

Macroprudential Policy and Housing Wealth Inequality: Evidence from the Euro Area

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Motivation

- ▶ Macroprudential policy (MaPP) has become a key tool for policy makers in addressing vulnerabilities within the financial system:
 - ▶ Lower the likelihood of financial crises ([Fernández-Gallardo, 2023](#)).
 - ▶ Reduce the severity of crises ([Jordà et al., 2021](#)).
 - ▶ Mitigate systemic and tail risks in the economy ([Franta and Gambacorta, 2020](#); [Galán, 2024](#)).

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- ▶ However, the distributional effects of MaPP on wealth inequality have been largely unexplored.
 - ▶ In this paper, we particularly focus on [housing wealth inequality](#).

Why Housing

- ▶ Housing is typically the largest component of household wealth ([Badarinza et al., 2016](#)). ▶ Housing share EA
- ▶ Housing wealth is a major driver of overall wealth inequality ([Paz-Pardo, 2024](#); [Daysal et al., 2023](#)).
- ▶ Macroprudential tightening has significant negative effects on house prices ([Cerutti et al., 2017](#)), but non-significant effects on stock prices ([Richter et al., 2019](#)).

Research Question

- ▶ **How do MaPP tightening shocks affect housing wealth inequality in the euro area?**
 - ▶ Through which mechanisms does MaPP affect housing wealth? (credit access vs. house prices).
 - ▶ Which groups are most affected? (bottom vs. middle vs. top income).
 - ▶ Are these effects heterogeneous across countries?
 - ★ We focus on the four largest economies in the EA: Germany, France, Italy, and Spain.

Preview of Main Results

- ▷ Tightening MaPP shock **reduces aggregate credit and house prices.**
- ▷ Net housing wealth falls across income groups:
 - ▶ France, Italy and Spain: **middle-income** households incur the largest losses.
 - ▶ Germany: losses are concentrated among the **bottom 20%**.
- ▷ As a result, **housing wealth inequality increases** across all countries, driven mainly by an **uneven contraction in credit.**

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 - ▶ Both channels operate simultaneously.

MaPP Shocks

- ▶ We use the **narrative-identified macroprudential policy shocks** approach by [Fernández-Gallardo and Payá \(2025\)](#).
- ▶ We isolate policy measures from MaPPED database that are:
 - ▶ Non-systematic (i.e., not responding to contemporaneous or expected macro-financial conditions).

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 - ▶ Different weights are assigned depending on the type of policy (activation/deactivation, change in scope, renewals, etc.).

MaPP shocks by country

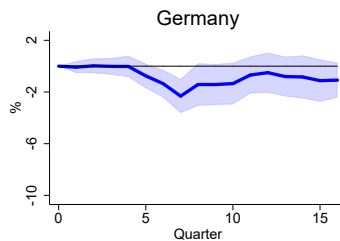
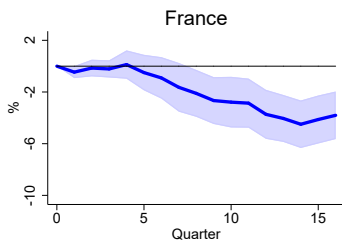
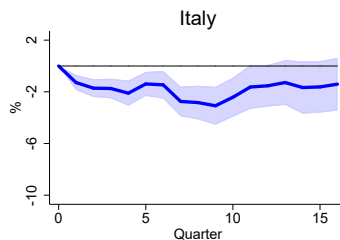
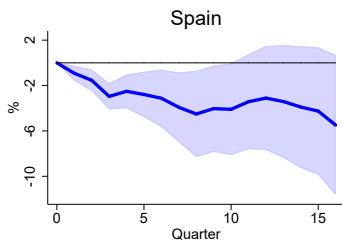
Local Projections: Baseline Specification

- ▶ We estimate the dynamic response of credit and house prices to an exogenous MaPP tightening shock using local projections (Jordà, 2005):

$$\Delta^h y_{t+h} = \alpha_h + \beta_h \text{MaPP}_t^{\text{shock}} + \sum_{\ell=0}^L \Gamma_{h,\ell} X_{t-\ell} + \varepsilon_{t+h}$$

