

Risk-Sharing and Monetary Policy Transmission

Sebastian Hauptmeier European Central Bank

Fédéric Holm-Hadulla European Central Bank

Théodore Renault Geneva Graduate Institute

European Economic Association - June 2022 Panel on Euro Area Monetary Policy

The views expressed here are those of the authors and do not necessarily reflect those of the European Central Bank.

Motivation

 \vartriangleright The classic OCA literature establishes a clear division of labor between

- Monetary policy, in response to symmetric shocks.
- Risk-sharing, to facilitate adjustment to asymmetric shocks.

(Mundell, 1961; McKinnon, R., 1963; Kenen, 1969; Farhi & Werning, 2017)

▷ The interaction between these macroeconomic stabilization tools has been, so far, under-explored.

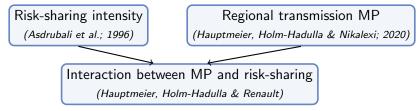
 \triangleright If MP exerts a uniform impact, its role in limiting average economic fluctuations is unaffected by risk-sharing mechanisms.

▷ Increasing evidence that monetary policy transmits unevenly. (Dedola and Lippi, 2005; Kaplan et al., 2018; Jordà et al., 2020)

 \triangleright The overall impact of MP might be therefore dependent on the risk-sharing architecture.

▷ Does risk-sharing reinforce or dampen MP transmission?

This paper



Using regional-level data and LLPs (Jordà, 2005), we:

(1) Estimate the degree of risk-sharing in EA countries. (Asdrubali et al.; 1996)

(2) Assess the effect of a MP shock on regional output, depending on:

- the level of risk-sharing in the country.
- and its breakdown into fiscal and market-based channels.

(3) Explore whether the interaction between MP and risk-sharing differs across poorer and richer regions.

Literature

This paper combines two strands of the literature:

Estimation of risk-sharing intensity.

United States. Asdrubali et al. (1996), Athanasouslis & Van Wincoop (2001)

Euro-area. Sørensen & Yosha (1998), Hepp & Von Hagen (2013), Furceri & Zdzienicka (2015), Burriel et al. (2020), Cimadomo et al. (2020).

▷ Asymmetric effects of monetary policy.

Household level. Coibion et al. (2017), Ampudia et al. (2018), Lenza & Slacalek (2018).

Industry level. Peersman & Smets (2005), Dedola & Lippi (2005).

Regional level. Hauptmeier et al. (2020).

State of the economy. Tenreyro & Thwaites (2016), Jordà et al. (2020), Alpanda et al. (2021), Eichenbaum et al. (2022).

Risk-sharing in euro area countries

Risk-sharing estimation

Main idea: under complete markets, consumption growth should not vary with the region's business cycle.

(Mace, 1991; Cochrane, 1991, Townsend, 1994).

$$\Delta \log C_t^k = \alpha_t + \frac{\beta}{\Delta} \log Y_t^k + \varepsilon_t^k$$

Incomplete smoothing if $\beta > 0$.

Asdrubali et al. (1996) propose a methodology that decomposes the risk-sharing equation into a system. • Back

 $\mathsf{GDP} \to \mathsf{Primary} \text{ income} \to \mathsf{Disposable} \text{ income} \to \mathsf{Consumption}$

Factor market channel Fiscal channel Regional data: Eurostat & Oxford Economics. (10 EA countries, 155 regions, 2000-2018 • Data sources • NUTS)

Risk-sharing estimation Methodology

Estimate the below equations, country-by-country, by panel OLS:

Factor market channel

$$\begin{split} &\Delta gdp_t^k - \Delta pi_t^k = \beta_K \times \Delta gdp_t^k + \alpha_{K,t} + \varepsilon_{K,t}^k \\ &\text{Fiscal channel} \\ &\Delta pi_t^k - \Delta di_t^k = \beta_F \times \Delta gdp_t^k + \alpha_{F,t} + \varepsilon_{F,t}^k \\ &\text{Credit market channel} \\ &\Delta di_t^k - \Delta c_t^k = \beta_C \times \Delta gdp_t^k + \alpha_{C,t} + \varepsilon_{C,t}^k \\ &\text{Unsmoothed} \\ &\Delta c_t^k = \beta_U \times \Delta gdp_t^k + \alpha_{U,t} + \varepsilon_{U,t}^k \end{split}$$

 $\beta_{\mathsf{K}} + \beta_{\mathsf{F}} + \beta_{\mathsf{C}} (= \beta_{\mathsf{S}}) = 1 - \beta_{\mathsf{U}}$

 $\beta\text{-coefficients}$ are the amount of risk-sharing achieved by the regions in the country.

