Exploring Differences in Household Debt across Euro Area Countries and the US

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Motivation

Household borrowing important for household **well-being** and **financial stability**

Sizeable differences in household borrowing **across countries**

Link differences to **household characteristics / economic environment**

Background

Decomposition methods based on counterfactuals

Oaxaca (1973) and **Blinder** (1973): gender wage differentials; race differences in income/ wealth distributions; evolution of income and wealth inequality across time

Internationally comparable household survey data

Blau and Kahn (JPE, 1996): Decompose differences in male wage inequality between the US and nine OECD countries – key role of labour market conditions

Bover (ROIW, 2010): Decompose wealth differences between the US and Spain – key role of household structure (esp. at the lower end)

Christelis, Georgarakos and Haliassos (REStat, 2013): Decompose differences in asset holdings and mortgages among older (50+) households between the US and eleven European countries – key role for economic conditions

Data

Household Finance and Consumption Survey (HFCS)

Countries: Germany, Netherlands, Belgium, Luxembourg, France, Austria, Italy, Spain, Portugal, Greece, Cyprus – 48,289 households

US Survey of Consumer Finances (SCF) – 6,482 households

Use all five implicates

PPP adjusted values: 2005 US Dollars

AMECO database: Housing Price Indicator (harmonized)

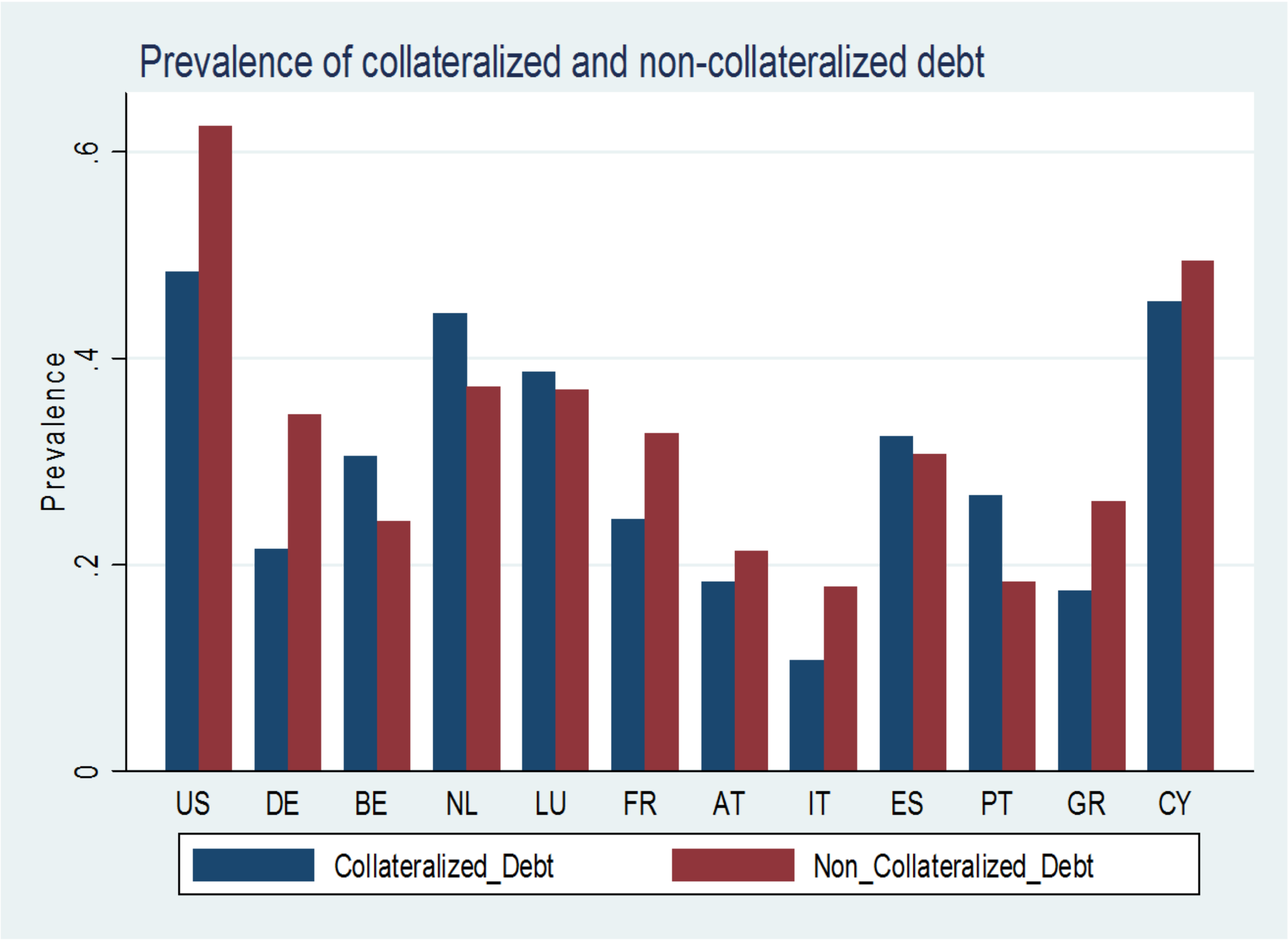
Debt types

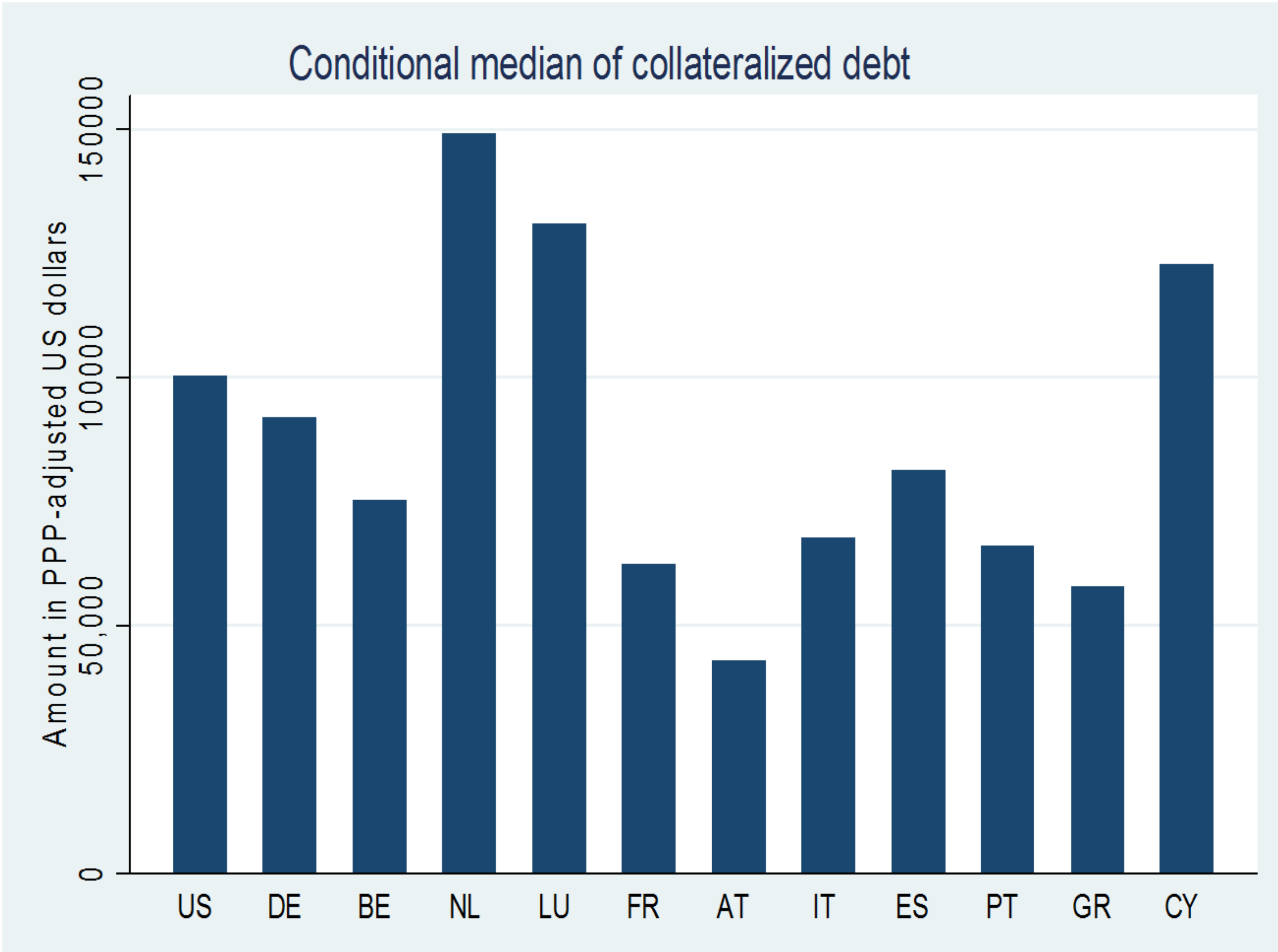
Collateralized debts (mortgages, home equity loans, debts for other real estate)

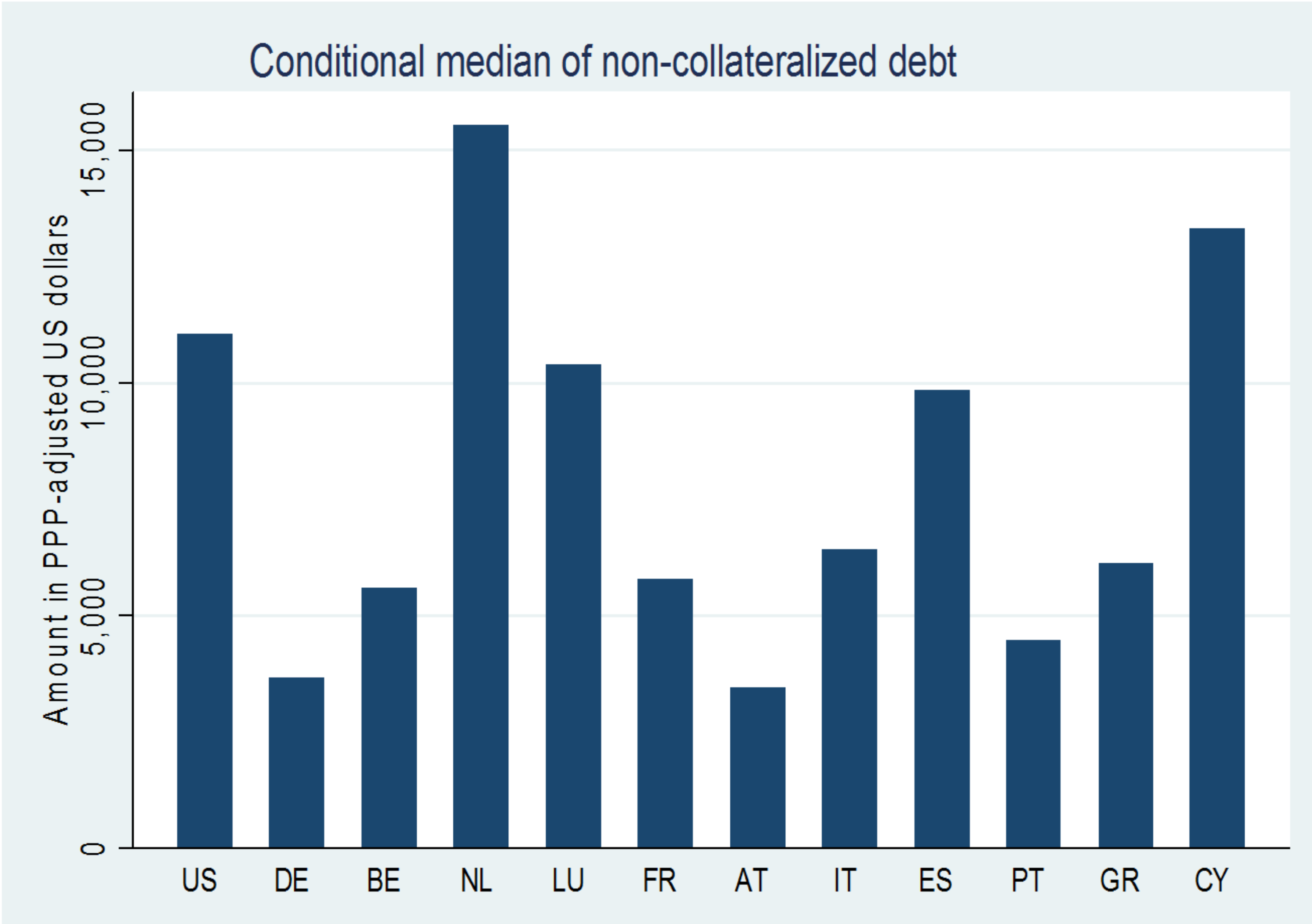
Non-collateralized debts (credit card balances, installment loans, overdrafts, other loans)