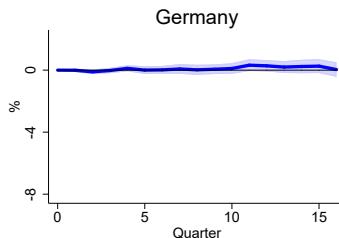
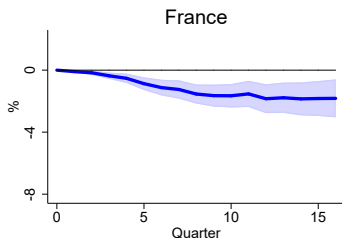
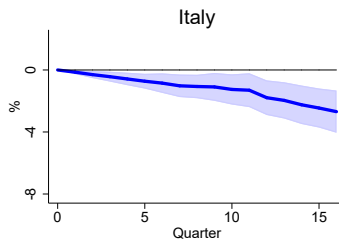
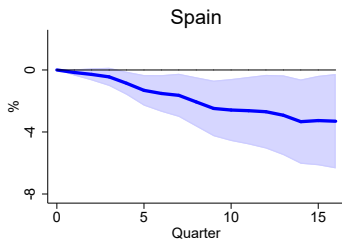
- ▶ Country-level regressions for Germany, France, Italy, and Spain.
- ▶ Time period: 1990Q1–2017Q4.
- ▶ Control variables: annual growth in real GDP, CPI, credit, house prices, and GDP growth forecasts.

IRFs for Credit



- ▶ Tightening MaPP **reduces credit** in all four countries; peak effect around 3–4 years.

IRFs for House Prices



- ▷ House prices **decline** in France, Italy, and Spain.
- ▷ **No significant effect** in Germany. Discussion

IRFs: Summary

- ▶ Credit falls after tightening MaPP in all four countries; peaks around 3–4 years after the shock.
- ▶ House prices decline in France, Italy, Spain; no effect in Germany.

Table 1: Average IRF responses to a one s.d. MaPP tightening shock

Country	IRF Credit (%)	IRF House Prices (%)
Spain	-4.02	-3.83
France	-3.40	-2.70
Italy	-1.94	-2.36
Germany	-1.02	0.00

Household Mapping: Data and Mechanism

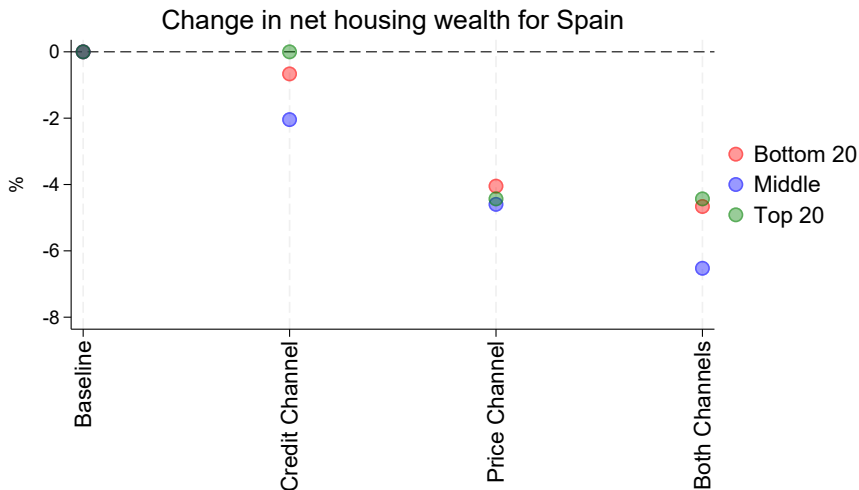
- ▶ **Micro Data:** HFCS 2010 wave → few MaPP actions from 2000 to 2010.

- ▶ **Credit channel:**

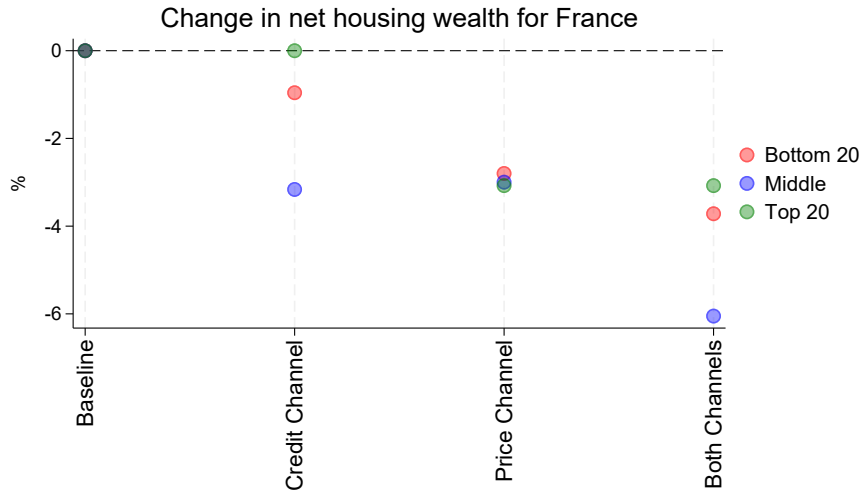
- ▶ For each country, we estimate a probit model for household i 's mortgage status C :

