Is Full Employment Sustainable?

Antonio Fatas
INSEAD

Very preliminary. This version: *March 11, 2019*

Introduction

The US economy started its current expansion phase in June 2009. This means that, as of March 2019, the expansion has lasted nine years and nine months. This is just a few months short of beating the longest expansion ever, which took place from March 1991 to March 2001.

As we approach this milestone, there are increasing concerns about the possibility of a recession in the coming years. But do expansions die of old age? Do risks of a recession increase as expansions get longer? If so, where are the risks coming from?

When answering these questions, we typically think of age of an expansion in terms of the number of quarters since the end of the previous recession. When we do that, we find that there is no correlation between the length of an expansion and the probability of a recession. Expansions do not seem to die of old age (Rudebusch (2016))

There is, however, an alternative way to approach the same question by thinking of an expansion as the period where economy regains full employment. As unemployment becomes low and reaches levels around or below what we consider the natural rate of unemployment, what are the chances the economy will be able to maintain this state for a number of years? Does "full employment" (i.e. low unemployment) automatically lead to imbalances that are the seeds of the next crisis? And what are those imbalances?

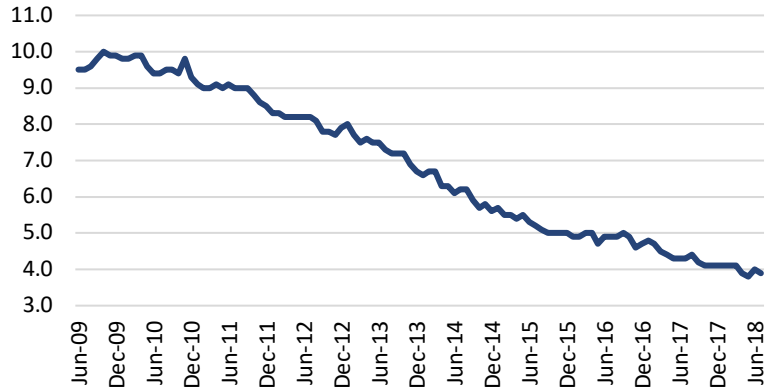
The V-Shape Unemployment Rate

After a trough, expansions are characterized by a fast-declining unemployment rate as the economy recovers from the recession, unemployment falls towards the natural rate of unemployment.[1] This is the case for the most recent expansion that can be characterized by a declining unemployment rate since the end of the last recession (June 2009) until today (Figure 1).

But now that unemployment has reached a state of "full employment", what happens next? Is full employment sustainable? Unemployment rates cannot go too far below the natural rate of unemployment. But can unemployment flatten over the coming years? Or does a low level of unemployment imply that the only way forward is an increase in unemployment linked to a new recessionary episode?

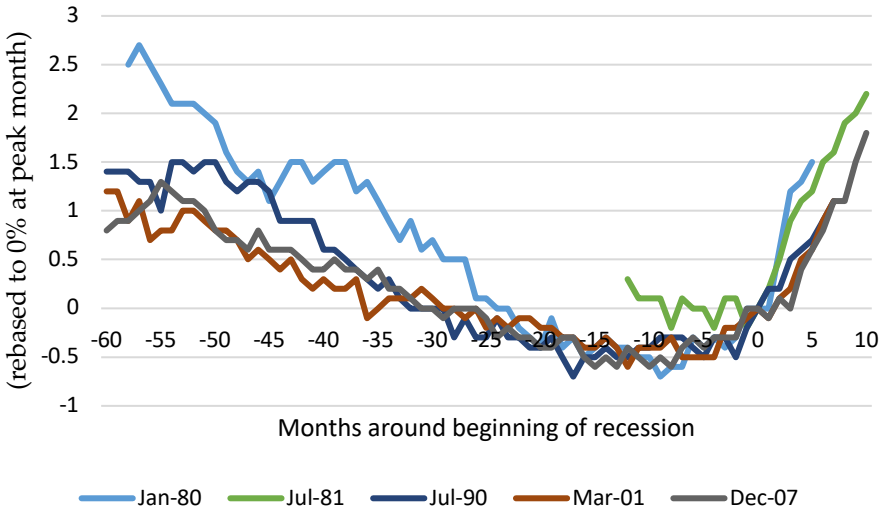
[1] There is, of course, uncertainty about the level of the natural rate of unemployment. It is not uncommon for this rate to be revised downwards as unemployment falls, as it is the case in the current US expansion.

Figure 1. Unemployment Rate (US)



A quick look at what happened in each of the previous five US recessions is that unemployment always bounced back quickly from its low levels. In Figure 2 we plot unemployment rates around the peak of each of the last cycles (i.e. zero represents the month the recession started). We plot the 5 years before the recession started and 10 months after the recession. Some series are shorter because either the previous expansion was shorter than 5 years or the recession lasted less than 10 months.

Figure 2. Unemployment Rate Around Recessions (US)



All cycles display a V-shape evolution for unemployment. Unemployment reaches its lowest point around 12-18 months before the recession and, in most cases, unemployment was already increasing in the months preceding the recession. What is interesting is the absence of a single episode of stable low unemployment (or full employment). It seems as if reaching a low level of unemployment *always* leads to dynamics that soon generate a recession.

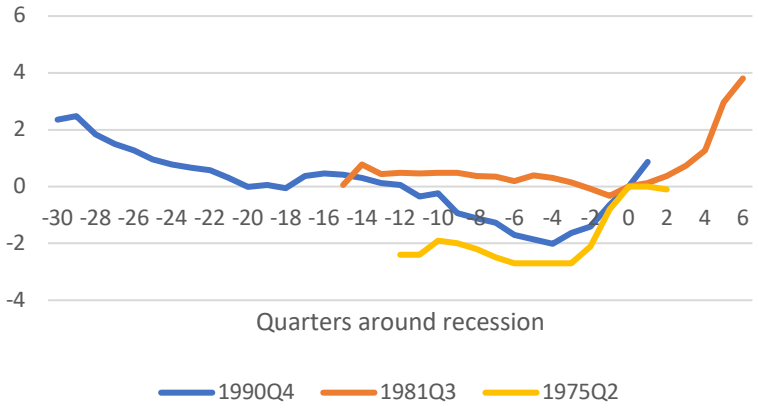
An interpretation of this stylized fact is that expansions, in the US, seem to die of old age as long as "age" is measured in terms of the level of the unemployment rate. Of course, some expansions might die early (out of a "car crash"), but no expansion lives beyond a few quarters after unemployment has reached full employment.

The result might sound obvious. Once unemployment rate is low, there is only one way for unemployment to go: up. But this ignores the possibility of a period of low and stable unemployment. One way to visualize that possibility is to look at other countries. A good example is Australia that has recently sustained a low unemployment rate for decades. After a recession in the early 1990s, unemployment increased and then started a decline through a path similar to any US expansions. By the year 2000 unemployment reached a low level that has remained mostly flat for years (Figure 3). In other words, the unemployment rate does not display V-shape dynamics but looks more like an open L-shape.

Figure 3. Unemployment Rate (Australia)

This pattern is indeed common for all cycles in Australia. Figure 4 plots the evolution of unemployment around the three most recent cycles and, in all cases, we see shapes that are different from the V-shape evolution of US unemployment.

Figure 4. Unemployment Rate Around Recessions (Australia)



A Quantitative Assessment of Unemployment Risk

The fundamental question we want to answer is whether as unemployment decreases there is a significant increase in the probability of a recession. Mechanically, because unemployment rates are mean reverting, we do expect high levels of unemployment to

precede decreases in unemployment while lower levels are likely to be observed before a crisis. But how strong is this effect quantitatively? Can low unemployment be seen as a *strong* predictor of recessions? And how does this relationship differ across countries?

As expected, a simple OLS regression using changes in US quarterly unemployment rates reveals that future changes in unemployment are negatively related to the current level of unemployment. Table 1 shows the coefficients of running a regression of changes in unemployment rate over the next 12 quarters (three years) on the initial level of unemployment:

$$(U_{t+12} - U_t) = \alpha + \beta U_t + \varepsilon_t$$

Table 1. Low unemployment as a predictor of increases in unemployment (US)

US	$U_{t+12} - U_t$
U_t	-0.771***
	(0.0641)
Constant	4.572***
	(0.398)
Observations	242
R-squared	0.376

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient is negative and significant with a relatively high R-squared.

When we run the same regression for another country (Australia, Table 2) we see also a negative coefficient although smaller in size (and the R-squared is also smaller).

Table 2. Low unemployment as a predictor of increases in unemployment (Australia)

Australia	$U_{t+12} - U_t$
U_t	-0.348***
	(0.0445)
Constant	2.322***
	(0.288)
Observations	196
R-squared	0.239

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the above analysis we are trying to predict any possible future changes of the unemployment rate, large and small, using the current unemployment rate. When we worry

about cyclical risk, we typically want to focus on recessionary episodes in which unemployment increases by a large amount at a fast pace. In other words, we want to focus on the tail risk of changes in unemployment, episodes that we call recessions.

Estimating the determinants of the tail risk of unemployment changes is related to the concept of value at risk used by financial institutions: focusing on the worst potential outcomes over a specific time window. The same analysis has been applied to business cycles by focusing on the tail risk of unemployment or GDP growth and we refer to this concept as GDP at risk (Cecchetti (2008), Kiley (2018) Adrian, Boyarchenko, and Giannone (Forthcoming)).

Empirically, we can isolate the effects on a particular part of the distribution by using quantile regressions. Unlike OLS that finds the best fit for the average of the changes in unemployment, quantile regression weights errors differently by putting larger weight on the errors near the quantile of the distribution that is of interest to the researcher. See Koenker and Hallock (2001) for details on the methodology and Kiley (2018) for a similar analysis of unemployment dynamics for the US.

We are interested in the tail risk of sharp unemployment increases, which are associated with recessions, and we will capture that by the 90th percentile coefficient. The question is whether low unemployment rates are followed by large increases in unemployment. We follow Table 3 and show, for the US, the results for three quantiles: the bottom 10%, the average (q50) and the 90th percentile of the distribution (Table 3). While all three coefficients are negative and significant, their size increases as we move from small changes in unemployment to large changes. This means that low unemployment rates are strong predictors of the tail risk of large increases in unemployment.

Table 3. Quantile regression unemployment (US)

	Dependent Variable: $U_{t+12} - U_t$		
Quantiles	q10	q50	q90
U_t	-0.548***	-0.774***	-1.062***
	(0.0433)	(0.0934)	(0.149)
Constant	1.651***	4.181***	8.635***
	(0.245)	(0.686)	(1.262)
Observations	242	242	242

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Interestingly, the same phenomenon is not present in other countries. Table 4 shows the same results for Australia and the coefficient does not increase in size as we move towards the 90th percentile of the distribution. In fact, the coefficient becomes smaller and it is not-significant for the 90th percentile. This suggests that, unlike in the US, low unemployment rates are not a good predictor of recessionary episodes in Australia (beyond the mean reversion effect present for all quantiles).

Table 4. Quantile regression unemployment (Australia)

	Dependent Variable: $U_{t+12} - U_t$		
Quantiles	q10	q50	q90
U_t	-0.276***	-0.412***	-0.141
	(0.0201)	(0.0635)	(0.141)
Constant	0.397***	2.463***	3.480***
	(0.131)	(0.473)	(0.616)
Observations	196	196	196

Standard errors in parentheses
*** p<0.01, **

If we apply the same analysis to all other countries for which quarterly unemployment rates is available, we can see both of these patterns. Some resemble the US pattern where the coefficient on unemployment rates increases as we move from the 10th to the 90th percentile (e.g. Greece or Sweden). While in other cases the coefficients are of similar size across the different parts of the distribution (e.g. Germany or the UK). An appendix at the end of this note contains results from quantile regressions for other countries.

Why is Low Unemployment Unsustainable?

The US pattern of unemployment before recessions suggests that low levels of unemployment as a strong predictor of sudden increases in unemployment, associated to crises. We do not observe in the data any sustained periods of low unemployment (we always see what we call V-Shape unemployment rates). But why is low unemployment unsustainable? What leads to a recession? There is an empirical academic literature ("Growth at Risk") that analyzes the factors leading to a recession. They tend to emphasize two set of variables: those associated to macroeconomic imbalances (such as inflation) and those associated to financial imbalances. For example, Kiley (2018) studies unemployment risk and uses credit growth, bond spreads and inflation as explanatory variables. Adrian, Boyarchenko, and Giannone (Forthcoming) study GDP growth risk and use the National Financial Conditions Index as their indicator of financial imbalances.[2]

We make use of some of these variables below to see if their introduction in our quantile regression makes the effect of unemployment level change. Once we control for these risks, do we still have low levels of unemployment predicting economic crisis (as captured by sudden and large increases in unemployment)?