Differences in **prevalence**

Differences in **conditional amounts outstanding**


Prevalence of collateralized and non-collateralized debt
Prevalence
0
.2
.4
.6
US
DE
BE
NL
LU
FR
AT
IT
ES
PT
GR
CY
Collateralized_Debt
Non_Collateralized_Debt


Conditional median of collateralized debt
Amount in PPP-adjusted US dollars
0
50,000
100000
150000
US
DE
BE
NL
LU
FR
AT
IT
ES
PT
GR
CY


Conditional median of non-collateralized debt
Amount in PPP-adjusted US dollars
0
5,000
10,000
15,000
US
DE
BE
NL
LU
FR
AT
IT
ES
PT
GR
CY

Decomposition

Using the US as a base:

$$Y^{US} - Y^{EA} = \{X^{US}\beta^{US} - X^{EA}\beta^{US}\} + \{X^{EA}\beta^{US} - X^{EA}\beta^{EA}\}$$

Covariate effects: Differences in the configuration of household characteristics (X's) between two countries

Coefficient effects: Differences in β's (i.e. the way the X's are 'valued' in the market) – differences 'economic environments'

Two stage decomposition:

1. **Aggregate decomposition**: 'covariate' vs. 'coefficient' effects
2. **Detailed decomposition**: contribution of each individual covariate (or corresponding β)

Decomposition Methods

Oaxaca (1973) and Blinder (1973) for the mean – wage gap decomposition

DiNardo, Fortin, and Lemieux (1996): Reweighting method

Machado and Mata (2005): Quantile regression-based method

Going beyond the mean is tricky (DFL, MM: *path dependent*)

Firpo, Fortin and Lemieux (2009): replace the dependent variable by the corresponding recentered influence function (**RIF**) of the distributional statistic of interest and perform a linear estimation

The conditional independence assumption (E(u|X)=0) usually invoked in Oaxaca-Blinder decompositions can be replaced by the weaker *ignorability* assumption to compute the aggregate decomposition (i.e. unobserved factors can correlate with X's as long as the correlation is the same in *US* and *EA*)

Covariates

Age (age<40; 40-49; 50-59; *60 plus*)

Marital status (couple; single; widowed; *divorced*)

Household size

Employment status (employed; self-employed; retired; other inactive; *unemployed*)

Education (college; high school; *less than high school*)

Income (*Q1*-Q4, re-assigned using the base country thresholds)

Financial wealth (*Q1*-Q4, re-assigned using the base country thresholds)

Real wealth (*Q1*-Q4, re-assigned using the base country thresholds)

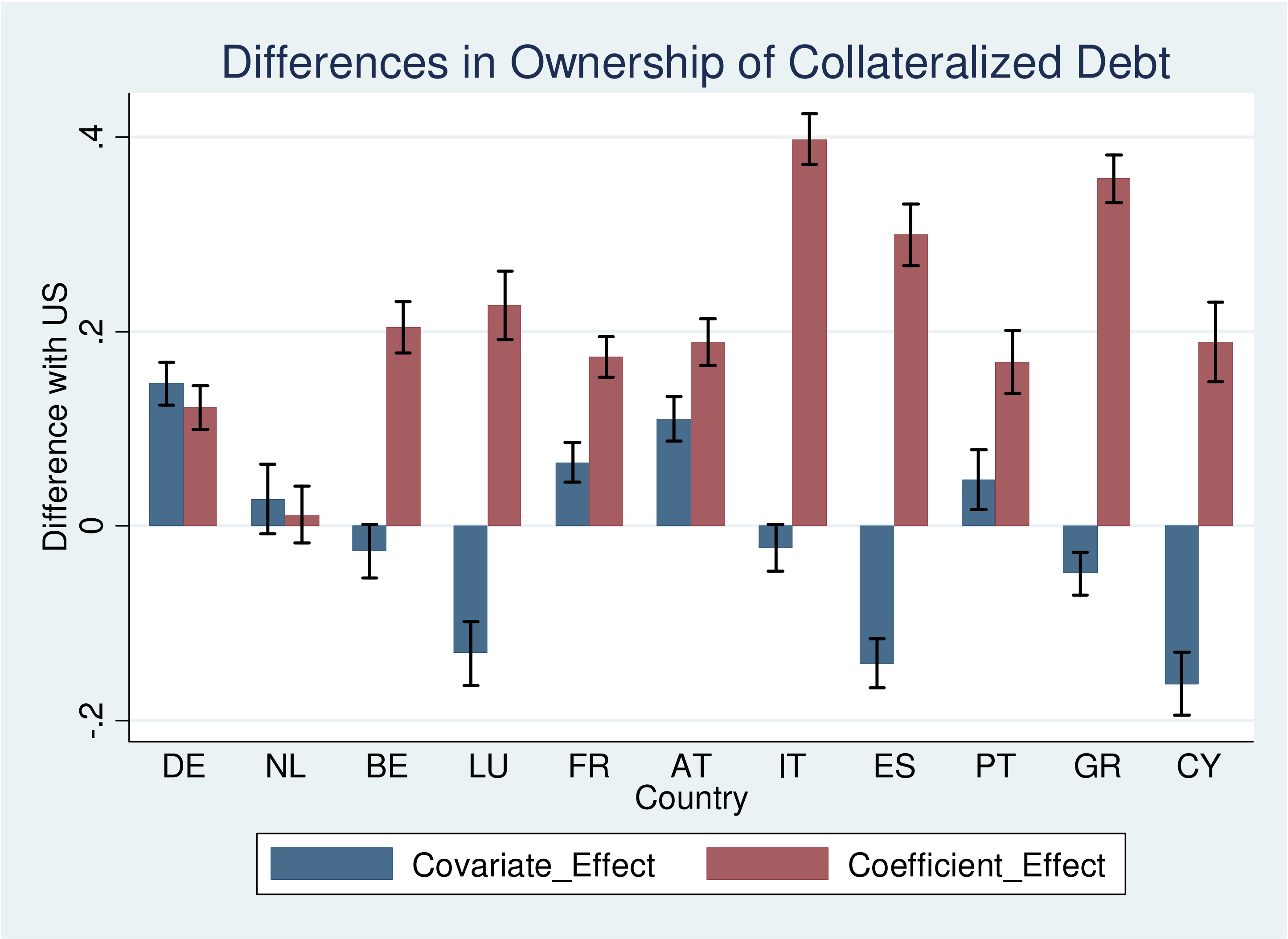
Inheritance received

Non-Collateralized Debt - additional covariates:

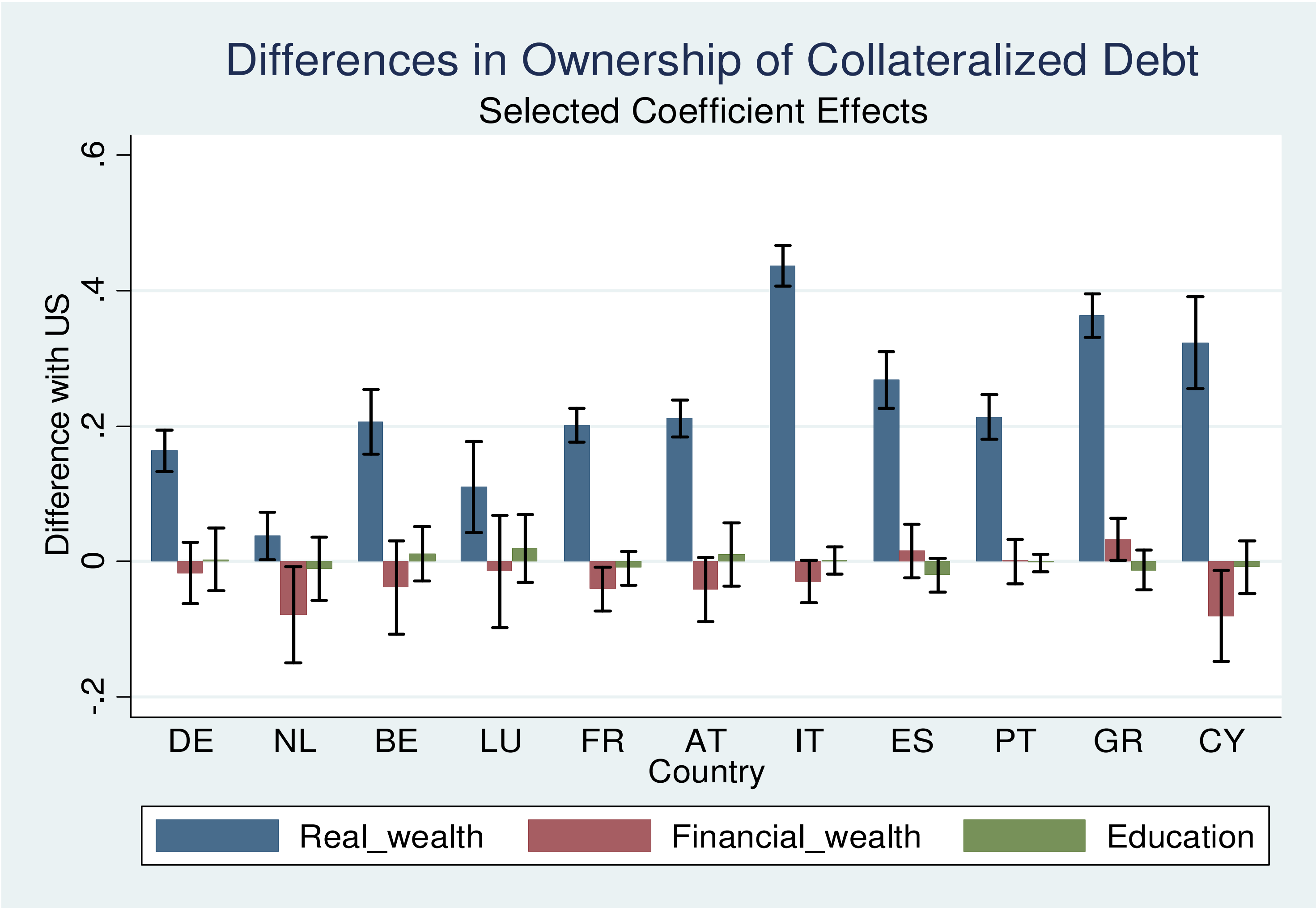
Last year's income **unexpectedly low**

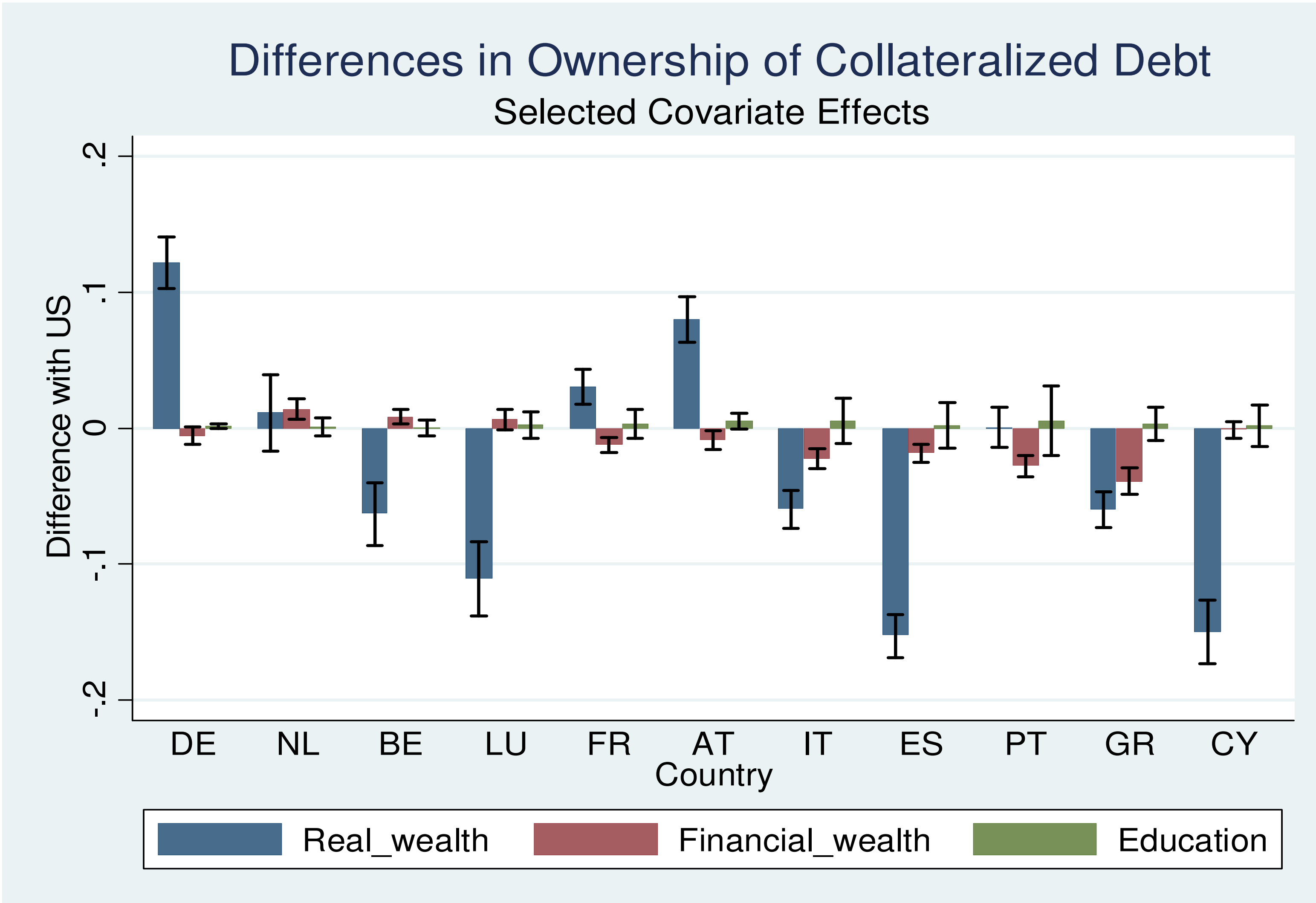