$$\Pr(C_i = 1 \mid X_i) = \Phi(X_i' \beta)$$

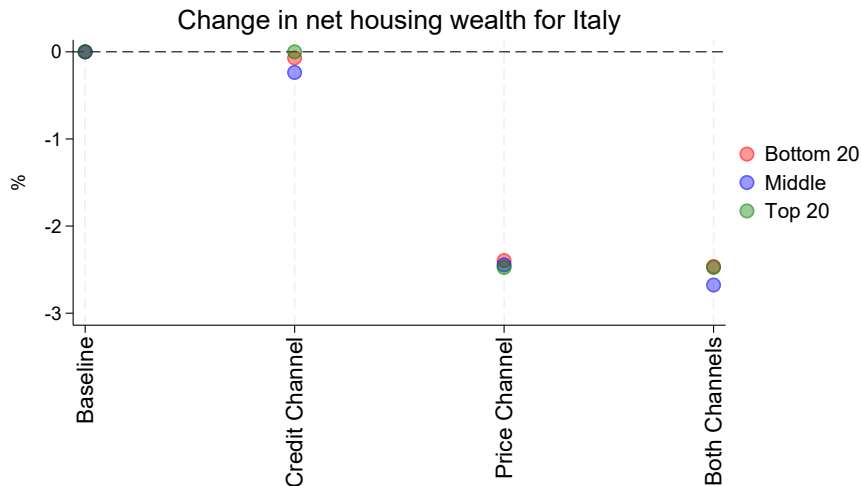
- ▶ X : income, marital status, education, number of children, age, wealth, and employment status.
 - ▶ Rank 2000–2010 mortgagors by \hat{C}_i ; exclude lowest \hat{C}_i until aggregate credit drop matches IRF.
- ▶ **Price channel:** proportional drop in housing values consistent with country IRF.



- ▶ **Middle-income** households bear the largest losses, driven by mortgage-market exclusion.

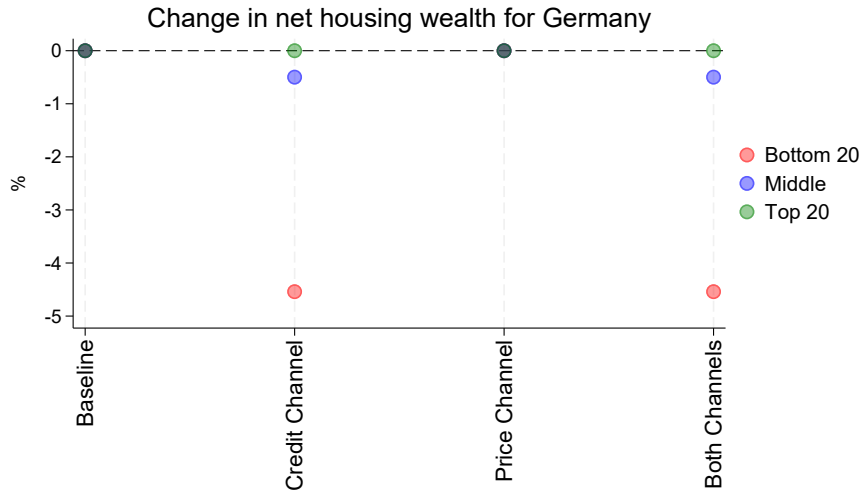


- ▷ Similar pattern: **middle-income** households are most affected through the credit channel.



- ▷ Consistent with Spain and France: the credit channel disproportionately affects the **middle class**.

Germany



- ▷ Different pattern: **bottom 20%** bears the largest burden due to lower initial indebtedness.

