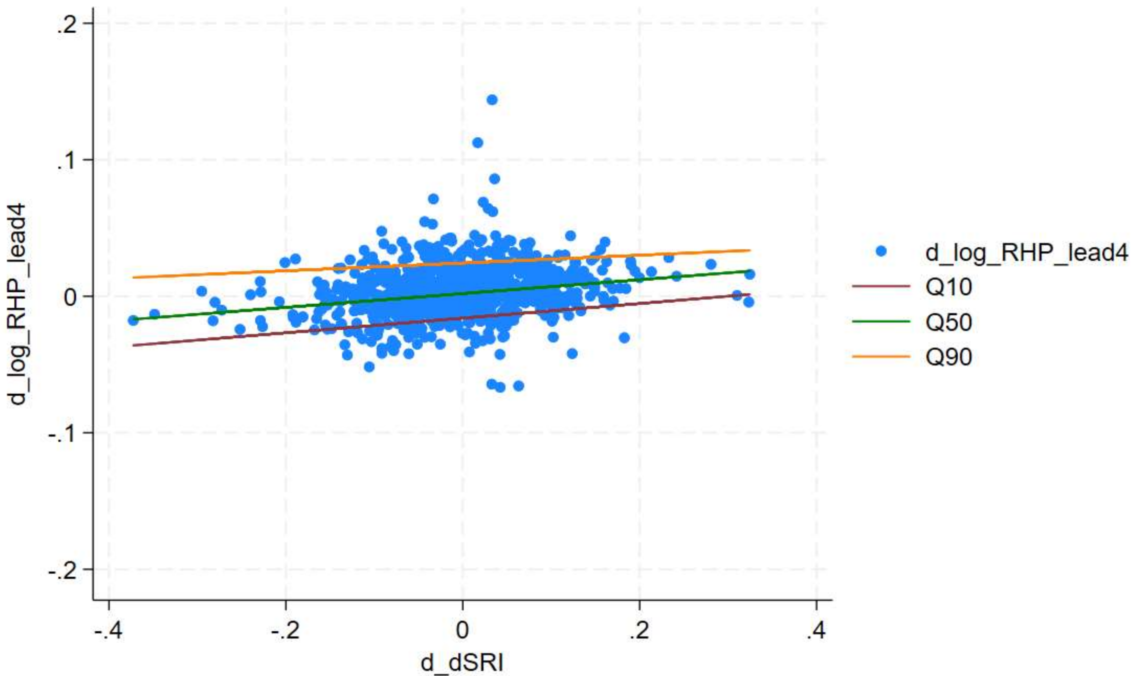

Figure A12: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of d-SRI.

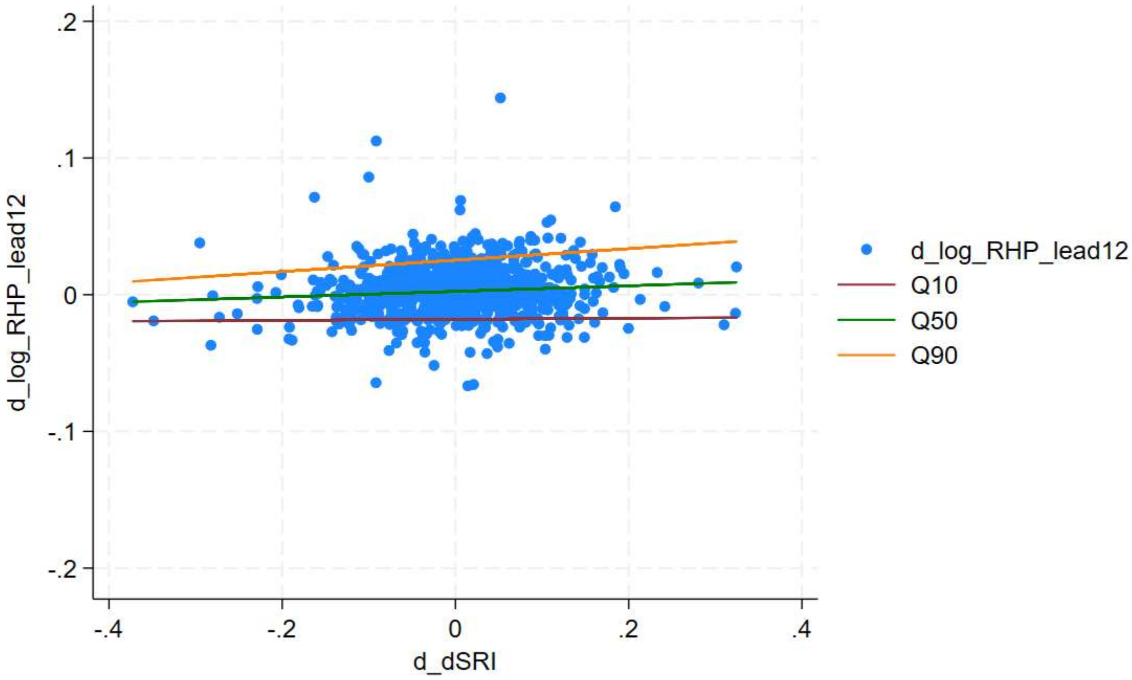

Figure A13: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of d-SRI.