We include each of these variables separately in our quantile regression in Table 5. Columns (1) to (3) present the results of including the previous 4 quarter level of inflation.[3] The

[2] Schularick and Taylor (2012)
[3] Source: Personal Consumption Expenditures: Chain-type Price Index, Index 2012=100, Quarterly, Seasonally Adjusted. https://fred.stlouisfed.org/series/PCECTPI

coefficient on inflation is positive (as it would be expected) but does not show a particular pattern across the three quantiles we present. The coefficients on the unemployment level are not very different from the ones we had before. We still see that low unemployment rates are significant to explain the tail risks of recessions.

We then introduce the growth of credit over the last 4 quarters.[4] Results are in columns (4) to (6). Not only the variable is significant, but its coefficient increases as we move from q10 to q90, confirming that fast credit growth tends to precede recessions. But what is more interesting is that the introduction of the credit variable changes the pattern of the coefficients on unemployment levels. Unemployment still displays a negative coefficient, highlighting the reversion to the mean that was apparent in the simple OLS regression, but now the coefficients for the different quantiles are similar. In fact, the q90 coefficient is now smaller than the q50 and similar to the q10 ones. Low levels of unemployment do not seem to be good predictors of the tail risk associated to recessions.

Table 5. Unemployment Quantile Regression with Controls (US).

	(1)	(2)	(3)	(4)	(5)	(6)
Quantiles	q10	q50	q90	q10	q50	q90
Unemployment	-0.579***	-0.908***	-1.020***	-0.477***	-0.711***	-0.529***
	(0.0462)	(0.0455)	(0.179)	(0.0407)	(0.0662)	(0.172)
Inflation	23.37***	42.21***	29.46***			
	(5.487)	(5.666)	(9.040)			
Credit				6.842***	10.41**	46.18***
				(2.031)	(4.337)	(13.78)
Constant	1.342***	3.906***	7.272***	1.176***	3.829***	4.790***
	(0.293)	(0.359)	(1.515)	(0.247)	(0.476)	(1.078)
Observations	242	242	242	242	242	242

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, we present in columns (7) to (9) the results of introducing the National Financial Conditions Index. The coefficient on the index is positive, as expected and there is some increase as we move from q10 to q90, but not consistent as in the credit growth variable. When it comes to the unemployment coefficients, they are all higher and we still see a pattern of increasing size as we move from q10 to q90.

[4] Source: Total Credit to Private Non-Financial Sector, Adjusted for Breaks, for United States, Percentage of GDP, Quarterly, Not Seasonally Adjusted: https://fred.stlouisfed.org/series/QUSPAM770A

Table 6. Unemployment Quantile Regression with Controls (US). (cont.)

	(7)	(8)	(9)
Quantiles	q10	q50	q90
Unemployment	-0.700***	-0.929***	-1.286***
	(0.0462)	(0.0796)	(0.120)
NFCI	0.578***	0.989***	0.856***
	(0.0689)	(0.214)	(0.261)
Constant	2.966***	5.649***	10.19***
	(0.329)	(0.514)	(1.052)
Observations	178	178	178

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusions

The results of Table 6 suggest that it is not the low level of unemployment rate that necessarily leads to a recession, but the imbalances that are associated to those low levels. In particular, out of the imbalances we have considered, credit growth seems to have the strongest explanatory power.

Appendix. Quantile Regressions for other countries.

The figures attached at the end of this note present the results of running a quantile regression as in Table 3 above for a sample of advanced economies. The figures present the coefficients on the three quantiles of interest (q10, q50 and q90). A future version of this draft will present detailed analysis of each of these countries.

References

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone, Forthcoming, Vulnerable Growth, *American Economic Review*.

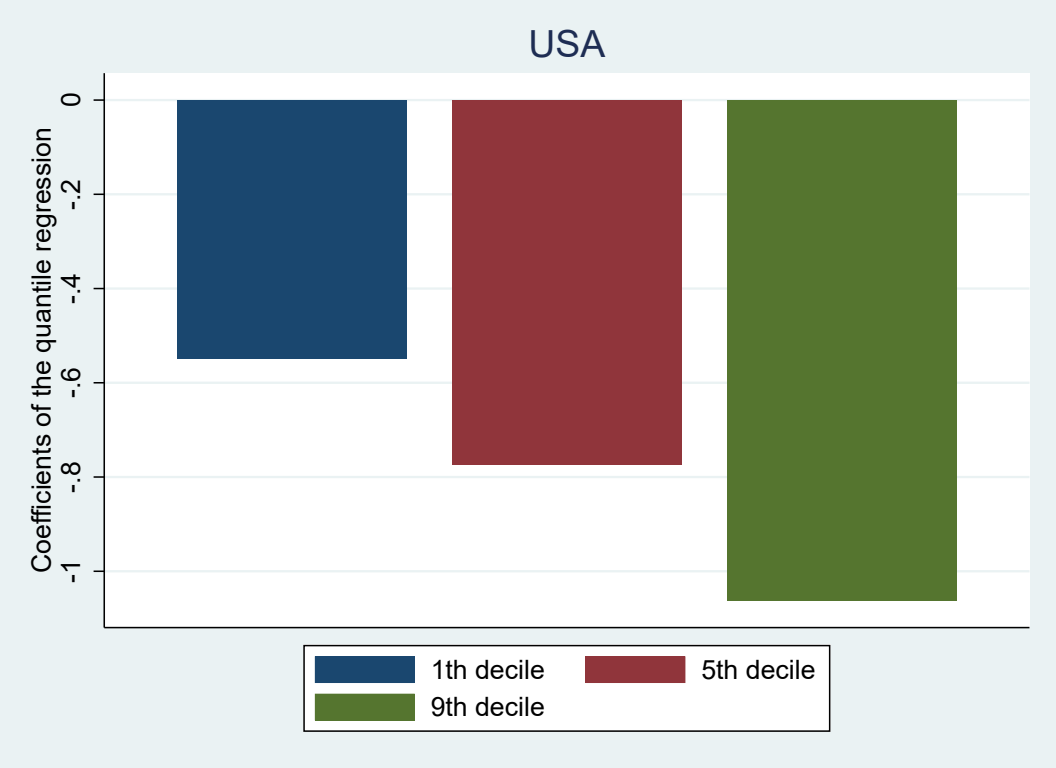
Cecchetti, Stephen G., 2008, Measuring the macroeconomic risks posed by asset price booms, *Asset prices and monetary policy* (University of Chicago Press).

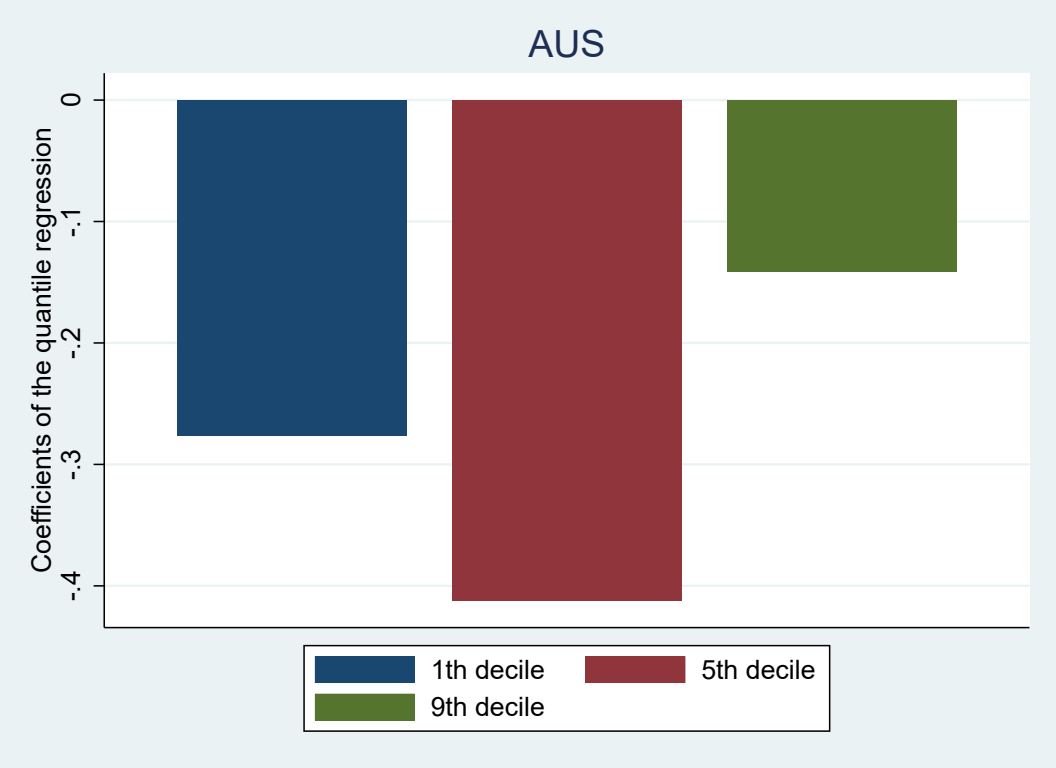
Kiley, Michael T., 2018, Unemployment Risk. Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System (US).

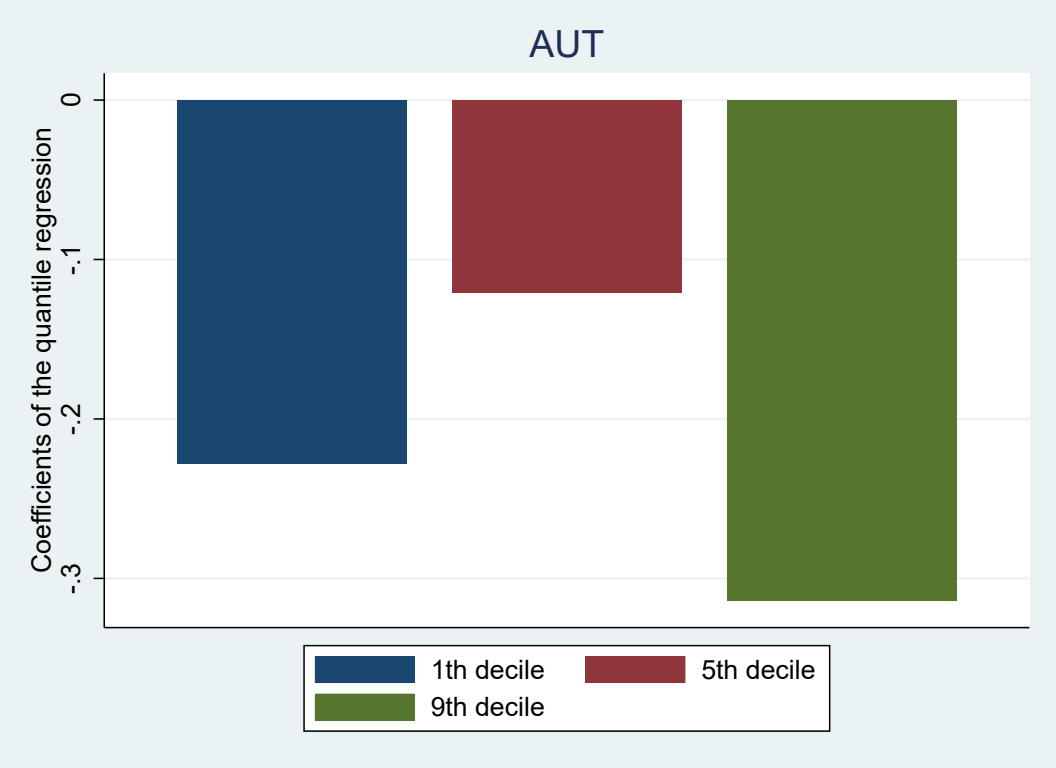
Koenker, Roger, and Kevin F. Hallock, 2001, Quantile Regression, *Journal of Economic Perspectives* 15, 143–156.