Expect next year's **income** to go up

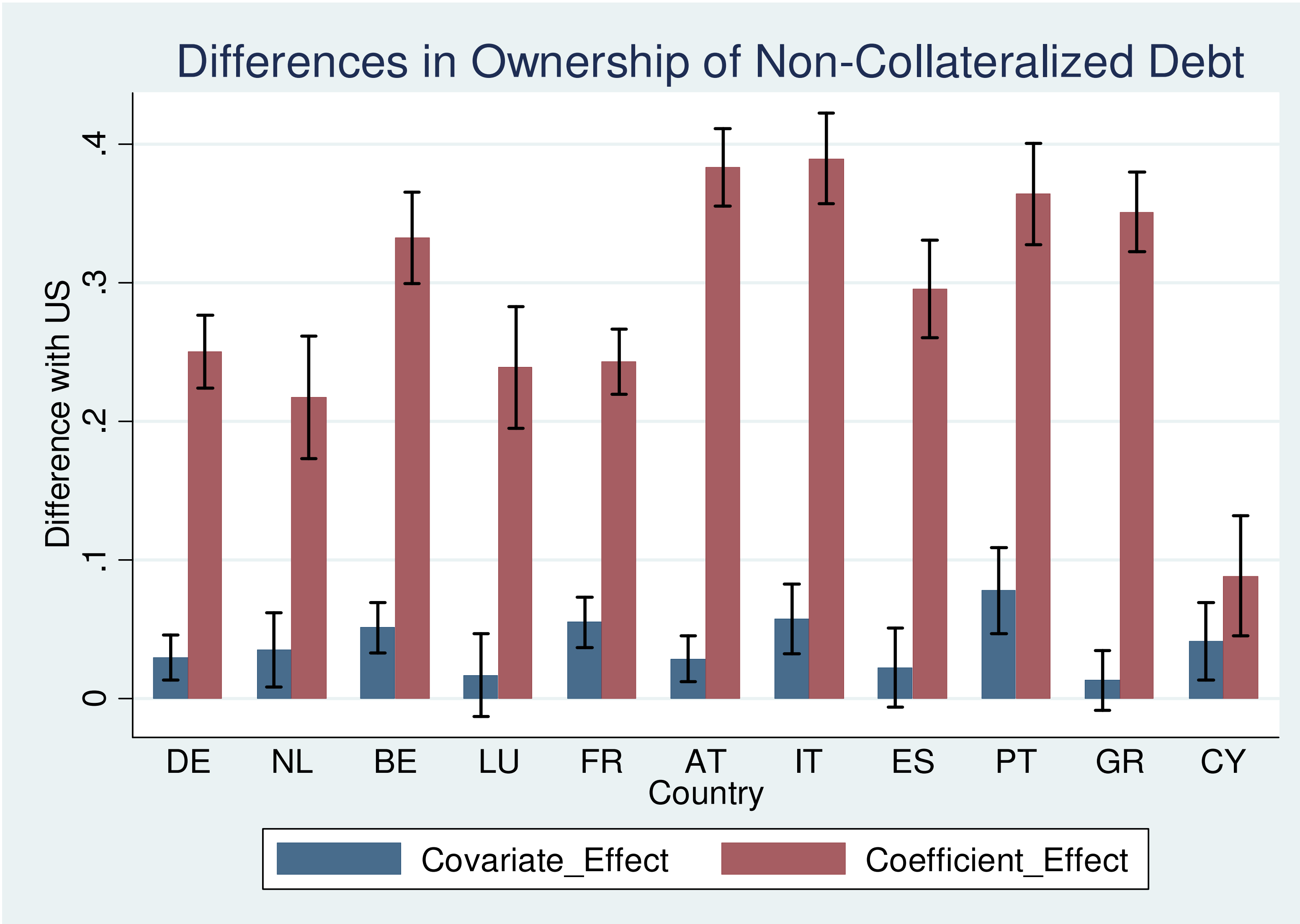
Willingness to assume **more than average financial risk**

