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Presentation for Bank of Italy Seminar

Structural VARs for Heterogeneous Panels;

With Applications to European Regional Income Dynamics and International Exchange Rate Dynamics

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Presentation Outline

I. General Overview

II. Details of Methodology

- econometric issues

- nontechnical summary

III. International Exchange Rate Dynamics

- data description

- identification strategy

- empirical results

IV. European Regional Income Dynamics

- data description

- identification strategy

- empirical results

VI. Conclusions

- and directions for future research,
  in macro and regional economics

I. General Motivation

Often interested to exploit multi-country or multi-regional dimensions for panel time series

Literature on nonstationary panels does this

- but focused on long run steady state issues

- unit roots, cointegration, etc.

But often interested in short run dynamic issues

- how to regions respond to over time to national and local business cycle variations

- what region specific characteristics determine the shape and size of the responses

- can patterns across countries better help us identify reasons for unusual exchange rate dynamics

Is it possible to exploit panel time series toward this end?

If so, need to be careful regarding treatment of three important issues

1. Dynamics likely to be heterogeneous

- if ignore heterogeneity and pool dynamics leads to inconsistent estimation

- estimates do not converge to mean values of heterogeneous parameters

- classic problem of latent heterogeneity in lagged dependent variables

(See *Pesaran and Smith*, *1995*, for review)

Background on older "dynamic panel" techniques:

- VARs for homogeneous panels already exist

  (See *Holz-Eakin, Newey and Rozen*, 1988)

- dynamic panel literature (Arellano and Bond, etc) is special cases of homogeneous panel VARs

- but homogeneity assumption almost certainly violated for any aggregrate data

    - would imply identical impulse responses in terms of size, shape, duration, etc.

    - not appropriate for macro or regional data

2. Time series dimension is likely to be short

- want to apply in circumstances when *T* dimension too short for conventional time series

- need to treat heterogeneous dynamics, but don't have advantage of superconsistency

Background comparison:

- for nonstationary panel methods dynamics do not need to be well estimated

- do not need to be estimated jointly with long run

- can be treated as nuisance feature in distributions for long run inference

- due to fact that dynamics have only second order impact relative to the long run levels

So not obvious that can recognize gains from panels

Solution: Use spatial dimension directly to construct confidence intervals

- results in relatively tight confidence intervals even with short T

- eliminates need for bootstrapping confidence intervals

- BUT, this brings into focus the next issue:

3. Cross sectional dependencies must be accommodated

- countries and regions likely to be interdependent

- if want inferences regarding spatial distribution of responses to be valid need to control for this

- but interdependencies likely to be dynamic

- which brings into focus the next issue:

4. Economic “forcing process” often unobserved

- i.e. most responses of interest are to “structural” economic shocks, not to observables

- need to deal with structural identification

- particularly given that need to accommodate dynamic interdependencies in responses to shocks

Solution: Use structural VAR approach so that can identify orthogonal shocks

- at both local and global level

- and use orthogonality to decompose composite shocks into local versus global shocks

- and thereby allow complex interactions in terms of responses to shocks

1.3 Relationship to other approaches

- *Canova and Ciccarelli (2004, 2009)*
  - Use Bayesian VAR estimation approach
  - Allow for time varying coefficients
  - Treat cross sectional dependency using factor model
  - Focus on responses to innovations in observables (not unobserved structural shocks)
  - Multi-country application: Response of other large economies to innovations in U.S. GDP

- *Eickmeier (2009)*
  - Use classical estimation approach
  - Do not allow for time varying coefficients
  - Also treat cross sectional dependency using factor model
  - Focus on idiosyncratic responses to common factor model shocks. Do not do pool or group responses to idiosyncratic shocks
  - Multicountry application: Heterogeneity of European country responses to European common shocks.

- *This paper*
  - By contrast emphasizes properties of full sample distribution of responses to both idiosyncratic and common shocks i
  - Uses spatial dimension for confidence intervals around group medians.
  - Emphasizes identification of structural shocks
  - Treats cross sectional dependency structurally by using restrictions on time effects to identify common shocks
  - Regional application: Explaining patterns of heterogeneous dynamics.

1.4 Econometric Technique

- Use panel SVAR to decompose responses to different unobserved structural shock
- Also distinguish common versus idiosyncratic structural shocks
- Allow heterogenous factor loading responses to common structural shocks
- Compute distributions of dynamic responses across i dimension
- Relate distributions to observed regional characteristics x_i

1.4.1 *Representation of Model Dynamics for Panel*

Dimensions:

$i = 1, ..., N$ members (regions)

$t = 1, ..., T_i$ time periods (years)

$y_{m,it}$, $m = 1, ..., M$ observed variables

as $M \times 1$ vector $z_{it} = (z_{1,it}, ..., z_{M,it})'$

where $z_{it} = y_{it} - \bar{y}_i$

$$\bar{y}_{it} = T^{-1} \sum_{t=1}^{T} y_{it} \; \forall \; i, m$$

- to accommodate fixed effects

Unobserved Shocks:

idiosyncratic shocks:

$\tilde{\epsilon}_{m,it}$, $m = 1, ..., M$

common shocks:

$\bar{\epsilon}_{m,t}$, $m = 1, ..., M_c$, $M_c \leq M$

composite shocks:

$\epsilon_{m,it}$, $m = 1, ..., M$, $\epsilon_{it} = (\epsilon_{1,it}, ..., \epsilon_{M,it})'$

such that:

$\epsilon_{m,it} = \lambda_{m,i}\bar{\epsilon}_{m,t} + \tilde{\epsilon}_{m,it} \;\; \forall\, i, t, m$

$E(\tilde{\epsilon}_{m,it}\bar{\epsilon}_{m,t}) = 0 \;\; \forall\, i, t, m$

$E(\epsilon_{it}\epsilon'_{it}) = I_{M\times M} \;\; \forall\, i, t$

$E(\epsilon_{m,it}) = E(\tilde{\epsilon}_{m,it}) = E(\bar{\epsilon}_{m,t}) = 0 \;\; \forall\, i, t, m$

Dynamics:

unit root properties:

$z_{m,it} \sim I(1) \; \forall \; m, i$

stationary Wald representation:

$\Delta z_{it} = A_i(L)\epsilon_{it}$

where $\quad A_i(L) = \sum_{j=0}^{Q_i} A_{ij} L^j$

long run impact matrix:

$A_i(1) = \lim_{Q_i \to \infty} \sum_{j=0}^{Q_i} A_{ij}$

typical recursive steady state restriction:

$A_i(1)_{(j,k)} = 0 \;\; \forall \; i, j < k$

1.4.2 *Estimation and Inference for Panel*

Estimation:

1. Estimate $R_i(L)\Delta z_{it} = \mu_{it}$ by OLS $\forall i$

where $R_i(L) = I - \sum_{j=1}^{P_i} R_{ij} L^j$

with P_i chosen by AIC $\forall i$

2. Compute $\Delta \bar{z}_t = N^{-1} \sum_{i=1}^{N} \Delta z_{it}$ $\forall t$

3. Estimate $\bar{R}(L)\Delta \bar{z}_t = \bar{\mu}_t$ by OLS

where $\bar{R}(L) = I - \sum_{j=1}^{P} \bar{R}_{ij} L^j$

with P chosen by AIC

Structural Identification:

Reduced form MA representation

(for composite shocks):

$$\Delta z_{it} = F_i(L)\mu_{it},$$

where $F_i(L) = R_i(L)^{-1}$, $F_i(0) = 0$

So that relates to structural form as:

$$\Delta z_{it} = F_i(L)\mu_{it} = A_i(L)\epsilon_{it},$$

$$\epsilon_{it} = A_i(0)^{-1}\mu_{it}$$

$$A(L)_i = F(L)_i A_i(0)$$

$$A(0)_i = R(1)_i A_i(1)$$

Orthogonality and arbitrary units

$$E(\epsilon_{it}\epsilon_{it}') = I_{M\times M} \ \ \forall\, i, t$$

Implies:

For contemporaneous covariance:

$$\begin{aligned} E(\mu_{it}\mu_{it}') &= E(A(0)_i\epsilon_{it}\epsilon_{it}'A(0)_i') \\ &= A(0)_iA(0)_i' \end{aligned}$$

For long run covariance of μ_{it}:

$$\begin{aligned} \Omega_i(1) &= E(F(1)_i\mu_{it}\mu_{it}'F(1)_i') \\ &= A(1)_iA(1)_i' \end{aligned}$$

Steady state identifying restriction

$$A_i(1)_{(j,k)} = 0 \ \ \forall\, i, j < k$$

Implies:

$$A_i(1) = Chol(\Omega_i(1))$$

So, <u>for composite shocks</u>:

$\epsilon_{it} = (\widehat{R}_i(1)\widehat{A}_i(1))^{-1}\widehat{\mu}_{it}$

$A_i(L) = \widehat{R}_i(L)^{-1}\widehat{R}_i(1)\widehat{A}_i(1)$

where $\widehat{A}_i(1)$ obtained from Cholesky of :

$\widehat{\Omega}_i(1) = (\widehat{R}_i(1)^{-1})\widehat{\Sigma}_i(\widehat{R}_i(1)^{-1})'$

$$\widehat{\Sigma}_i = T^{-1}\sum_{t=1}^{T}\hat{\mu}_{it}\hat{\mu}_{it}'$$

Similarly, <u>for common shocks</u>:

$$\bar{A}(1)_{(j,k)} = 0 \;\; \forall \; j < k$$

Implies:

$$\bar{A}(1) = Chol(\bar{\Omega}(1))$$

So that:

$$\bar{\epsilon}_t = (\widehat{R}(1)\widehat{A}(1))^{-1}\widehat{\mu}_t$$

$$\bar{A}(L) = \widehat{R}(L)^{-1}\widehat{R}(1)\widehat{A}(1)$$

where $\widehat{A}(1)$ obtained from Cholesky of :

$$\widehat{\Omega}(1) = (\widehat{R}(1)^{-1})\widehat{\Sigma}(\widehat{R}(1)^{-1})'$$

$$\widehat{\Sigma} = T^{-1}\sum_{t=1}^{T}\hat{\mu}_t\hat{\mu}_t'$$

Decompositions:

Estimate common factor loadings, $\lambda_{m,i}$, as:

$$\epsilon_{m,it} = \lambda_{m,i}\bar{\epsilon}_{m,t} + \tilde{\epsilon}_{m,it} \quad \text{by OLS} \quad \forall\ i, m$$

composite variances contributions:

$$D_{i,s}(k,\ell) = \frac{(\sum_{j=0}^{s-1} A_{i,j}e(\ell)e(\ell)'A'_{i,j})(\ell,\ell)}{\Psi_{i,s}(k,k)}$$

for a given step s, country i,

for shocks $\ell = 1, ..., M$,

for variables $k = 1, ...M$

where $\Psi_{i,s} = \sum_{j=0}^{s-1} A_{i,j}A'_{i,j}$

and $e(l)$ is the l^{th} unit vector

common variances contributions:

$$\overline{D}_{i,s}(k,\ell) = \frac{(\sum_{j=0}^{s-1} \bar{A}_j e(\ell)\lambda_i\lambda'_i e(\ell)'\bar{A}'_j)(\ell,\ell)}{\Psi_{i,s}(k,k)}$$

idiosyncratic variances contributions:

$$\widetilde{D}_{i,s} = D_{i,s} - \overline{D}_{i,s}$$

Group inference:

group mean estimates:

$D_s^{N_1}(k,\ell) = N_1^{-1} \sum_{i=1}^{N_1} D_{i,s}^R(k,\ell)$

for any given variable, $k = 1, ..., M$,

shock, $\ell = 1, ..., M$,

response step, $s = 0, ..., Q_i$,

for any $N_1 \epsilon N$ group of countries,

of the decomposition matrices:

$D_{i,s}^R(k,\ell) \epsilon \{D_{i,s}, \overline{D}_{i,s}, \widetilde{D}_{i,s}\}$

standard errors:

$\sigma_{D_s^{N_1}(k,\ell)} =$

$\sqrt{N_1^{-1} \sum_{i=1}^{N_1} \left(D_{i,s}^R(k,\ell) - D_s^{N_1}(k,\ell)\right)^2}$

confidence intervals:

use fractiles from sampling distributions of

$D_{i,s}^R(k,\ell)$

Nontechnical Summary

Step 1: Estimate composite reduced form VARs separately for each member *i*

Step 2: Apply identification scheme to obtain estimates of composite structural shocks for each member *i*

Step 3: Use cross sectional averages at each point in time for each variable to extract common effects

Step 4: Estimate common reduced form VAR

Step 5: Apply identification scheme to obtain estimates of composite structural shocks for each member *i*

Step 6: For each member *i* estimate member specific loading vectors for response to common shocks

Step 7: Use estimated loading vectors to decompose composite shocks into common versus idiosyncratic shocks

Step 8: For each member *i* compute structural impulse responses and variance decompositions for common and idiosyncratic shocks

Step 9: Compute sample distribution across *i* for each time period of impulse responses and variance decompositions

Step 10. Use sample distribution to compute group mean (or median) responses and decompositions

Step 11. Use sample distribution to compute spatial confidence intervals for responses and decompositions

- in contrast to time series SVARs, do not require bootstrap for confidence intervals

Step 12. Regress heterogeneous responses for given step s_i against vector of observable member specific characteristics x_i .

4. Empirical illustration: Sources of Nominal and Real Exchange Rate Rigidity

Basic idea:

Use identified panel SVAR technique to address puzzle in exchange rate literature

Find that structural identification provides possible resolution to puzzle

- for pure time series would require considerable data

- with panel approach get tight confidence intervals

1.1 Motivation

Real exchange rates notorious for slow adjustment

Conventional explanation:

- Aggregate prices are slow to adjust
- Consistent with sticky price macro models

Early empirical puzzle (Rogoff, 1996, others):

- RER adjustment even slower than P adjustment
- Hard to reconcile with conventional idea

Recent twist to puzzle:

(Engle, Morley 2001, Cheung, Lai, Bergman 2004):

- Decompose real e into P and nominal E adjustment
- nominal E adjusts much slower than P
- Appears to contradict conventional explanations

Engle and Morley (2001):

- 6 countries individually
- state space Kalman filter approach
- with PPP imposed
- estimate speed to close $P - P^{ss}$, $E - E^{ss}$ gaps consistent with PPP
- P half-life: 3-6 months , E half-life: 2-15 years

Cheung, Lai, Bergman (2004):

- 5 countries individually
- VECM cointegrated VAR approach
- with PPP imposed
- estimate speeds for P and E to close PPP gap
- P half-life: 1 -2 years, E half-life: 3-6 years

Why might central banks care about this puzzle?

Puzzle impacts logic of one classic argument for floating exchange rates:

- If trade sector important, may want to minimize real e fluctuations
- If believe real e often mean reverting in response to shocks, want quick return to "parity"
- If P adjustment is slow and sticky, then need nominal E to be able to do the adjusting
- But if E adjustment slow (possibly even slower than P) destroys this argument

Empirical Question: Can structural panel time series approach contribute toward resolving these puzzles?

Expect relative speeds to be sensitive to shock type

Begin agnostically:

- Initially use simple sticky price open economy framework for guidance
- Then consider possible refinements and deeper implications

Empirical Strategy:

1. Work with panel of countries

- use group mean dynamics
- allows one to establish patterns in dynamic distributions
- while allowing heterogeneous dynamics

2. Do not impose long run PPP

- Consider that some shocks may adhere to PPP (i.e. long run neutral on real e)
- Others may not (i.e. induce permanent real e movement)

Regarding long run PPP testing:

unit root tests for e often problematic

both time series and panel versions

Used new test here:

Pedroni,Vogelsang,Wagner,Westerlund (2008)

- untruncated kernel approach
- only test that retains power with short T when have incidental deterministic trends
- robust to any form of cross sectional dependence
- does not require any choice of lag or bandwidth truncation

Clearly rejects unconditional PPP in this sample

- both without and with incidental trends (e.g. Balassa-Samuelson version)

3. Consider implications of long run P neutrality

- some shocks potentially neutral on P for small open economies with flexible E.

  (e.g. real AD shocks that induce short run e response to maintain real interest parity may appear neutral on P - details later)

  (e.g. supply shocks accommodated with procyclic monetary response may also appear neutral on P - details later)

- Other shocks may not be neutral on P

  (e.g. nominal shocks, or unaccommodated supply shocks)

4. Distinguish common vs. idiosyncratic shocks

- Expected to have very different dynamic responses

  (e.g. common versus idiosyncratic shocks that are non-neutral on P have very different implications for E)

1.2 Data

E : log bilateral U.S. nominal exchange rates

P: log local CPI , $P*$: log U.S. CPI

e: computed log real exchange rates

$$\log e = \log E + \log P - \log P*$$

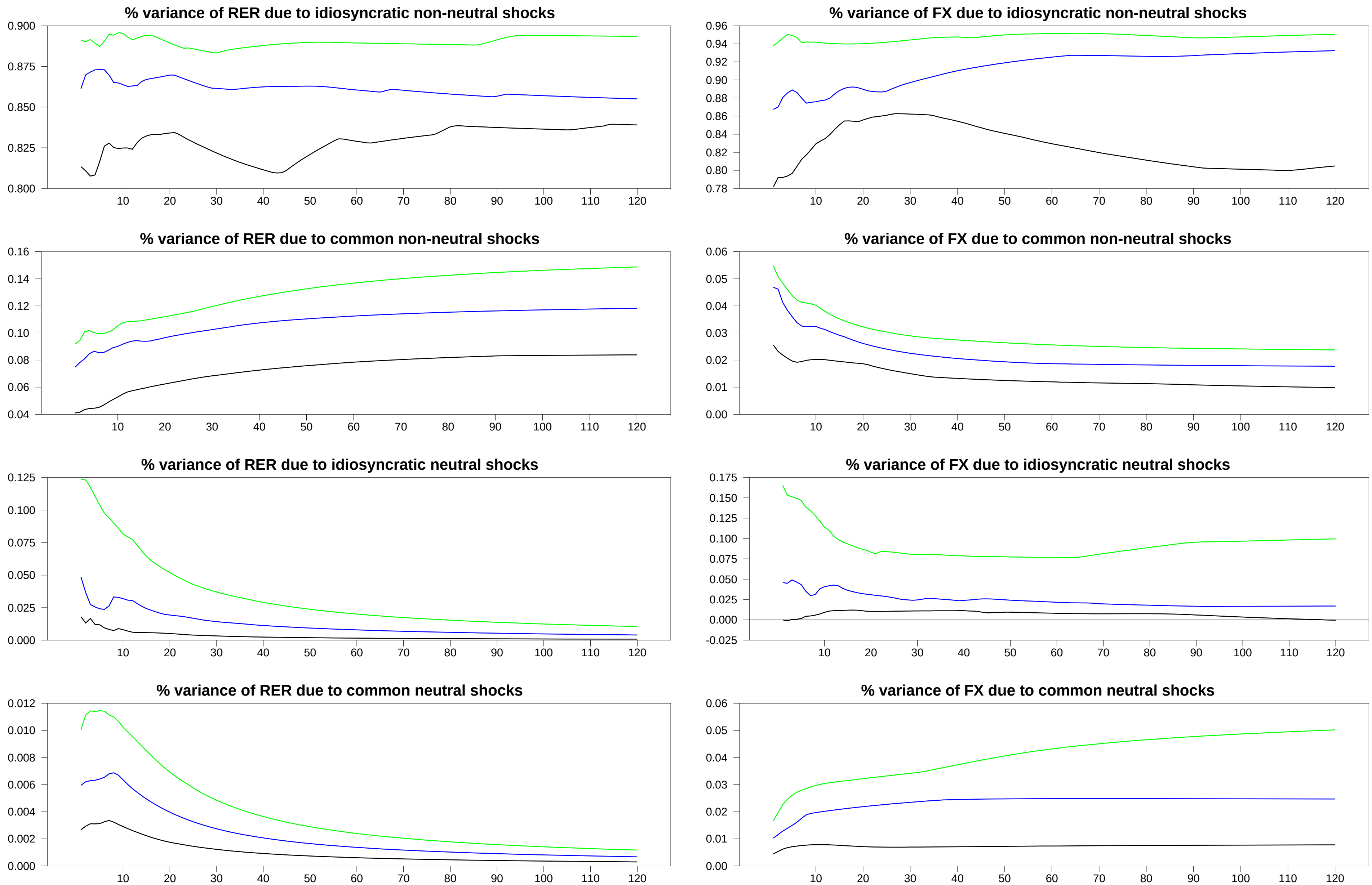
(CPI, FX rebased to 1995 for conformity)

time span: Monthly, Jan 1980 - Dec 1998

countries: Industrial $(N = 20, T = 228)$

Var Decomps to shocks neutral on RER vs. non-neutral on RER

Recursive (RER,FX) identification

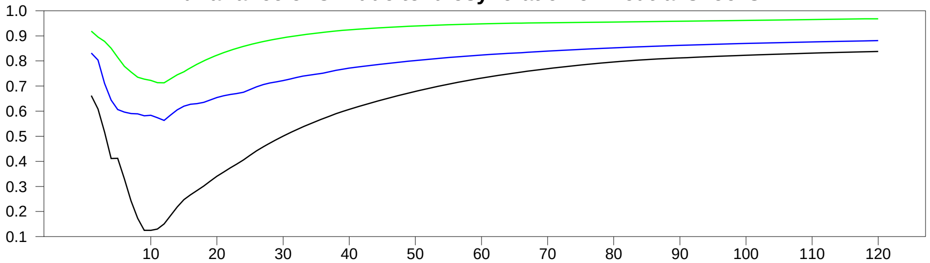


Summary: Most FX (and RER) variation is due to shocks that are non-neutral on FX.

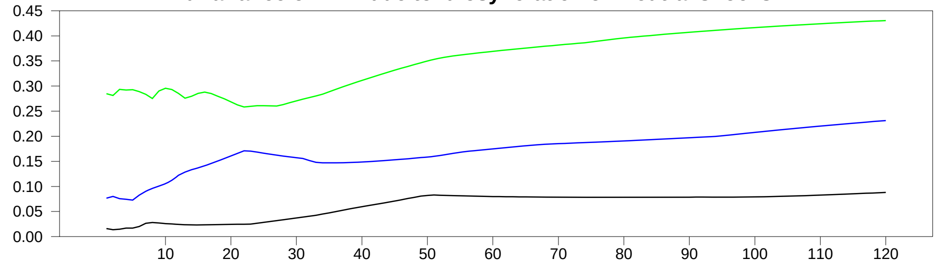
Var Decomps to shocks neutral on CPI vs. non-neutral on CPI

Recursive (CPI,RER) identification

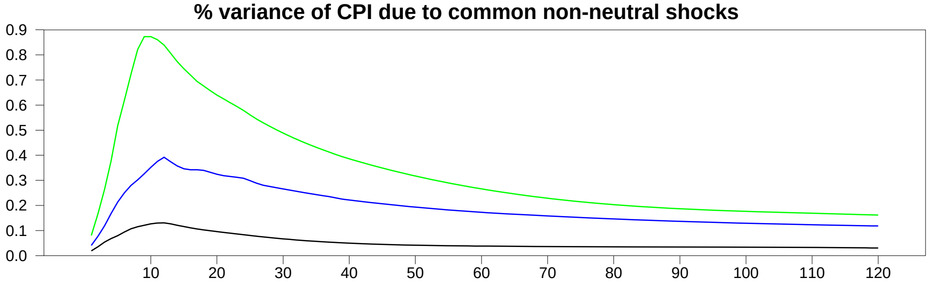
% variance of CPI due to idiosyncratic non-neutral shocks



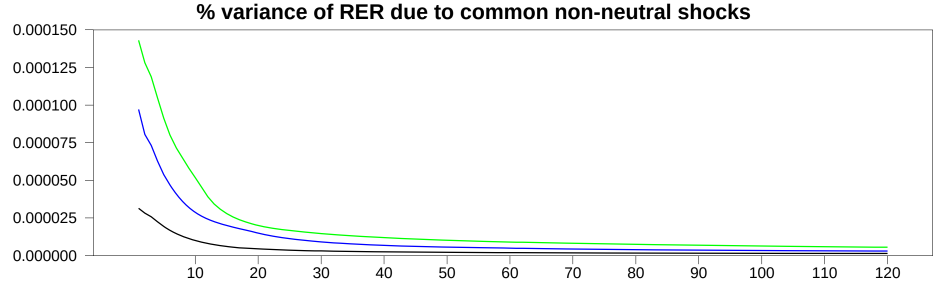
% variance of RER due to idiosyncratic non-neutral shocks



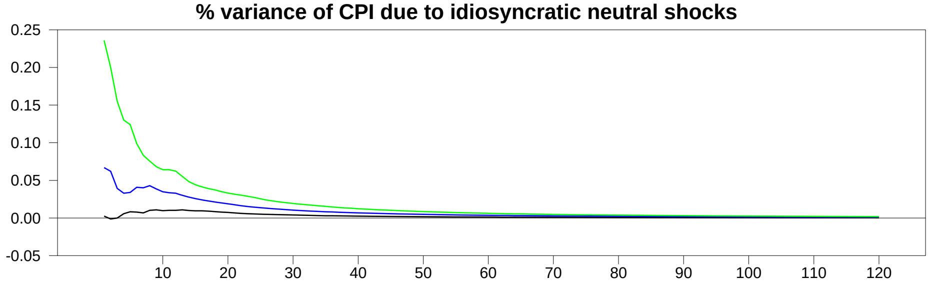
% variance of CPI due to common non-neutral shocks



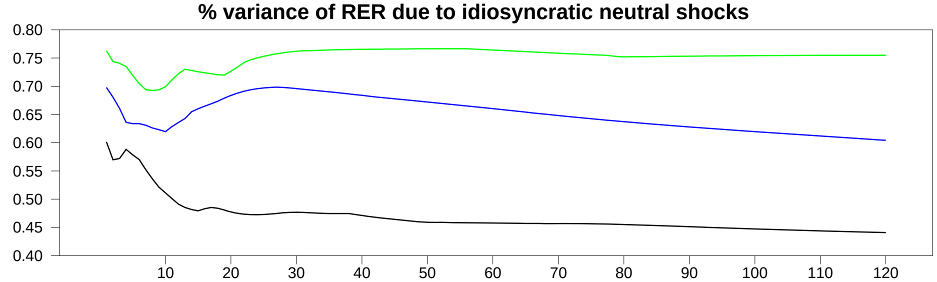
% variance of RER due to common non-neutral shocks



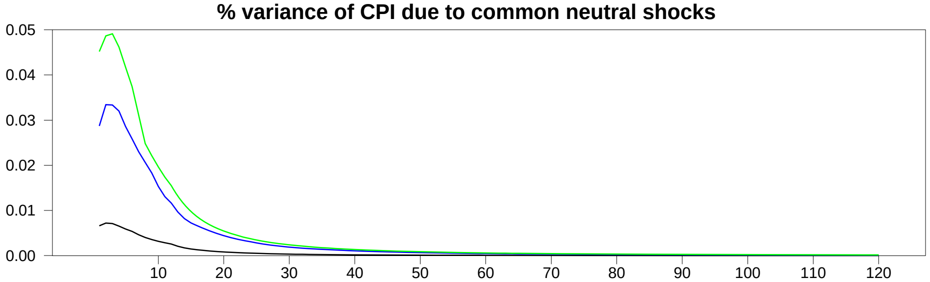
% variance of CPI due to idiosyncratic neutral shocks