Risk-sharing estimation using differentiated data • Regression table

The amount of risk-sharing may vary with the length of the shock. *(ASY, 1996).*

Following ASY (1996), we run the previous equations with differentiated data using intervals j = 1, ..., 5.

$$\Delta^{j}gdp_{t}^{k} - \Delta^{j}pi_{t}^{k} = \beta_{K,j}^{c} \times \Delta^{j}gdp_{t}^{k} + \alpha_{K,t} + \varepsilon_{K,t}^{k}$$

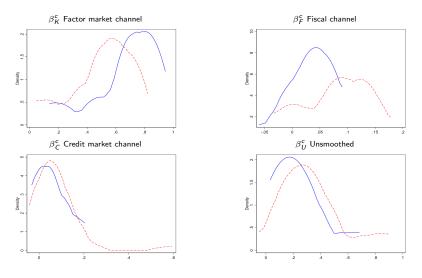
where $\Delta^j x_t^k = x_t^k - x_{t-j}^k$.

Hence, $\beta_{K,j}^c$ is the share of shocks smoothed by the factor market channel for regions in country *c* after *j* periods.

Risk-sharing estimation

Densities of the country-specific $\beta\text{-coefficients}$ for all EA countries.

Intervals j = 1 and j = 5



Risk-sharing & monetary policy

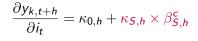
How does risk-sharing interact with monetary policy?

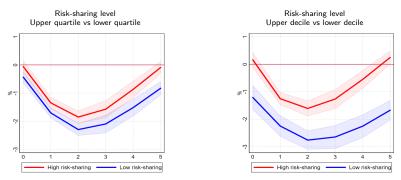
We augment Hauptmeier et al. (2020) LLP framework with risk-sharing :

$$y_{k,t+h} = \alpha_{k,h} + \left(\kappa_{0,h} + \kappa_{S,h} \times \beta_{S,h}^{c}\right)i_{t} + \gamma_{h}\mathbf{X}_{k,t} + \delta_{h}\mathbf{X}_{c,t} + \theta_{h}\mathbf{X}_{t} + \varepsilon_{k,t+h}$$

- $\triangleright y_{k,t+h}$: log GDP in region k in year t + h(Source: Eurostat Regional dataset; NUTS-2 level)
- $ightarrow i_t$: euro area short-term interest rate (AWM database), extended from 2014 using the Lemke & Vladu (2017) shadow interest rate
- $\triangleright \beta_{S,h}^{c}$: risk-sharing achieved in country c after h periods
- \triangleright Controls: (i) region-specific: $X_{k,t}$, (ii) country-specific: $X_{c,t}$ and (iii) euro area-specific: $X_t \land Control variables$
- ▷ Sample consists of 155 regions over 18 years
- Bootstrapped Driscoll and Kraay standard errors

Results





Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) quartiles or deciles of $\hat{\beta}_{S,h}^{c}$. The Driscoll-Kraay standard errors are boostrapped using 1000 iterations.



Interrelation of private and public risk-sharing

We break down aggregate risk-sharing by channels:

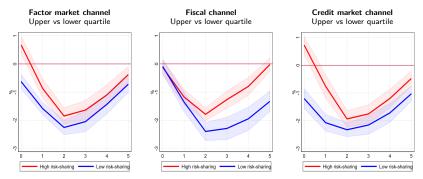
$$y_{k,t+h} = \alpha_{k,h} + \left(\kappa_{0,h} + \kappa_{K,h} \times \beta_{K,h}^{c} + \kappa_{F,h} \times \beta_{F,h}^{c} + \kappa_{C,h} \times \beta_{C,h}^{c}\right) i_{t}$$

+ Controls + $\varepsilon_{k,t+h}$

- $\triangleright y_{k,t+h}$: log GDP in region k in year t+h
- \triangleright *i*_t: euro area short-term interest rate (AWM database), extended from 2014 using the Lemke & Vladu (2017) shadow interest rate
- $\triangleright \beta_{K,h}^{c}, \beta_{F,h}^{c}, \beta_{C,h}^{c}$: risk-sharing achieved in country c after h periods through fiscal and market-based channels
- ▷ Controls same as before



Results



Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) quartiles of $\beta_{K,h}^c$, $\beta_{F,h}^c$ or $\beta_{C,h}^c$. The Driscoll-Kraay standard errors are boostrapped using 1000 iterations.

Table results V Dpper vs lower decile

Interpretations

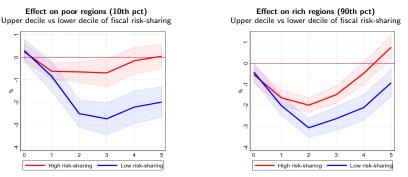
- ▷ The channels differ in their time profile:
 - ▷ Private risk-sharing dampens MP up to one year after the shock.
 - ▷ Fiscal risk-sharing mitigate the MP shock over longer horizons.
- ▷ As downturns become more persistent, banks gradually pare back their lending activity (Asdrubali et al. 1996).
- Similarly, HH may be forced to divest their international asset holdings as the downturn drags.
- Lagged fiscal response to changing economic circumstances consistent with:
 - ▷ Discretionary fiscal policies (Asdrubali et al. 1996 ; Buettner, 2002).
 - ▷ Sluggish automatic stabilizers (Bouadballah et al, 2020).
- The results point to complementarities between private and public risk-sharing channels over time.