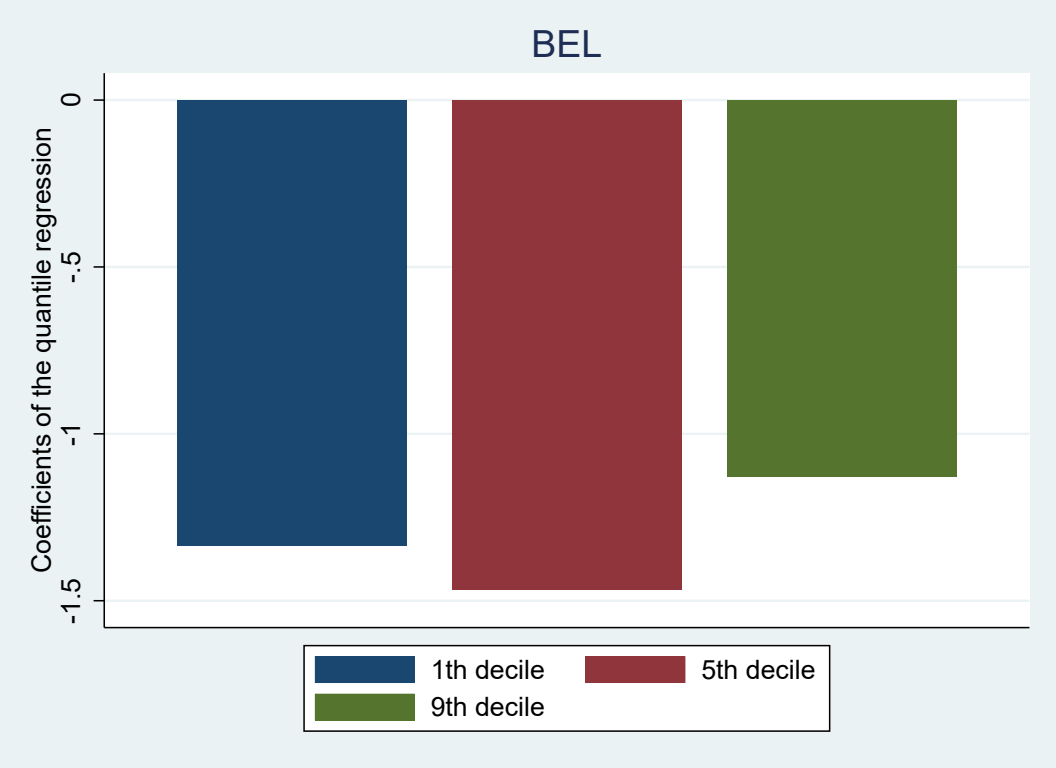
Rudebusch, Glenn D., 2016, Will the Economic Recovery Die of Old Age? Federal Reserve Bank of San Francisco Economic Letters.

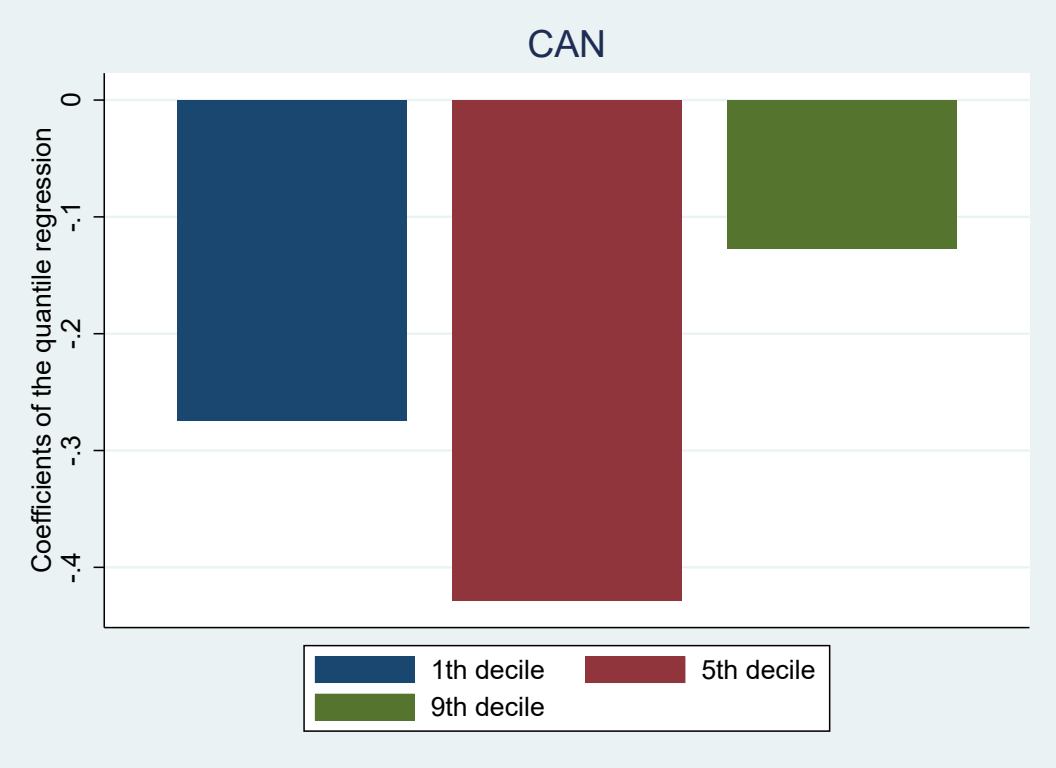
Schularick, Moritz, and Alan M. Taylor, 2012, Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008, *American Economic Review* 102, 1029–61.

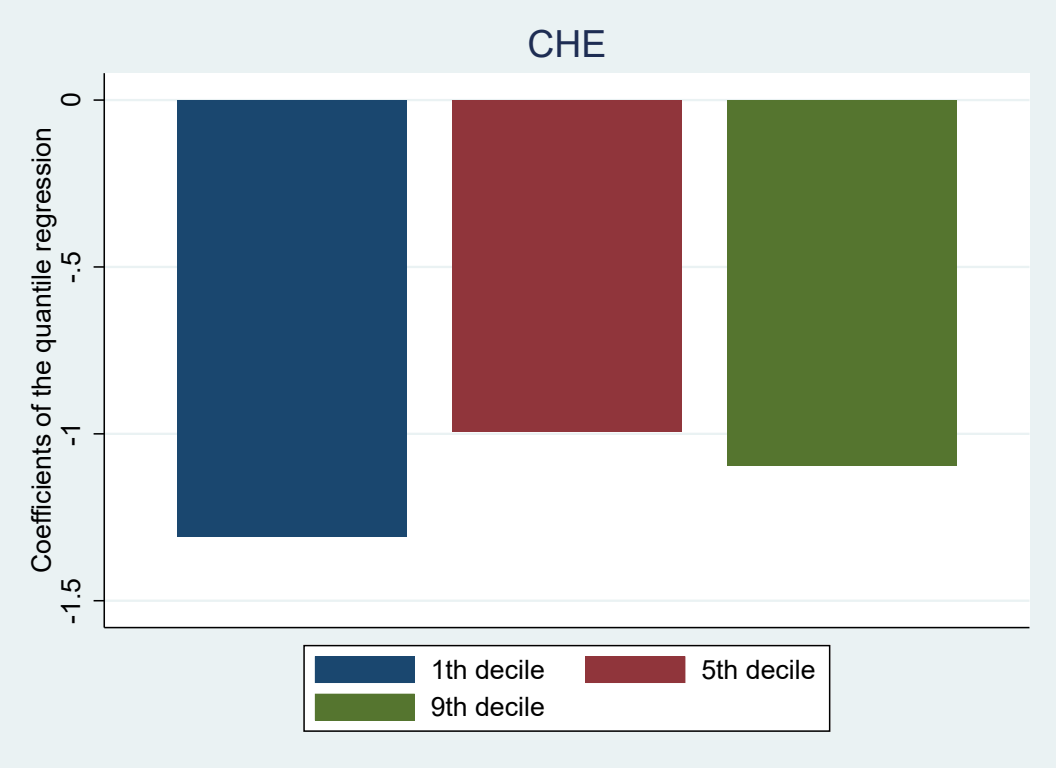

USA
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile

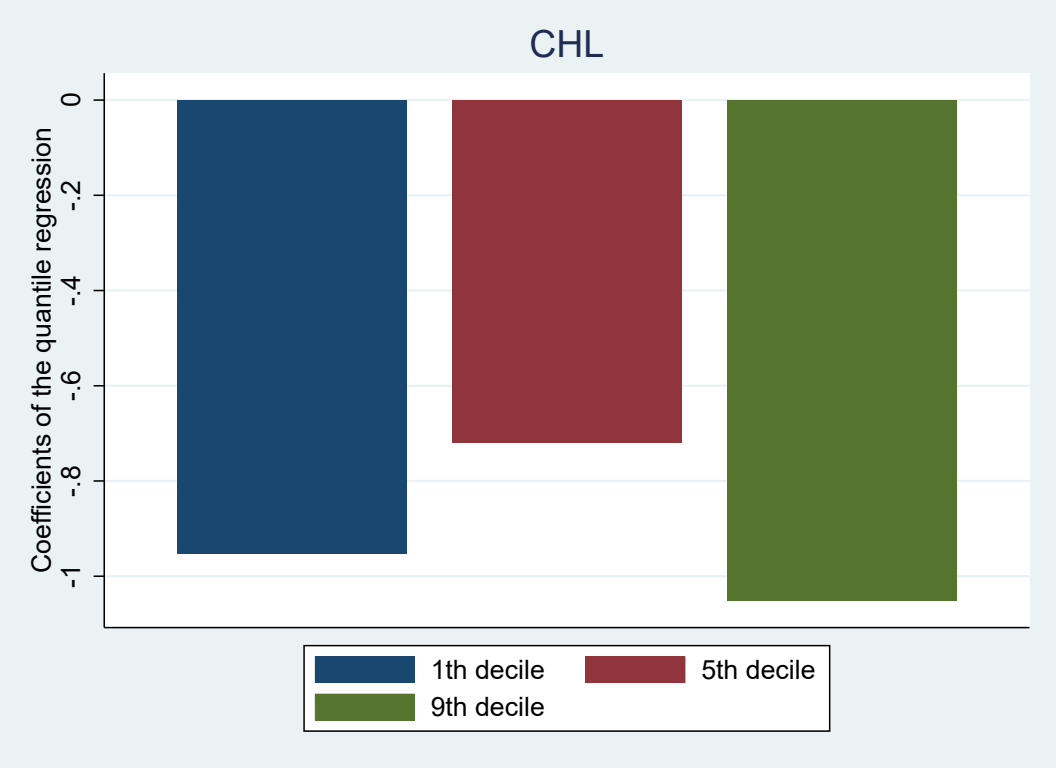

AUS
Coefficients of the quantile regression
0
-.1
-.2
-.3
-.4
1th decile
5th decile
9th decile

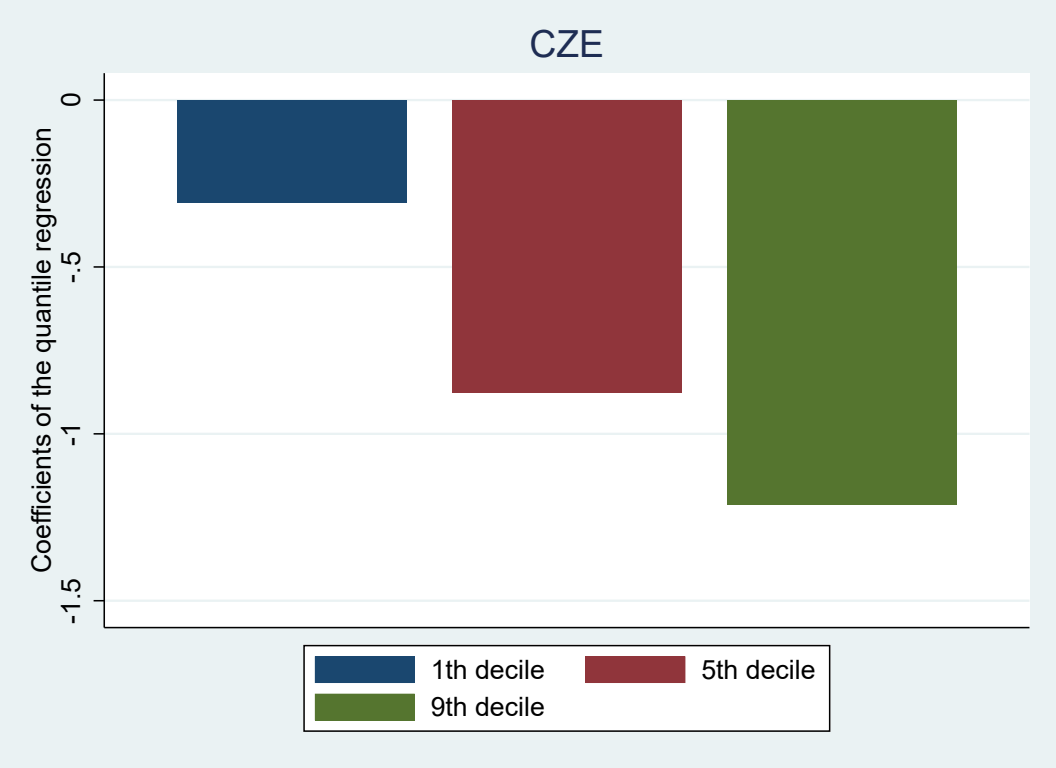

AUT
Coefficients of the quantile regression
0
-.1
-.2
-.3
1th decile
5th decile
9th decile