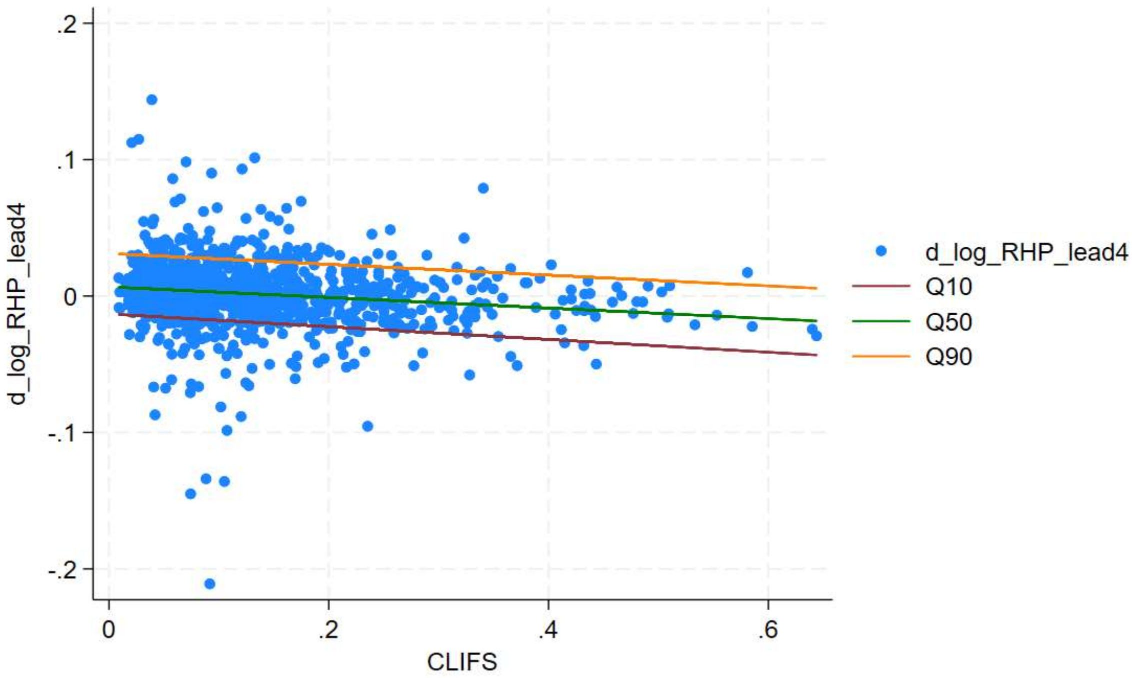

Figure A14: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on CLIFS.

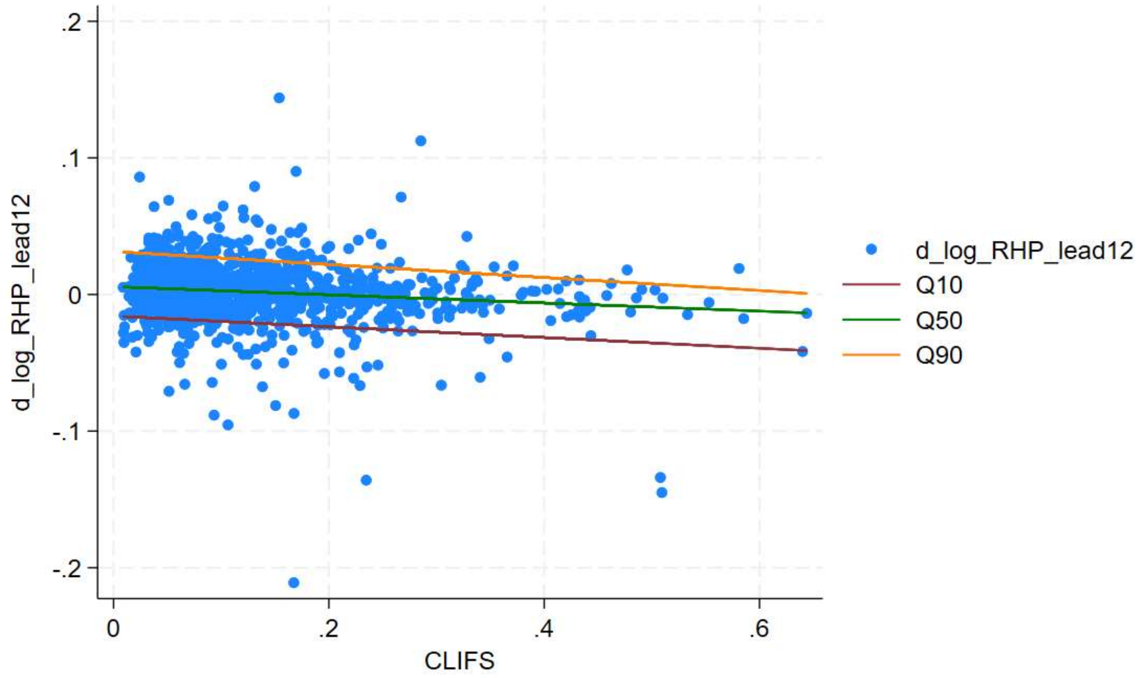

Figure A15: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on CLIFS.