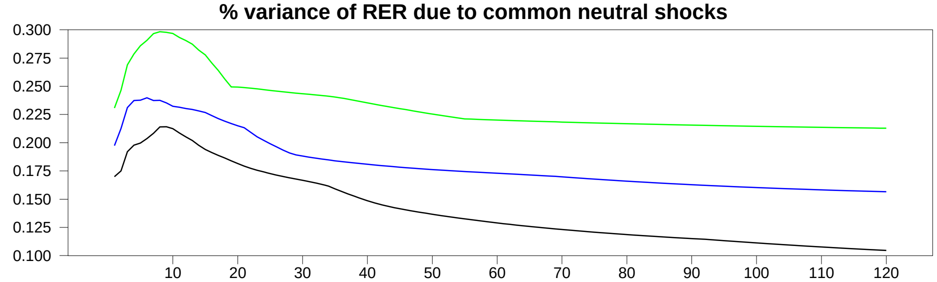
% variance of RER due to idiosyncratic neutral shocks



% variance of CPI due to common neutral shocks



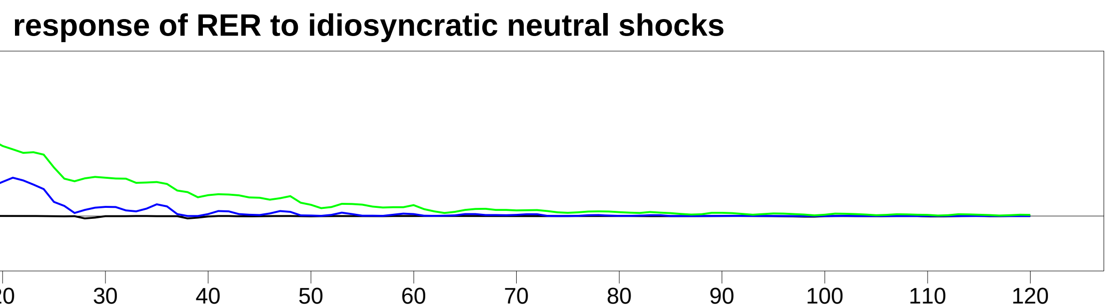
% variance of RER due to common neutral shocks

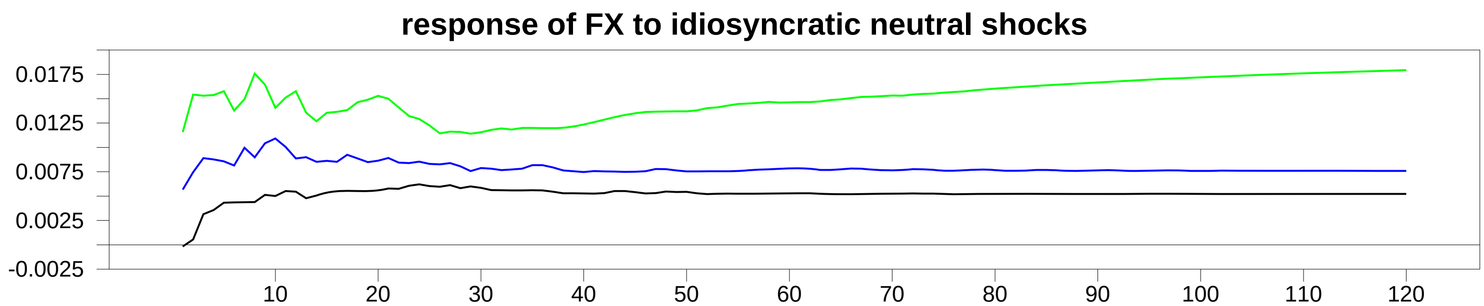


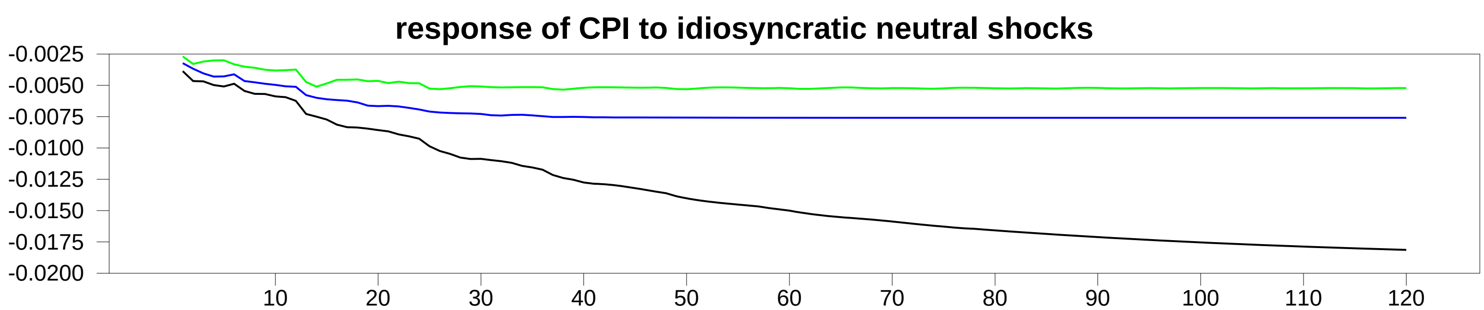
. . . . Summary: Most RER variation is due to shocks that are neutral on CPI.

Imp Responses to shocks neutral on RER vs. non-neutral on RER

Recursive (RER,FX) identification





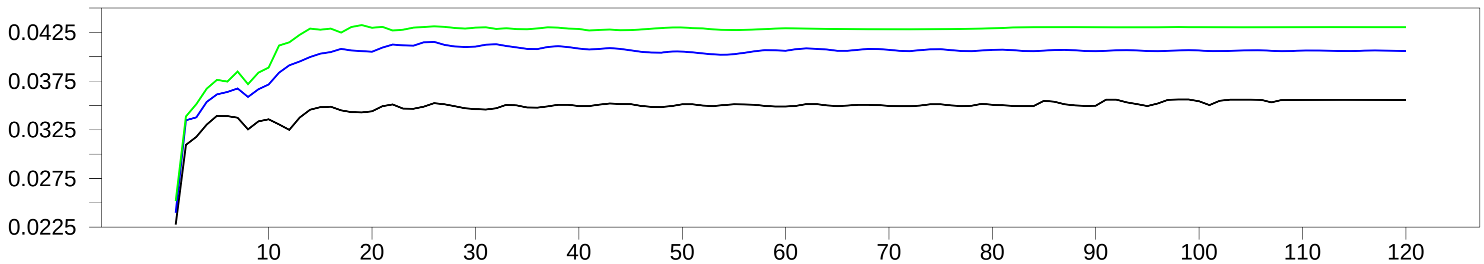


. . . . Half-lives (months): . . . RER: 25 (4 , 25) , . . . FX: 2 (3 , 2) , . . . CPI: 13 (32 , 13) . . . .

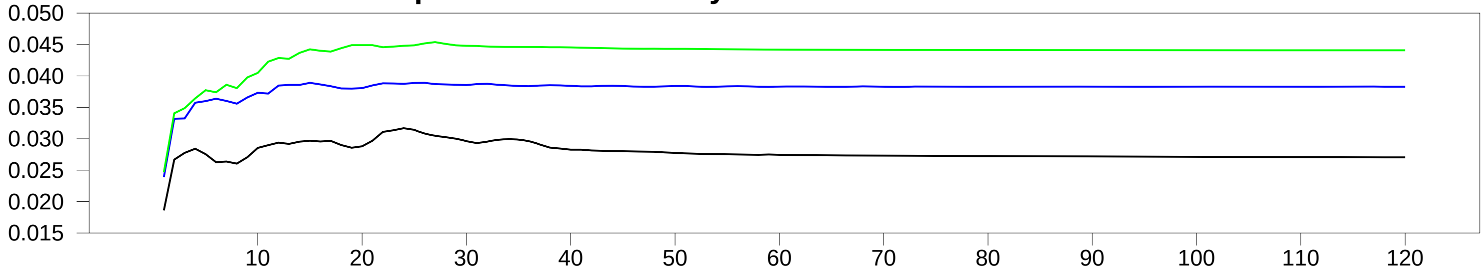
Imp Responses to shocks neutral on RER vs. non-neutral on RER

Recursive (RER,FX) identification

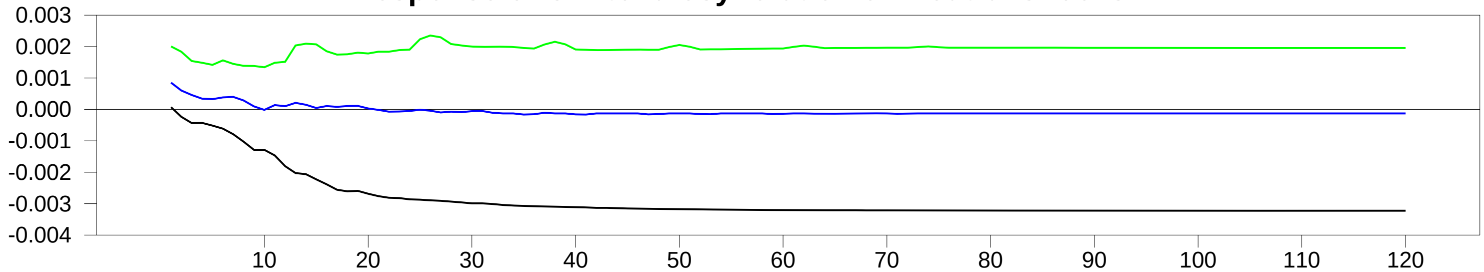
response of RER to idiosyncratic non-neutral shocks



response of FX to idiosyncratic non-neutral shocks



response of CPI to idiosyncratic non-neutral shocks

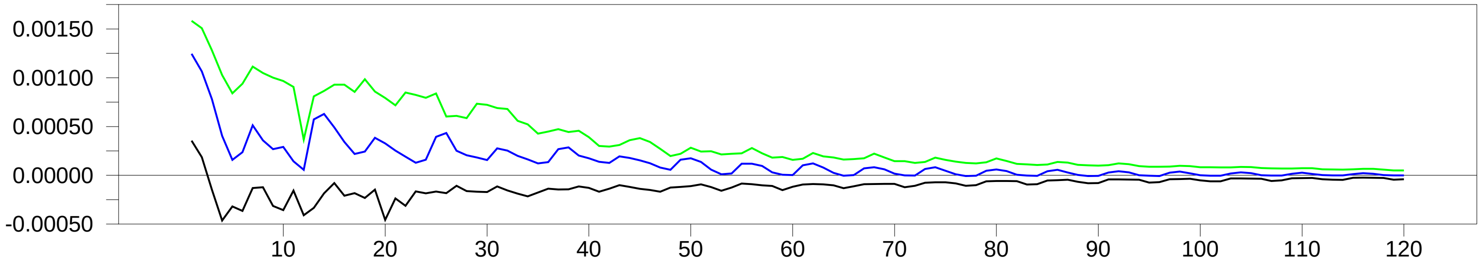


. . . . Half-lives (months): . . . RER: 2 (2 , 3) , ... FX: 2 (2 , 3) , ... CPI: 4 (12 , 2) . . . .

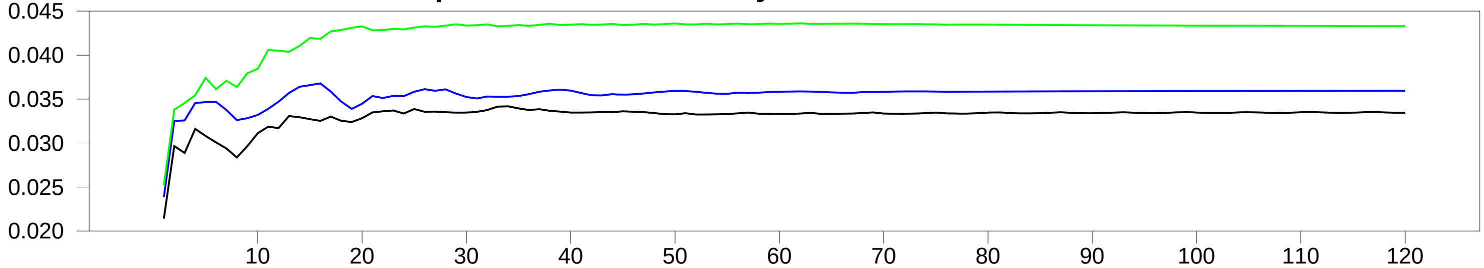
Imp Responses to shocks neutral on CPI vs. non-neutral on CPI

Recursive (CPI,RER) identification

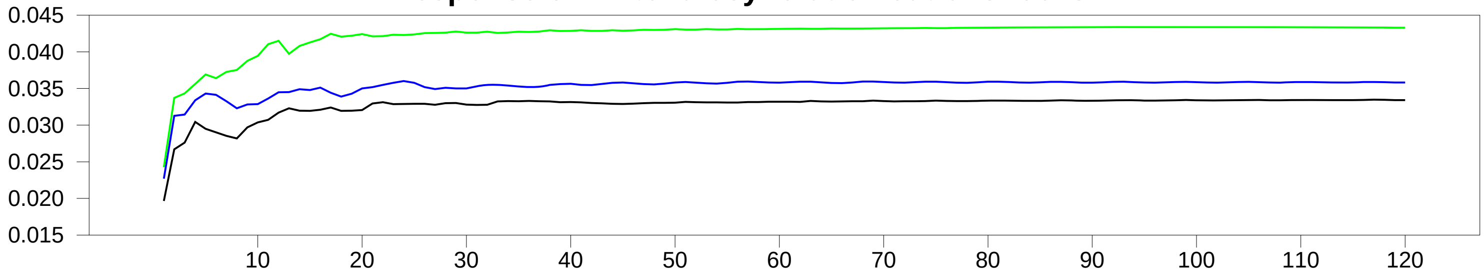
response of CPI to idiosyncratic neutral shocks



response of RER to idiosyncratic neutral shocks



response of FX to idiosyncratic neutral shocks

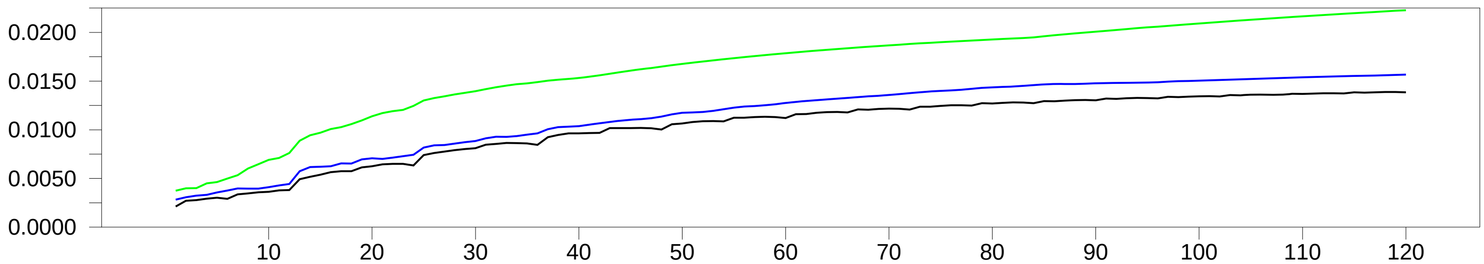


. . . . Half-lives (months): . . . CPI: 4 (3 , 12) , . . . RER: 2 (2 , 3) , . . . FX: 2 (2 , 3) . . . .

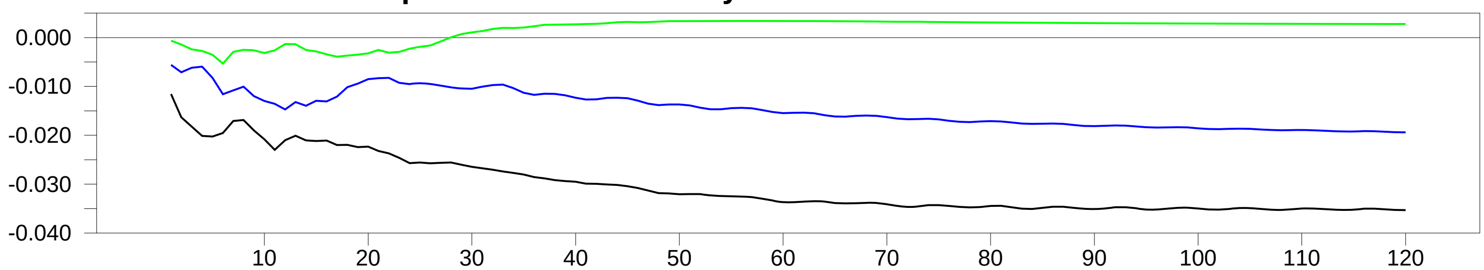
Imp Responses to shocks neutral on CPI vs. non-neutral on CPI

Recursive (CPI,RER) identification

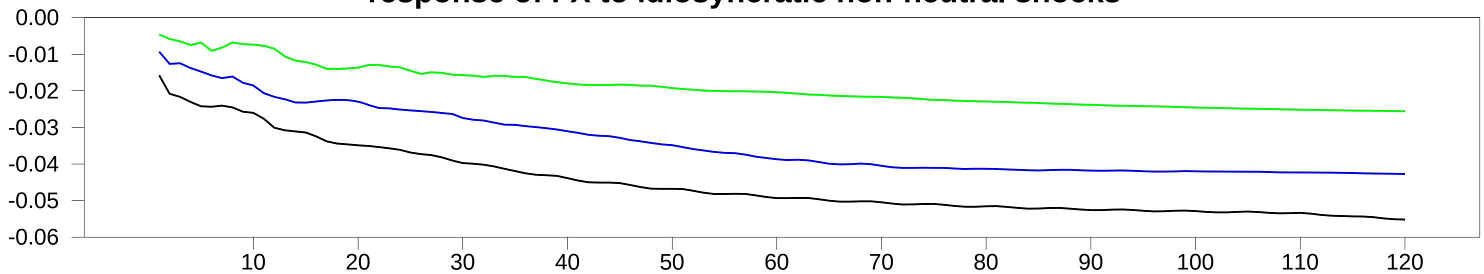
response of CPI to idiosyncratic non-neutral shocks



response of RER to idiosyncratic non-neutral shocks



response of FX to idiosyncratic non-neutral shocks



. . . . Half-lives (months): . . . CPI: 32 (29 , 26) , . . . RER: 10 (22 , 31) , . . . FX: 28 (23 , 26) . . .

1.4 Summary of Results

1. Most of variance in nominal E and real e is due to shocks that are:

- **a.** long run non-neutral on e,
- **b.** and long run neutral on P.

2. For shocks that are <u>neutral on real e</u>:

- **a.** real e adjustment is slow (25 months)
- **b.** P adjustment is moderate (13 months)
- **c.** nominal E adjustment is fast (2 months)

3. For shocks that are <u>non-neutral on real e</u>:

- **a.** real e adjustment is fast (2 months)
- **b.** P adjustment is fast (4 months)
- **c.** nominal E adjustment is fast (2 months)

4. For shocks that are neutral on P:

a. real e adjustment is fast (2 months)

b. P adjustment is fast (4 months)

c. nominal E adjustment is fast (2 months)

5. For shocks that are non-neutral on P:

a. real e adjustment is moderate (10 months)

b. P adjustment is slow (32 months)

c. nominal E adjustment is slow (28 months)

Interpreting the Results Structurally

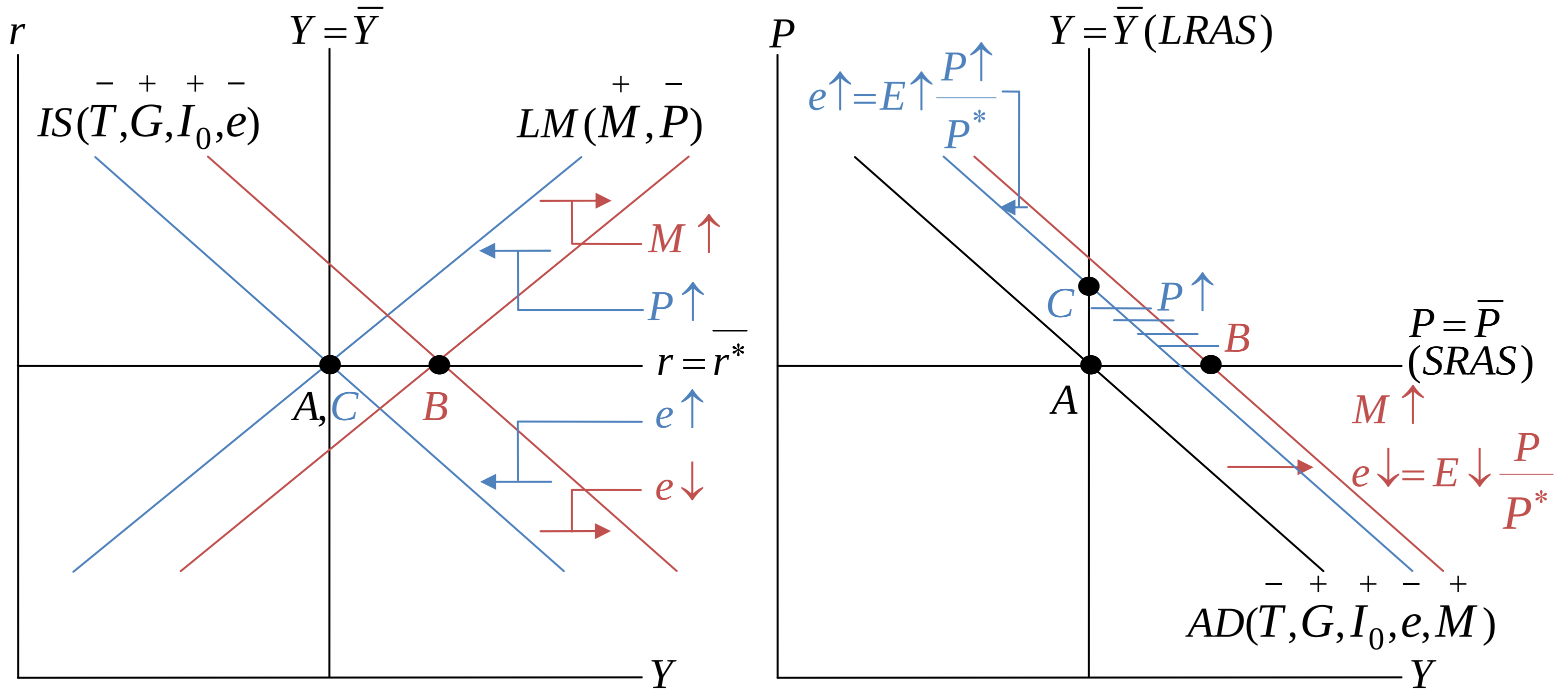
Responses:

shock	real e	P	nom E	%var of e
nominal:	slow	moderate	fast	small
real AD:	fast	fast-small	fast	large
LRAS:	moderate	slow	slow	small
AS+M:	fast	fast-small	fast	large

These patterns should seem *very* familiar!

... How familiar? ...