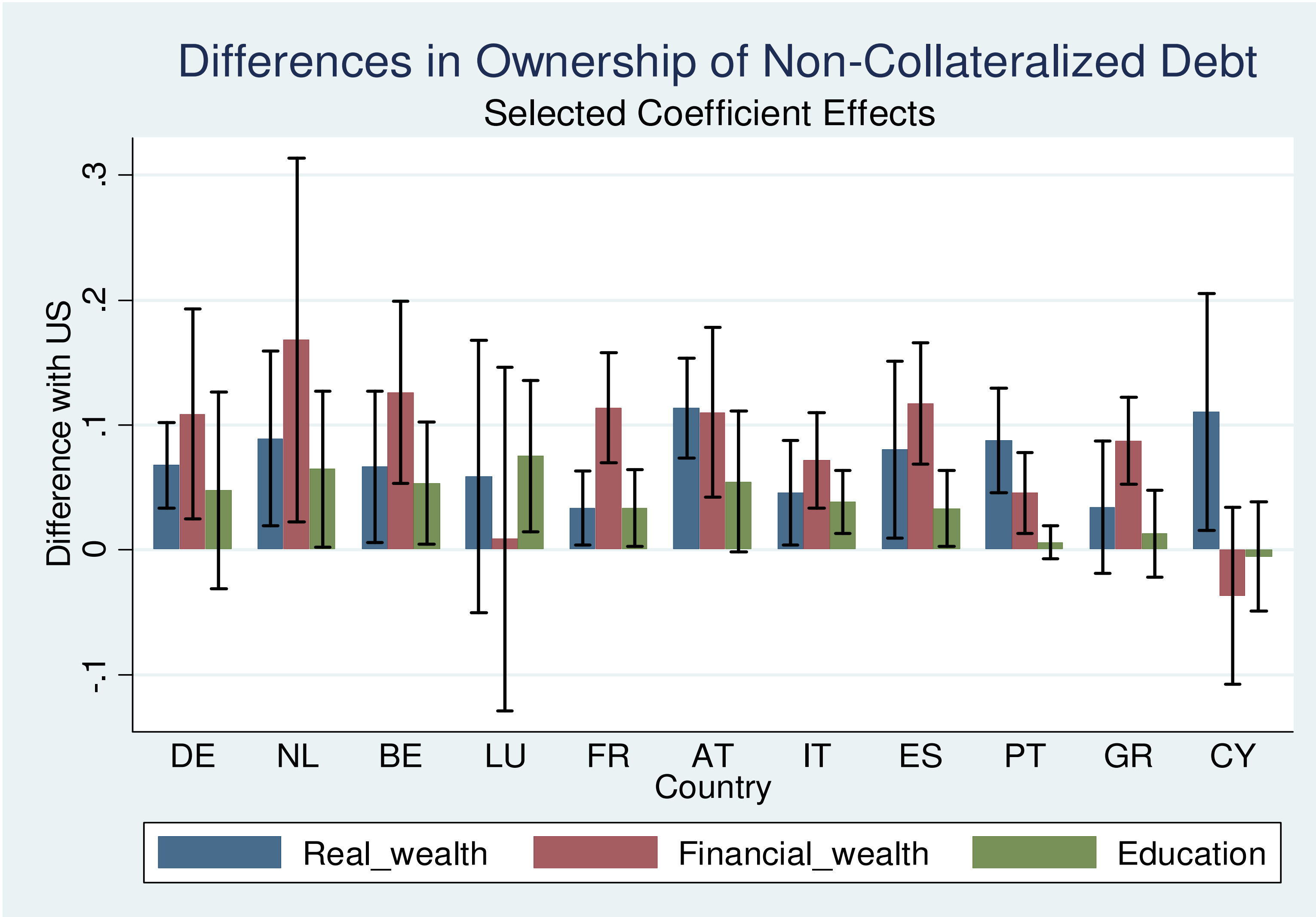


Differences in Ownership of Collateralized Debt
Difference with US
.4
.2
0
-.2
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect

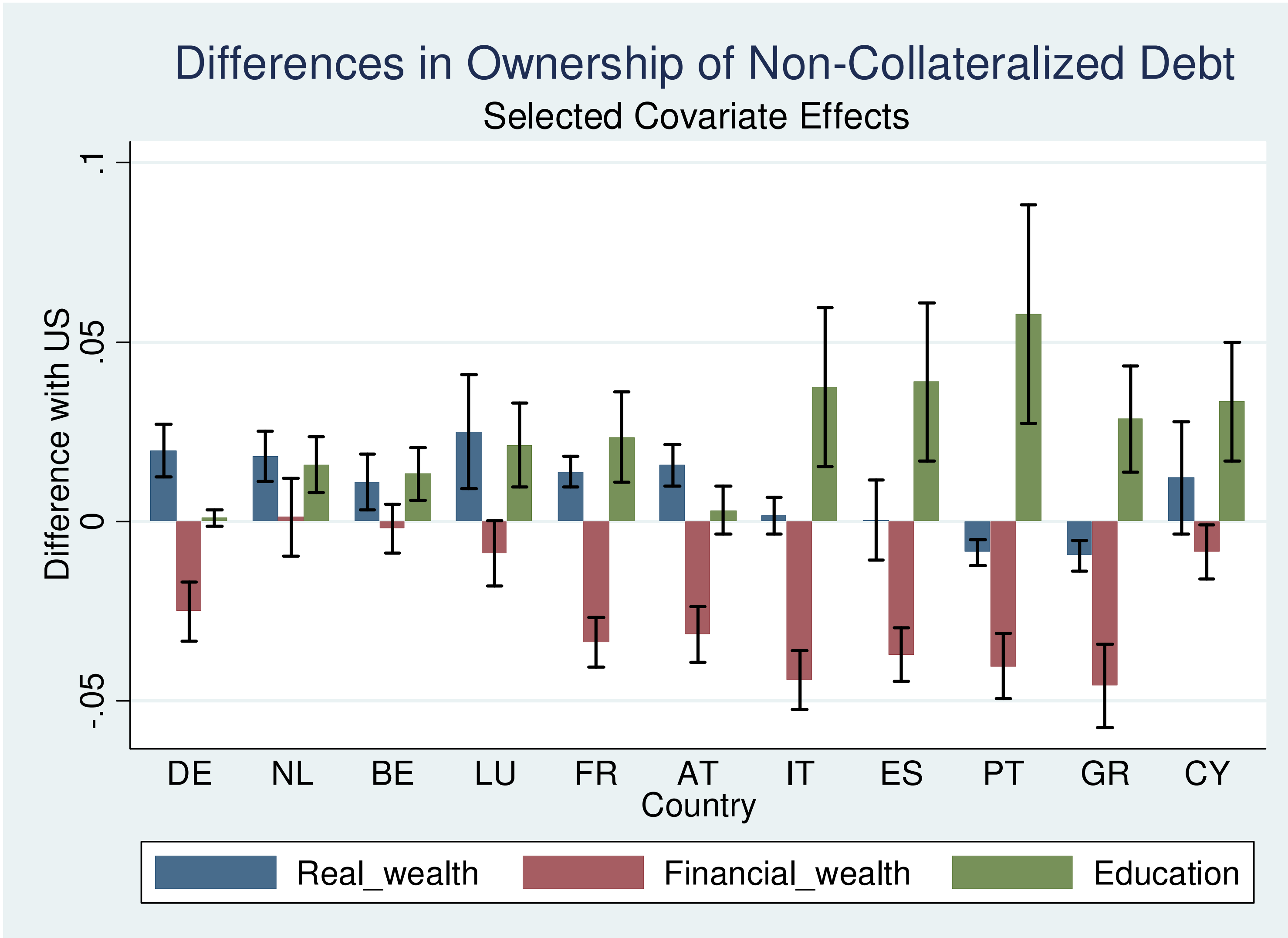

Differences in Ownership of Collateralized Debt
Selected Coefficient Effects
Difference with US
-.2
0
.2
.4
.6
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education