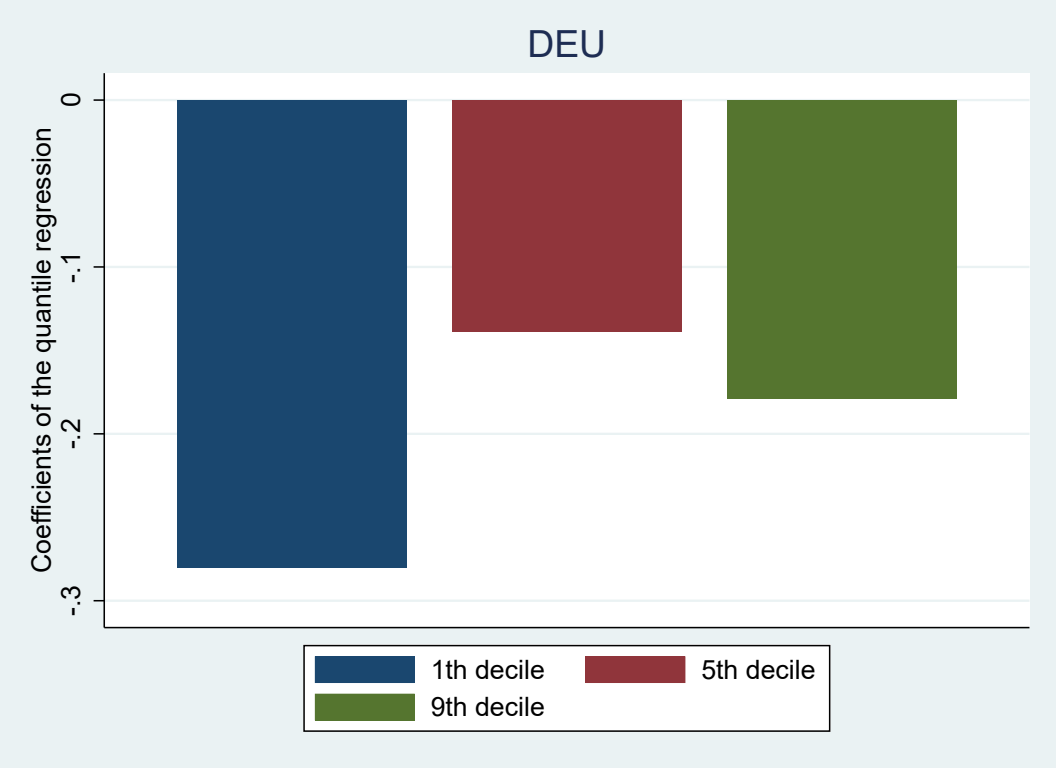

BEL
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

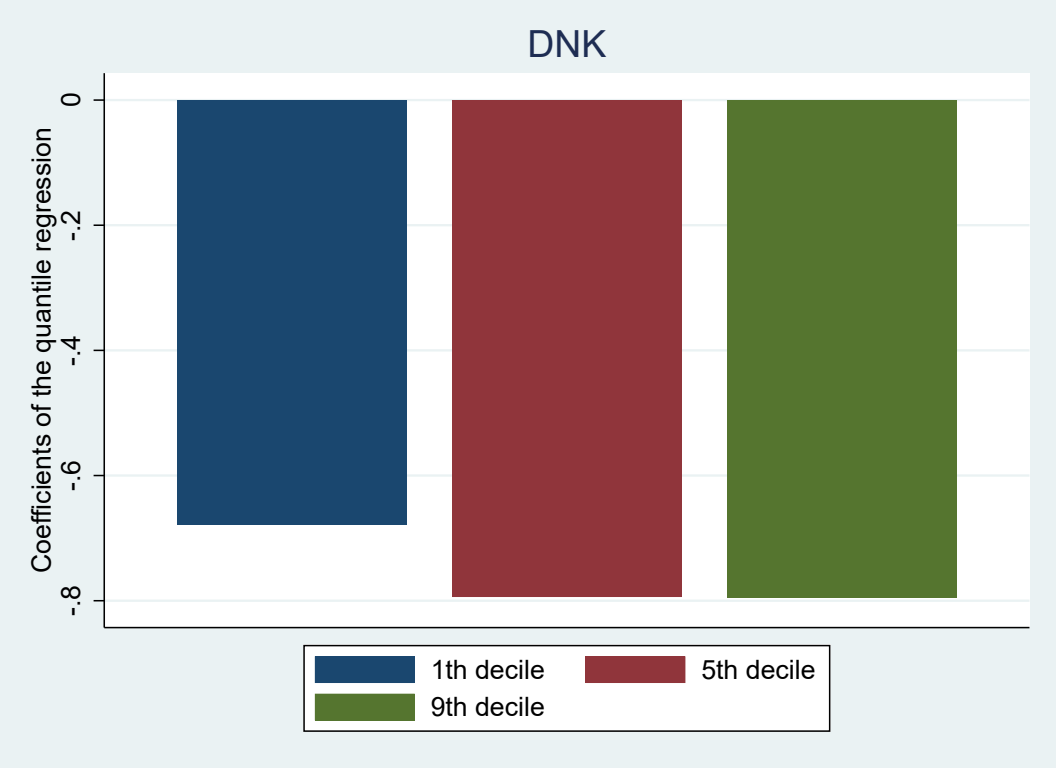

CAN
Coefficients of the quantile regression
0
-.1
-.2
-.3
-.4
1th decile
5th decile
9th decile


CHE
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile


CHL
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile

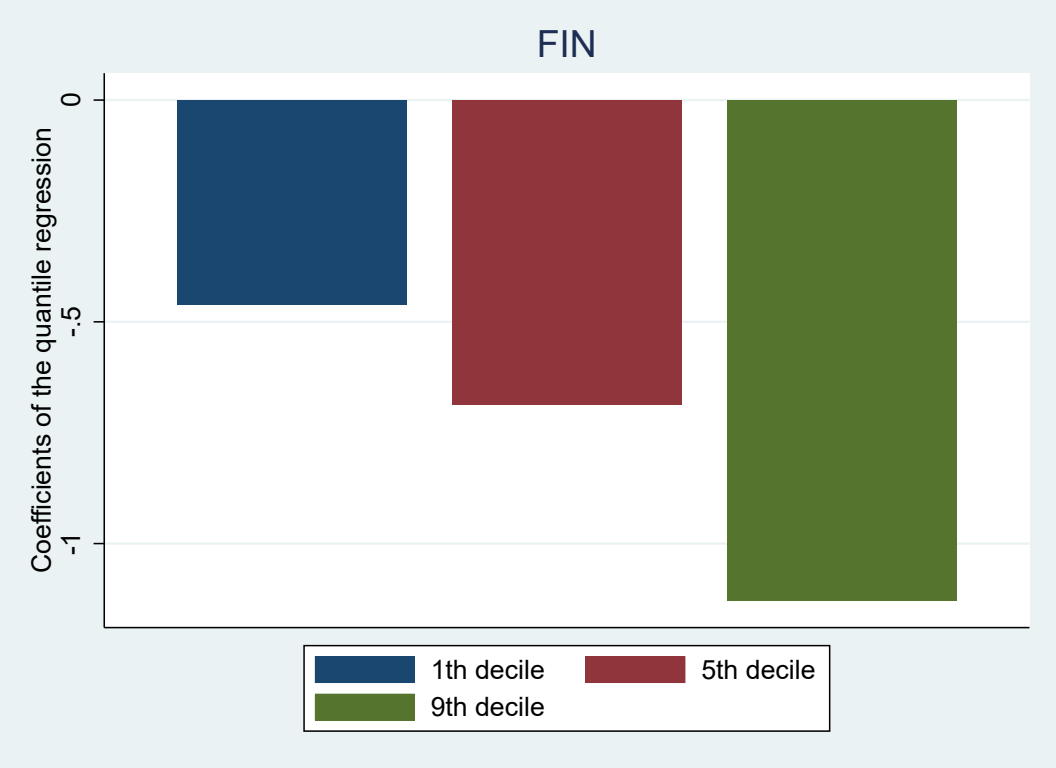

CZE
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile


DEU
Coefficients of the quantile regression
0
-.1
-.2
-.3
1th decile
5th decile
9th decile

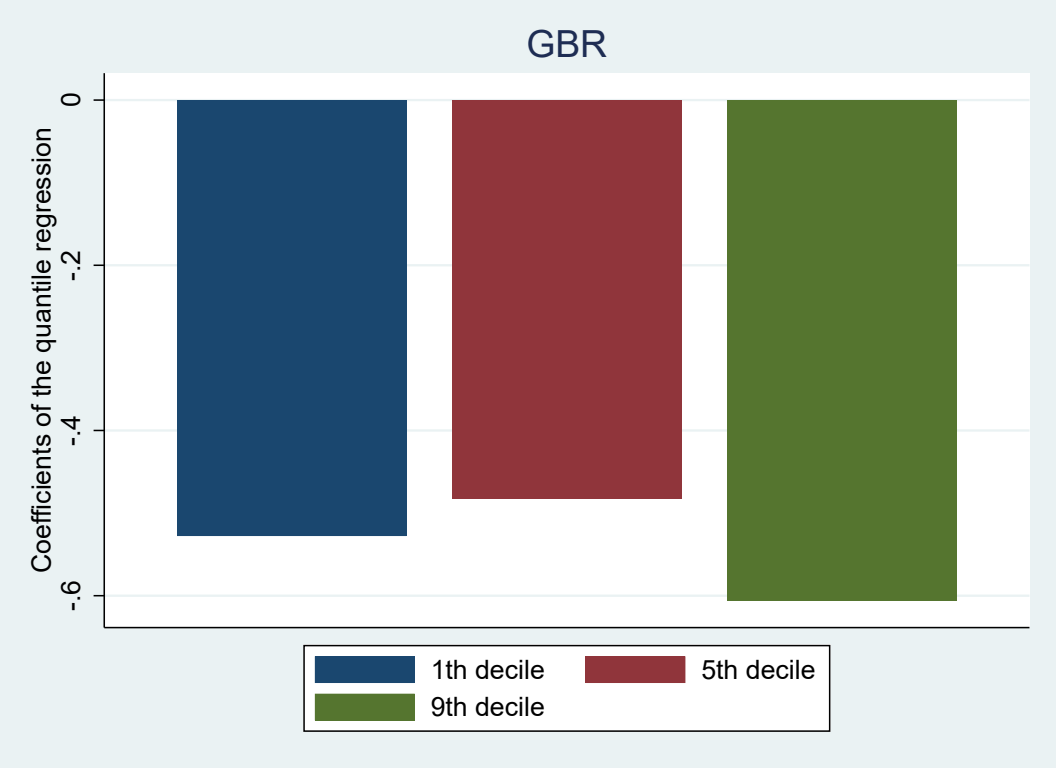

DNK
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
1th decile
5th decile
9th decile