Nominal Shocks ($M\uparrow$)



A => B short run (a.k.a. "fast") before any P adjustment

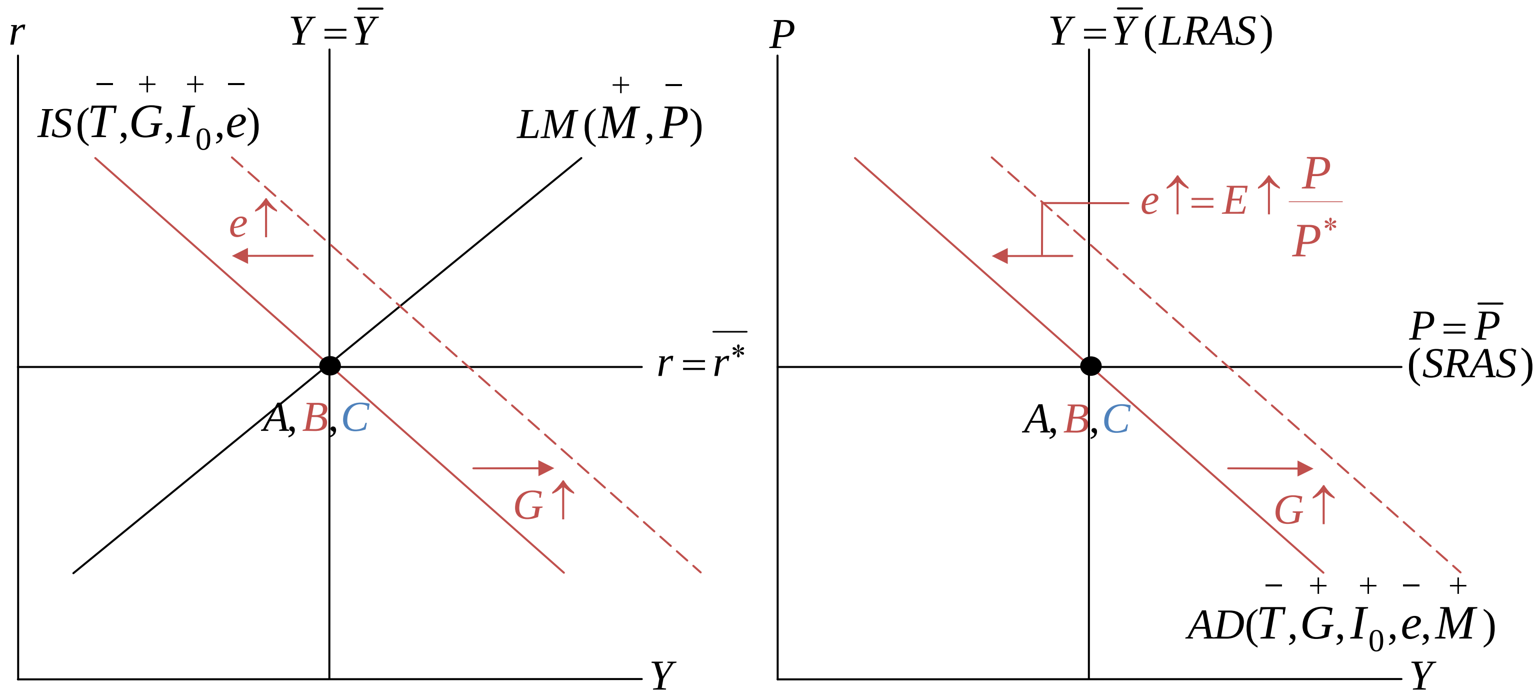
B => C long run (a.k.a. "slow") after P fully adjusts

Results:

<u>Long run</u>: real e neutral, P non-neutral

<u>Dynamics</u>: real e slow, nom E slow, P slow

Real AD Shocks ($G\uparrow$)



A => B short run (a.k.a. "fast") before any P adjustment

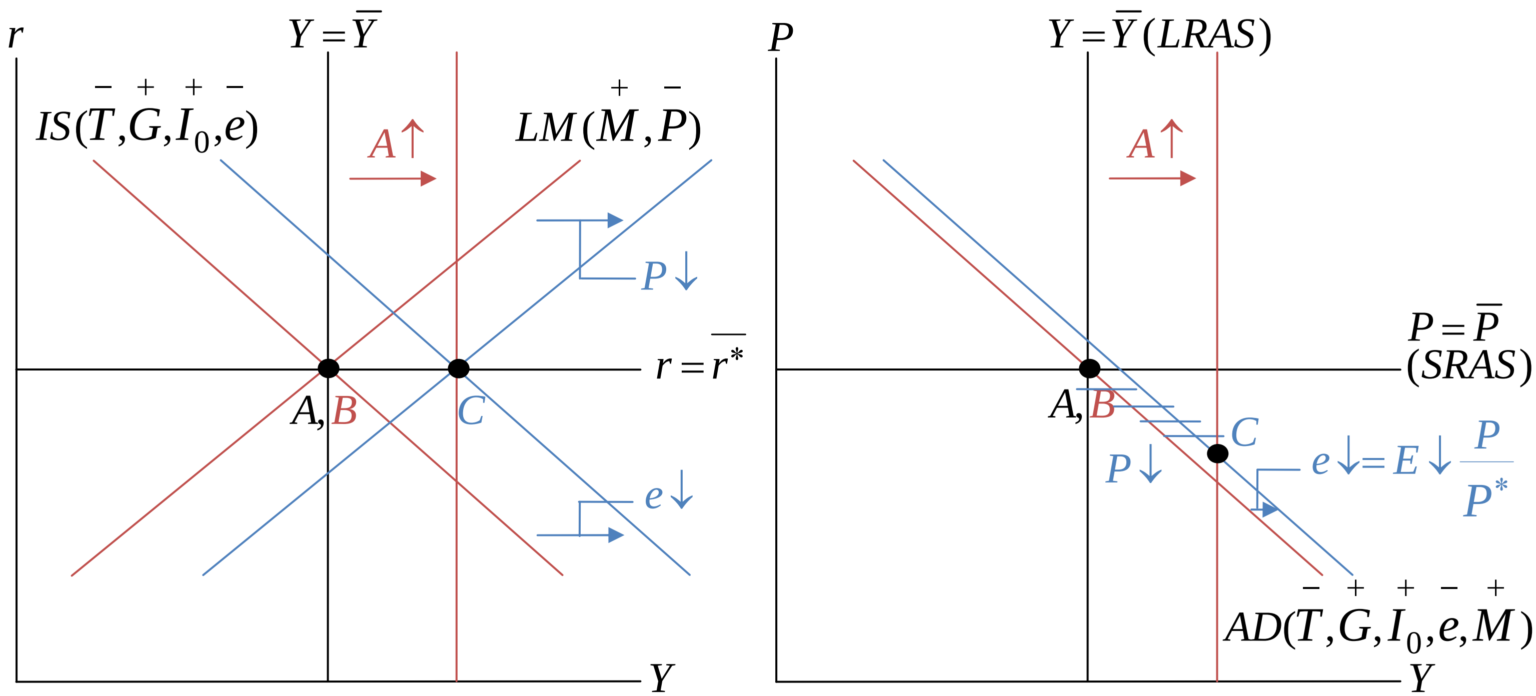
B => C long run (a.k.a. "slow") after P fully adjusts

Results:

<u>Long run</u>: real e non-neutral, P neutral

<u>Dynamics</u>: real e fast, nom E fast, P fast-small

AS Shocks ($A\uparrow$)



A => B short run (a.k.a. "fast") before any P adjustment

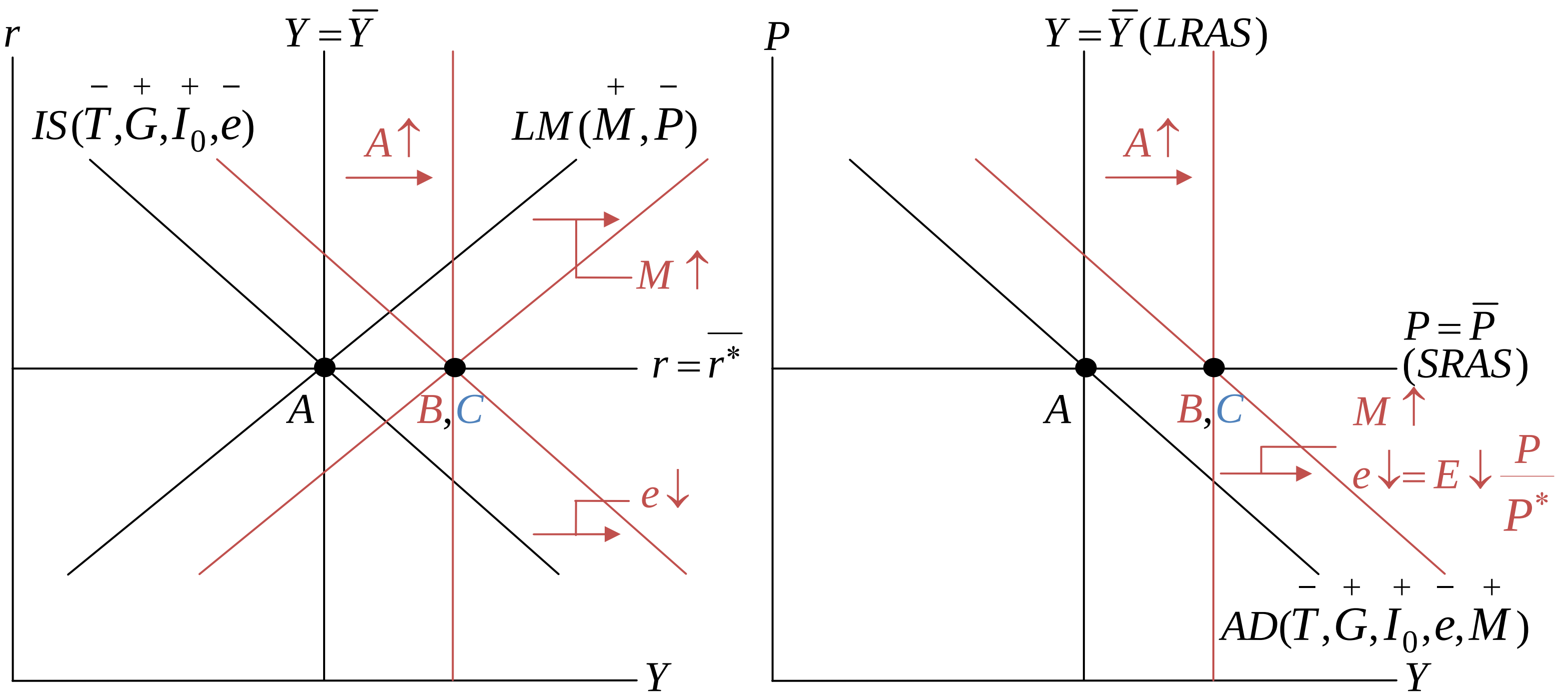
B => C long run (a.k.a. "slow") after P fully adjusts

Results:

<u>Long run</u>: real e non-neutral, P non-neutral

<u>Dynamics</u>: real e slow, nom E slow, P slow

M.P. accommodated AS shocks ($A\uparrow, M\uparrow$)



A => B short run (a.k.a. "fast") before any P adjustment

B => C long run (a.k.a. "slow") after P fully adjusts

Results:

Long run: real e non-neutral, P neutral

Dynamics: real e fast, nom E fast, P slow-small

Interpreting the Results Structurally

Responses:

shock	real e	P	nom E	%var of e
nominal:	slow	moderate	fast	small
real AD:	fast	fast-small	fast	large
LRAS:	moderate	slow	slow	small
AS+M:	fast	fast-small	fast	large

Possible that puzzle has been artifact of poorly suited econometrics?

- new results consistent with what anticipate
- new panel time series approach produces structurally sensible results

Conclusions:

Results consistent with many standard sticky price small open economy models

Speedy adjustment of nominal exchange rate to real side disturbances favors “shock absorption role”

Favors inflation targeting for small open economies over exchange rate targeting

- will be interesting to group countries according to different monetary and exchange rate regimes

- could correlate response patterns with regime choices, or other factors, even if static

Examples: Size of economy, degree of openness, degree of dollarization, indebtedness, etc.

General Implications of panel methodologies

What can small emerging economies with limited time series data do for empirical analysis?

Tradeoffs among different possible approaches:

i. avoid empirical work, informally adjust results from countries for which work has been done

ii. do empirical work with limited domestic data, bearing in mind may be unreliable

iii. consider multi-country panel time series techniques that accommodate heterogeneity

Current explorations appear to show that panel SVAR approach works well even with very short panels

5. Empirical illustration: Heterogeneous Income Dynamics among Regions of Europe.

- based on *Pedroni (2010)*

<u>Basic idea</u>:

Use identified panel SVAR technique to investigate patterns and reasons for heterogeneous dynamics in European regions

Examine spatial distributions of responses to supply and demand shocks and relate to known characteristics of regions

Use long run Blanchard & Quah identification
- for supply versus demand shocks
- but also decompose into regional vs. national
- also differ in allowing for unit root in unemployment

Finding: National demand responses (e.g. fiscal & monetary) favor some region types over others.

1.2 Motivation for empirical illustration

- European regional economies exhibit substantial heterogeneity in dynamics during business cycles
  - to supply shocks originating at both local and national levels
  - as well as to local and national demand interventions

- Movement toward greater fiscal autonomy among European regions
  - recognizes importance of economic heterogeneity
  - argues in favor of locally tailored responses to business cycles

- Useful to know which regional characteristics shape heterogeneous responses
  - which more amenable to national versus local fiscal responses?
  - which create asymmetries between local and national supply effects versus fiscal responses?
  - which create asymmetries in unemployment versus output effects?

Data: *Cambridge Econometrics Regional European*

Variables:

a. For first stage panel SVAR:

Output and unemployment by regions.

Three countries, 61 regions.

Annual data, 1980 - 2007.

b. For second stage cross sectional analysis:

i. Regional Population

ii. Sectoral Employment Location Quotients for:
Agriculture
Construction
Mining, quarrying and energy supply
Coke, refined petro, nuclear fuel and chemicals
Hotels and restaurants
Financial intermediation

Countries and Regions:

<u>Spain</u> (18 regions - excluding *Canary Islands*)

Galicia
Principado de Asturias
Cantabria
Pais Vasco
Comunidad Foral de Navarra
La Rioja
Aragón
Comunidad de Madrid
Castilla y León
Castilla-la Mancha
Extremadura
Cataluña
Comunidad Valenciana
Illes Balears
Andalucia
Región de Murcia
Ciudad Autónoma de Ceuta
Ciudad Autónoma de Melilla

<u>Italy</u> (21 regions)

Piemonte
Valle d'Aosta/Vallée d'Aoste
Liguria
Lombardia
Provincia Autonoma Bolzano-Bozen
Provincia Autonoma Trento
Veneto
Friuli-Venezia Giulia
Emilia-Romagna
Toscana
Umbria
Marche
Lazio
Abruzzo
Molise
Campania
Puglia
Basilicata
Calabria
Sicilia
Sardegna

<u>France</u> (22 regions, excluding overseas departments)

Île de France
Champagne-Ardenne
Picardie
Haute-Normandie
Centre
Basse-Normandie
Bourgogne
Nord - Pas-de-Calais
Lorraine
Alsace
Franche-Comté
Pays de la Loire
Bretagne
Poitou-Charentes
Aquitaine
Midi-Pyrénées
Limousin
Rhône-Alpes
Auvergne
Languedoc-Roussillon
Provence-Alpes-Côte d'Azur, *Corse*

Basic Identification Scheme:

$z_{it} \sim (lnY_{it}, U_{it})^{/}$ demeaned, where $z_{it} \sim I(1)\ \forall\, i$

- *Pedroni, Vogelsang, Wagner & Westerlund (2010)* panel unit root tests used to confirm, including U_{it}^{*}

$\Delta z_{it} = A(L)_i \varepsilon_{it}$ unrestricted

except that for long run steady state, z_{it}^{*}

$z_{it}^{*} = A(1)_i \varepsilon_{it}$, $A(1)_{12,i} = 0\ \forall\, i$

and $E[\varepsilon_{it} \varepsilon_{it}^{/}] = I_m$

with corresponding national and regional decompositions such that

$\varepsilon_{m,it} = \lambda_{m,i} \varepsilon_{m,t} + \tilde{\varepsilon}_{m,it}\ \ \forall\, i, m$.

Second Stage Cross Sectional Analysis:

For given step, s , of estimated $A(L)_i$ response matrix

use regional characteristics, x_i, to estimate

conditional distributions $E[A(L)_i|x_i]_s$

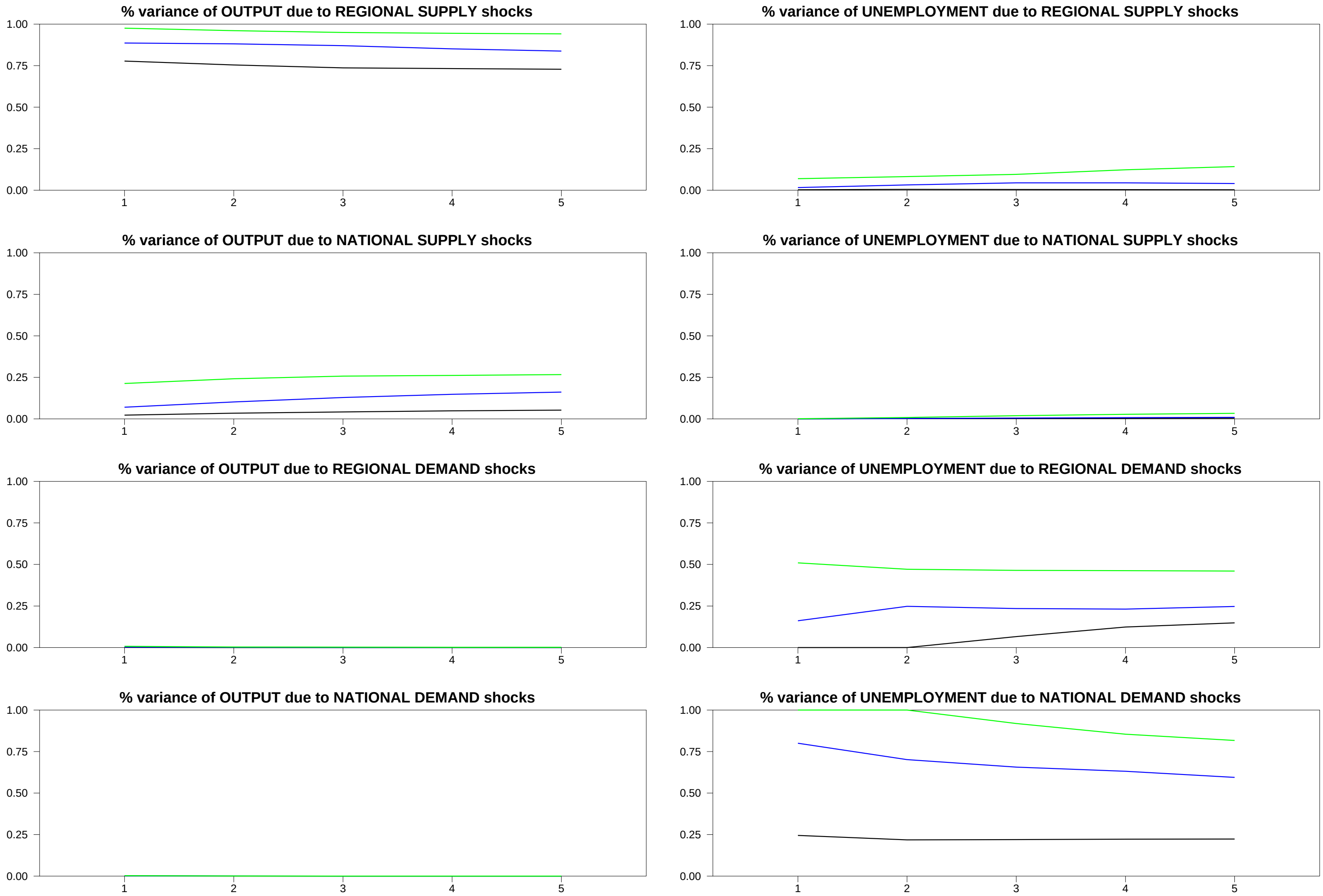
For bivariate case, can depict with scatter plots.

- characterizes heterogeneous responses in terms of region specific features

- can also interpret as reflecting nonlinearities for impulse responses based on interactions with x_i

SPANISH Variance Decompositions

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

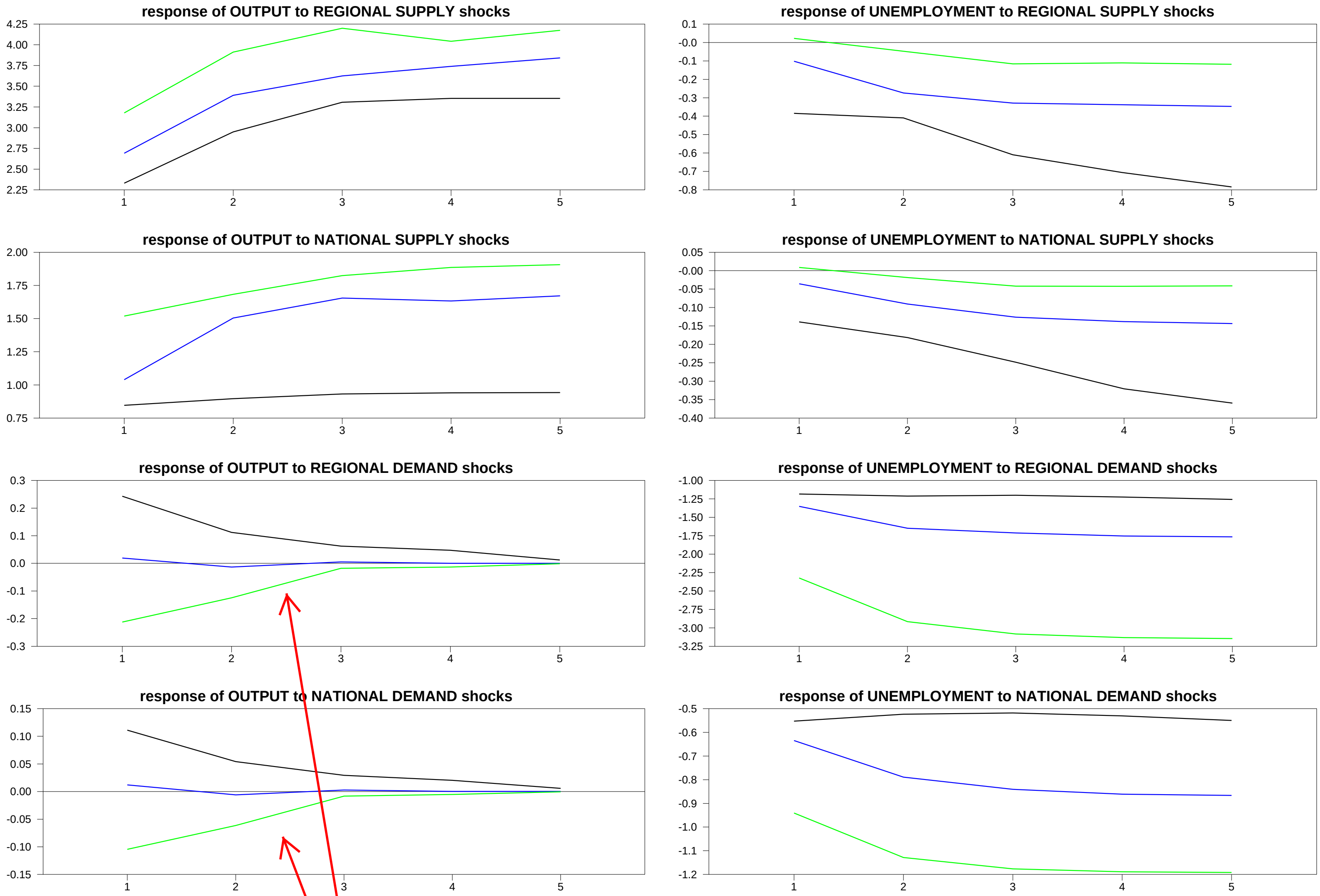


Most variation in output due to SUPPLY shocks (especially LOCAL).

Most variation in Unemployment due to DEMAND shocks (esp. NATIONAL).

SPANISH Impulse Responses

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

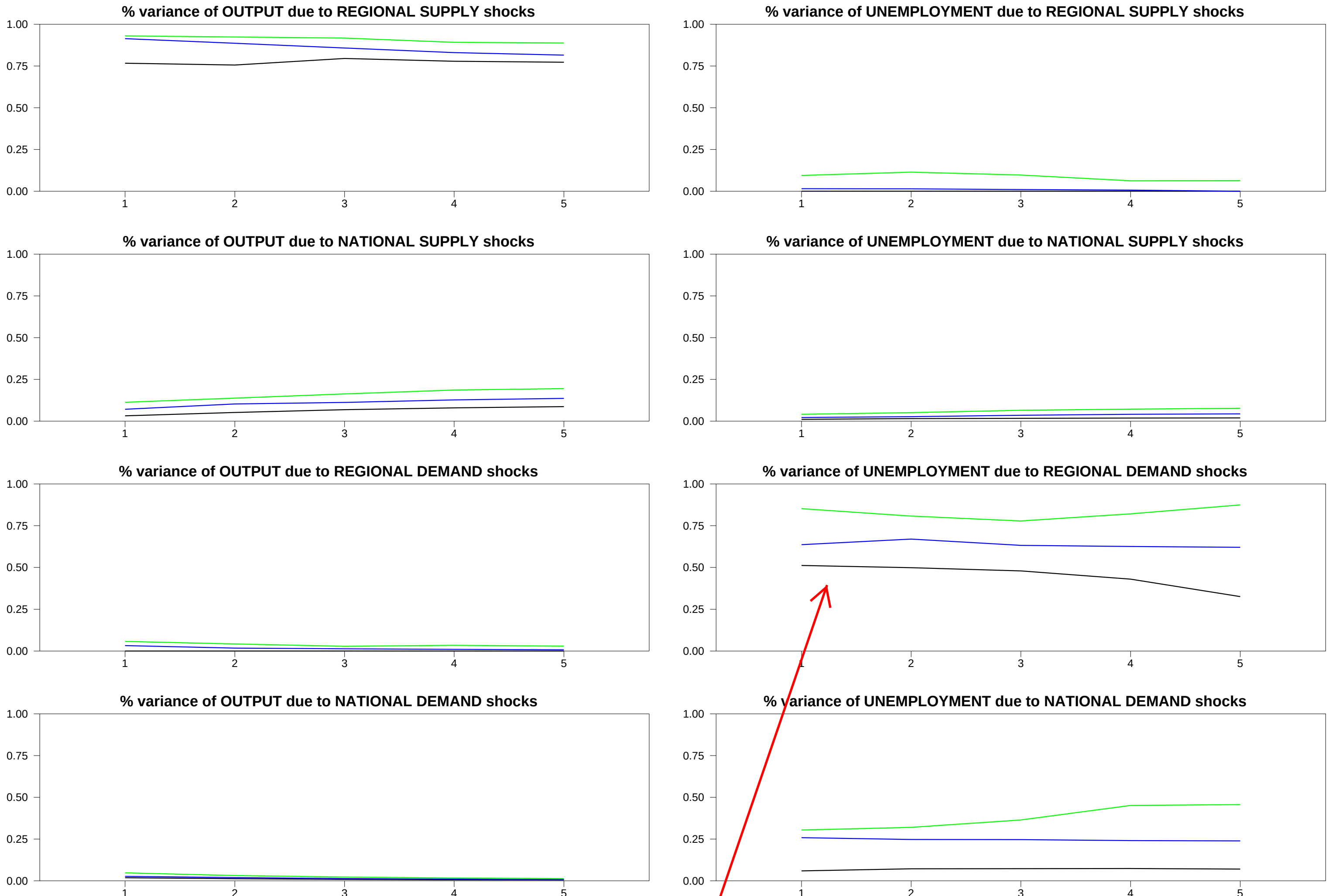


Some negative responses - very different than Italy and France.

But variance contribution also less than in Italy and France.

ITALIAN Variance Decompositions

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

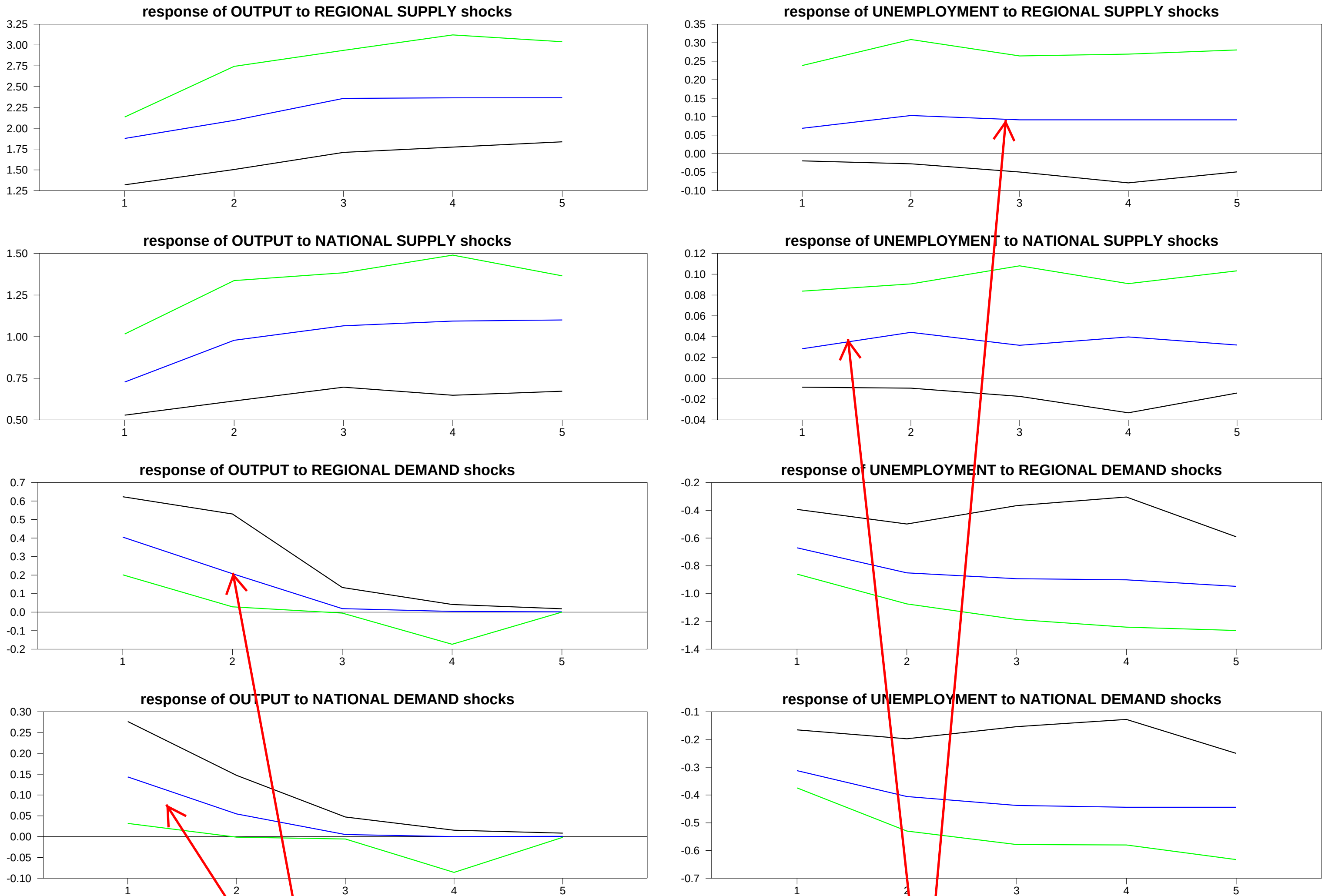


Regional shocks more important than for Spain.