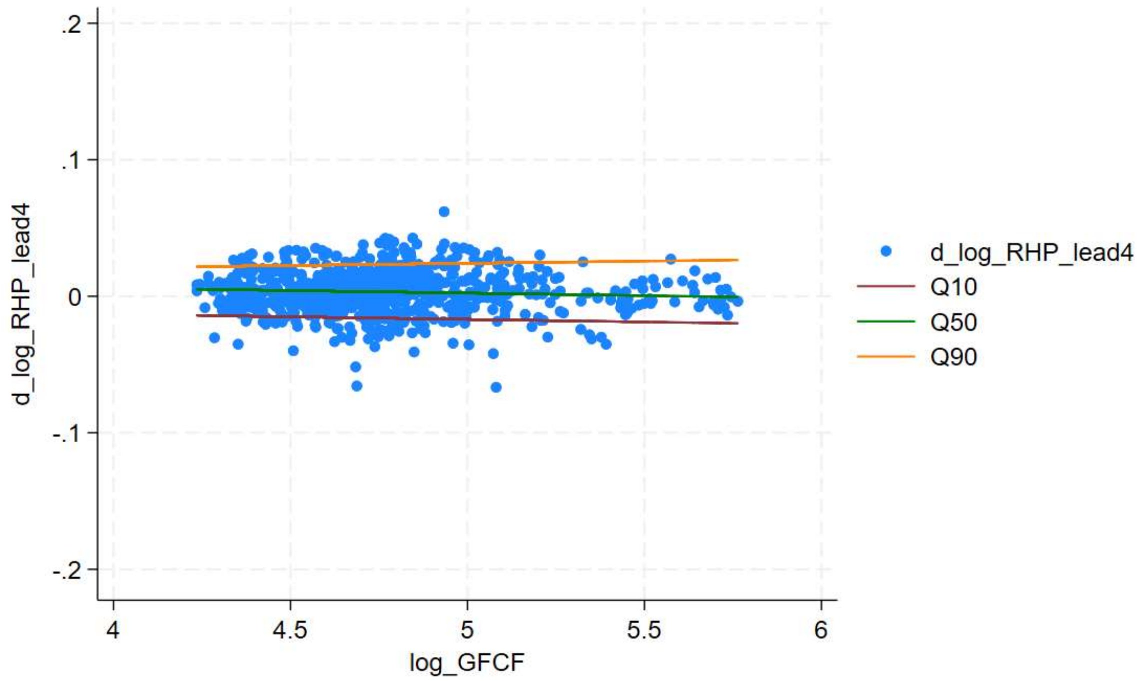

Figure A16: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on log of GFCF dwellings.

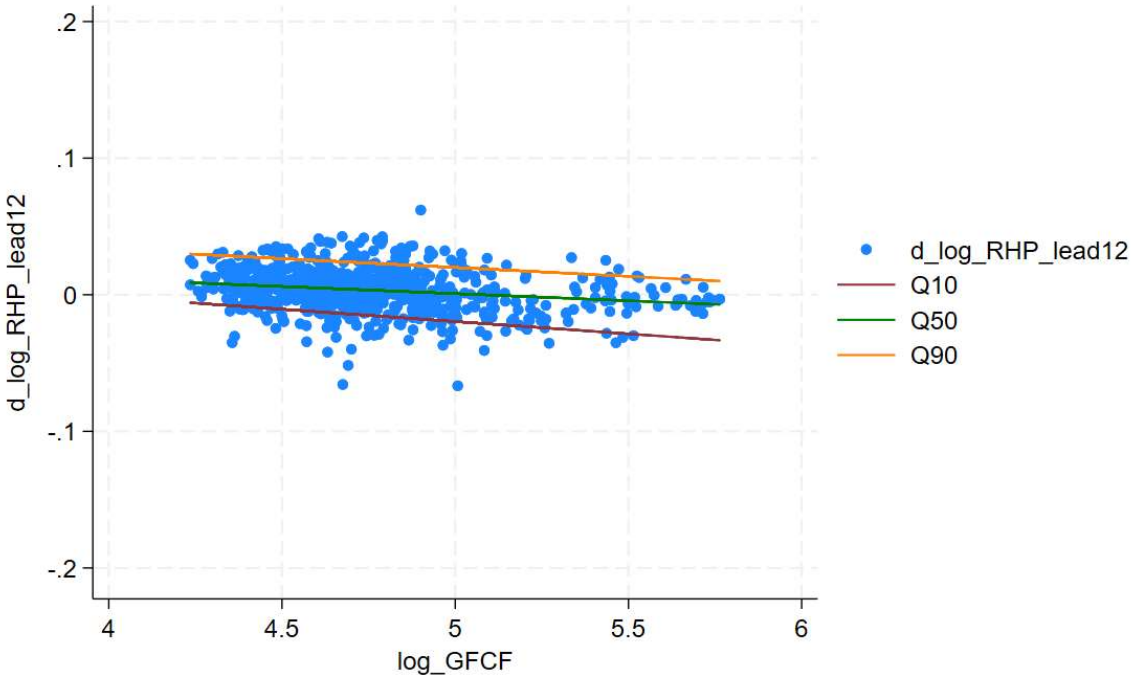

Figure A17: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on log of GFCF dwellings.