Possible Explanations

- ▷ **Germany:** Bottom 20 has relatively low initial LTV ratios. Consequently, losing both their mortgage and home in our simulation places a disproportionately high burden on their net housing wealth.

▷ LTV

- ▷ **Price channel:** The largest declines tend to occur in the income quintiles where mortgage liabilities represent a larger proportion of housing value.

▷ DTA

Who Loses More?

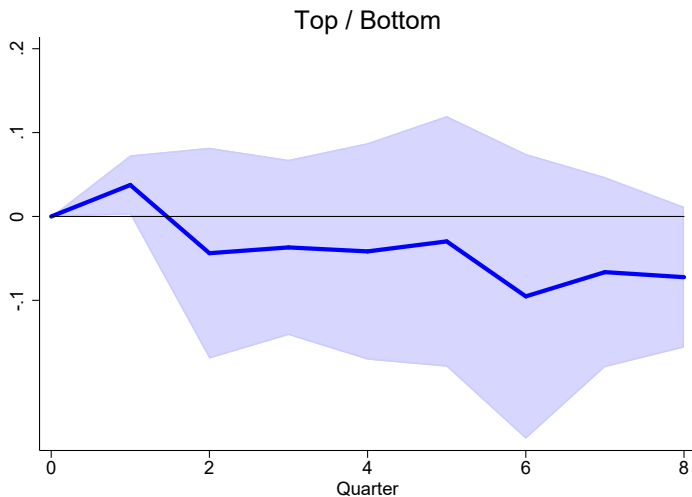
- ▶ Consistent pattern in Spain, France, and Italy: largest losses for the middle quintile.
- ▶ Germany is the exception: bottom 20% experiences the largest decline.
- ▶ Channel decomposition:
 - ▶ **Credit channel dominates** inequality effects: uneven denial of mortgages across the household distribution.
 - ▶ **Price channel**: homogeneous reduction in net housing wealth.

Aggregate Effects of MaPP on Housing Wealth Inequality

- ▶ The reduced-form micro simulation captures short-run partial-equilibrium channels (credit access and house prices), but abstracts from **general equilibrium effects** and **household behavioral responses**.
- ▶ We therefore complement the micro evidence with **aggregate time-series** data on housing wealth inequality from the DWA.
- ▶ Panel local projections for Germany, France, Italy, Spain from 2011Q4–2017Q4.

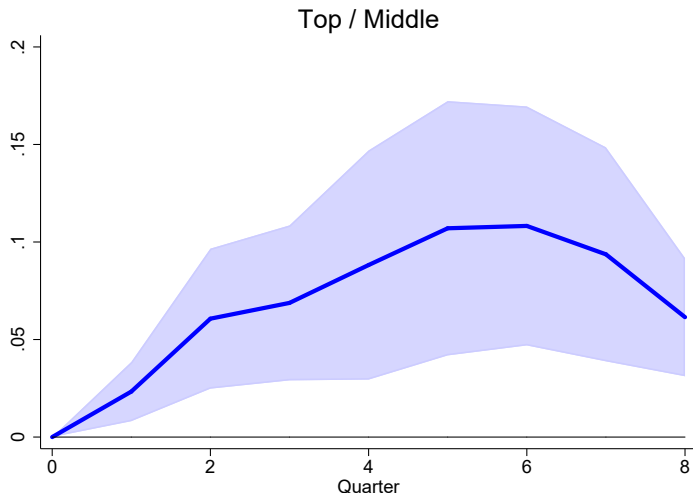
$$\Delta^h y_{i,t+h} = \alpha_{i,h} + \beta_h \text{MaPP}_{i,t}^{\text{shock}} + \sum_{\ell=0}^L \Gamma_{h,\ell} X_{t-\ell} + \varepsilon_{i,t+h}$$