(Especially for Unemployment respond to demand).

ITALIAN Impulse Responses

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

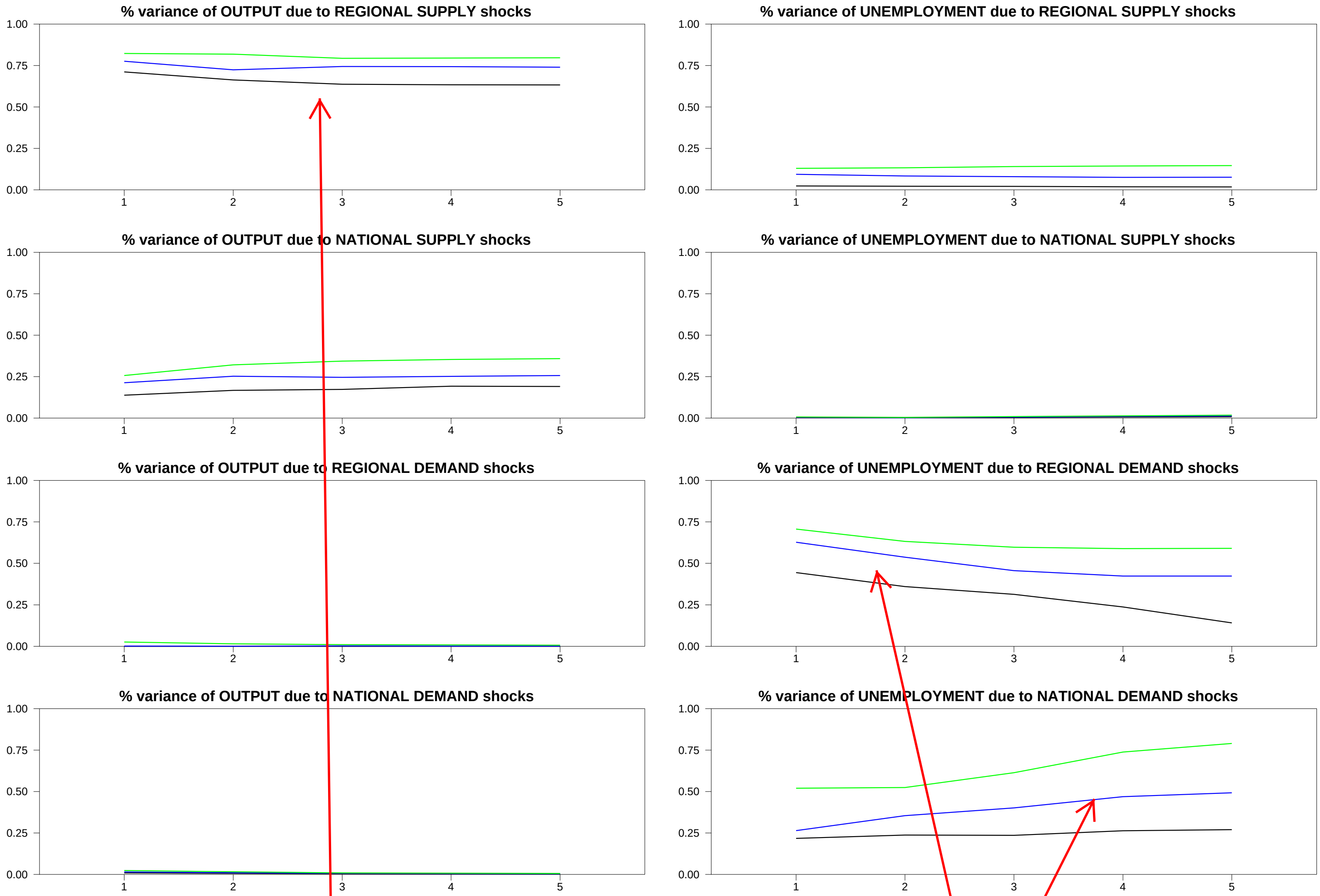


Output responses more in line with expectations.

But unemployment responses unusually positive in some regions.

FRENCH Variance Decompositions

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

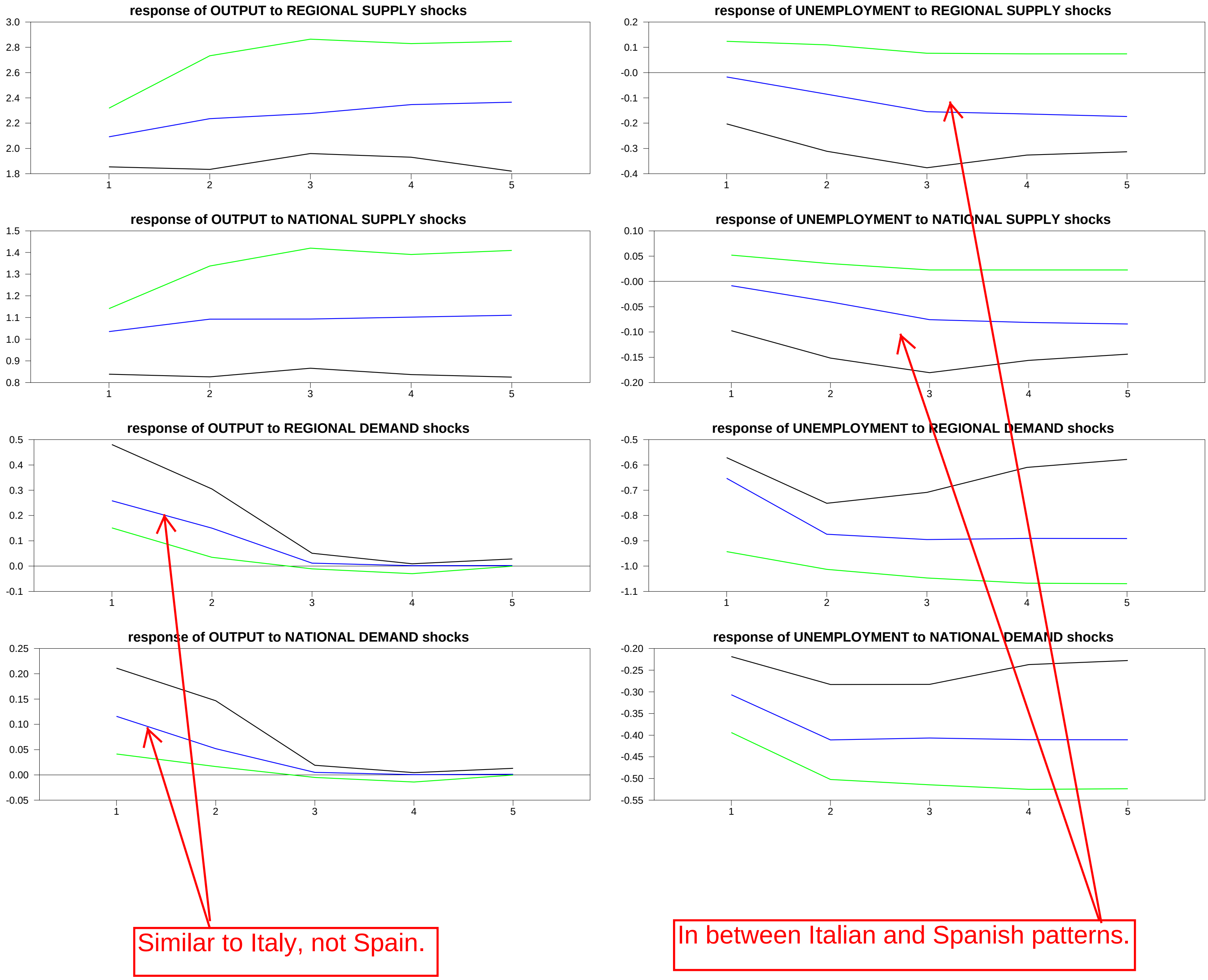


For supply shocks, REGIONAL LESS IMPORTANT than in Spain or Italy.

For demand shocks,distributions between National and Regional more similar to Italy than Spain.

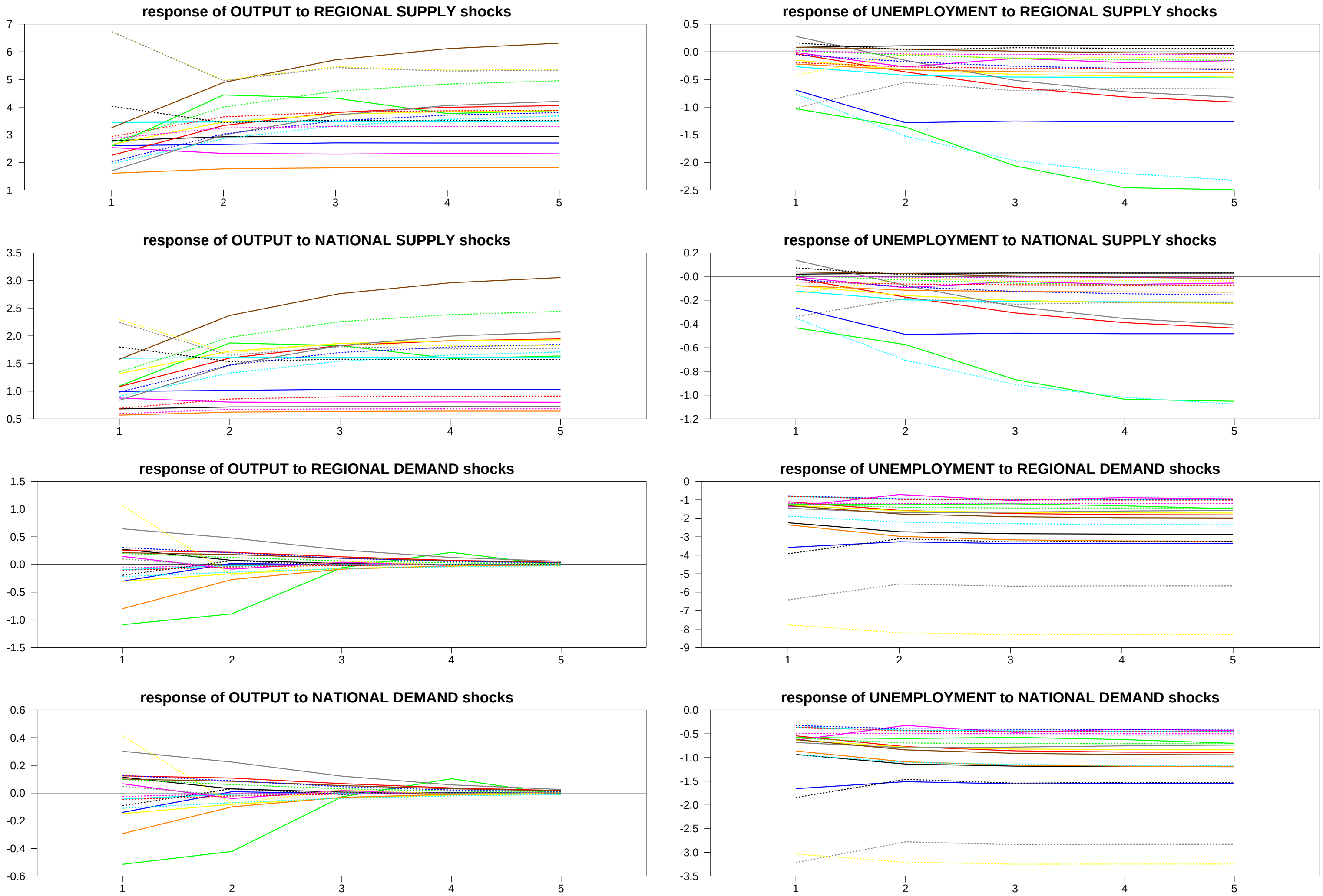
FRENCH Impulse Responses

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*

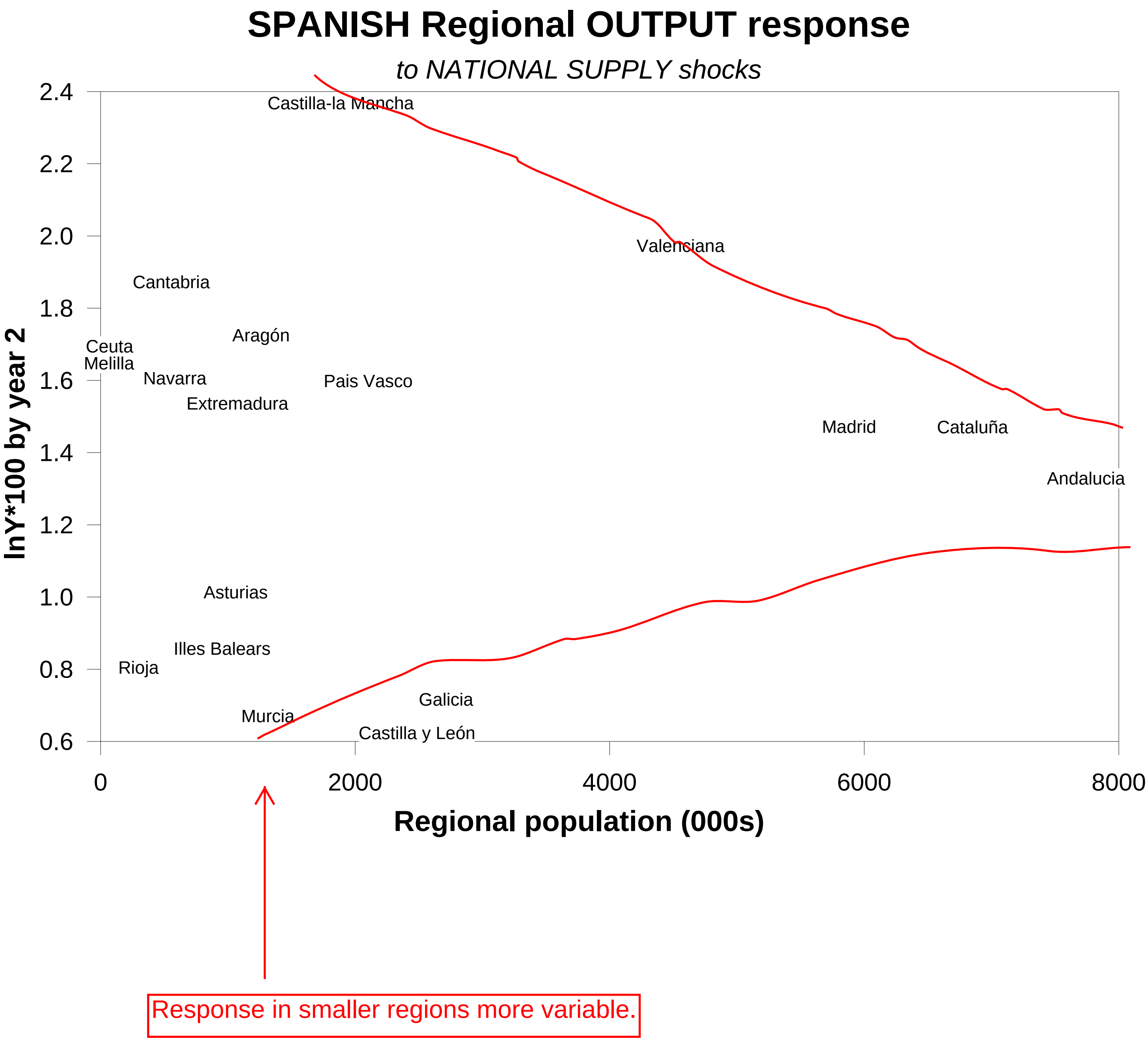


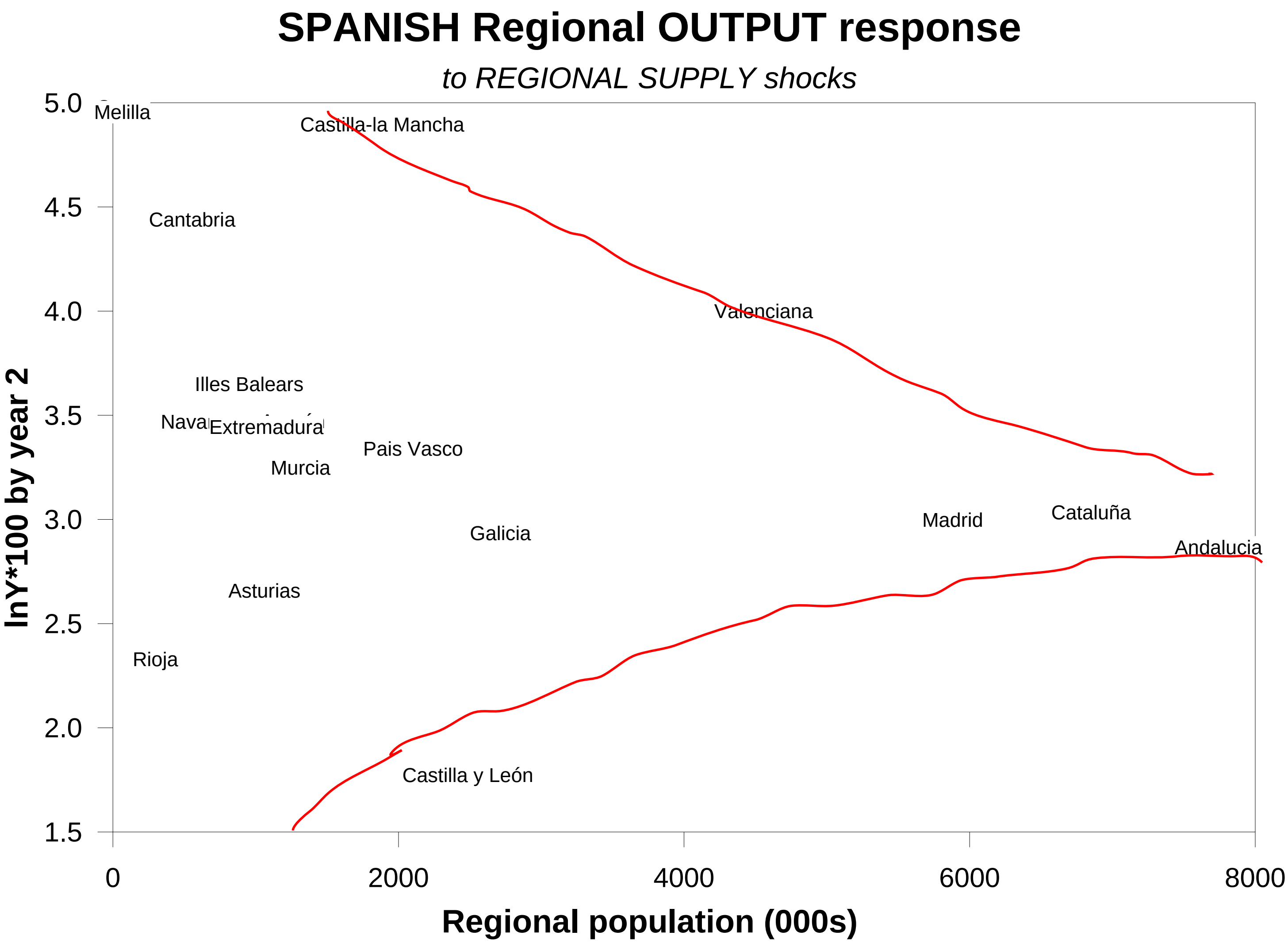
SPANISH Individual Country Impulse Responses

*LR Triangular SVAR: [lnY*100, Unemp %]` = A(1)*[SUPPLY, DEMAND]`*



<u>Next</u>:   Study patterns of distributions of responses among regions of each country.

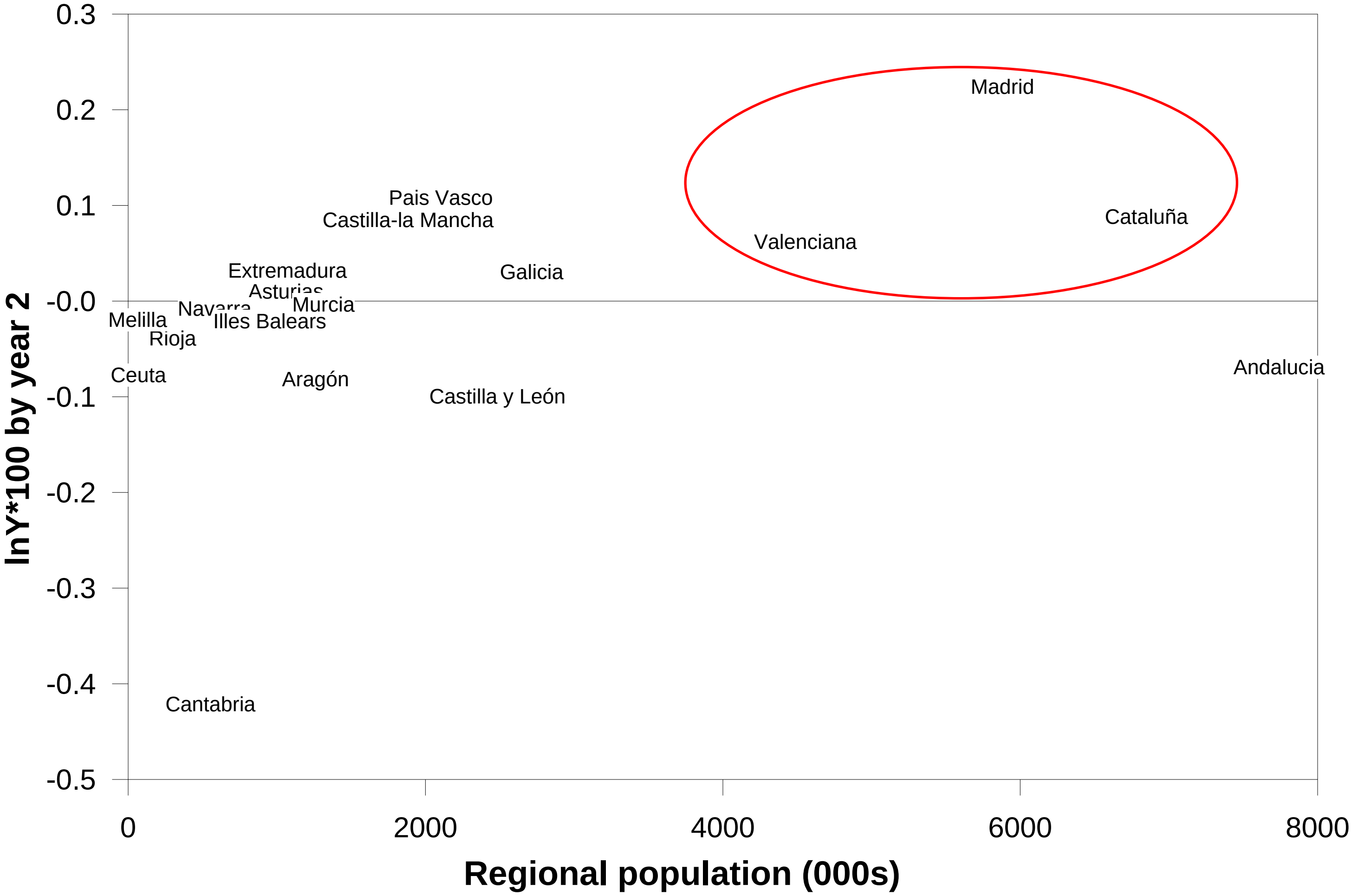

SPANISH Regional OUTPUT response
to NATIONAL SUPPLY shocks
lnY*100 by year 2
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0
2000
4000
6000
8000
Regional population (000s)
Castilla-la Mancha
Valenciana
Cantabria
Aragón
Ceuta
Melilla
Navarra
Pais Vasco
Extremadura
Madrid
Cataluña
Andalucia
Asturias
Illes Balears
Rioja
Galicia
Murcia
Castilla y León
Response in smaller regions more variable.