Heterogeneity across regions

- ▷ Explore whether the interaction of risk-sharing with the transmission of MP varies between poor and rich regions.
- ▷ Given its redistributive character, we focus on fiscal risk-sharing.
- ▷ Fiscal instruments may attenuate disposable income fluctuations and stabilize consumption and output (Brown, 1955).
- ▷ The stabilization role of fiscal policy may be reinforced if targeted towards agents with larger MPC (Blinder, 1975; Parker et al, 2011).
- ▷ As poorer geographical units tend to host a larger share of vulnerable agents, these mechanisms may also operate at the regional level (Hauptmeier et al., 2020).

Heterogeneity across regions

- Quantify the dynamic impact of exogenous changes in MP across the regional GDP distribution for different levels of risk-sharing.
- ▷ Combine Jordà (2005)'s LP method with quantile estimation techniques.



Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) deciles of $\hat{\beta}^{c}_{F,h}$ in poor (10th percentile) and rich (90th percentile) regions. Standard errors are clustered at the time and regional-level and are boostrapped using 1000 iterations.

Interpretation

- Pronounced differences in the degree to which fiscal risk-sharing shapes the transmission of MP to rich vs. poor regions.
- ▷ With weak fiscal risk-sharing, GDP in poor regions exhibit a strong and persistent contraction.
- Strong fiscal risk-sharing also dampens the MP shock for rich regions, but the persistence is much less accentuated than for poor regions.
- \triangleright Risk-sharing is forceful in preempting long-lived hysteresis effects of MP in poor regions.

Conclusion

Our results show:

- ▷ Risk-sharing shapes the real effects of MP shocks
 - ▷ With high risk-sharing, regions experience a shallower output contraction...
 - \triangleright and are less prone to hysteresis.
- Public risk-sharing benefits poor regions by shielding them against hysteresis.
- ▷ Fiscal and market-based risk-sharing emerge as complements.
- Provide support on the merits of deeper fiscal and financial integration in the EA (Bénassy-Quéré et al., 2018; Draghi, 2018; Lane, 2021).

Thank you!

Appendix

Regional disparities arise both within and between EA countries

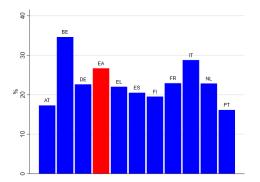


Figure: Coefficient of variation of real GDP per capita (2018)

Note: The coefficient of variation (CV) is calculated as the ratio of the standard deviation to the mean of all NUTS-2 regions within each country in 2018. The red bar indicates the CV of all EA countries, using national real GDP per capita in 2018.

Factor market channel: the wedge between **output** and **primary income** corresponds to the net income streams (capital and labour) receivable from and payable to other regions and countries.

Fiscal channel: the wedge between **primary** and **disposable income** stems from the difference between tax payments to and transfer payments from the government.

Credit market channel: the wedge between **disposable income** and **consumption** reflects economic agents' debt accumulation minus savings in each period.

Asdrubali et al. (1996) methodology •Back

Starting the accounting identity,

$$GDP^{k} = \frac{GDP^{k}}{PI^{k}} \frac{PI^{k}}{DI^{k}} \frac{DI^{k}}{C^{k}} C^{k}$$

where k is an index of regions.

Taking logs and differences of the identity, multiply both sides by $\Delta \log GDP$, and take the cross-sectional average to obtain the variance decomposition

$$\begin{aligned} \mathsf{var}\{\Delta gdp\} =& \mathsf{cov}\{\Delta gdp, \Delta gdp - \Delta pi\} \\ &+ \mathsf{cov}\{\Delta gdp, \Delta pi - \Delta di\} \\ &+ \mathsf{cov}\{\Delta gdp, \Delta di - \Delta c\} \\ &+ \mathsf{cov}\{\Delta gdp, \Delta c\} \end{aligned}$$

where gdp, pi, di and c are in log values and in real terms.

Asdrubali et al. (1996) methodology •Back

We obtain the following relation by dividing by $var{\Delta gdp}$ and rearranging:

$$\beta_{\mathsf{K}} + \beta_{\mathsf{F}} + \beta_{\mathsf{C}} = 1 - \beta_{\mathsf{U}}$$

where

$$\beta_{K} = \operatorname{cov}\{\Delta gdp, \Delta gdp - \Delta pi\}/\operatorname{var}\{\Delta gdp\}$$
$$\beta_{F} = \operatorname{cov}\{\Delta gdp, \Delta pi - \Delta di\}/\operatorname{var}\{\Delta gdp\}$$
$$\beta_{C} = \operatorname{cov}\{\Delta gdp, \Delta di - \Delta c\}/\operatorname{var}\{\Delta gdp\}$$
$$\beta_{U} = \operatorname{cov}\{\Delta gdp, \Delta c\}/\operatorname{var}\{\Delta gdp\}$$

 β_K is the OLS estimate of the slope in the cross-sectional regression of $\Delta \log GDP$ on $\Delta \log GDP - \Delta \log PI$

List of variables and controls **Back**

Time sample: 2000 to 2018, annual frequency

Country sample: Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain.