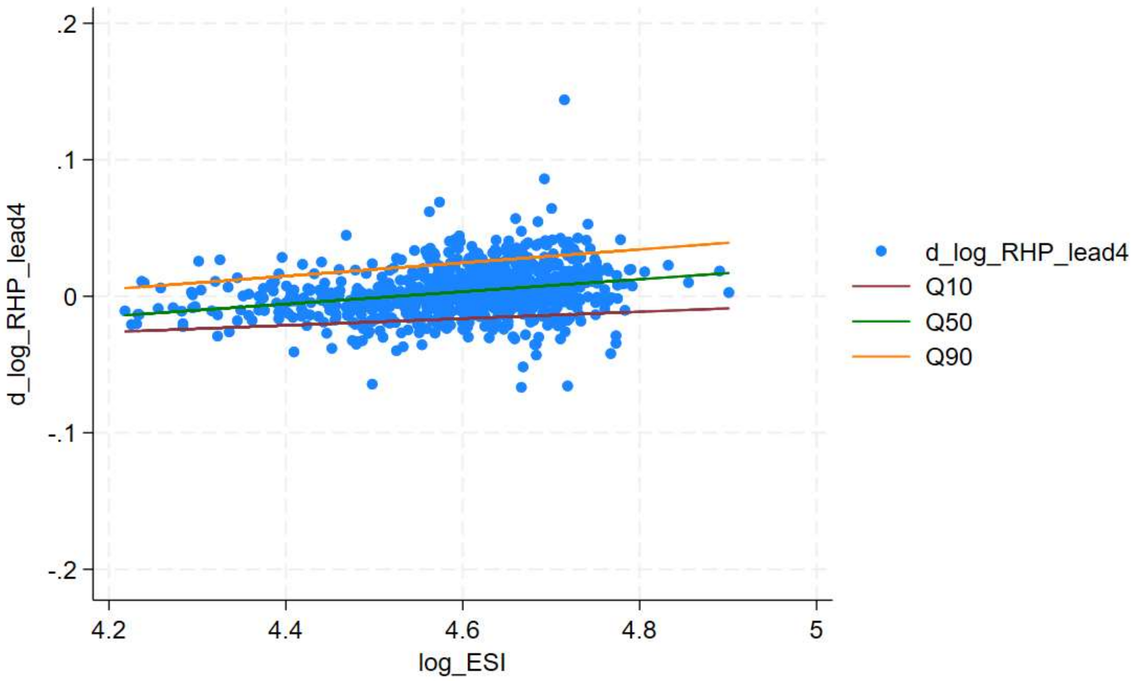

Figure A18: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on log of ESI.

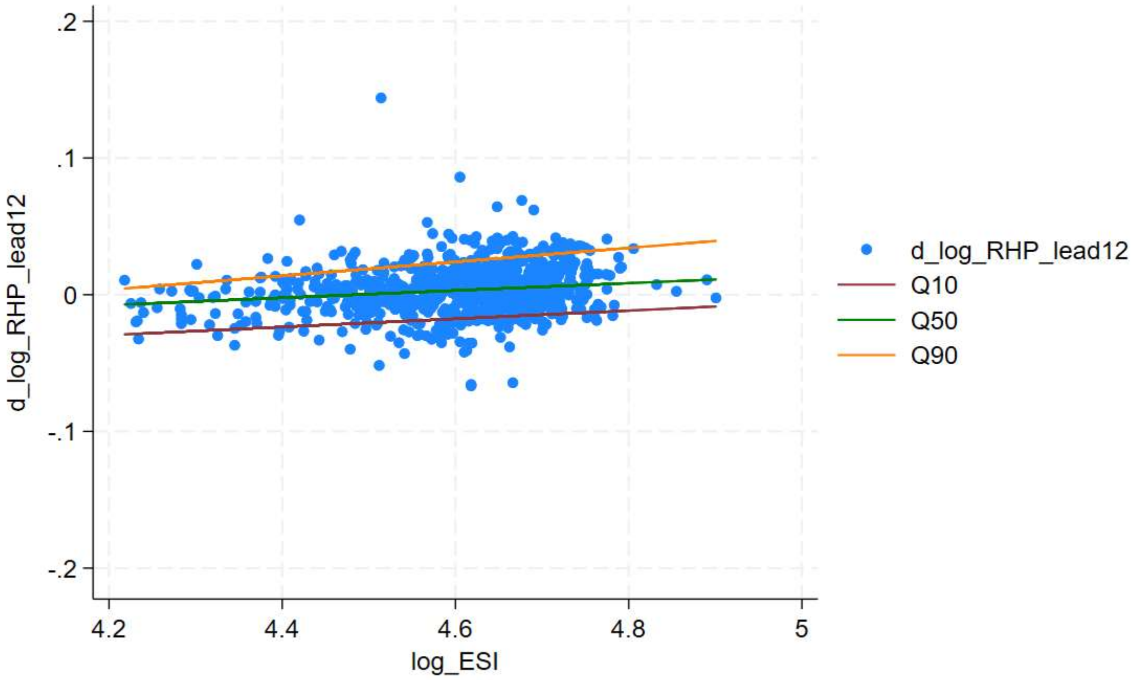

Figure A19: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on log of ESI.