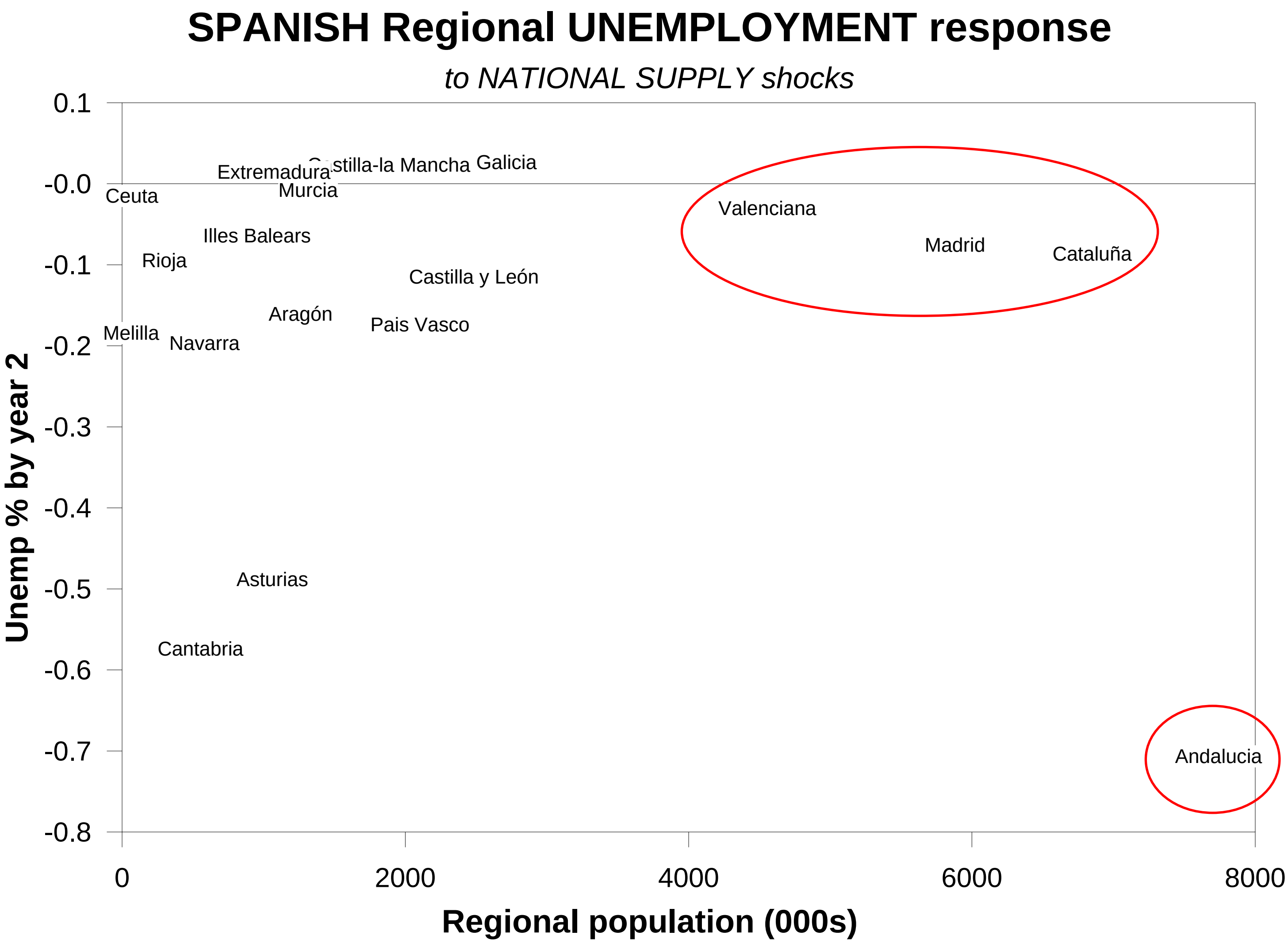
Similar pattern for regional shocks

SPANISH Regional OUTPUT response

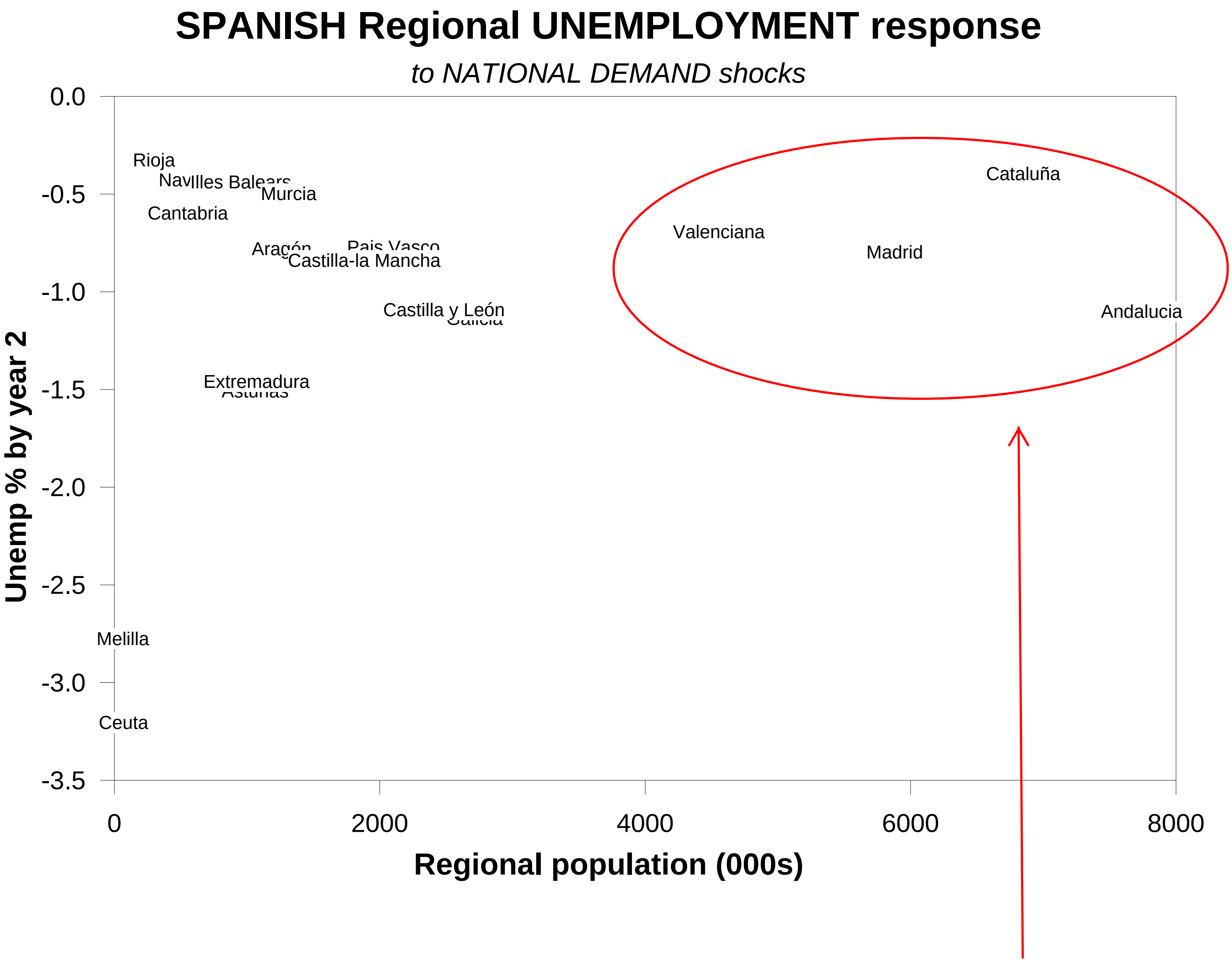
to NATIONAL DEMAND shocks



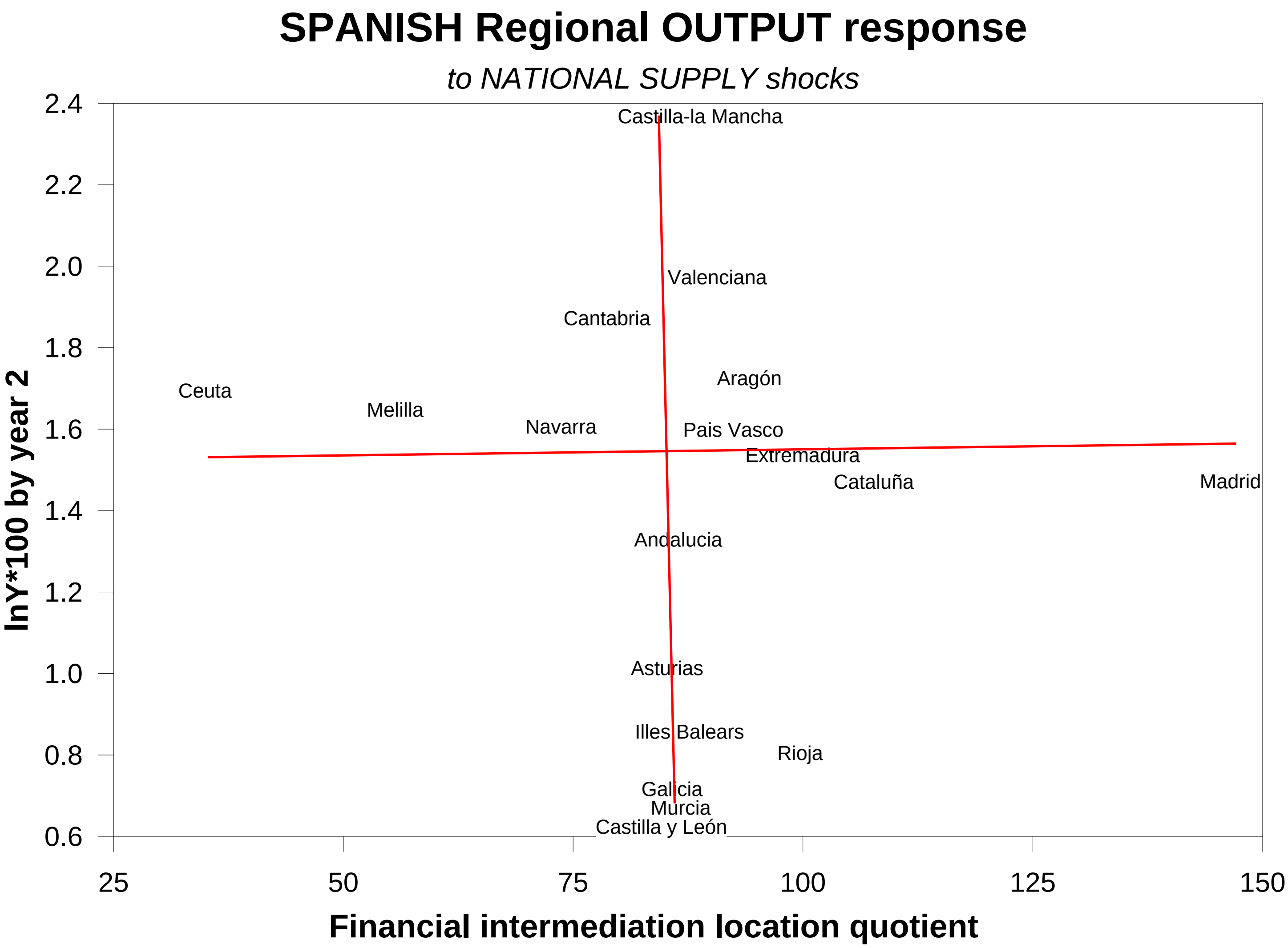
National response favors some regions



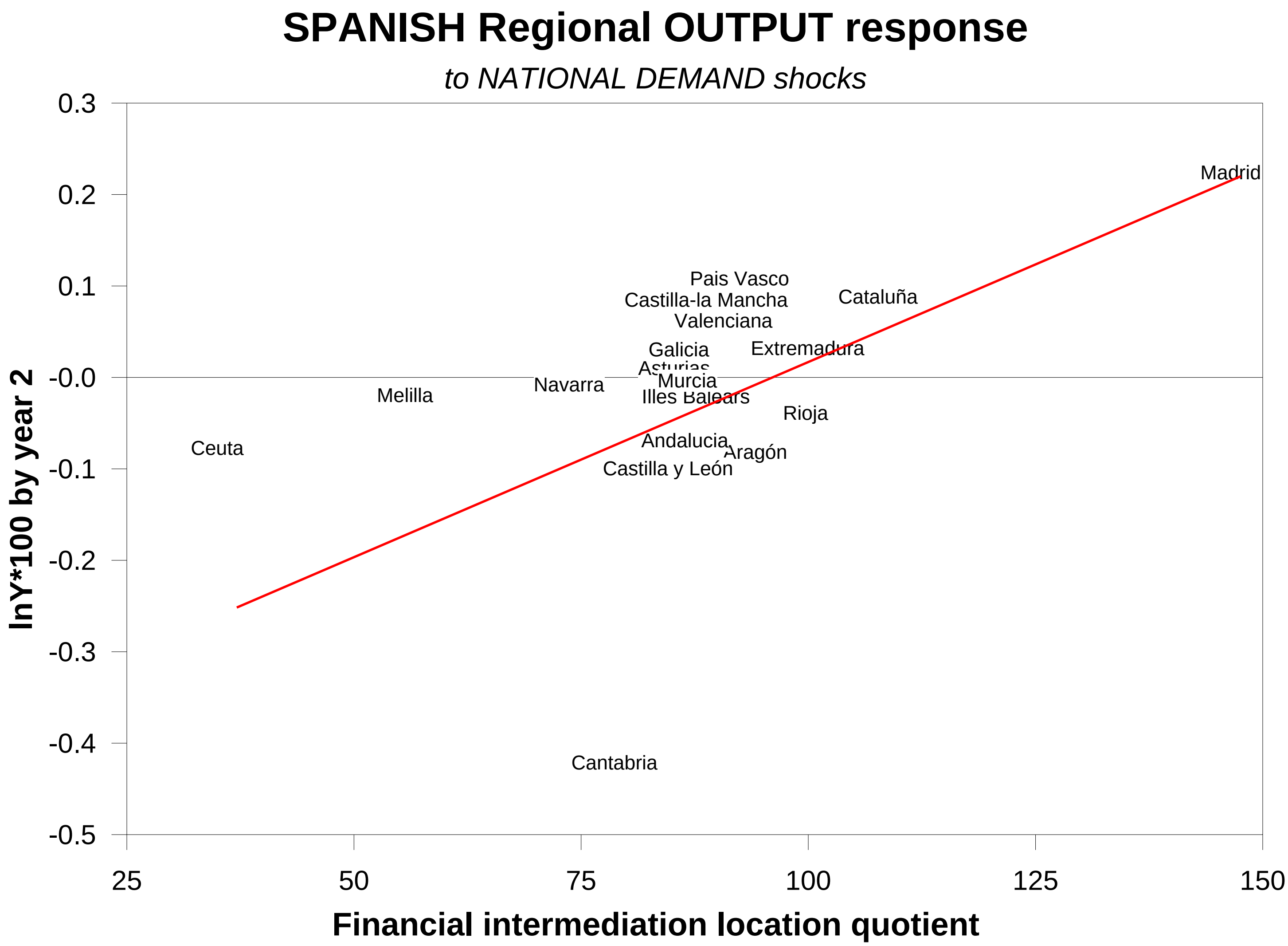
Notice pattern not just about size, since
econ supply shocks favor differently



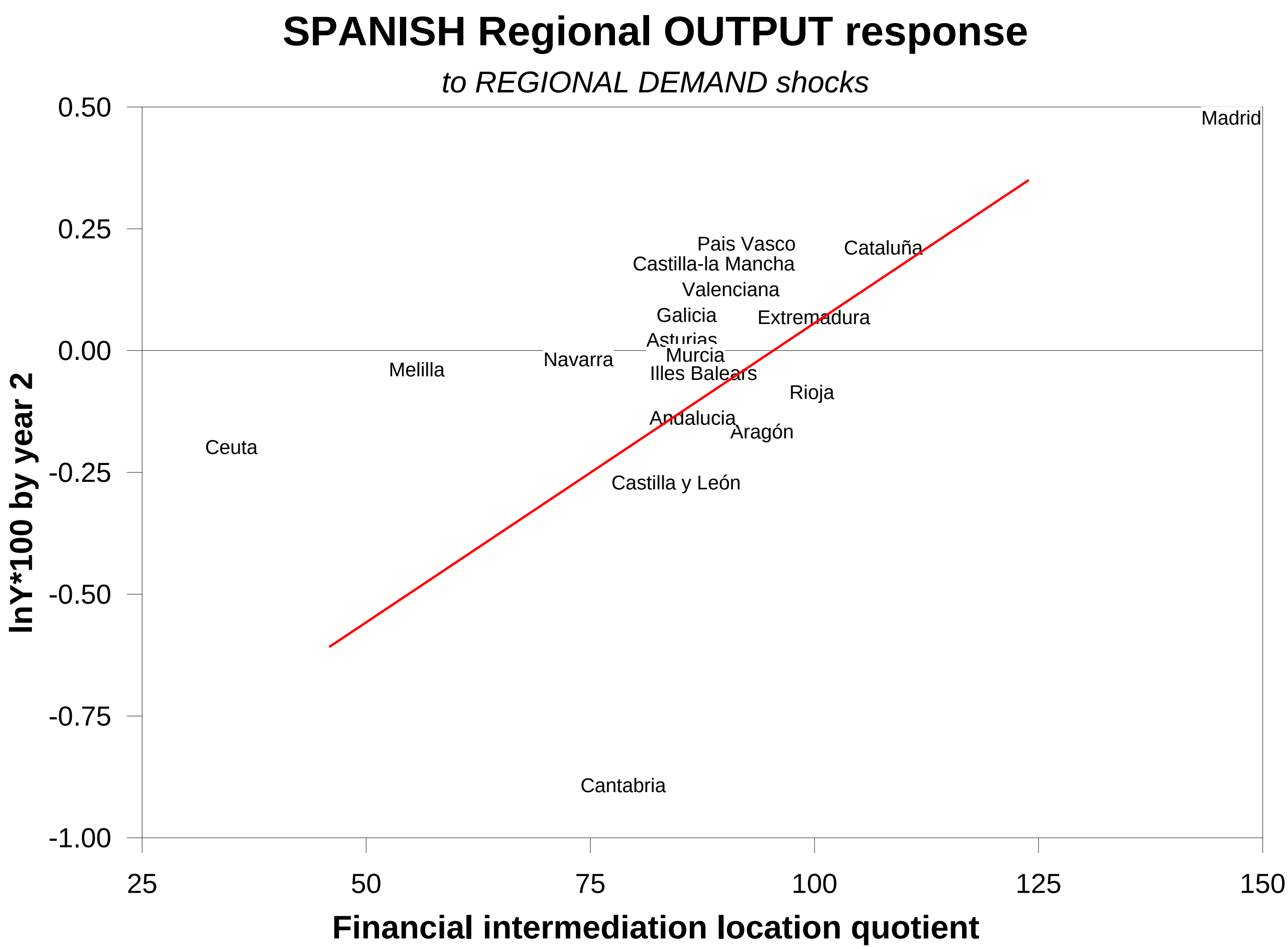
National demand response (monetary, fiscal)
symmetric external supply shock effect
for Valencia, Madrid, Cataluna - but NOT ANDALUCIA



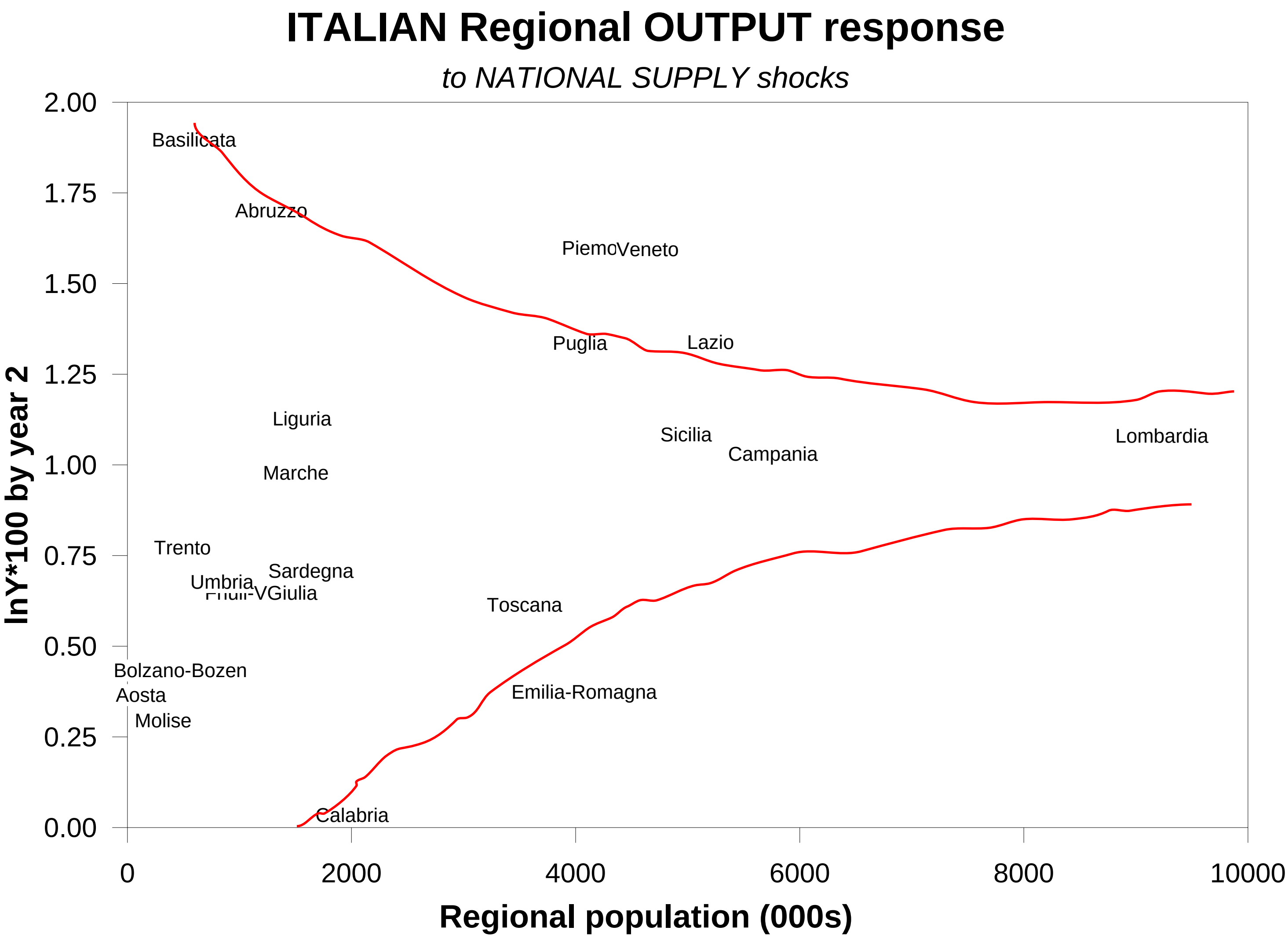
Low and high financial has less variation
in response to "exogenous" Supply shock



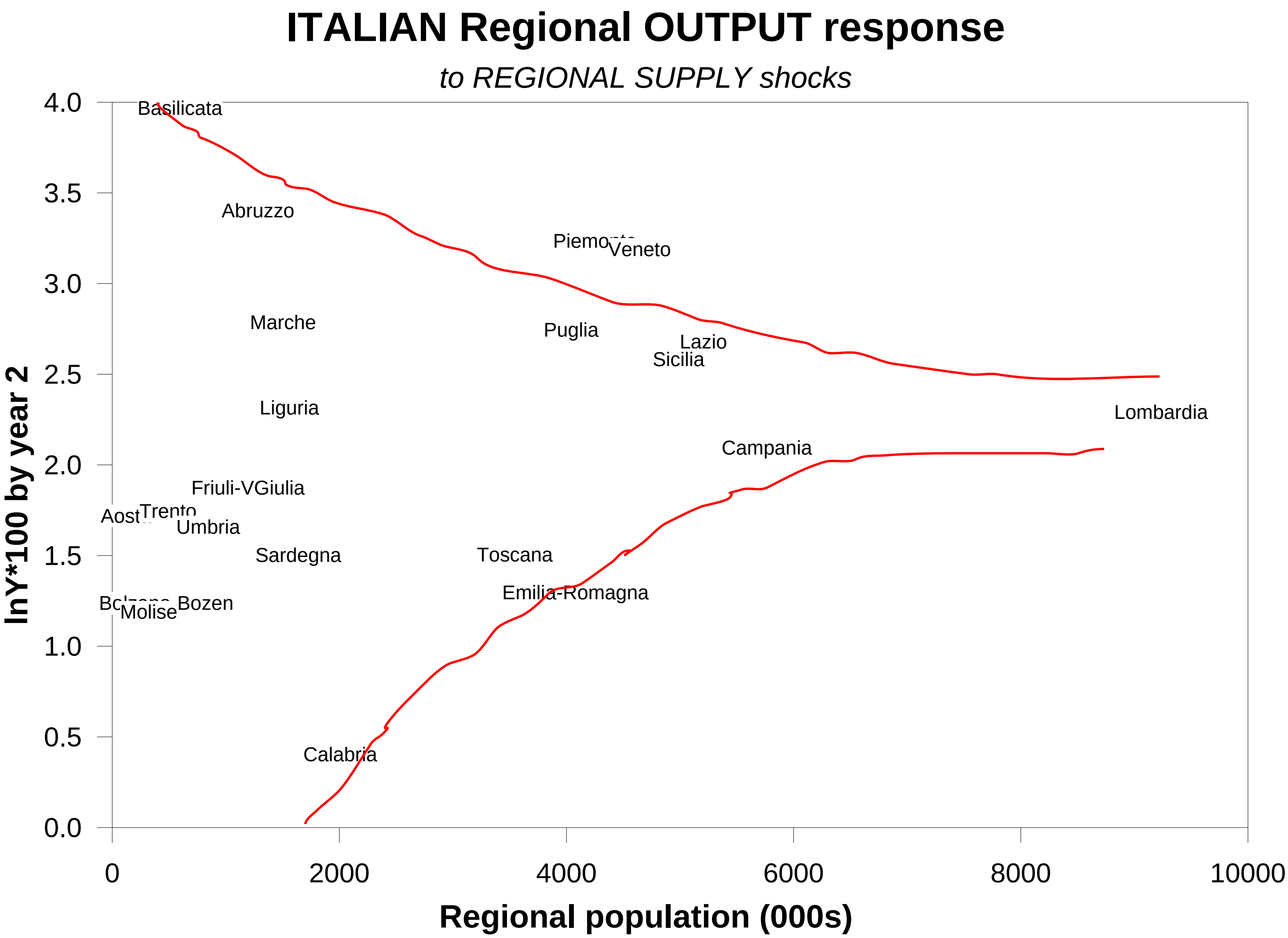
But national "endogeneous" government response favors finance intensive regions