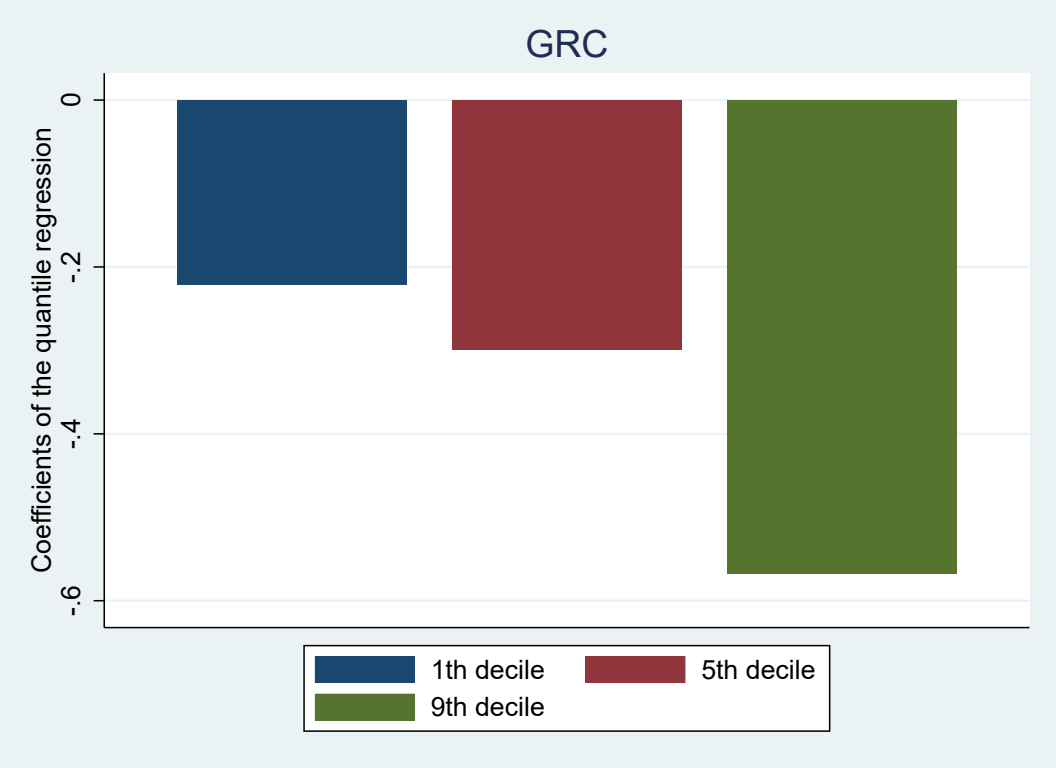

ESP
Coefficients of the quantile regression
0
-.2
-.4
-.6
1th decile
5th decile
9th decile

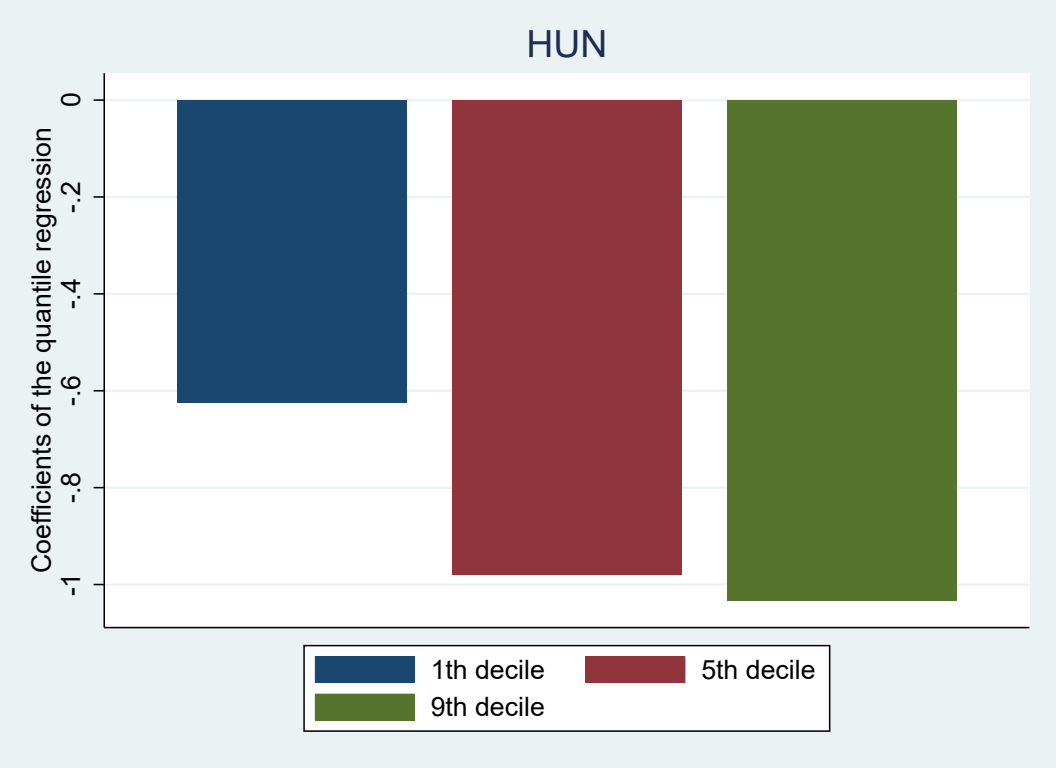

EST
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

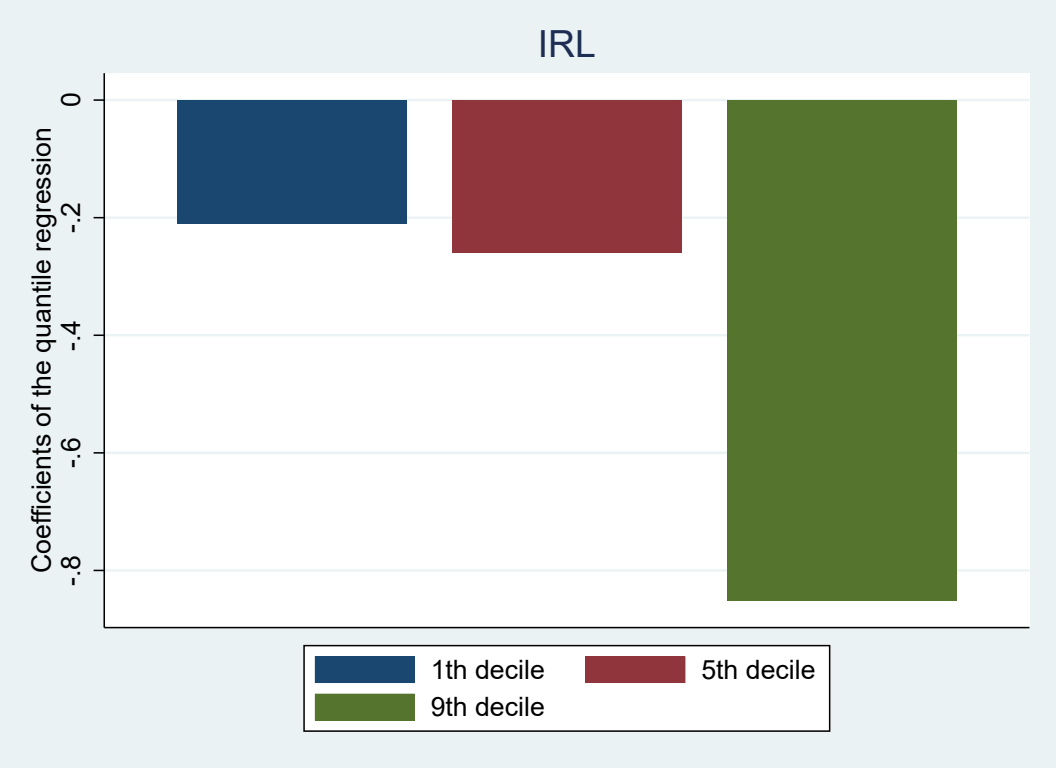

FIN
Coefficients of the quantile regression
0
-.5
-1
1th decile
5th decile
9th decile


FRA
Coefficients of the quantile regression
0
-.1
-.2
-.3
-.4
-.5
1th decile
5th decile
9th decile

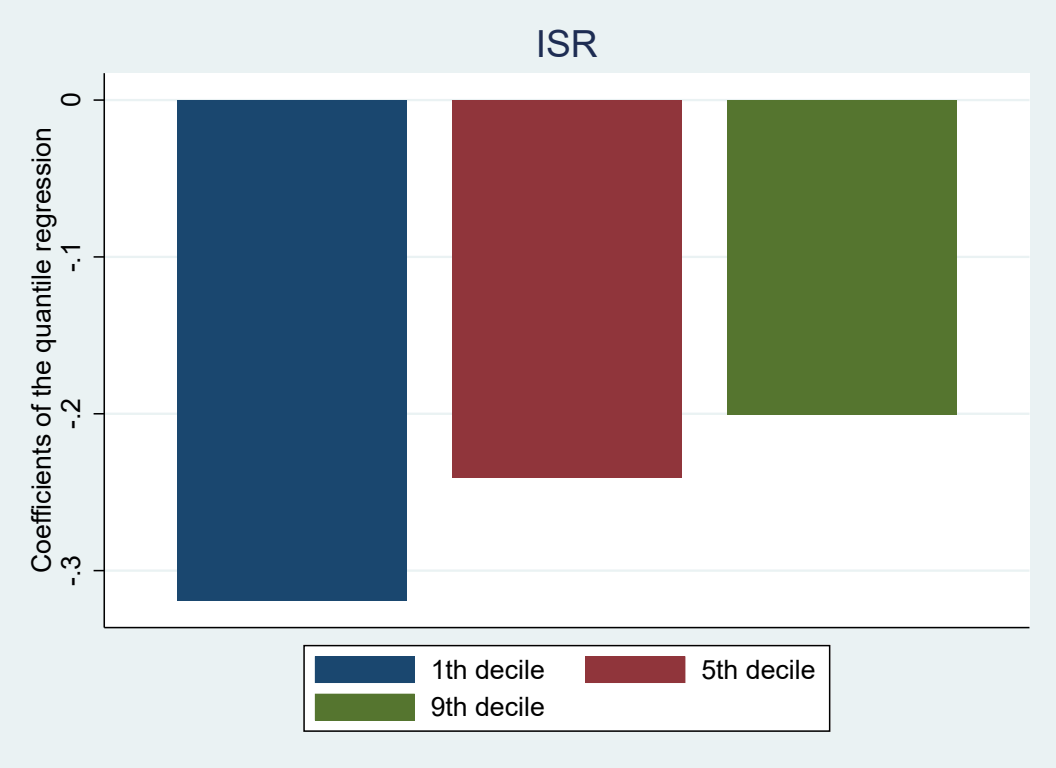

GBR
Coefficients of the quantile regression
0
-.2
-.4
-.6
1th decile
5th decile
9th decile

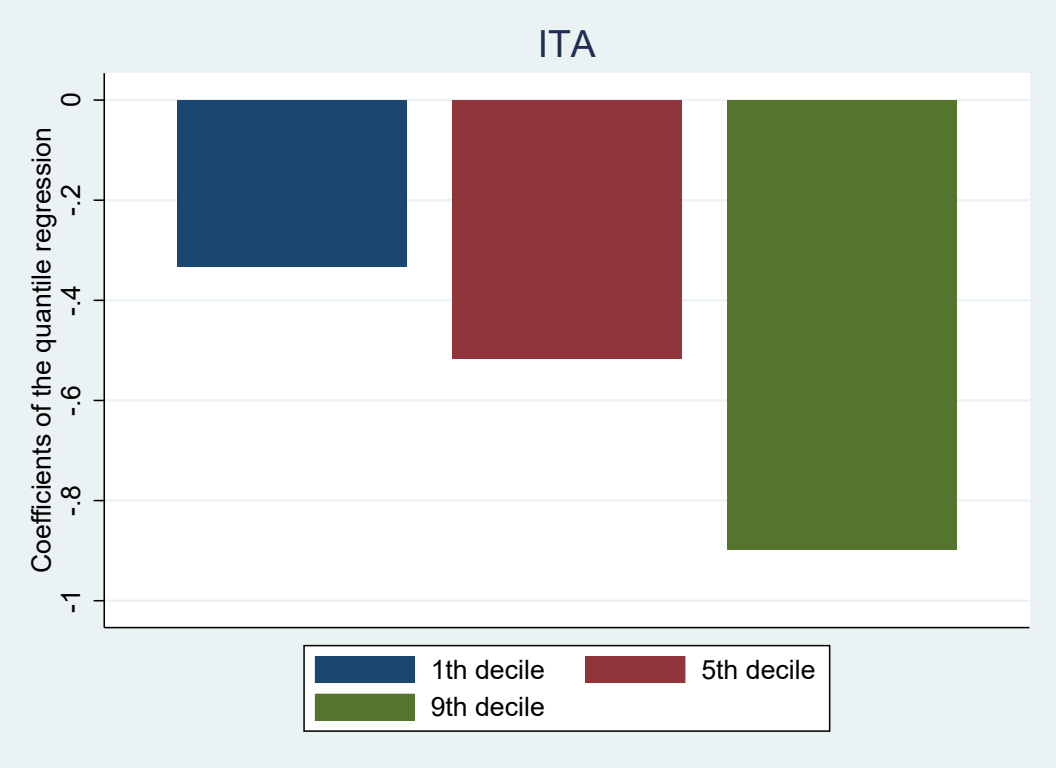

GRC
Coefficients of the quantile regression
0
-.2
-.4
-.6
1th decile
5th decile
9th decile