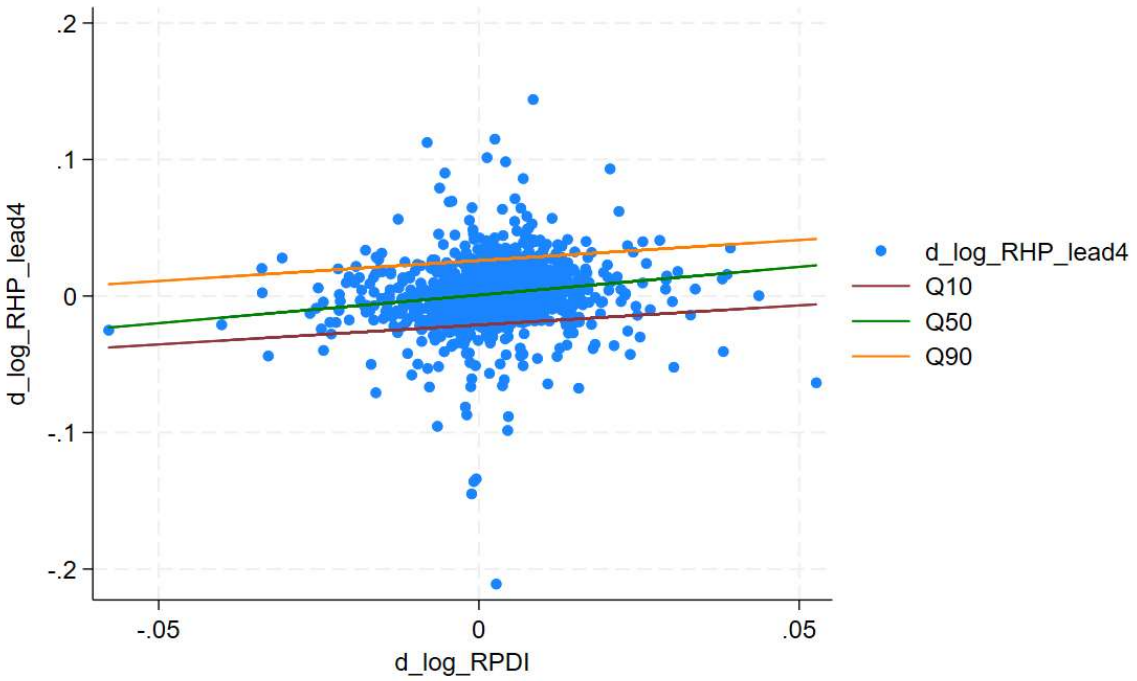

Figure A20: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of log of RPDI.

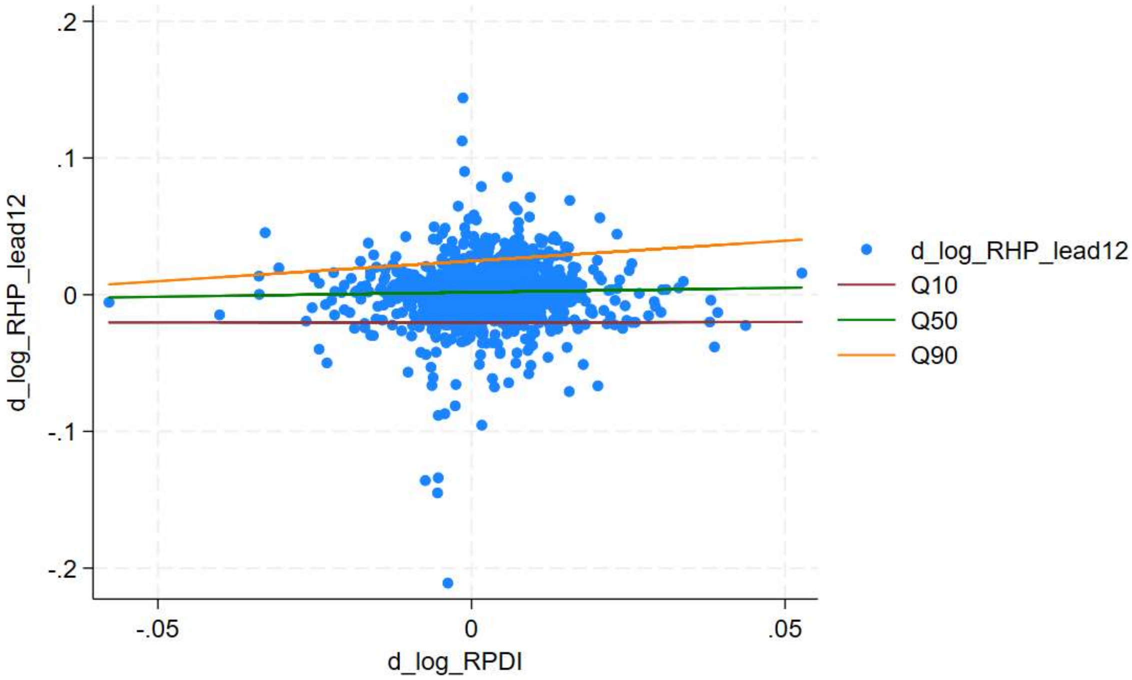

Figure A21: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of log of RPDI.