	Variable	Level	Note	Source
Risk-sharing	GDP	Regional	ln	Eurostat
	Primary income	Regional	In	Eurostat
	Disposable income	Regional	In	Eurostat
	Consumption	Regional	In	Oxford Economics
Monetary policy	Short-term interest rate	Euro area	percent per annum	AWM database
	Shadow interest rate	Euro area	percent per annum	Lemke & Vladu (2017)
Control variables	Population	Regional	In	Eurostat
	HICP	National	In	Eurostat
	Stock market index	National	In	OECD
	Government debt	National	% of GDP	Eurostat
	10y gov bond yield	National		ECB
	Structural primary balance	National	First-diff	AMECO
	GDP	Euro area	In	Eurostat
	HICP	Euro area	ln	Eurostat

NUTS classification Back

The NUTS classification breaks down the EU Member States into four levels.

- The highest level (NUTS-0) corresponds to the nation state.
- The lower levels (NUTS-1 to NUTS-3) subdivide national territories into ever more granular units based on population thresholds and existing administrative structures.

Our analysis uses NUTS-2 data, which offer the most granular regional breakdown with sufficient variable coverage to estimate the degree of risk-sharing within each country.

NUTS-2 regions are defined as hosting between 800,000 and 3,000,000 inhabitants and typically refer to Provinces, Regions and, in some cases, States.

Descriptive statistics

	GDI	D	Prim. income		Disp. income		Consum	ption
	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Austria	41,128	17	26,628	5	22,545	3	20,860	2
Belgium	36,521	35	24,708	14	19,918	9	19,255	6
Finland	40,929	20	24,237	16	21,205	9	21,590	11
France	29,859	23	21,145	12	19,047	6	17,568	4
Germany	37,345	23	26,398	16	21,174	9	19,508	7
Greece	14,494	22	9,988	17	9,774	12	11,127	8
Italy	28,190	29	18,612	26	17,088	20	17,272	20
Netherlands	39,254	23	25,209	10	18,866	5	18,324	4
Portugal	18,507	19	11,339	16	11,619	13	11,824	9
Spain	23,982	21	15,273	20	14,245	17	13,952	18
Euro area	29,664	27	20,888	30	17,727	24	17,225	20

Note: Figures refer to real per capita GDP, primary income, disposable income and consumption in 2018 at the NUTS-2 level, except for the euro area row, which is based on NUTS-0 (country-level) data. The coefficient of variation (CV) is computed as the ratio of the standard deviation to the mean of all NUTS-2 (NUTS-0) units within each country (the euro area) in 2018.

Estimation of the β_{K}^{c} -coefficients using differentiated data \bullet Back

	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
AT	0.568***	0.461***	0.350	0.320	0.327	0.301
	[0.105]	[0.165]	[0.223]	[0.251]	[0.286]	[0.291]
BE	0.736***	0.802***	0.730***	0.772***	0.725***	0.737***
DE	[0.121]	[0.179]	[0.191]	[0.229]	[0.221]	[0.254]
DE	0.785***	0.707***	0.679***	0.645***	0.643***	0.611***
	[0.0583]	[0.0540]	[0.0529]	[0.0485]	[0.0458]	[0.0464]
EL	0.756***	0.793***	0.717***	0.650***	0.549*	0.464
	[0.115]	[0.153]	[0.204]	[0.241]	[0.288]	[0.296]
ES	0.138**	0.0780	0.0653	0.0601	0.0523	0.0458
	[0.0541]	[0.0495]	[0.0458]	[0.0410]	[0.0394]	[0.0382]
FI	0.824***	0.638***	0.506***	0.499***	0.495***	0.469***
	[0.0456]	[0.0896]	[0.103]	[0.109]	[0.0991]	[0.142]
FR	0.811***	0.706***	0.706***	0.690***	0.637***	0.635***
	[0.0919]	[0.0871]	[0.0941]	[0.107]	[0.128]	[0.142]
IT	0.539***	0.443***	0.412***	0.397***	0.386***	0.423***
	[0.0317]	[0.0317]	[0.0374]	[0.0448]	[0.0522]	[0.0511]
NU	0.044***	0.077***	1.050***	0.007***	0.006***	0.002***
NL	0.944***	0.977***	1.058***	0.997***	0.926***	0.823***
	[0.0699]	[0.0699]	[0.146]	[0.133]	[0.119]	[0.115]
PT	0.295*	0.157	0.0920	0.0433	0.0471	0.0666
	[0.179]	[0.136]	[0.110]	[0.115]	[0.117]	[0.148]
Observations	2790	2635	2480	2325	2170	2015

Note: This table reports the estimation of β_K using differentiated intervals, j = 0...5. Standard errors are bootstrapped using 1000 iterations. * / ** / *** indicate 1% / 5% / 10% significance level.