Housing Wealth Inequality: Top 20 vs. Bottom 20



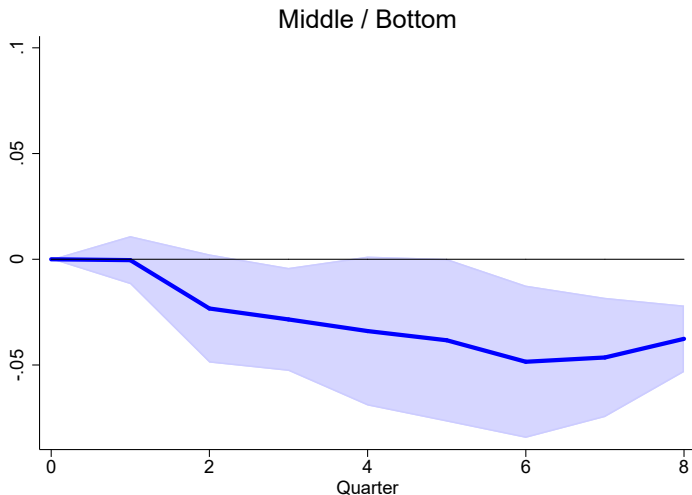
- ▶ MaPP tightening **widens** the housing wealth gap between top and bottom income households.

Housing Wealth Inequality: Top 20 vs. Middle



- ▶ Middle-income households **lose ground** relative to the top 20 after tightening.

Housing Wealth Inequality: Middle vs. Bottom 20



- ▷ The gap between middle and bottom narrows.
- ▷ Macroprudential tightenings tend to **raise** housing wealth inequality in the short to medium run, **consistent with** the reduced-form simulation results.

Robustness Checks

- ▶ Alternative control specifications for the aggregate response of credit and house prices:
 - ▶ US VIX, which helps account for global factors influencing domestic household credit and house prices.
 - ▶ Short-term interest rates to control for potential monetary policy interlinkages with macroprudential policy.
- ▶ Heterogeneous drop in house prices across income groups:
 - ▶ We find no significant differences across house price quintiles using provincial-level data for Spain.
- ▶ Households grouped by net total wealth.

Conclusion

- ▶ Tightening MaPP reduces wealth more for lower-income households, **widening housing wealth inequality**.
- ▶ While macroprudential policies are primarily aimed at safeguarding financial stability, their **distributional consequences** should not be overlooked.
- ▶ These findings highlight the potential need for **complementary housing policies** to help offset the adverse effects of mortgage market exclusion, particularly for lower- and middle-income households.

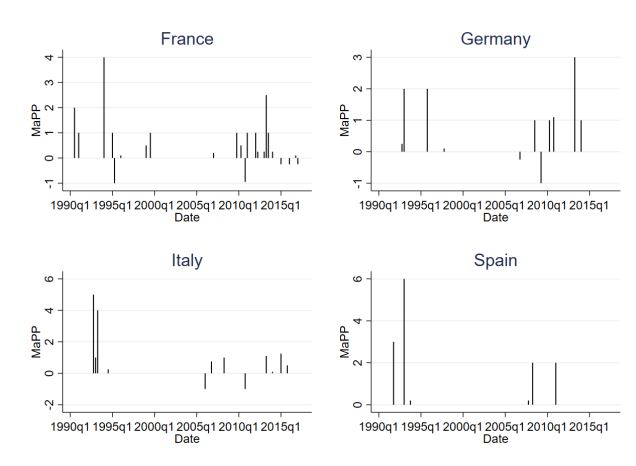
Thank you

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Questions and discussion

MaPP Shocks by Country



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Why Germany Differs on Prices

- ▷ Lower homeownership, deep rental market, conservative mortgage practices ([Kuhn and Grabka, 2018](#)).
- ▷ House prices historically less sensitive to macro/MP shocks; slow adjustment ([Corsetti et al., 2022](#)).

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Mortgage Characteristics

Variable	Income Quintile	Germany	Spain	France	Italy
Loan-to-Value (%)	Bottom 20	52.26	96.51	45.46	84.89
	Middle	76.46	114.87	42.05	81.84
	Top 20	76.90	111.96	39.25	74.74
Amount Borrowed (€ thousand)	Bottom 20	1.03	0.86	0.76	0.63
	Middle	1.07	1.13	0.86	0.91
	Top 20	1.59	1.51	1.48	1.47
Mortgage Duration (Years)	Bottom 20	14.90	24.78	17.77	17.43
	Middle	15.83	26.31	18.24	20.24
	Top 20	14.54	24.91	16.97	20.49
HRP Age (Years)	Bottom 20	33.84	41.34	44.27	50.77
	Middle	49.19	39.83	42.06	42.94
	Top 20	45.77	43.04	41.19	44.52

LTV indicates the initial LTV for the main residence at the time of acquisition, except for France, where it reflects the

outstanding LTV. Age refers to the HRP. *Source:* HFCS, wave 2010.