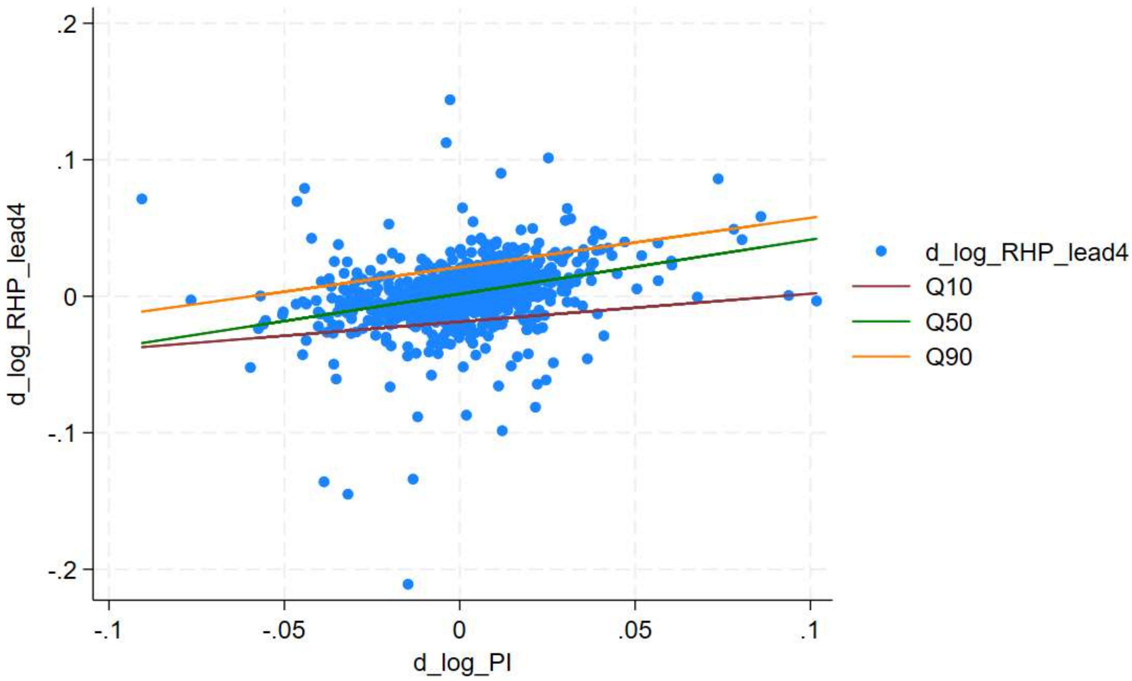

Figure A22: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 1 year ahead on first difference of log of Price to Income.

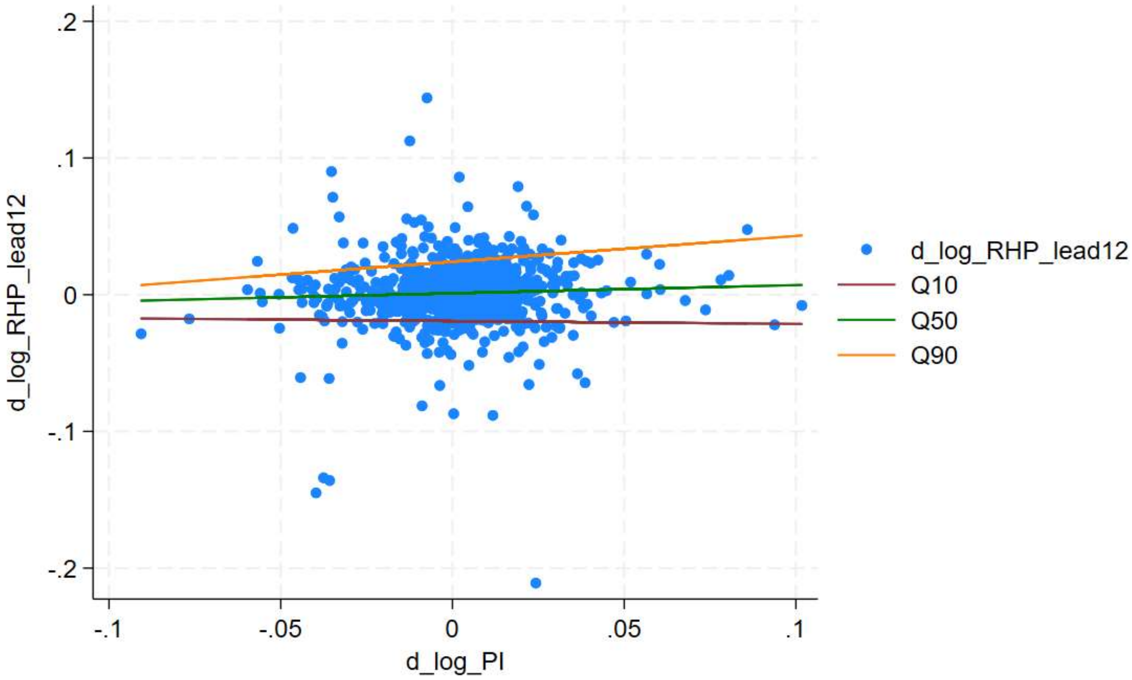

Figure A23: Scatter plot and results for Q10, Q50 and Q90 of pooled regression for first difference of log RHP 3 years ahead on first difference of log of Price to Income.