Estimation of the β_F^c -coefficients using differentiated data \bullet Back

	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
AT	0.0587***	0.0664*	0.0533	0.0372	0.0350	0.0302
	[0.0193]	[0.0363]	[0.0546]	[0.0741]	[0.0866]	[0.0988]
BE	0.0340	-0.00729	-0.0346	-0.0321	-0.0324	-0.0338
DL	[0.0340]	[0.0696]	[0.0610]	[0.0743]	[0.0712]	[0.0809]
	[0.0500]	[0.0050]	[0.0010]	[0.0145]	[0.0712]	[0.0005]
DE	0.0186	0.0486***	0.0737***	0.0862***	0.0895**	0.106**
	[0.0137]	[0.0172]	[0.0233]	[0.0333]	[0.0390]	[0.0469]
EL	-0.00928	0.00924	0.0574	0.0970	0.0906	0.0865
EL	[0.0868]	[0.0829]	[0.0806]	[0.0863]	[0.108]	[0.126]
	[0.0000]	[0.0029]	[0.0000]	[0.0003]	[0.100]	[0.120]
ES	0.0383	0.0314	0.0275	0.0126	0.000426	-0.0115
	[0.0324]	[0.0392]	[0.0502]	[0.0589]	[0.0567]	[0.0607]
-						
FI	0.0902	0.102***	0.0462	0.0197	-0.00499	-0.0139
	[0.0559]	[0.0288]	[0.0515]	[0.0625]	[0.0613]	[0.0615]
FR	0.0684**	0.0978***	0.101***	0.105***	0.154***	0.178***
	[0.0339]	[0.0295]	[0.0279]	[0.0340]	[0.0386]	[0.0435]
IT	0.0810***	0.112***	0.123***	0.122***	0.121***	0.113***
	[0.0295]	[0.0307]	[0.0309]	[0.0315]	[0.0375]	[0.0428]
NL	-0.0599	-0.0147	0.0427	0.0393	0.0383	0.0433
NL.	[0.0889]	[0.111]	[0.110]	[0.111]	[0.114]	[0.120]
	[1110000]	[]	[]	[]	[*	[]
PT	0.0317	0.0562	0.0530	0.0800	0.0931	0.0943
	[0.0916]	[0.0872]	[0.0938]	[0.115]	[0.107]	[0.103]
Observations	2787	2631	2476	2321	2167	2013

Note: This table reports the estimation of β_F using differentiated intervals, j = 0...5. Standard errors are bootstrapped using 1000 iterations. * / ** / *** indicate 1% / 5% / 10% significance level.

Estimation of the β_{C}^{c} -coefficients using differentiated data \bullet Back

	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
AT	0.0699	0.102	0.143*	0.173**	0.182*	0.204*
	[0.0575]	[0.0672]	[0.0855]	[0.0880]	[0.0972]	[0.104]
DE	0.0107	0.0106	0.0261*	0.0110	0.0240	0.0210
BE	0.0107 [0.0234]	0.0196 [0.0150]	0.0261* [0.0159]	0.0112 [0.0226]	0.0240 [0.0258]	0.0318 [0.0321]
	[0.0254]	[0.0150]	[0.0129]	[0.0220]	[0.0256]	[0.0521]
DE	-0.0109	-0.0158	-0.00824	0.00240	0.00327	0.00475
	[0.0107]	[0.0155]	[0.0156]	[0.0155]	[0.0162]	[0.0170]
EL	0.0378	0.0307	0.0441	0.0572	0.0930	0.122
	[0.0422]	[0.0370]	[0.0441]	[0.0608]	[0.0726]	[0.0839]
ES	0.141	0.0956	0.0791	0.0631	0.0690	0.0691
20	[0.0874]	[0.0971]	[0.115]	[0.123]	[0.131]	[0.137]
		[]	L1		1 1	[· · ·]
FI	0.0537	0.201***	0.468**	0.568**	0.582**	0.595**
	[0.0598]	[0.0710]	[0.215]	[0.287]	[0.292]	[0.279]
FR	0.0404*	0.0595**	0.0477*	0.0491	0.0542	0.0478
· · ·	[0.0240]	[0.0236]	[0.0282]	[0.0323]	[0.0393]	[0.0427]
	[0:02:10]	[0.0200]	[0:0202]	[0.0020]	[0.0050]	[0.0121]
IT	0.204***	0.182***	0.154**	0.140*	0.133	0.109
	[0.0452]	[0.0598]	[0.0744]	[0.0790]	[0.0914]	[0.103]
NI	0 0200	0.0522	0.0720	0.0666	0.0500	0.0404
NL	-0.0328	-0.0532	-0.0739	-0.0666	-0.0529	-0.0424
	[0.0436]	[0.0430]	[0.0524]	[0.0586]	[0.0546]	[0.0501]
PT	0.104**	0.125***	0.131**	0.145**	0.141*	0.149*
	[0.0494]	[0.0480]	[0.0598]	[0.0666]	[0.0735]	[0.0843]
Observations	2787	2631	2476	2321	2167	2013

Note: This table reports the estimation of β_C using differentiated intervals, j = 0...5. Standard errors are bootstrapped using 1000 iterations. * / *** / *** indicate 1% / 5% / 10% significance level.