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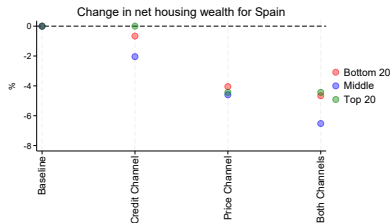
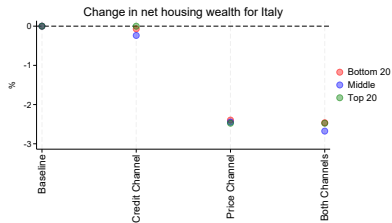
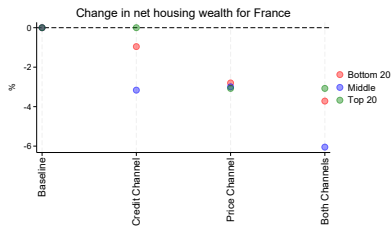
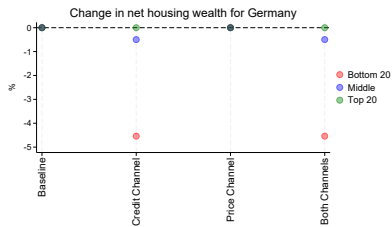
Debt-to-Asset Ratios and Homeownership

Variable	Income Quintile	Germany	Spain	France	Italy
Debt to Assets (Total Housing) [%]	Bottom 20	5.98	6.17	4.15	1.08
	Middle	21.03	23.62	12.78	4.82
	Top 20	35.22	20.87	14.75	6.16
Homeownership Rate [%]	Bottom 20	22.23	80.78	48.41	59.18
	Middle	54.68	90.90	67.99	74.08
	Top 20	85.59	89.07	92.73	89.77

All values are percentages. *Source:* HFCS, wave 2010.

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All Countries: Net Housing Wealth by Income Quintile



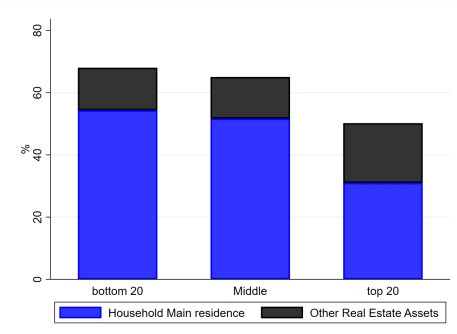
Gini Coefficients for Net Housing Wealth

Country	Baseline	Credit Channel	Price Channel	Both Channels	
Germany	0.812	0.814	0.812	0.814	
Spain	0.583	0.586	0.587	0.590	Each
France	0.677	0.681	0.678	0.682	
Italy	0.619	0.619	0.619	0.619	

counterfactual represents the Gini coefficient of net housing wealth across income groups relative to a baseline scenario. *Source:* HFCS, wave 2010.

Housing Assets Share

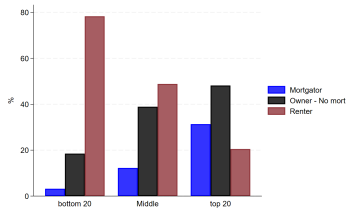
Figure 2: Total housing assets as a share of total household assets by income quintile (Euro Area)



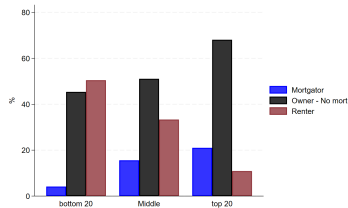
"Bottom 20%" = Q1; "Middle" = Q3; "Top 20%" = Q5. *Source: HFCS, wave 2010.*

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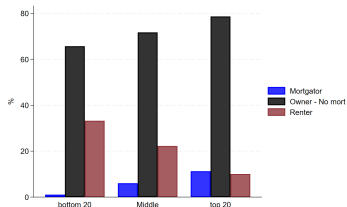
Mortgagors by Country



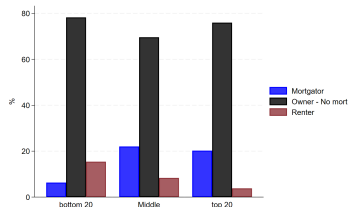
(a) Germany



(b) France



(c) Italy



(d) Spain