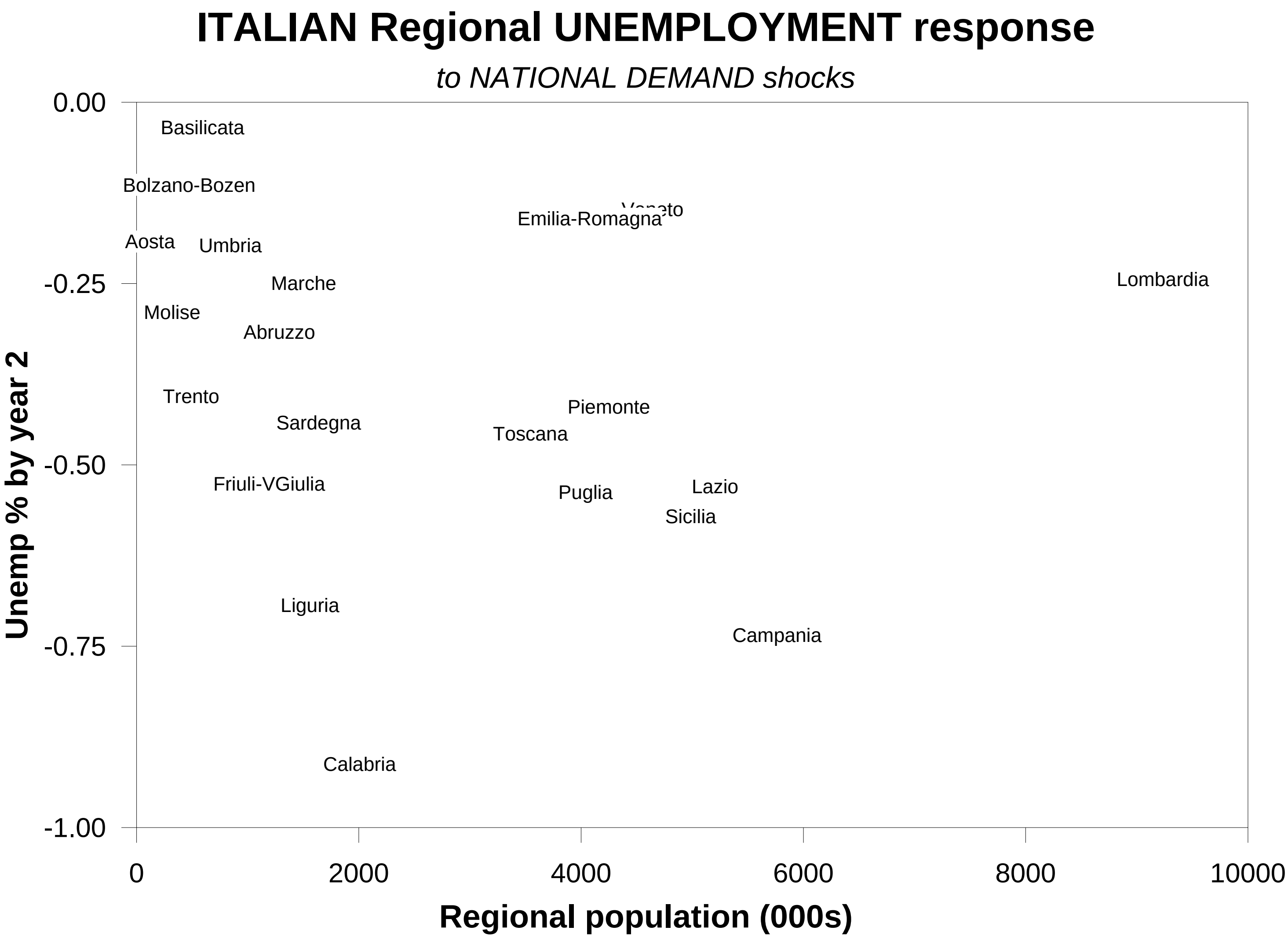


Local government responses similar



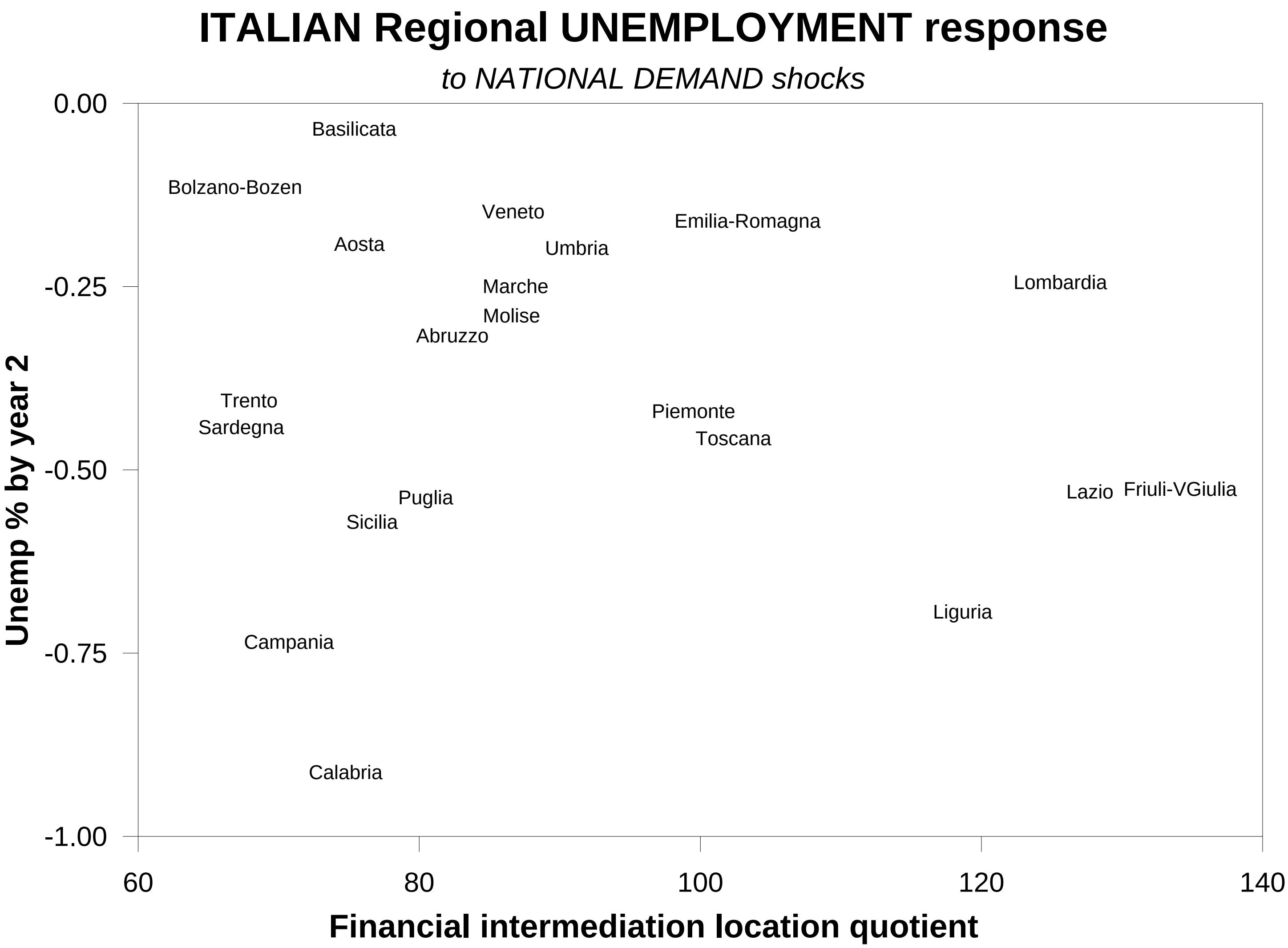
Similar pattern as Spain


ITALIAN Regional OUTPUT response
to REGIONAL SUPPLY shocks
lnY*100 by year 2
Regional population (000s)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
2000
4000
6000
8000
10000
Basilicata
Abruzzo
Piemonte
Veneto
Marche
Puglia
Lazio
Sicilia
Liguria
Lombardia
Campania
Friuli-VGiulia
Aosta
Trento
Umbria
Sardegna
Toscana
Emilia-Romagna
Bolzano-Bozen
Molise
Calabria

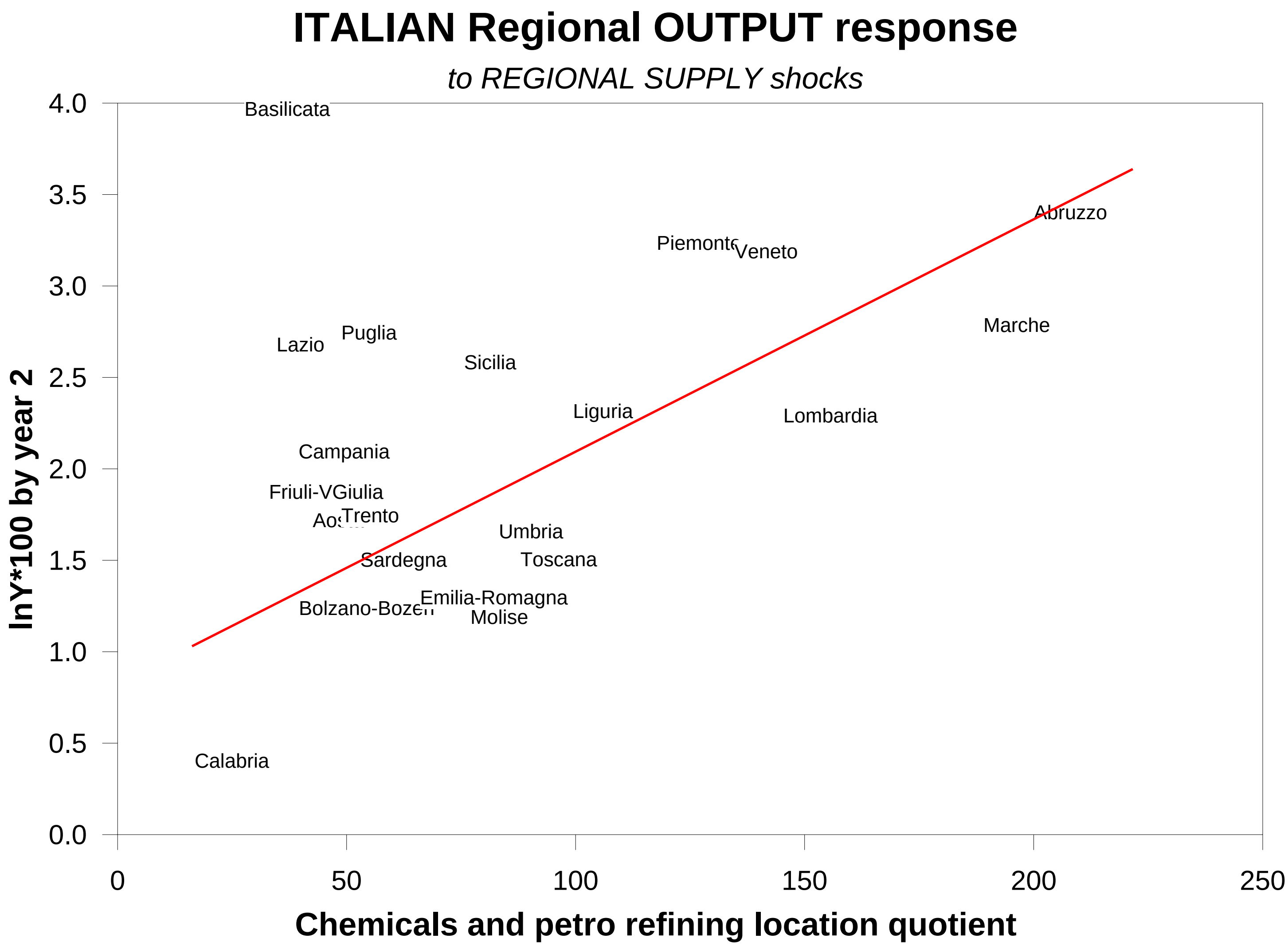


But national (government) demand response different than Spain.

Does not appear to target high income regions



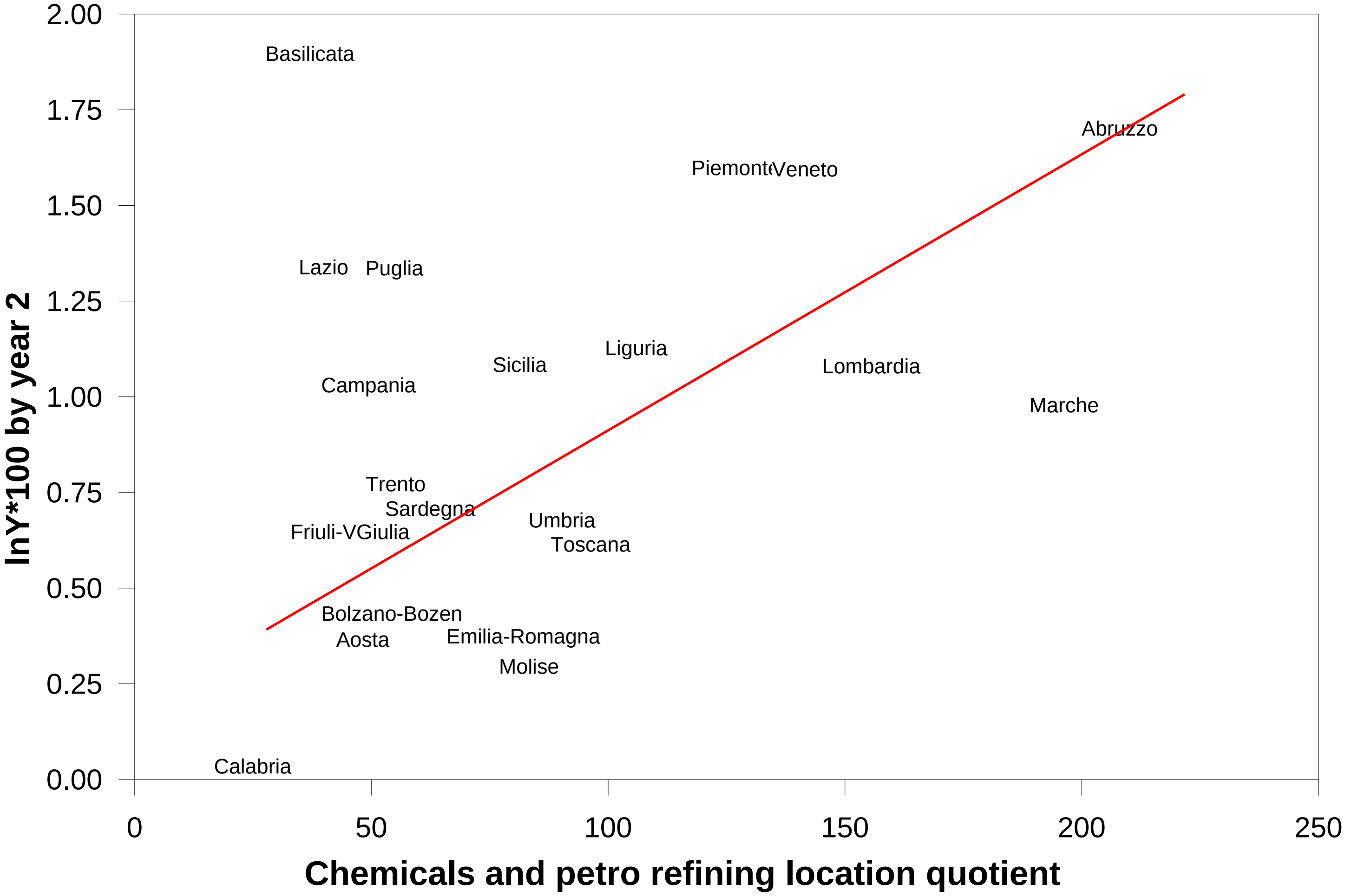
Unlike Spain, also no pattern
for financial intensive regions



Strong pattern for local supply effect
on heavy manufacturing

ITALIAN Regional OUTPUT response

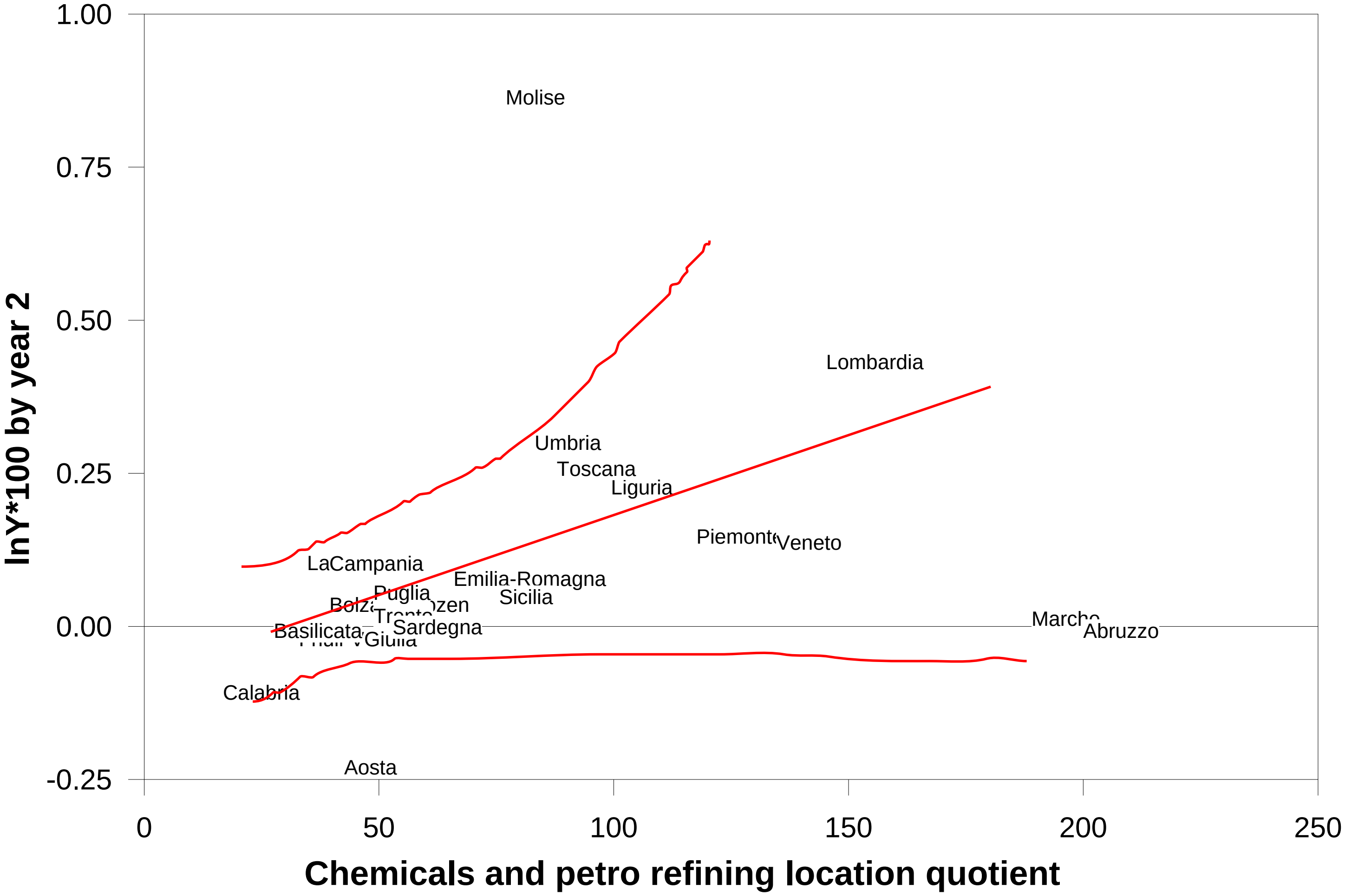
to NATIONAL SUPPLY shocks



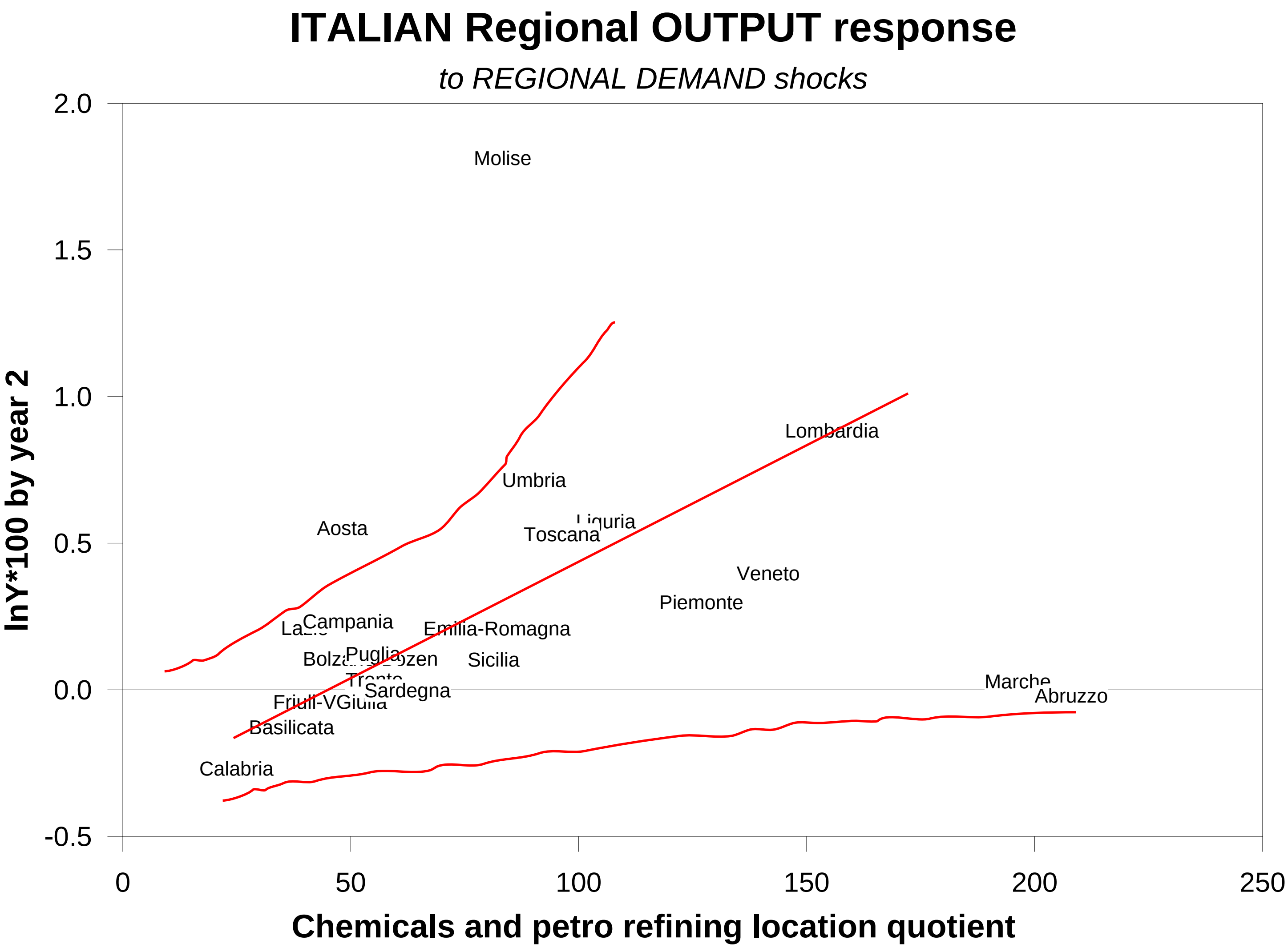
Also for response to
national supply shocks

ITALIAN Regional OUTPUT response

to NATIONAL DEMAND shocks



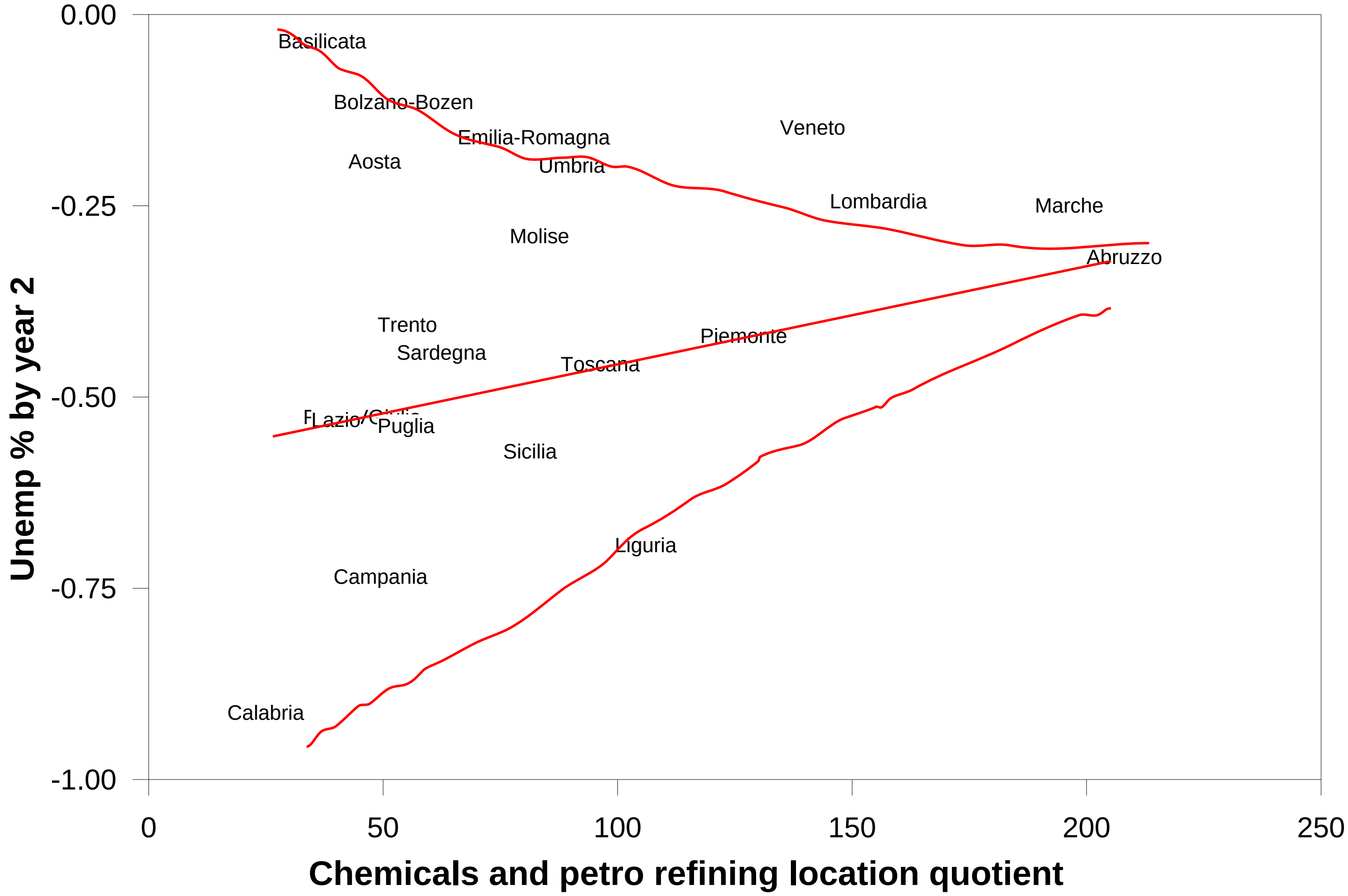
Response to national demand more varied for heavier manufacturing