Estimation of the β_U^c -coefficients using differentiated data \bullet Back

	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
AT	0.304***	0.371***	0.454***	0.469***	0.456***	0.464***
	[0.0706]	[0.0943]	[0.125]	[0.135]	[0.153]	[0.160]
BE	0.220	0.185	0.278	0.249	0.283	0.265
DL	[0.147]	[0.193]	[0.181]	[0.207]	[0.194]	[0.213]
	[0.1.1]	[0.150]	[0.101]	[0.201]	[0.13 1]	[0:210]
DE	0.207***	0.260***	0.255***	0.267***	0.264***	0.278***
	[0.0555]	[0.0431]	[0.0371]	[0.0347]	[0.0331]	[0.0355]
EL	0.203**	0.155	0.182	0.188	0.245	0.296
	[0.0971]	[0.117]	[0.136]	[0.184]	[0.245]	[0.281]
	[0:0011]	[0.111]	[0.100]	[0.101]	[0.210]	[0.201]
ES	0.683***	0.795***	0.828***	0.864***	0.878***	0.897***
	[0.105]	[0.0957]	[0.106]	[0.113]	[0.124]	[0.145]
FI	0.0320	0.0589	-0.0198	-0.0874	-0.0721	-0.0497
	[0.0570]	[0.0889]	[0.138]	[0.202]	[0.204]	[0.253]
	[0.0510]	[0.0005]	[0.130]	[0.202]	[0.204]	[0.200]
FR	0.0802	0.137***	0.146**	0.156*	0.155*	0.139
	[0.0623]	[0.0507]	[0.0651]	[0.0819]	[0.0929]	[0.105]
IT	0.176***	0.263***	0.311***	0.341***	0.360***	0.356***
	[0.0268]	[0.0534]	[0.0739]	[0.0834]	[0.107]	[0.112]
	[0.0200]	[0.0554]	[0.0755]	[0.0034]	[0.107]	[0.112]
NL	0.148	0.0913	-0.0266	0.0307	0.0888	0.176
	[0.0939]	[0.0684]	[0.102]	[0.117]	[0.134]	[0.150]
PT	0.570***	0.662***	0.724***	0.732***	0.718***	0.690***
FI	[0.171]	[0.125]	[0.115]	[0.146]	[0.131]	[0.133]
Observations	2790	2635	2480	2325	2170	2015
			2.00	2520		

Note: This table reports the estimation of β_U using differentiated intervals, j = 0...5. Standard errors are bootstrapped using 1000 iterations. * / *** / *** indicate 1% / 5% / 10% significance level.

Generated regressor • Back

When an estimated regressor is subject to sampling error, i.e. a generated regressor, the ordinary least squares (OLS) estimator is potentially biased (Pagan, 1984; Murphy & Topel, 1985). Consider a simple model:

$$y_i = \alpha_i \cdot \beta + \mathbf{X}_i \gamma + \varepsilon_i$$

Suppose that α_i is unknown and needs to be estimated by its sample counterpart $\hat{\alpha}_i$. Because $\hat{\alpha}_i$ differs from α_i as a result of sampling error, we write:

$$\hat{\alpha}_i = \alpha_i + u_i$$

where u_i is the sampling error. Therefore,

$$y_i = \hat{\alpha}_i \cdot \beta + \mathbf{X}_i \gamma + \tilde{\varepsilon}_i \quad \tilde{\varepsilon}_i = \varepsilon_i - u_i \cdot \beta$$

We follow the literature (Wooldridge, 2014) in bootstrapping both stages of the procedure

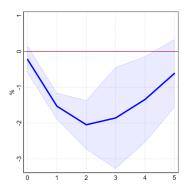
- 1. the estimation of risk-sharing
- 2. the LLPs

Baseline model and results **Back**

Hauptmeier et al (2020)

$$y_{k,t+h} = \alpha_{k,h} + \kappa_h i_t + \gamma_h \mathbf{X}_{k,t} + \delta_h \mathbf{X}_{c,t} + \theta_h \mathbf{X}_t + \varepsilon_{k,t+h}$$

Figure: Impact of monetary policy on regional output



Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands.

Identification • Back

- Monetary policy is by construction endogenous to economic prospects
- Regionally disaggregated data offer a novel answer to this identification challenge
- Regional conditions do not enter the central bank objective function
- So, controlling for macro and financial factors factors, variation in policy is exogenous to regional GDP
- **Robustness check:** results hold when running the same regressions without the 20 largest regions.