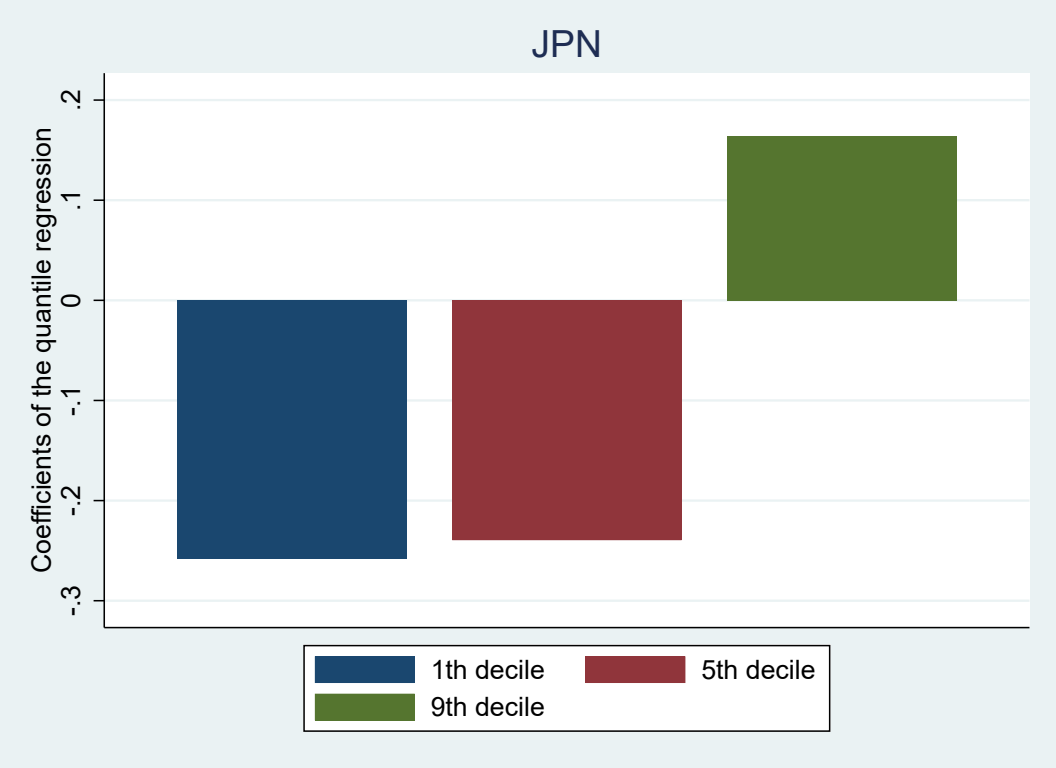

HUN
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile

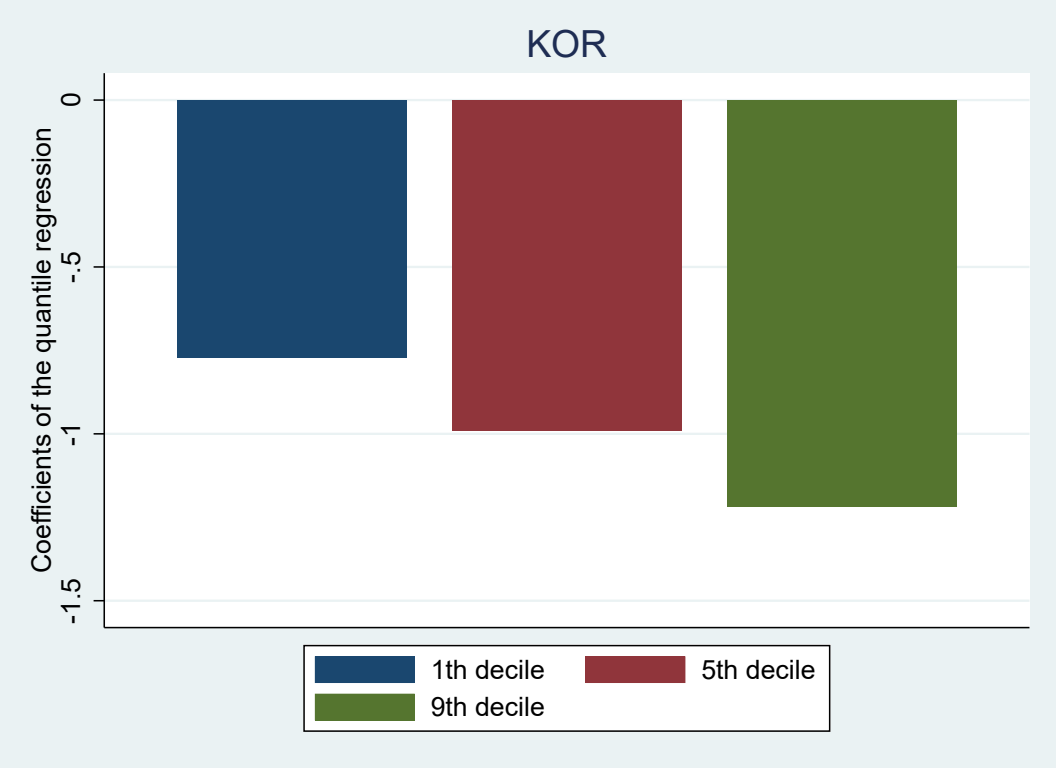

IRL
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
1th decile
5th decile
9th decile

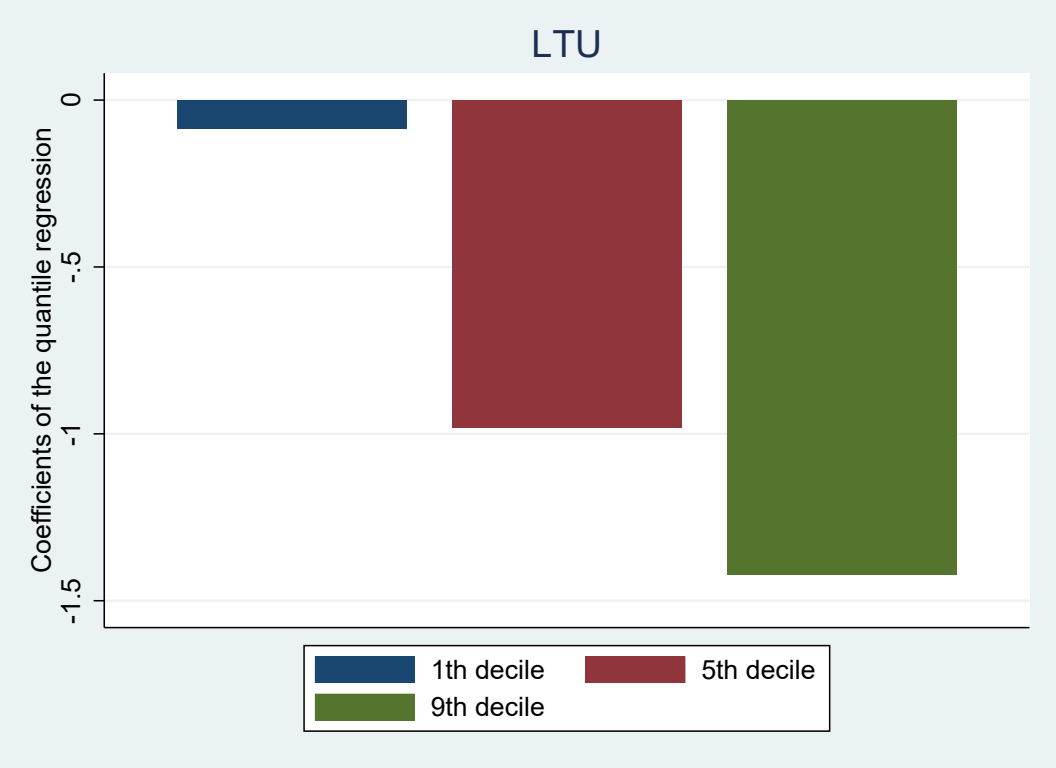

ISL
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

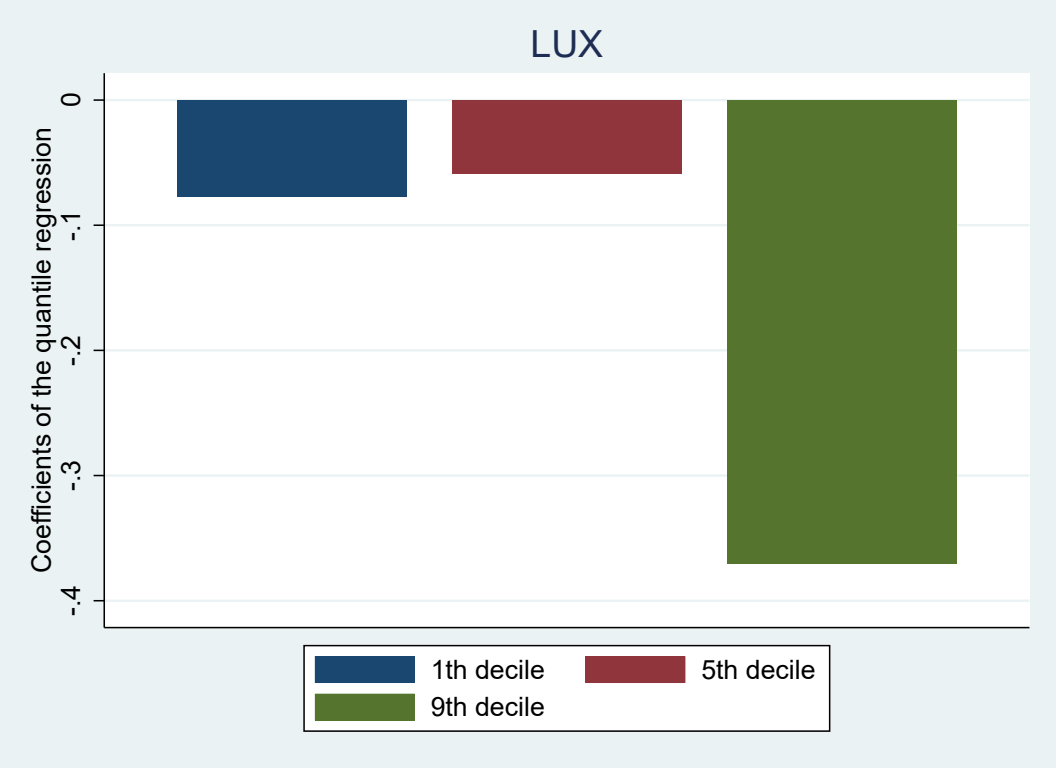

ISR
Coefficients of the quantile regression
0
-.1
-.2
-.3
1th decile
5th decile
9th decile