Similar to regional demand

ITALIAN Regional UNEMPLOYMENT response

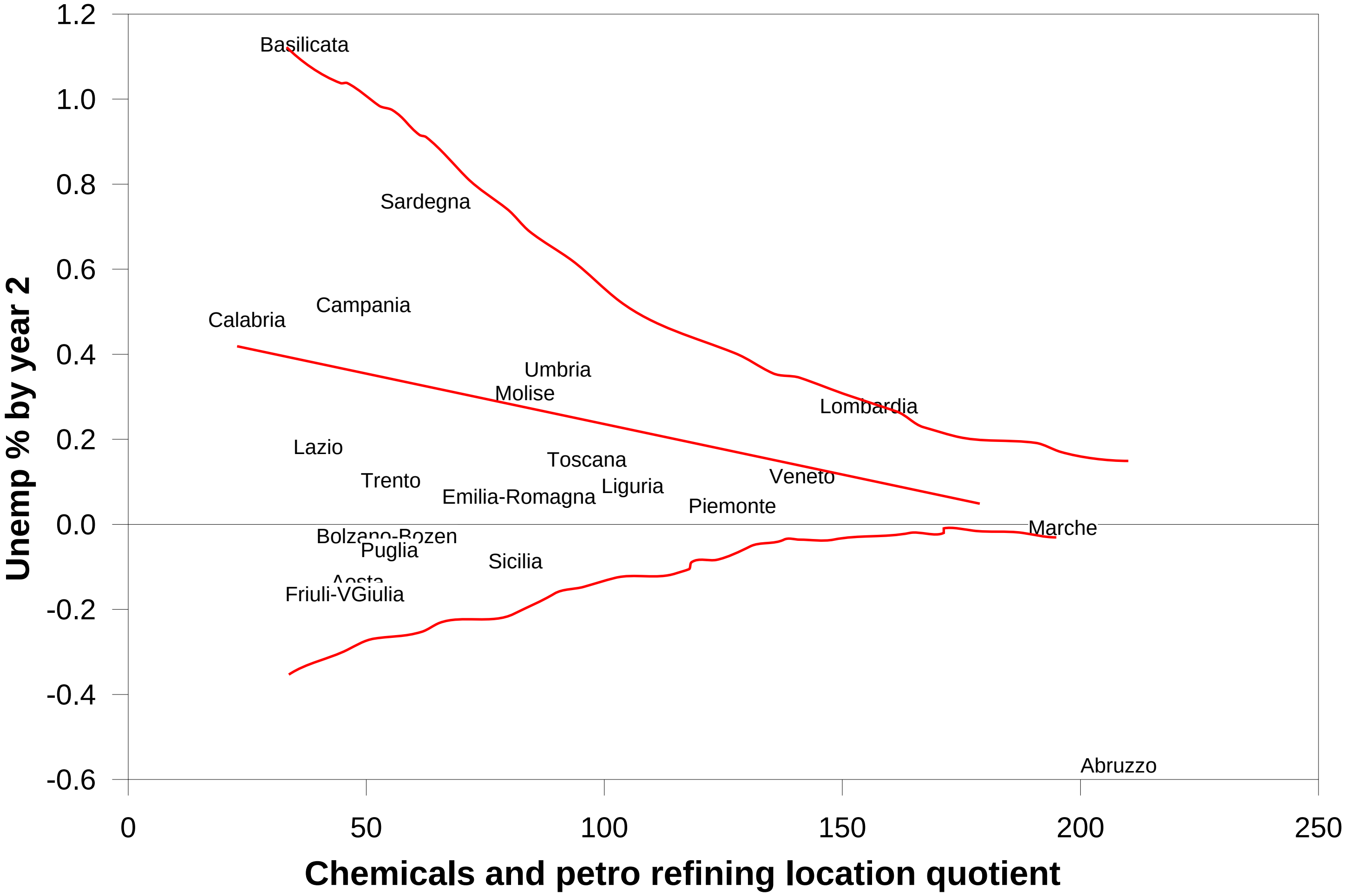
to NATIONAL DEMAND shocks



Heteroskedasticity of unemployment response reversed

ITALIAN Regional UNEMPLOYMENT response

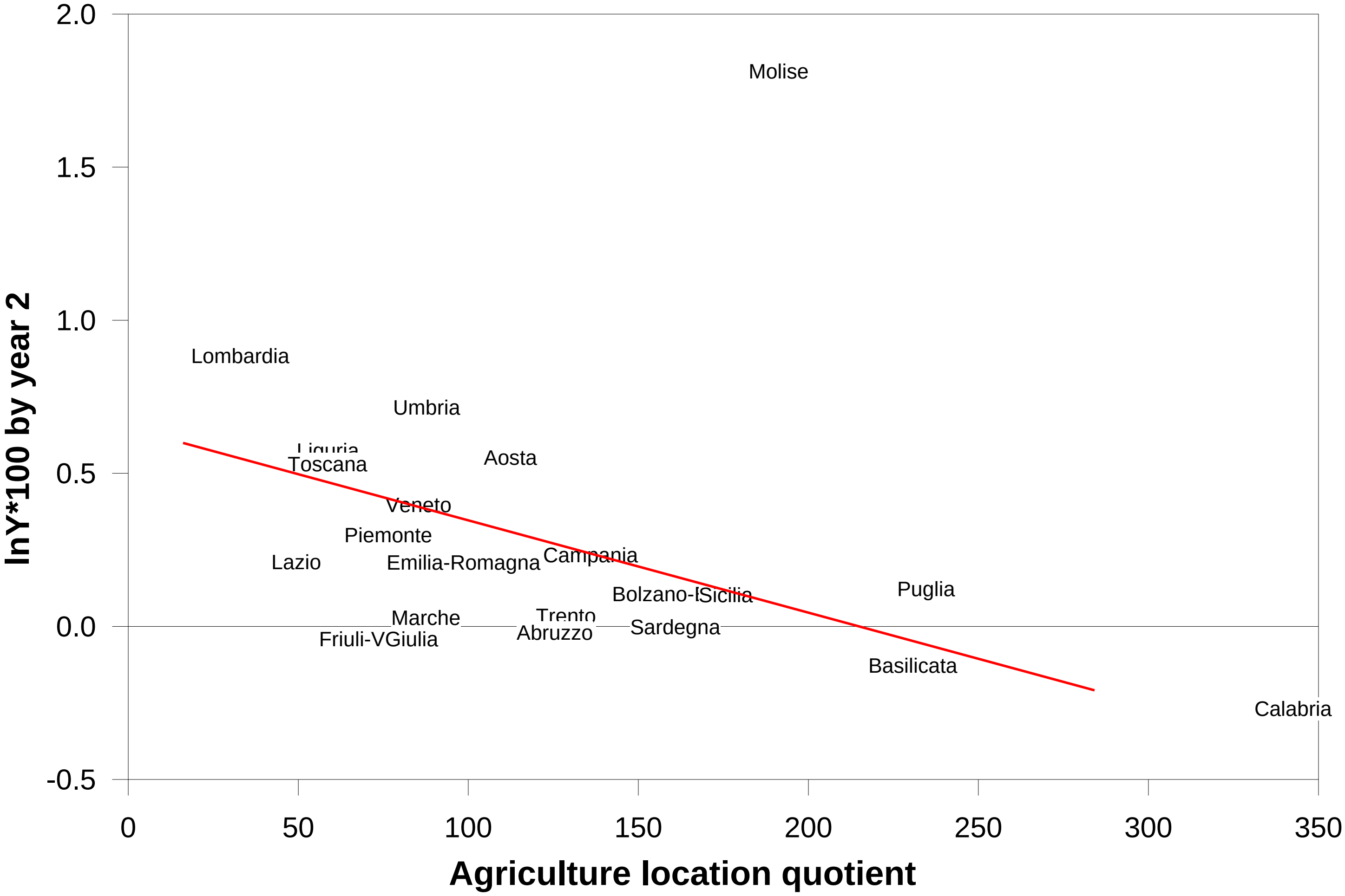
to REGIONAL SUPPLY shocks



Unemployment response perverse for some regions
- increases for positive supply shock.

ITALIAN Regional OUTPUT response

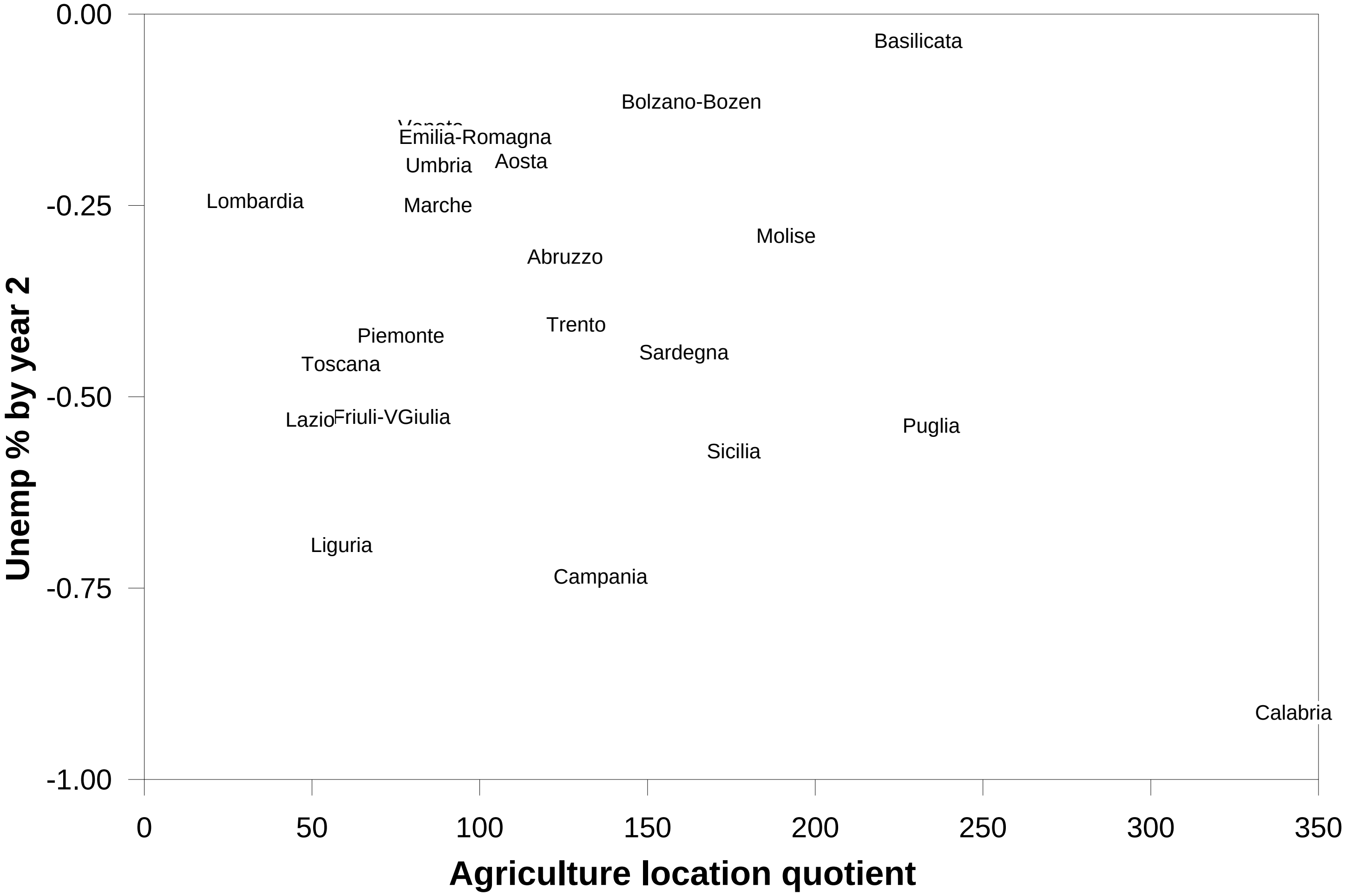
to REGIONAL DEMAND shocks



Local responses bigger in non-agricultural regions

ITALIAN Regional UNEMPLOYMENT response

to NATIONAL DEMAND shocks

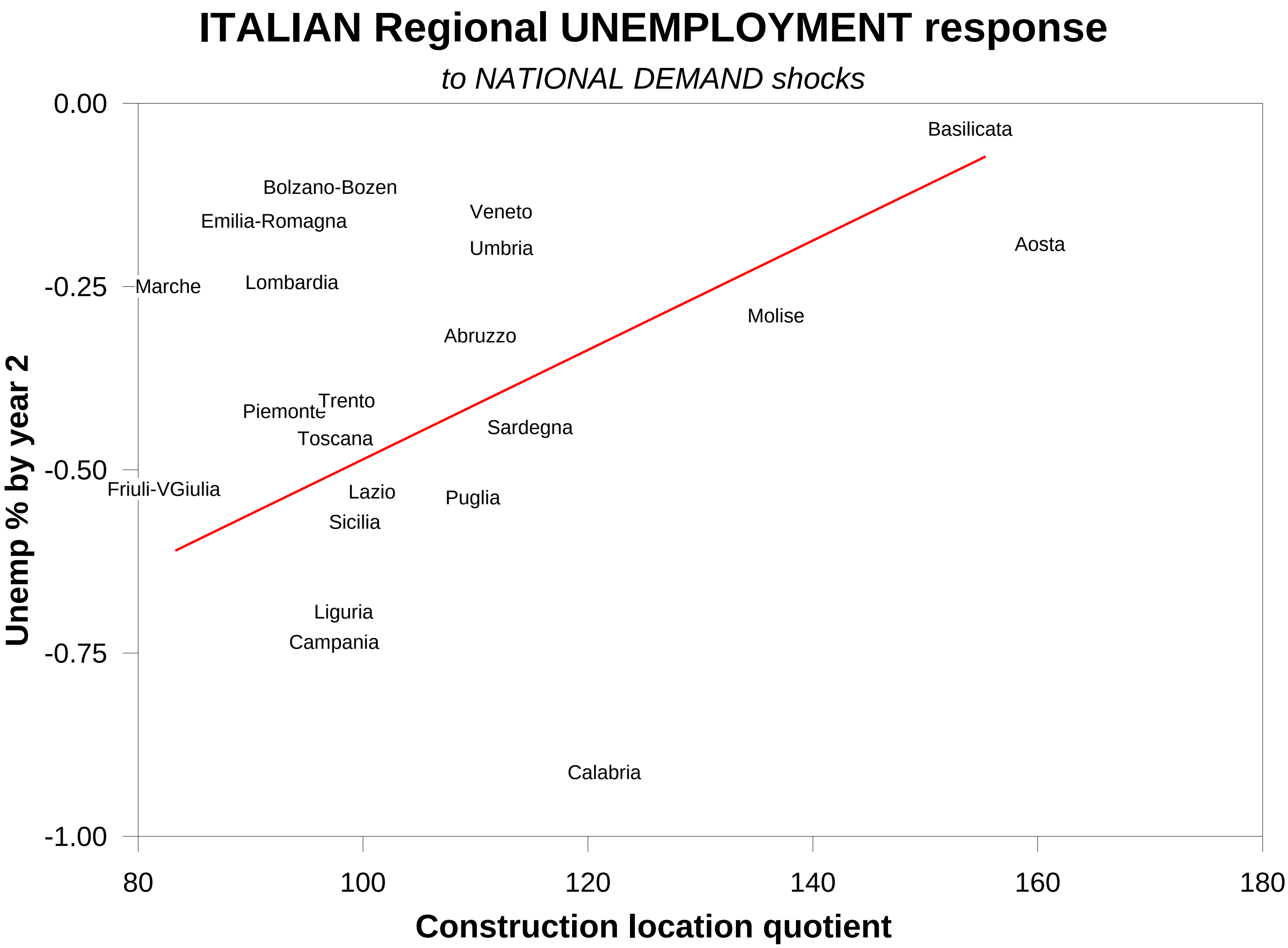


Pattern weak and opposite for national shocks.

ITALIAN Regional UNEMPLOYMENT response

to REGIONAL SUPPLY shocks

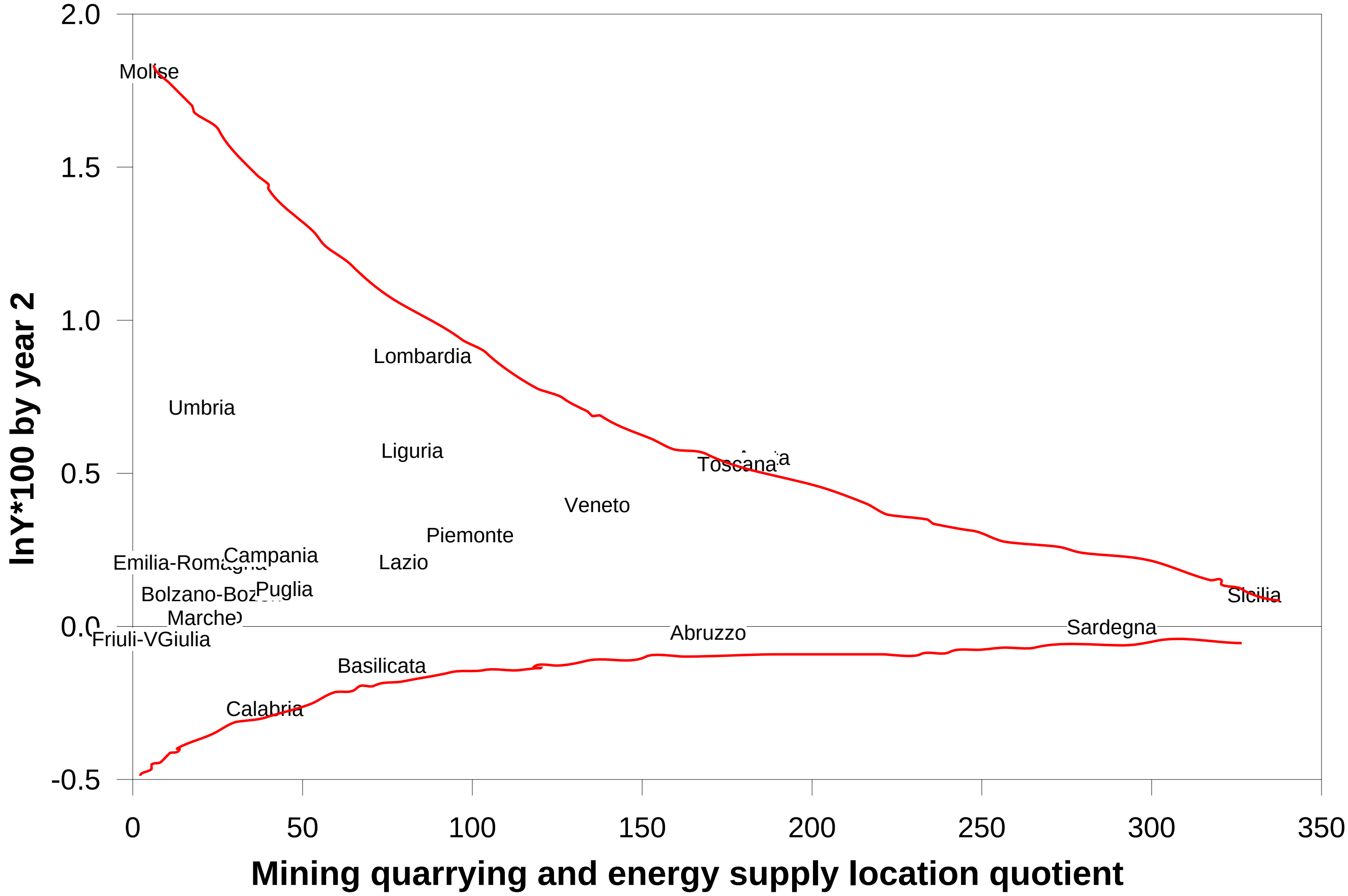
Unusual relationship - positive regional supply shocks
create unemployment in construction intensive regions



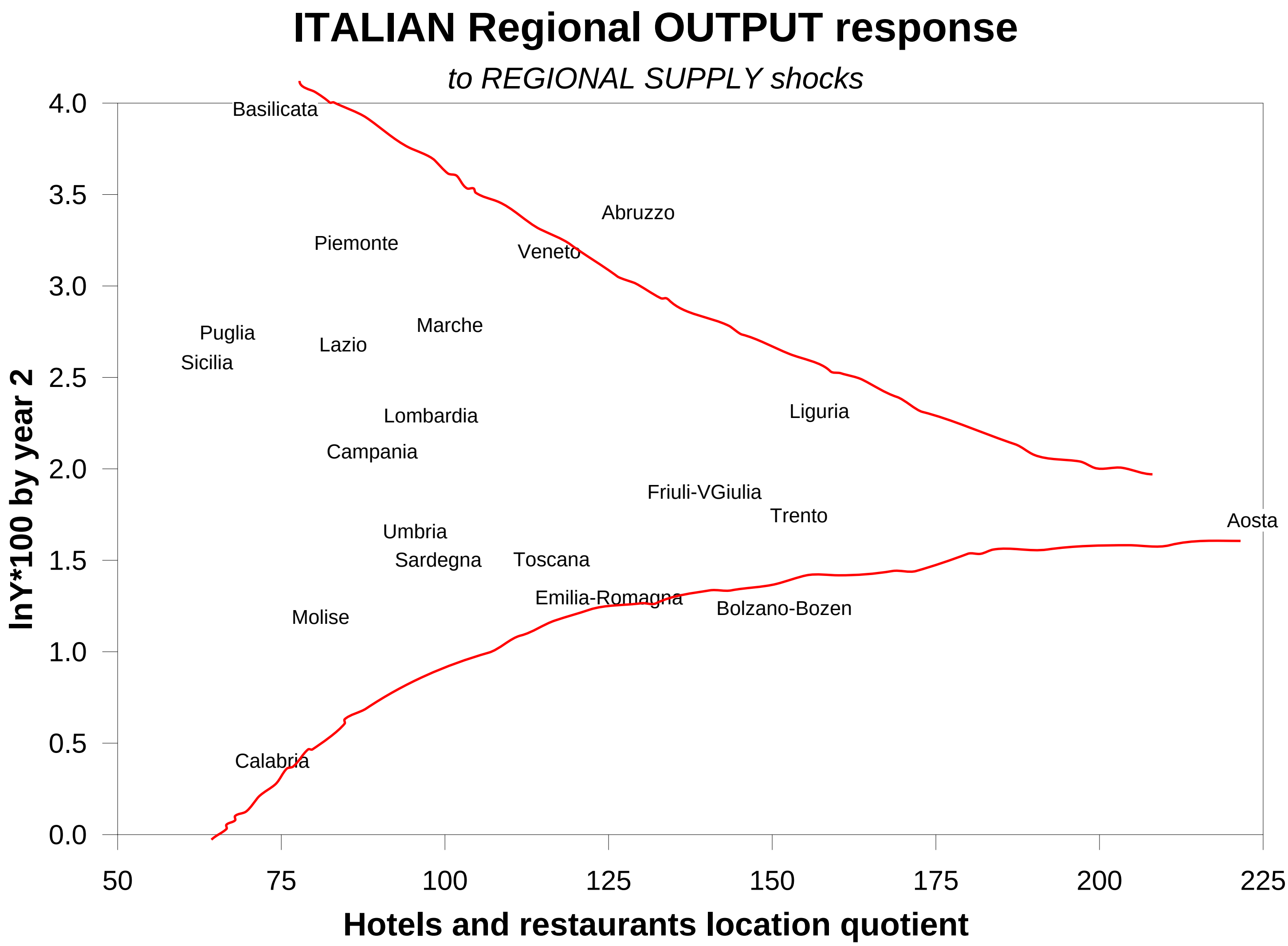
National demand shocks lower unemployment,
but less so for more construction intensive regions

ITALIAN Regional OUTPUT response

to REGIONAL DEMAND shocks



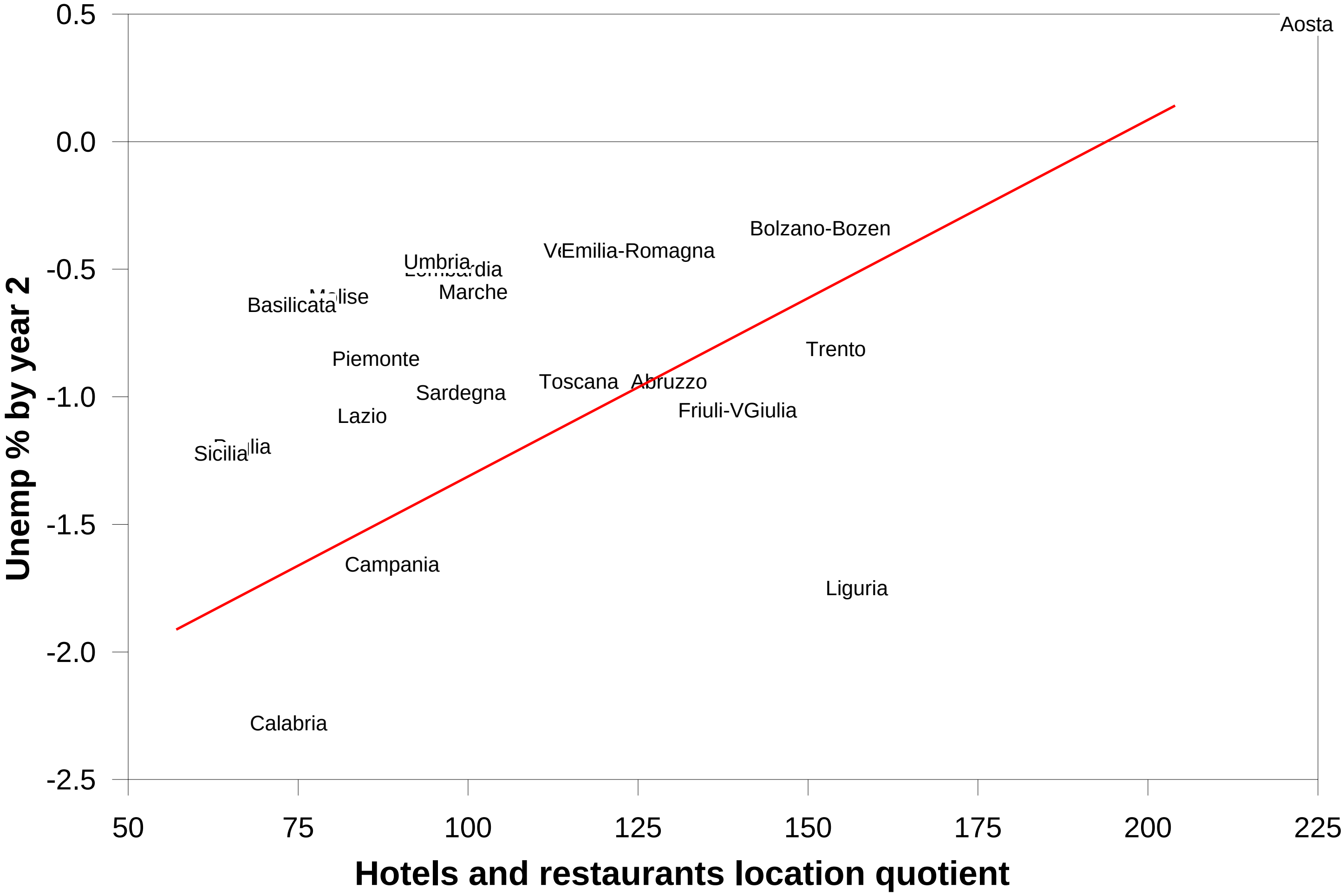
Regions with more mining and energy supply experience less variation in response to regional demand



tourism intensive regions less susceptible to variations in GDP stemming from supply shocks