"[The ECB's] single monetary policy will adopt a euro areawide perspective; it will not react to specific regional or national developments"

ECB Governing Council Press Release, 13 October 1998

Risk-sharing and monetary policy - results table • Back

Table: Baseline estimates for coefficients on the short-term interest rate and the interaction with the fraction of shared risk .

	h = 0	h = 1	<i>h</i> = 2	h = 3	<i>h</i> = 4	h = 5
i _t	-0.331*** (0.121)	-1.593*** (0.111)	-2.092*** (0.124)	-1.853*** (0.181)	-1.279*** (0.183)	-0.556*** (0.134)
$i_t \times \hat{\beta}^{c}_{S,h}$	0.486*** (0.136)	0.364*** (0.115)	0.387*** (0.108)	0.477*** (0.109)	0.582*** (0.108)	0.681*** (0.101)
Observations	2945	2790	2635	2480	2325	2170
Within R2	0.705	0.698	0.663	0.595	0.529	0.514
Number of regions	155	155	155	155	155	155

Note: This table reports the estimation of the baseline model when risk is shared. We do not report the estimations of the control variables. $\beta^c_{5,h}$ are standardized. The Driscoll and Kraay (1998) standard errors are given in parenthesis. Standard errors are bootstrapped using 1000 interactions. * / *** / *** indicate 1% / 5% / 10% significance level.

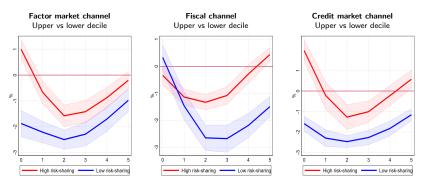
Risk-sharing and monetary policy - results table Pack

	h = 0	h = 1	<i>h</i> = 2	<i>h</i> = 3	<i>h</i> = 4	h = 5
i _t	-0.106	-1.290***	-2.051***	-1.842***	-1.272***	-0.562***
	(0.143)	(0.145)	(0.156)	(0.202)	(0.206)	(0.159)
$i_t \times \hat{\beta}^h_{K,h}$	1.177***	0.619***	0.348***	0.337***	0.297**	0.269**
	(0.192)	(0.164)	(0.131)	(0.124)	(0.132)	(0.124)
$i_t \times \hat{\beta}^h_{F,h}$	-0.0335	0.114	0.536***	0.648***	0.735***	0.759***
	(0.169)	(0.181)	(0.117)	(0.121)	(0.110)	(0.107)
$i_t \times \hat{\beta}^h_{C,h}$	1.293***	0.813***	0.396**	0.491***	0.659***	0.716***
	(0.216)	(0.234)	(0.177)	(0.137)	(0.135)	(0.135)
Observations	2945	2790	2635	2480	2325	2170
Within R2	0.735	0.716	0.680	0.613	0.550	0.533
Number of regions	155	155	155	155	155	155

Table: Baseline estimates for coefficients on the short-term interest rate and the interaction with the fraction of shared risk, through the different channels.

Note: This table reports the estimation of equation ??. We do not report the estimations of the control variables. $\hat{\beta}_{K,h}^c, \hat{\beta}_{L,h}^c, \hat{\beta}_{C,h}^c, \hat{\beta}_{C,h}^c$ are standardized. Driscoll-Kraay standard errors are given in parenthesis. Standard errors are bootstrapped using 1000 interactions. * / *** | **** indicate 1% / 5% / 10% significance level.

IRFS for 10th vs 90th pct of risk-sharing Dack



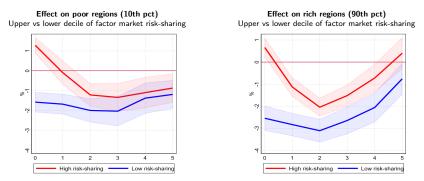
Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) deciles of $\beta_{K,h}^{c} / \beta_{F,h}^{c} / \beta_{C,h}^{c}$. Driscoll-Kraay standard errors are boostrapped using 100 iterations.

Quantile regressions Back

- Quantile regression models characterize the entire conditional distribution of a dependent variable conditional on a set of regressors (Koenker & Basset, 1978).
- Provide a flexible way to explore heterogeneity in the response of MP and its interaction with risk-sharing.
- ▷ In the presence of fixed effects, quantile estimation suffers from incidental parameter problems (Lancaster, 2000).
- ▷ To address this issue, we emplow the quantiles-via-moments estimator by Machado & Santos Silva (2019).

Risk-sharing, inequality and monetary policy **Pack**

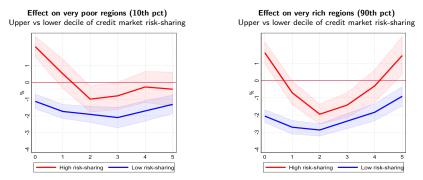
Study the effect of monetary policy on poor vs rich regions, depending on levels of risk-sharing through factor markets.



Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) deciles of $\hat{\beta}_{K,h}^c$. Standard errors are clustered at the time and regional-level and are boostrapped using 1000 iterations.

Risk-sharing, inequality and monetary policy **Pack**

Study the effect of monetary policy on poor vs rich regions, depending on levels of risk-sharing through credit markets.

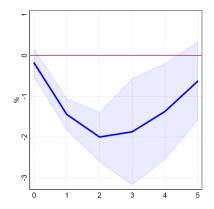


Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. Red (blue) lines depict the estimates for the upper (lower) deciles of $\hat{\beta}_{C,h}^2$. Standard errors are clustered at the time and regional-level and are boostrapped using 1000 iterations.

Robustness checks

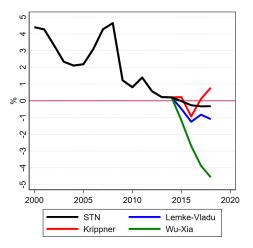
Excluding the largest regions

Impact of monetary policy on regional aggregates when excluding the largest regions



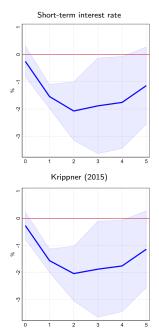
Note: Vertical axis refers to impact of 100 basis point rate hike on regional GDP (in %). Horizontal axis refers to horizon of IRF (in years). Solid lines denote point estimates and shaded areas denote 90% confidence bands. The 20 largest regions are excluded for each year.

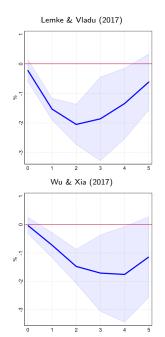
Shadow rates for the Euro area



Note: The short-term interest rate (STN) is extended by adding the cumulative changes of the shadow rates developed by Lemke & Vladu (2017), Krippner (2015) and Wu-Xia (2017)

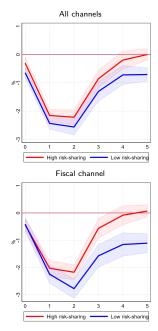
Shadow rates for the Euro area

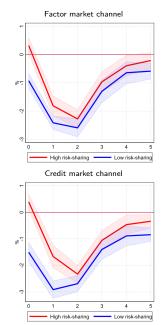




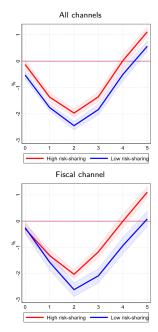
23 / 28

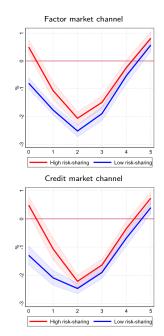
Adding oil prices and the real effective exchange rate



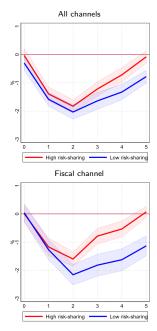


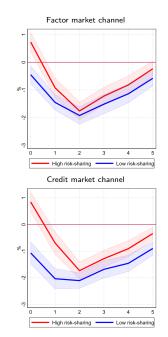
Alternative control variables





Forward-looking variables





Does MP affects risk-sharing?

There is evidence that risk-sharing varies over the business cycle. (Hoffmann & Stewen, 2011; Furceri & Zdzienicka, 2015)

Does the stance of MP influence risk-sharing?

We follow the approach of Hoffmann & Stewen (2011) and look at:

$$\Delta c_t^k = a_U \times \Delta g dp_t^k + b_U \Delta i_t \times \Delta g dp_t^k + \alpha_t + \varepsilon_{U,t}^k$$

so that $\beta_U(t) = a_U + b_U \times \Delta g dp_t^k$, the fraction of unshared risk that varies with Δi_t .

Does MP affects risk-sharing?

	AT	BE	DE	EL	ES	FI	FR	IT	NL	PT
∆gdp	0.280***	0.139	0.153***	0.212**	0.690***	-0.00175	0.0756	0.213***	0.202**	0.570***
	[0.0621]	[0.114]	[0.0479]	[0.0915]	[0.0995]	[0.0775]	[0.0587]	[0.0286]	[0.102]	[0.175]
$\Delta gdp \times \Delta i_t$	-0.0585	-0.0858	-0.0743***	0.0342	0.0718	-0.0290	-0.0172	0.0523	0.143*	0.182*
	[0.0567]	[0.121]	[0.0258]	[0.0443]	[0.0745]	[0.0473]	[0.0298]	[0.0421]	[0.0821]	[0.0939]
Observations	162	198	684	234	342	90	396	378	216	126

Table: Estimates for time-varying β_U -coefficients for EA countries

Note: This table reports the estimation of the standard risk-sharing equation, depending on the stance of monetary policy. Standard errors are reported in parenthesis and are bootstrapped using 100 iterations. * / ** / *** indicate 1% / 5% / 10% significance level.

 \Rightarrow No clear evidence that MP affects risk-sharing.