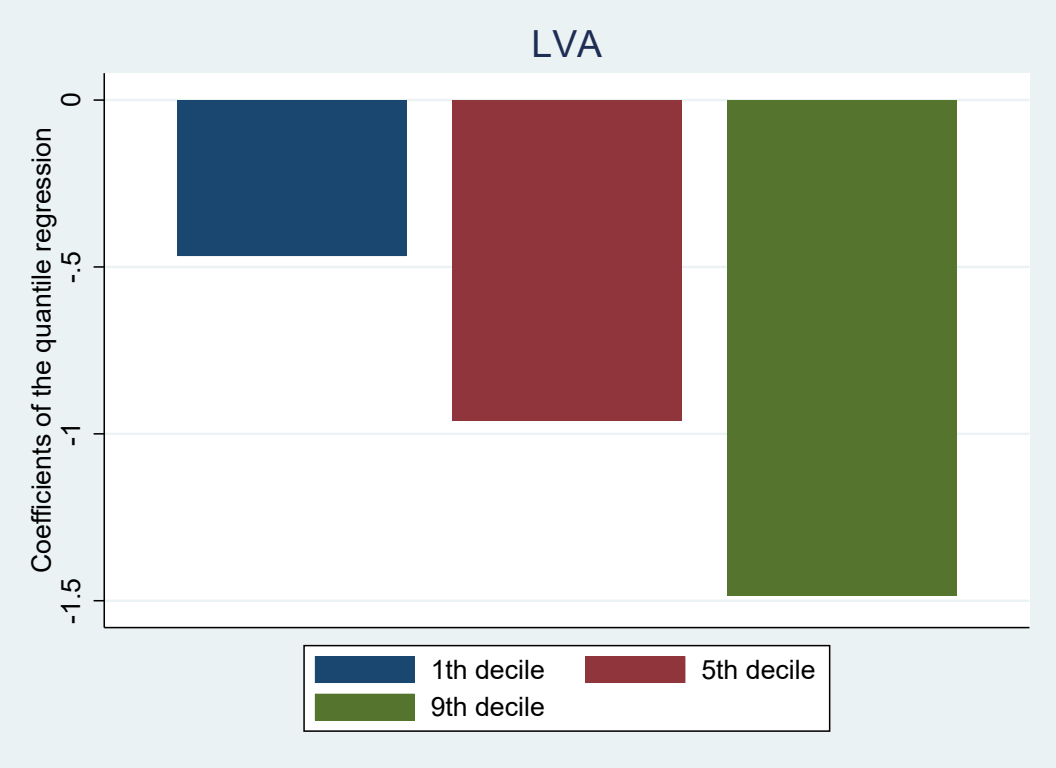

ITA
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile

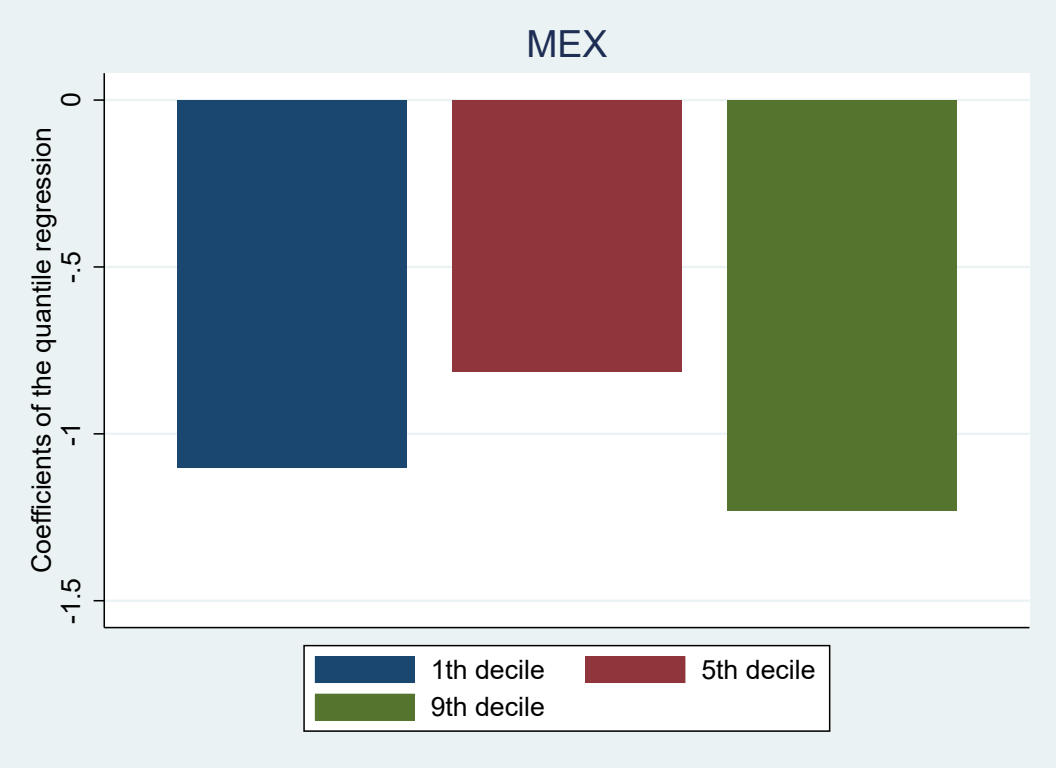

JPN
Coefficients of the quantile regression
-.3
-.2
-.1
0
.1
.2
1th decile
5th decile
9th decile

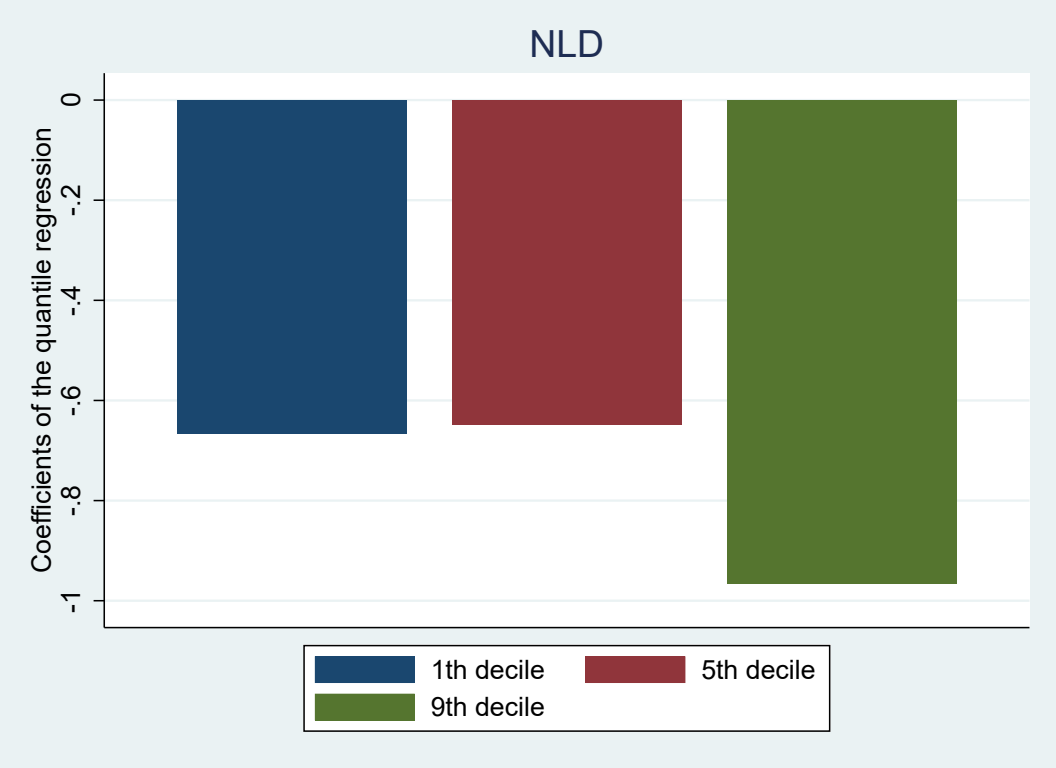

KOR
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

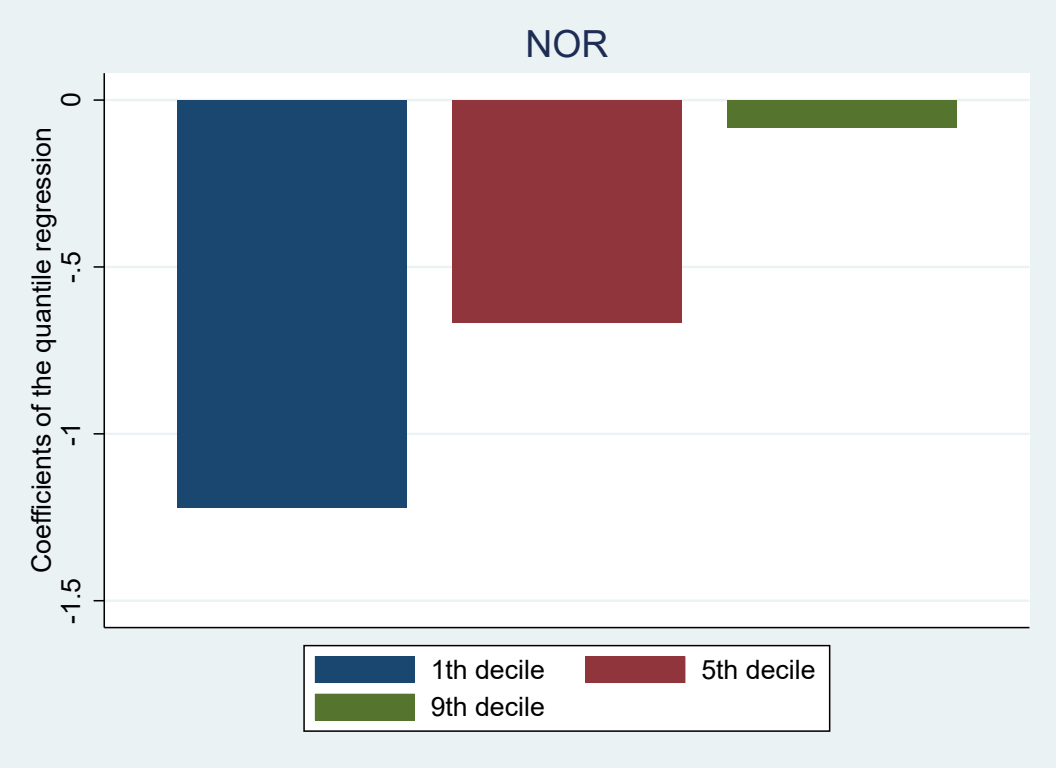

LTU
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

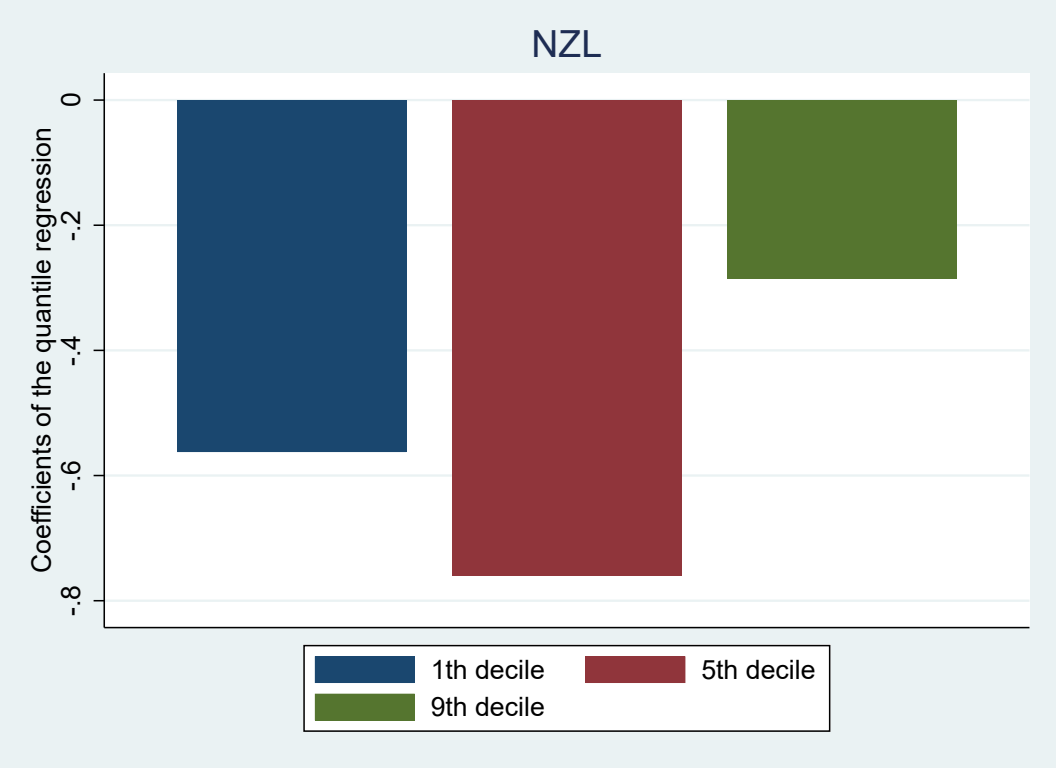

LUX
Coefficients of the quantile regression
0
-.1
-.2
-.3
-.4
1th decile
5th decile
9th decile