ITALIAN Regional UNEMPLOYMENT response

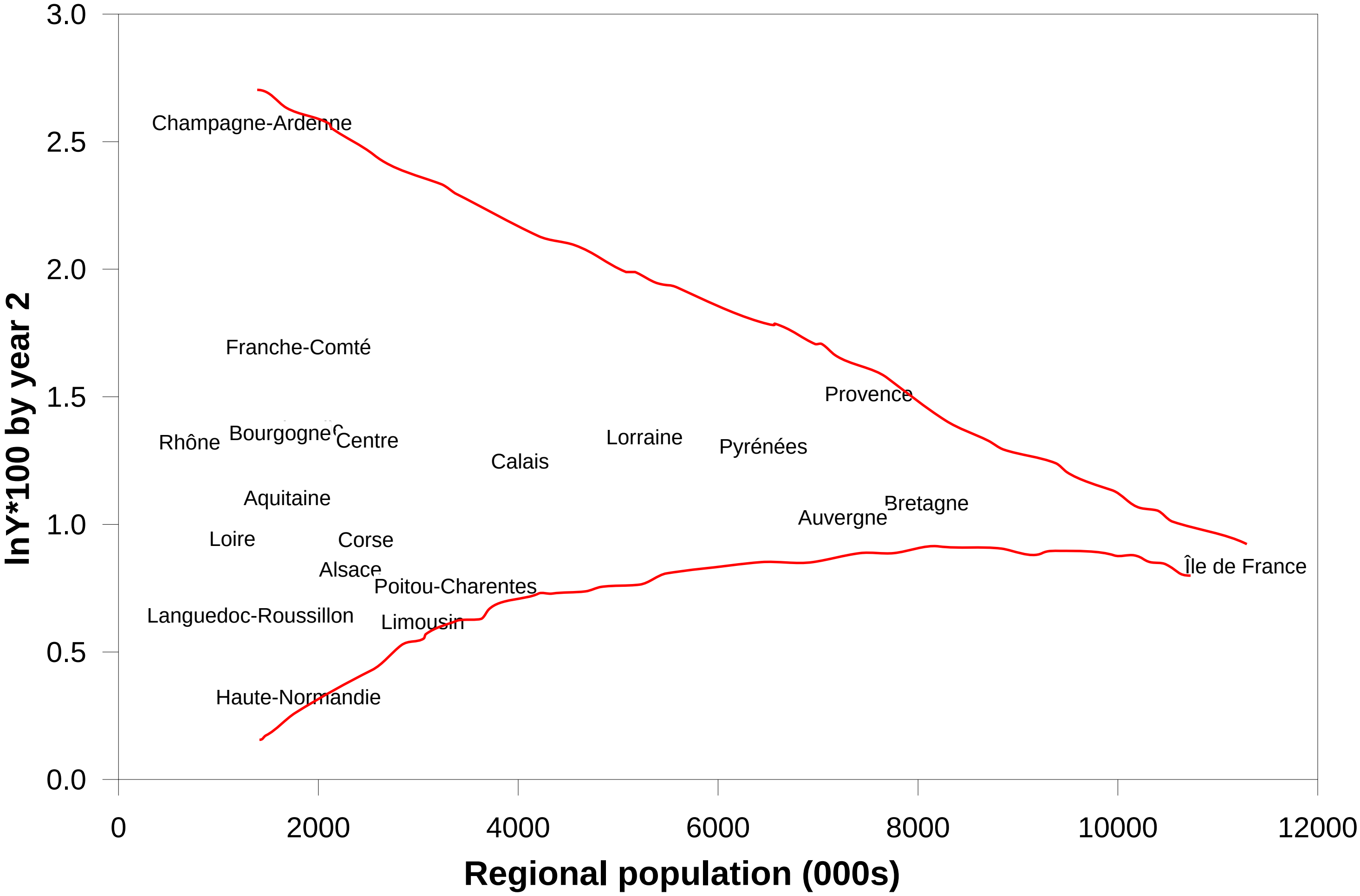
to REGIONAL DEMAND shocks



Local demand stimulus not more active in tourist intensive areas

FRENCH Regional OUTPUT response

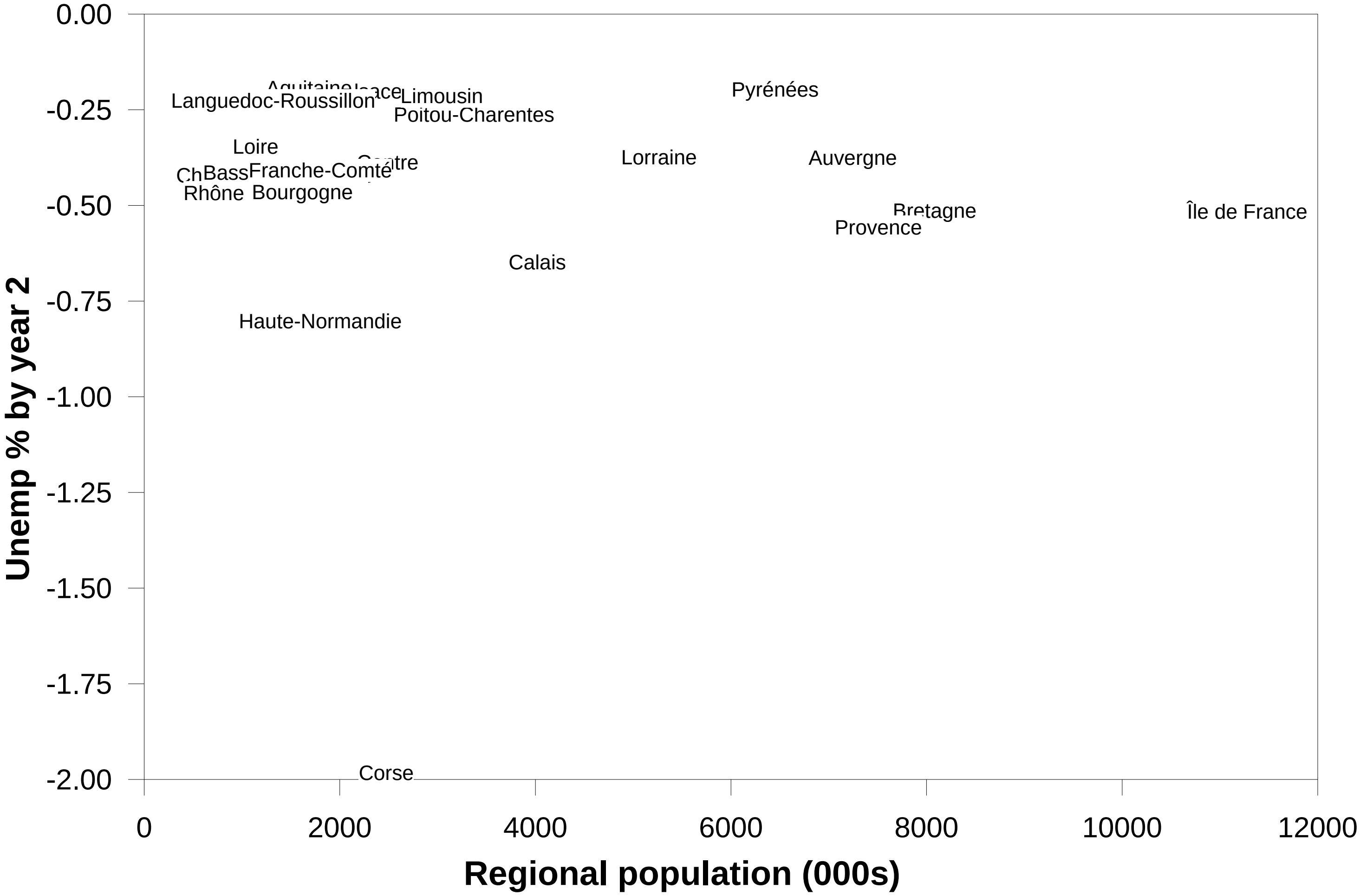
to NATIONAL SUPPLY shocks



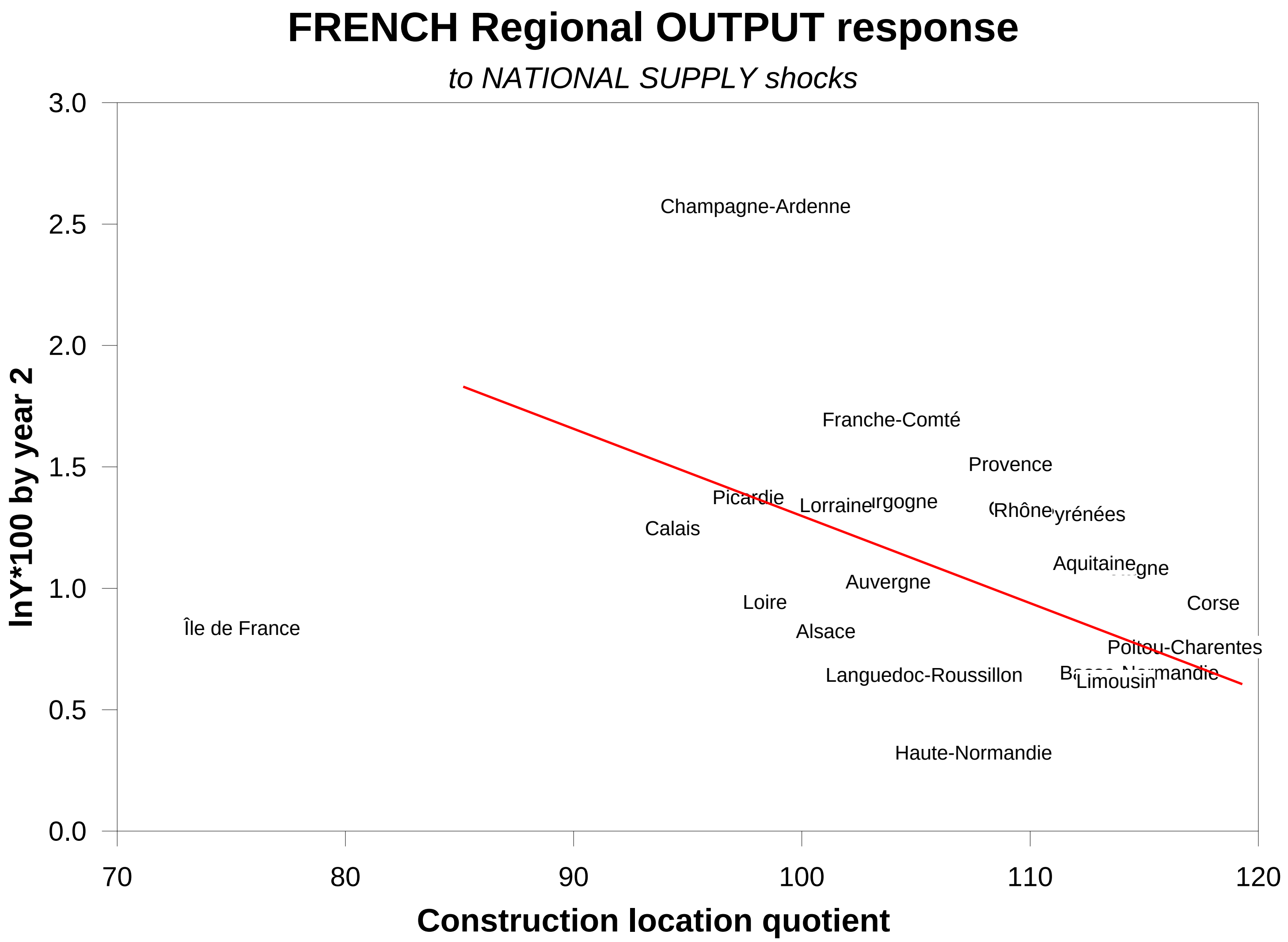
Similar pattern as Spain and Italy.

FRENCH Regional UNEMPLOYMENT response

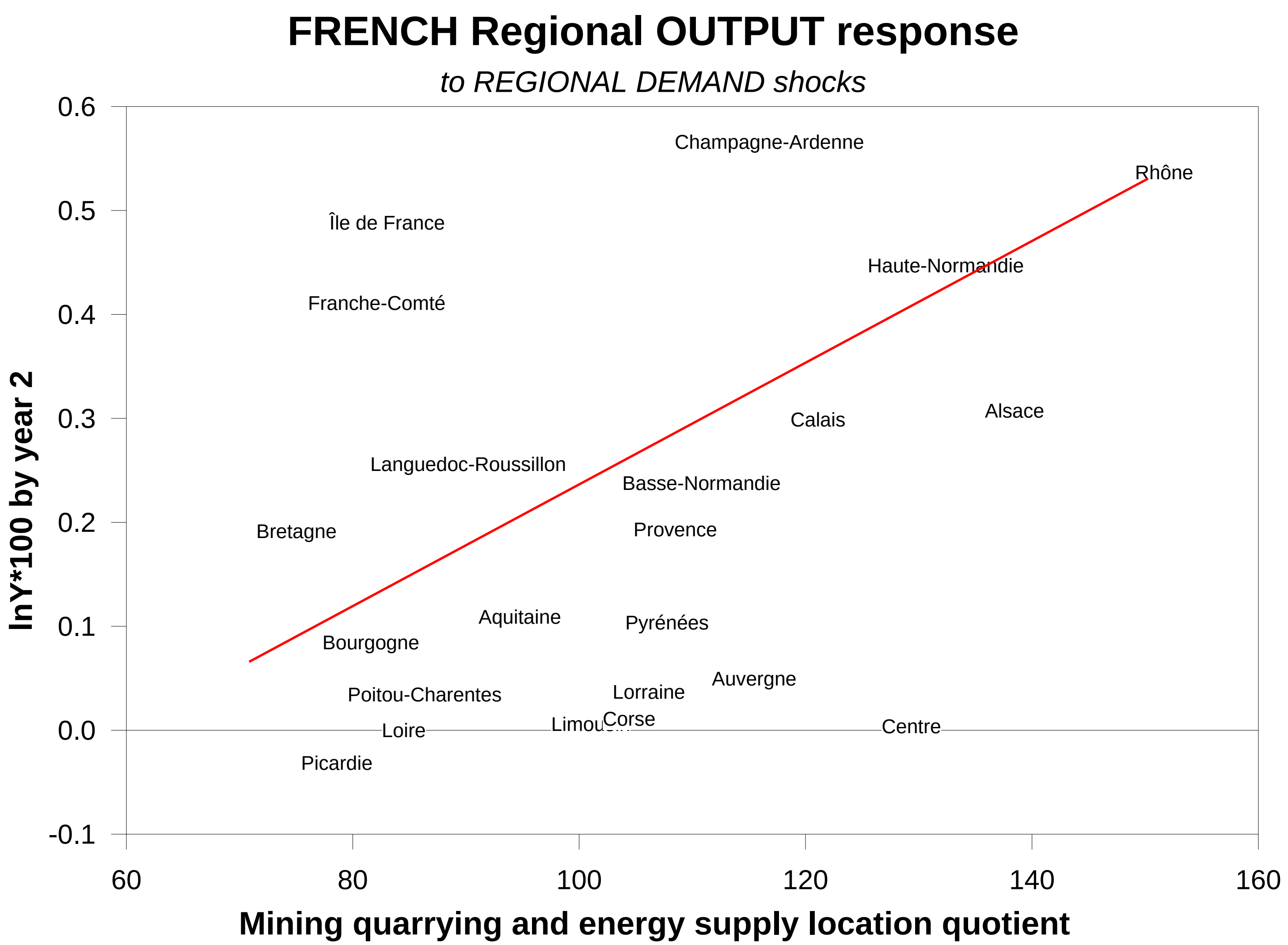
to NATIONAL DEMAND shocks



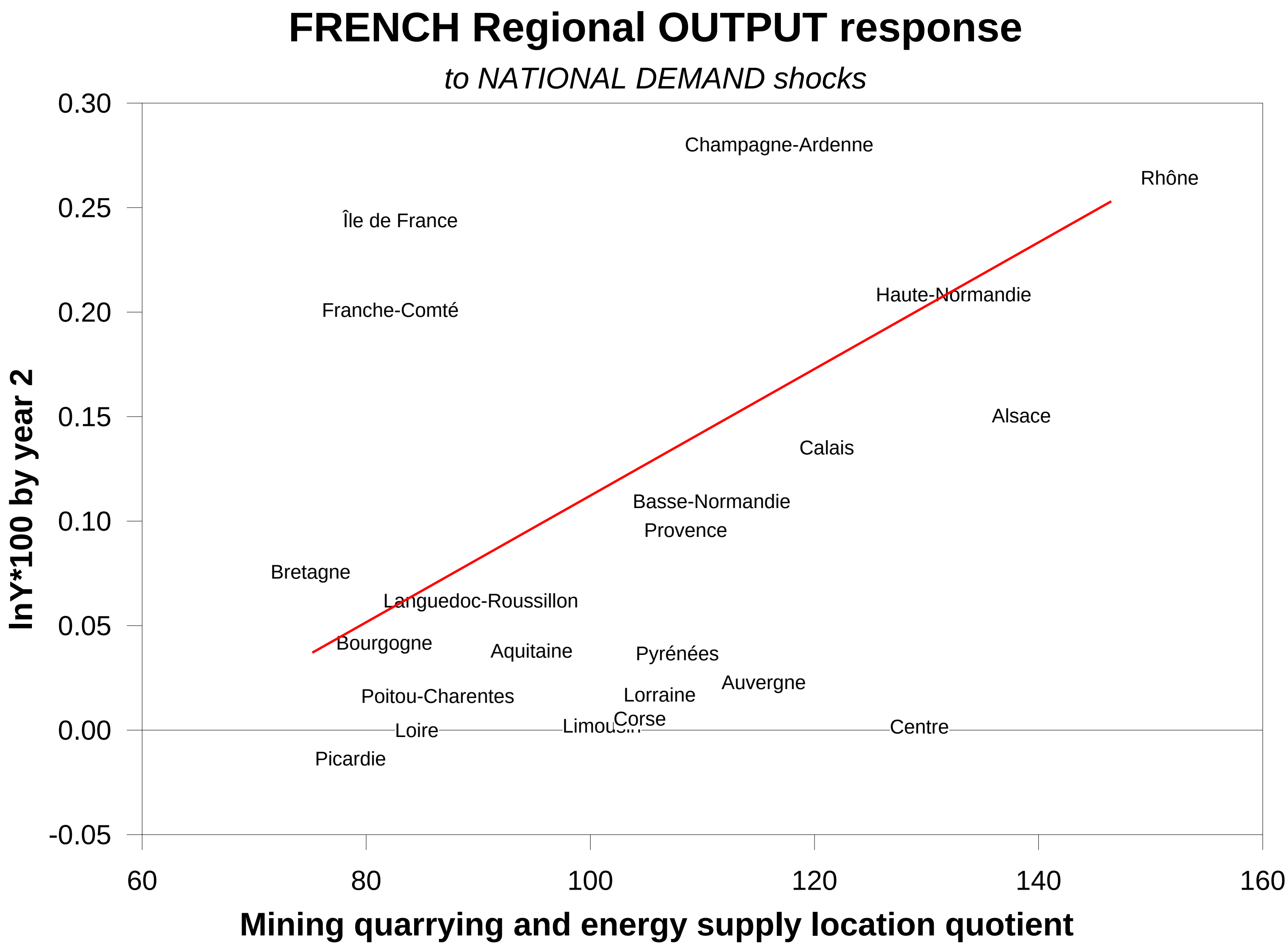
More closely resemble Italy (no preference toward bigger regions).
But size of responses more homogeneous than Italy.



Construction intensive regions experience smaller responses to regional supply shocks.



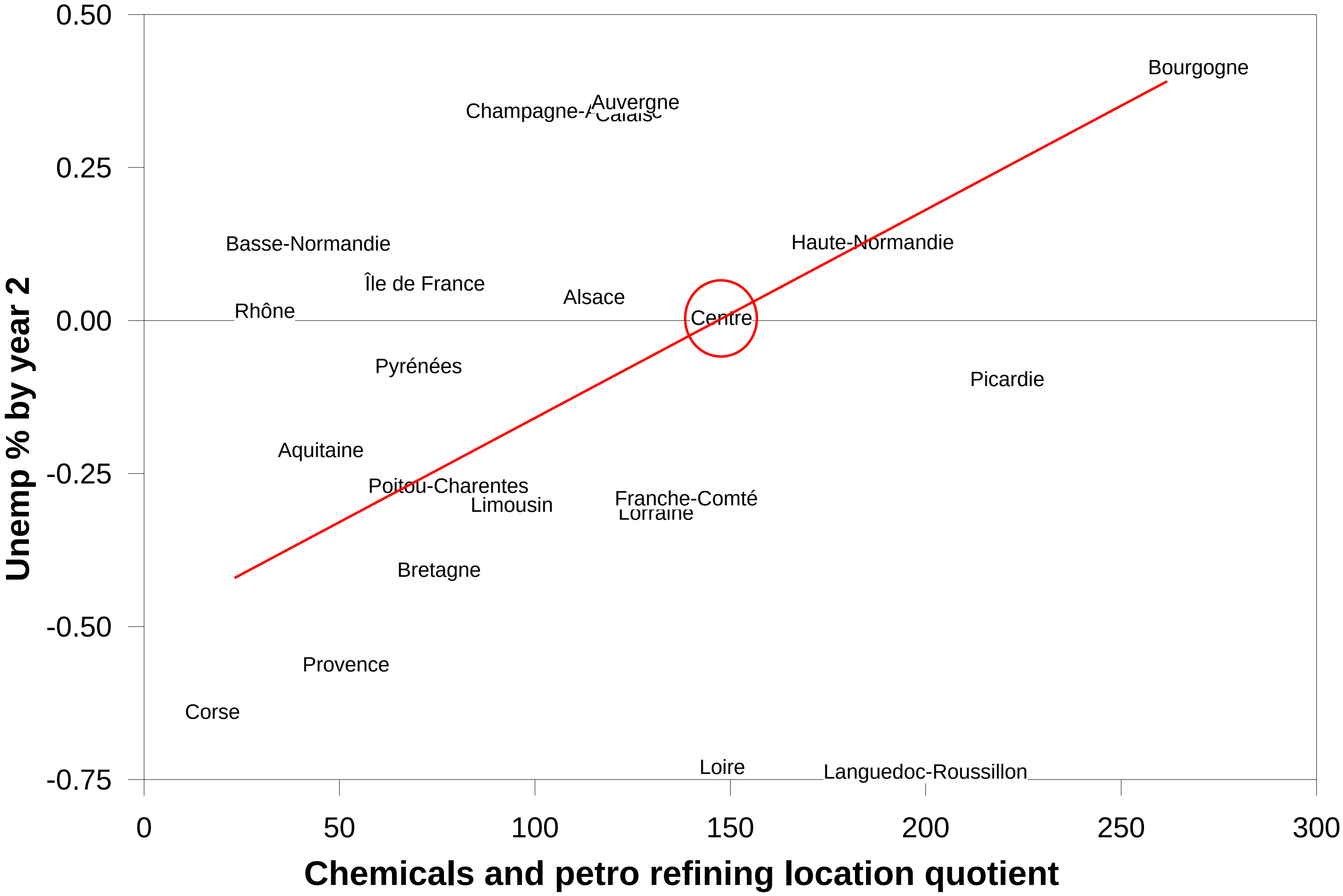
Different pattern than Italy. Responsiveness to local demand stimulation sensitive to resource extraction.



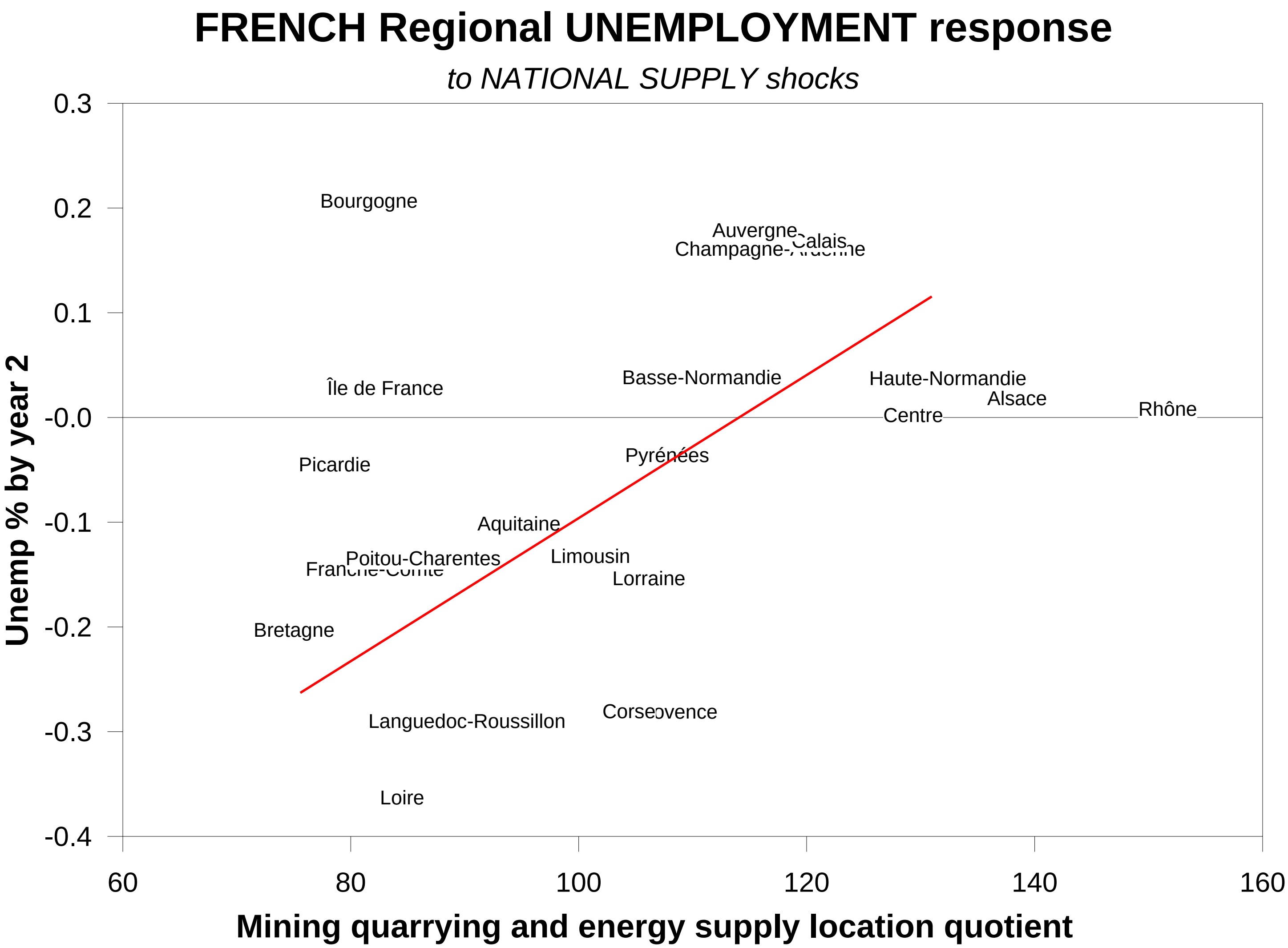
Similar pattern for national demand shocks.

FRENCH Regional UNEMPLOYMENT response

to REGIONAL SUPPLY shocks



Similar pattern as in Italy.



Also similar for national shocks.

Other Examples of Panel SVAR Applications:

(Work in Progress)

"The Contribution of Housing Markets to the Great Recession" *Pedroni & Sheppard (2010)*

- uses Moody's regional U.S. metropolitan level data

- studies role of local U.S. housing markets in contributing to current U.S. and Global recession

"Monetary Policy in Low Income Countries" *Mishra, Montiel, Pedroni & Spilimbergo (2010)*

- uses country level IFS data

- studies differences in effectiveness and transmission mechanisms of monetary policy among countries