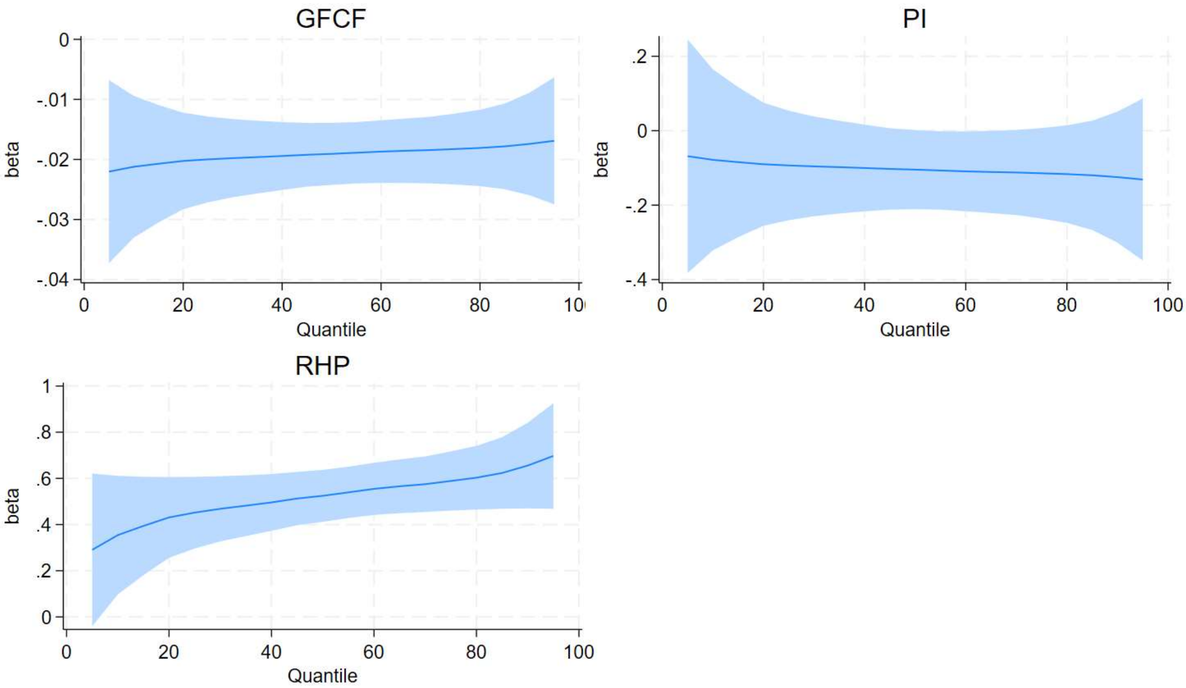

Figure A24: Betas for covariates depending on quantile for model with h=4.

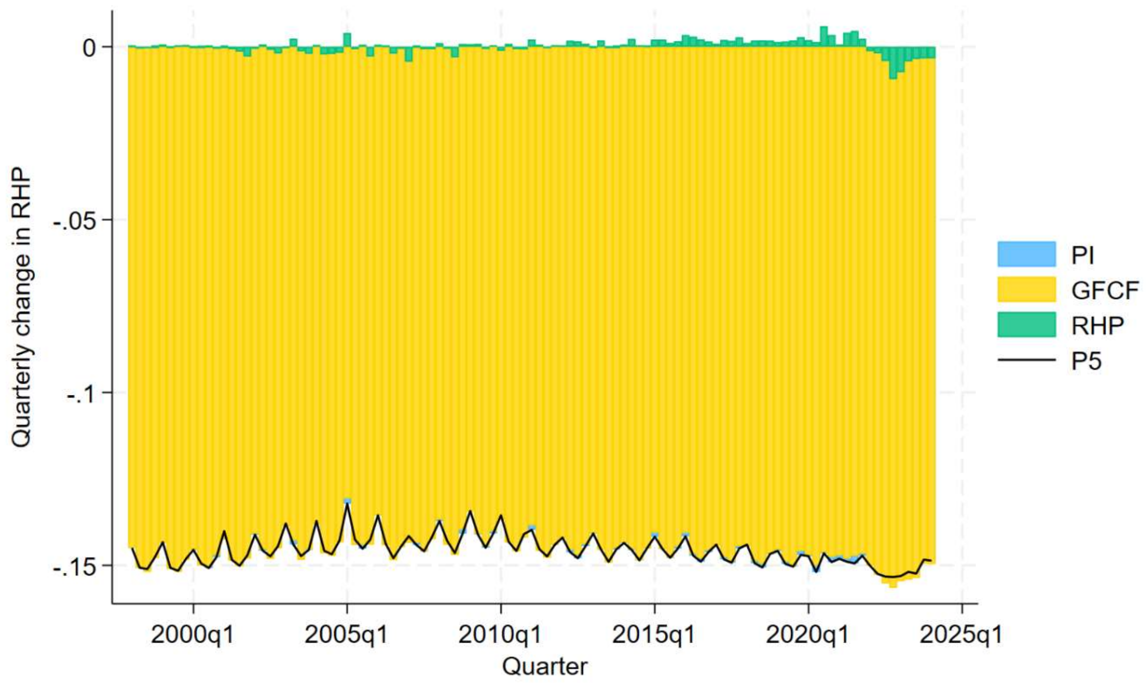

Figure A25: Effects of optimal factors for HaR in Germany with h=12.