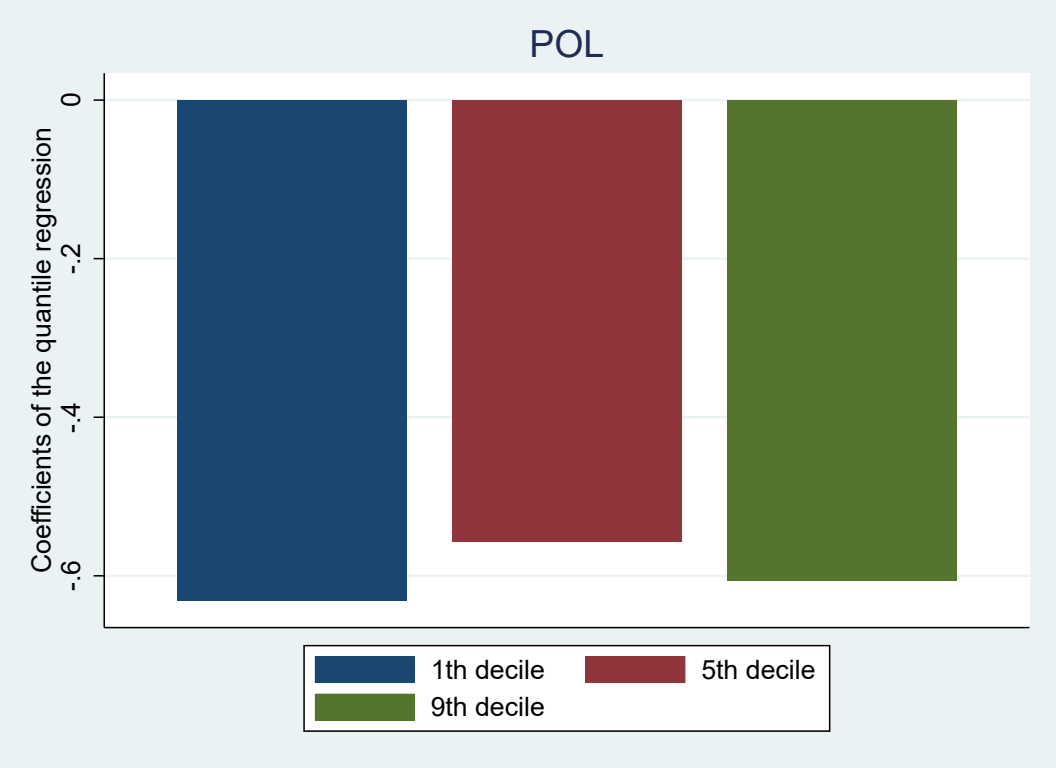

LVA
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

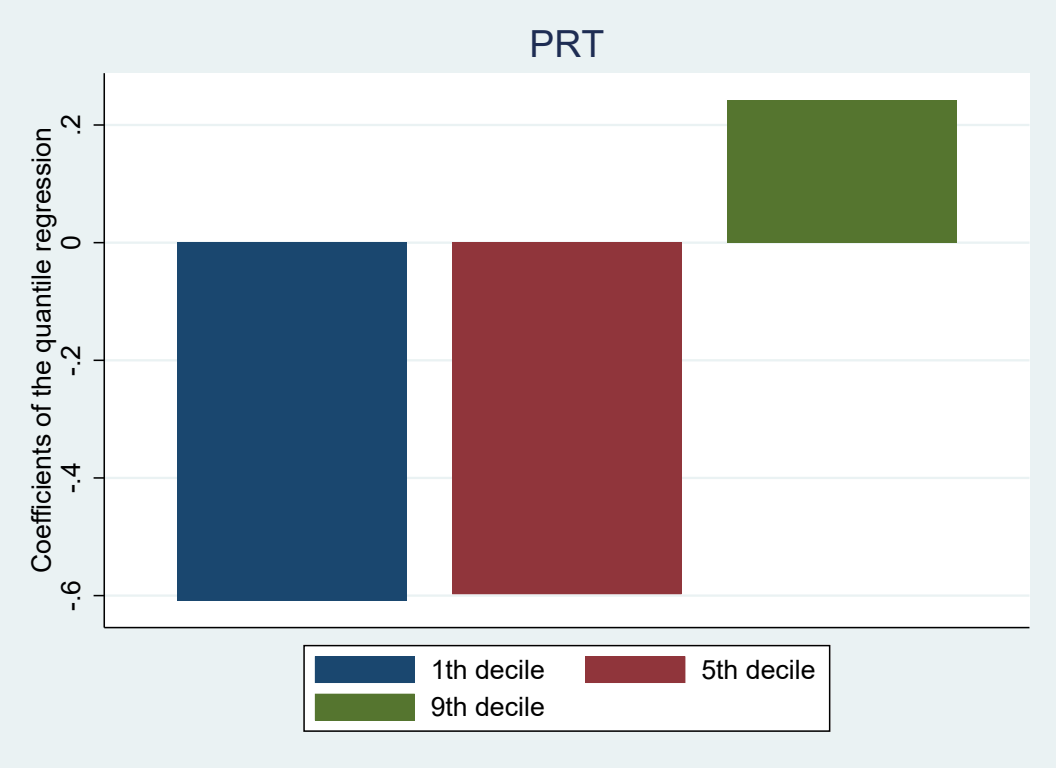

MEX
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

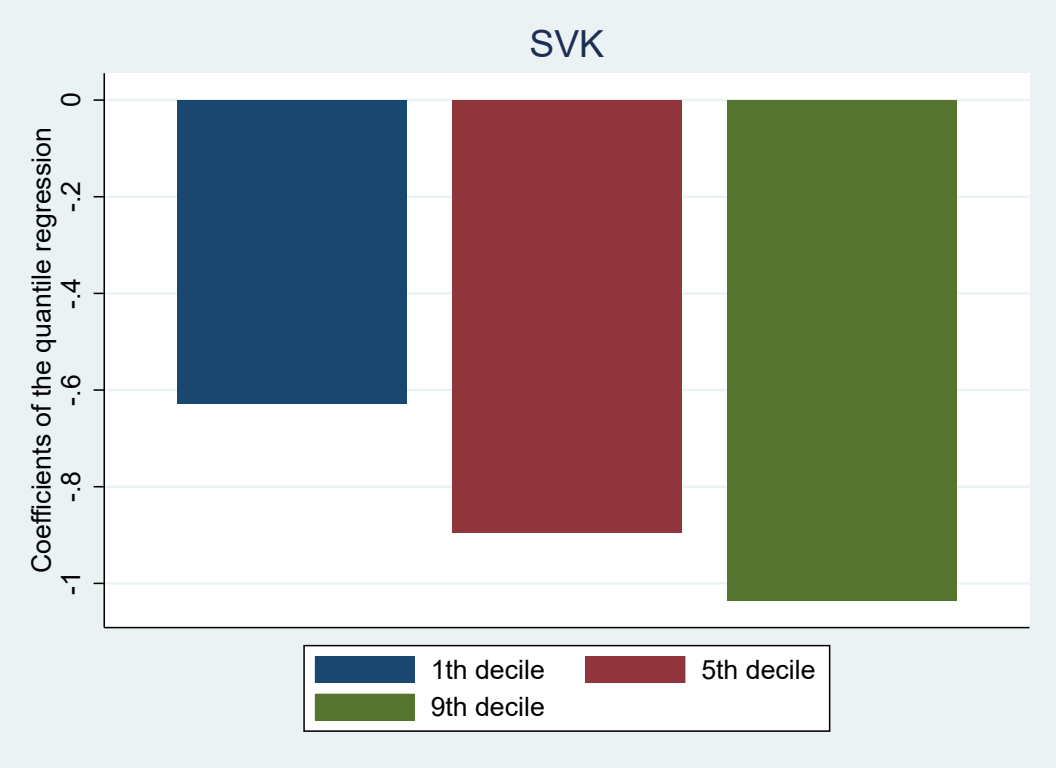

NLD
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile


NOR
Coefficients of the quantile regression
0
-.5
-1
-1.5
1th decile
5th decile
9th decile

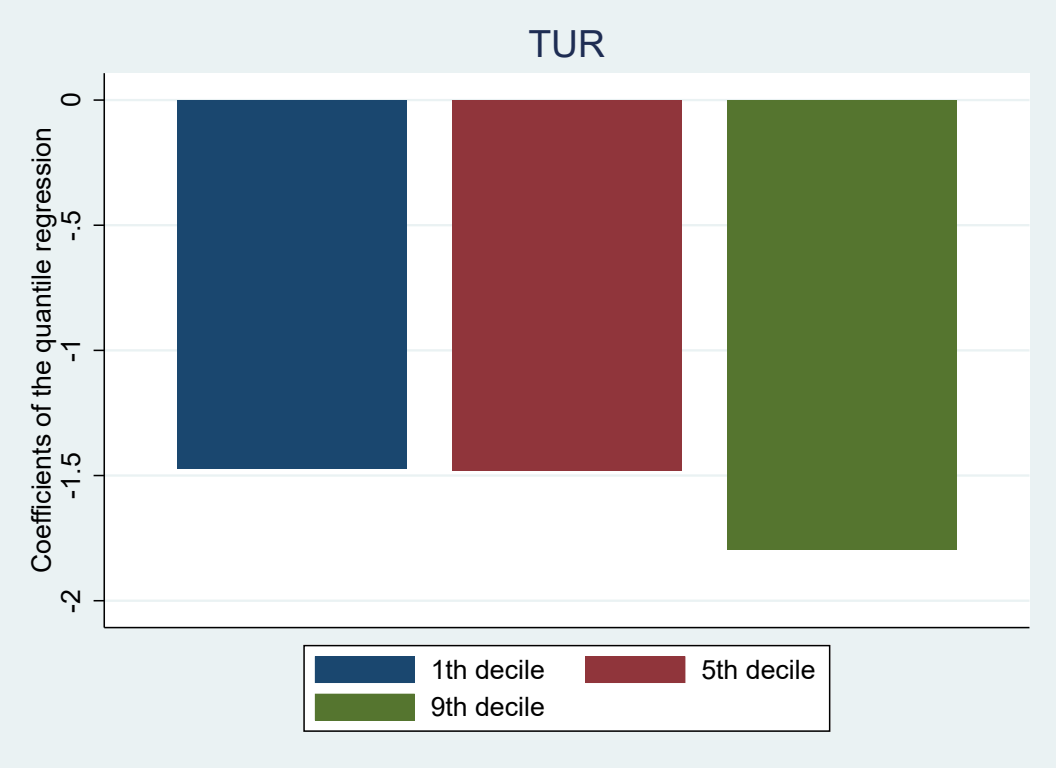

NZL
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
1th decile
5th decile
9th decile

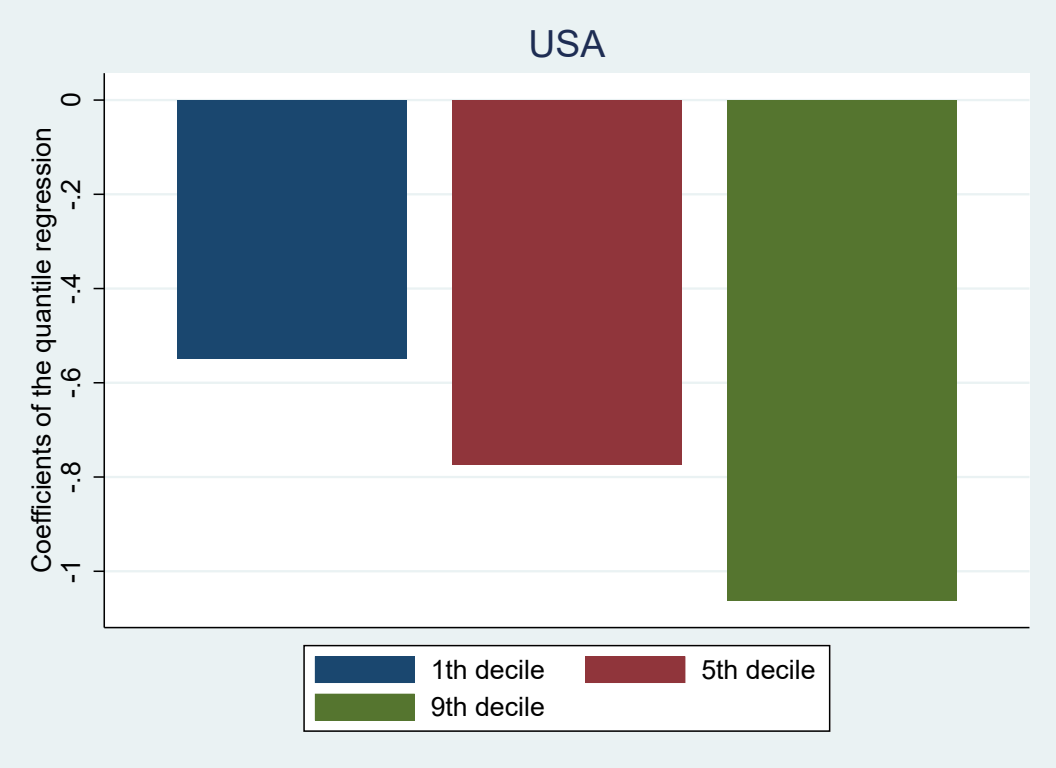

POL
Coefficients of the quantile regression
0
-.2
-.4
-.6
1th decile
5th decile
9th decile


PRT
Coefficients of the quantile regression
-.6
-.4
-.2
0
.2
1th decile
5th decile
9th decile


SVK
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile


SWE
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile


TUR
Coefficients of the quantile regression
0
-.5
-1
-1.5
-2
1th decile
5th decile
9th decile


USA
Coefficients of the quantile regression
0
-.2
-.4
-.6
-.8
-1
1th decile
5th decile
9th decile