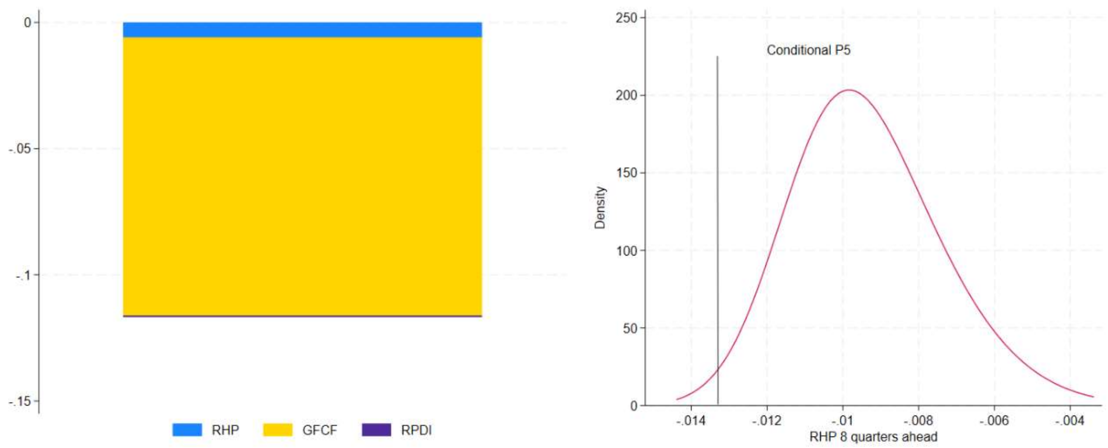

Figure A26: Decomposition and pdf for DE with h=8 using data Q1 2024.

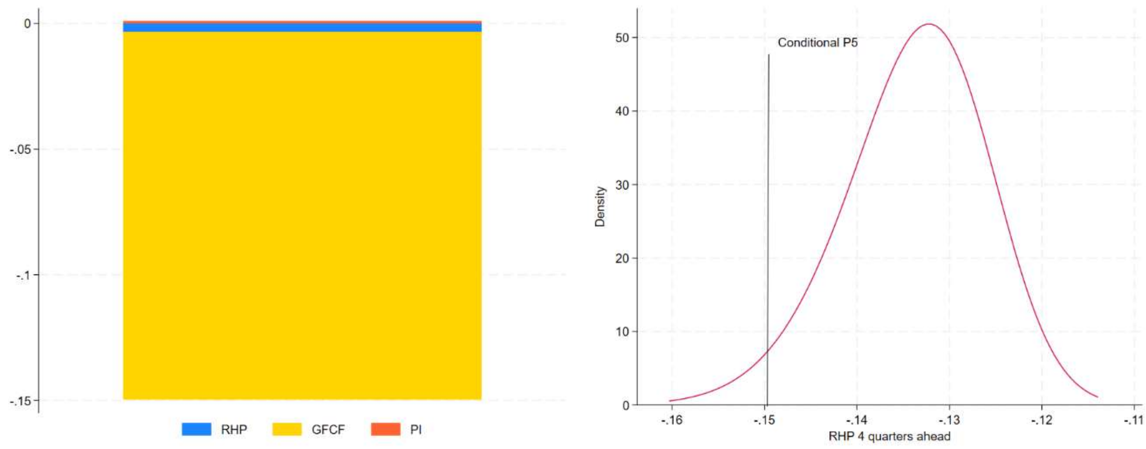

Figure A27: Decomposition and pdf for DE with h=12 using data Q1 2024.

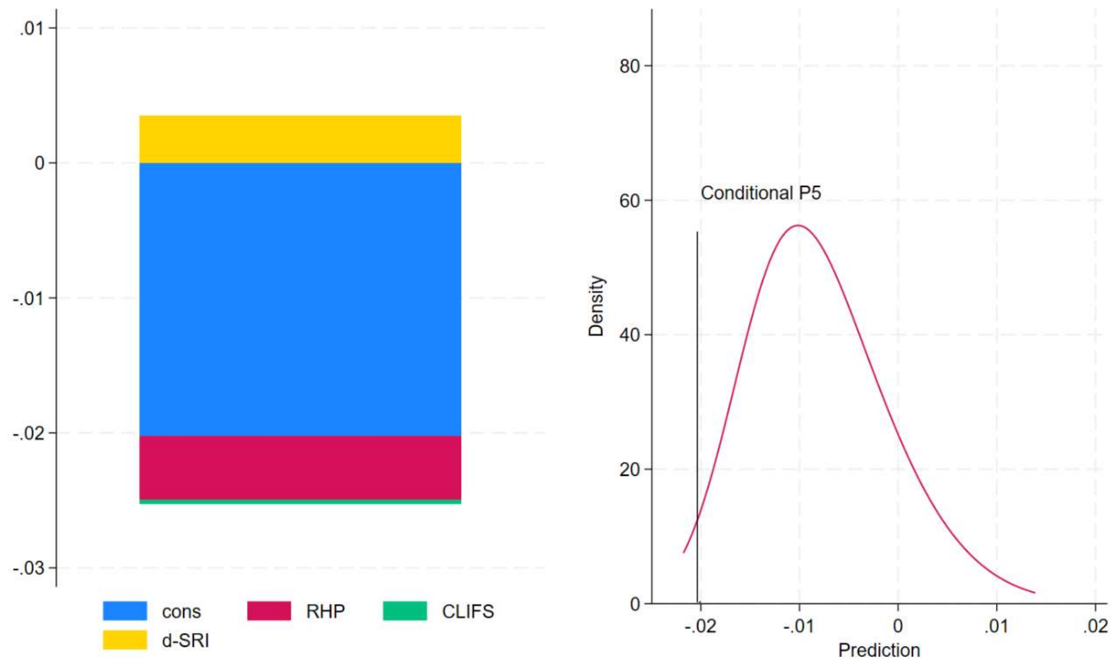

Figure A28: Decomposition and pdf from the single entity model for DE with h=4 using data Q1 2024.