Differences in Ownership of Collateralized Debt
Selected Covariate Effects
Difference with US
.2
.1
0
-.1
-.2
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education


Differences in Ownership of Non-Collateralized Debt
Difference with US
0
.1
.2
.3
.4
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect



Differences in Ownership of Non-Collateralized Debt
Selected Coefficient Effects
Difference with US
-.1
0
.1
.2
.3
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education



Differences in Ownership of Non-Collateralized Debt
Selected Covariate Effects
Difference with US
.1
.05
0
-.05
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education

Collateralized Debt – conditional amounts

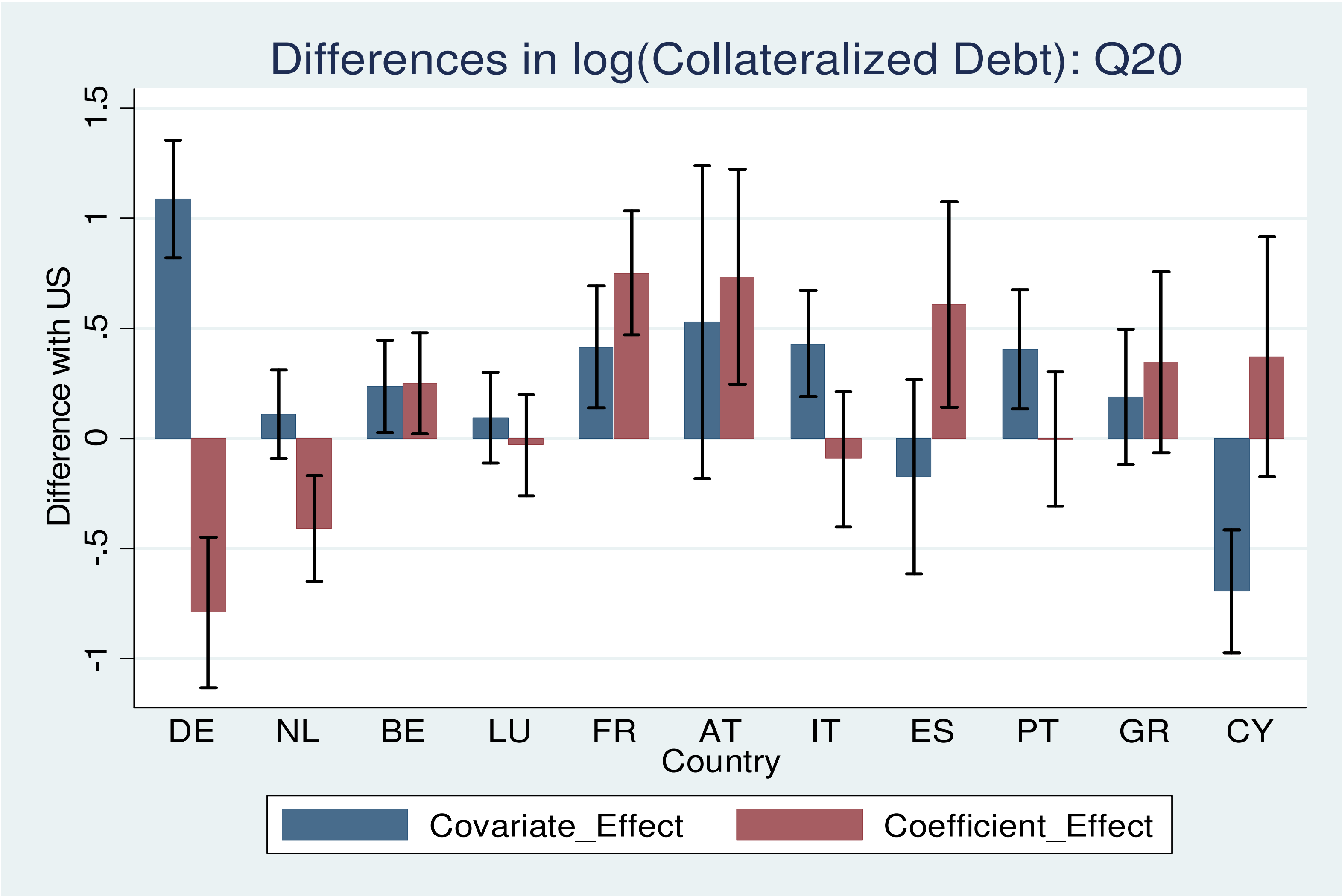
Additional covariates:

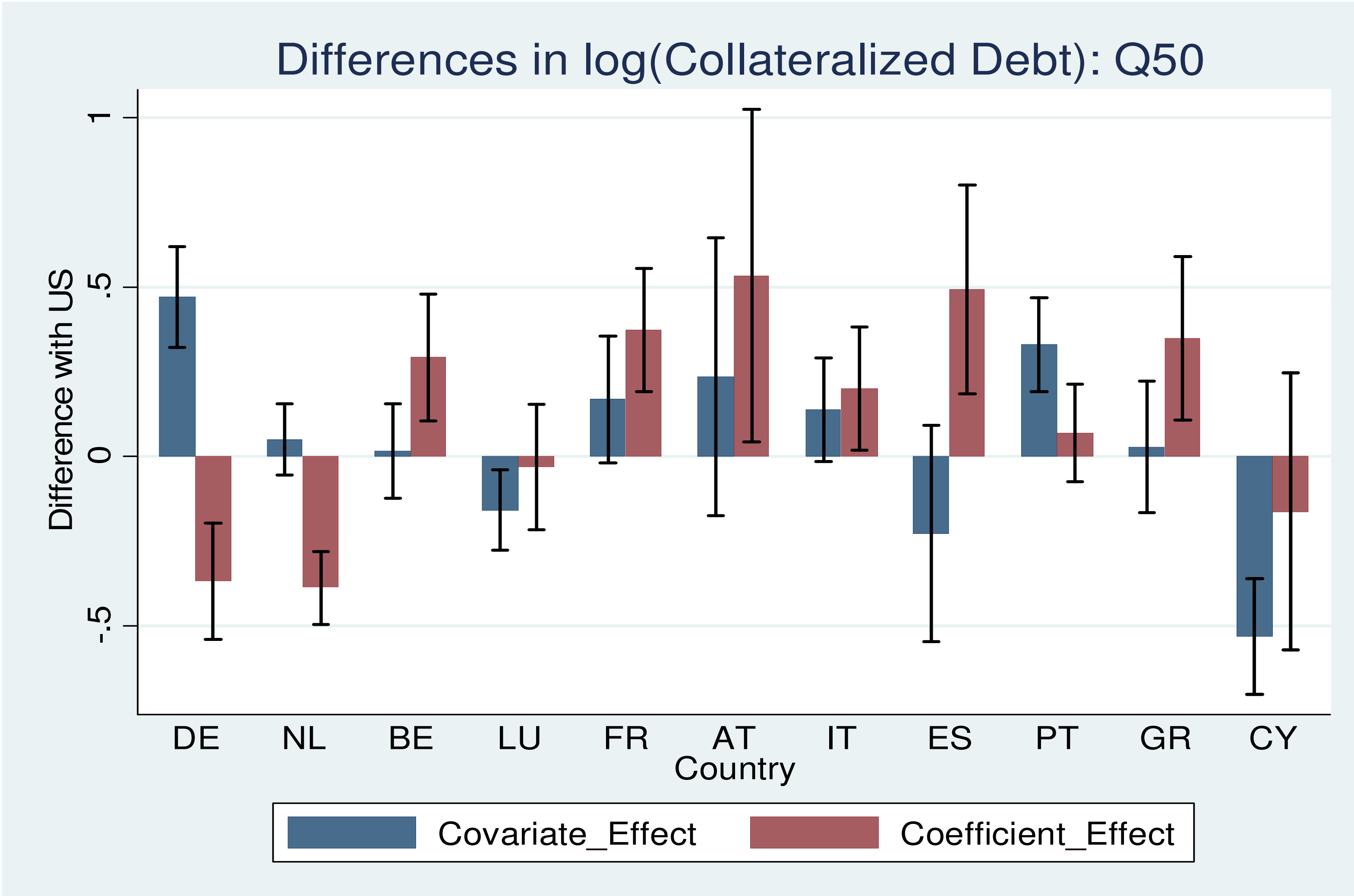
Year T_m that (the largest) outstanding mortgage was taken is known – merge with AMECO data

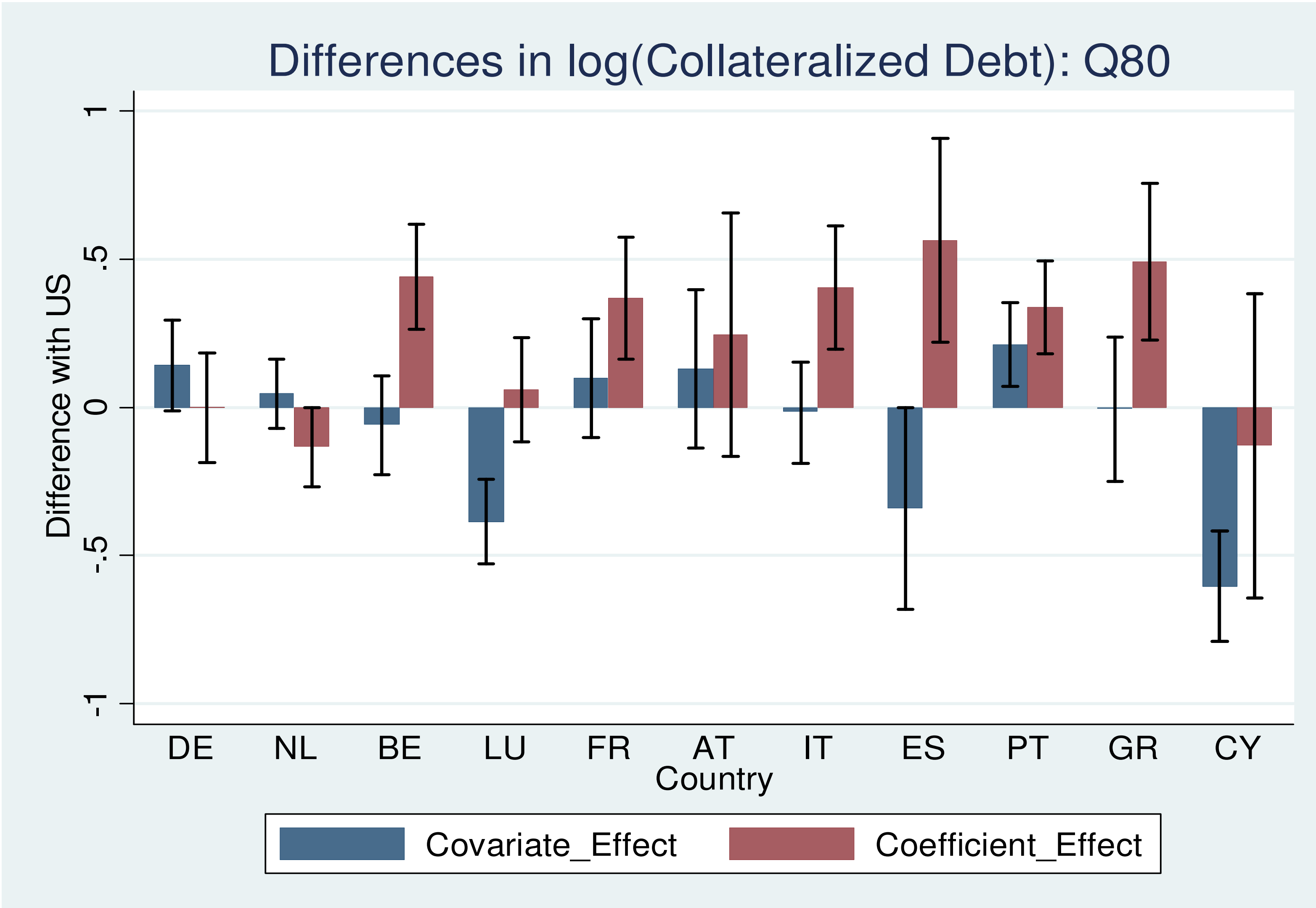
- Cumulative growth of housing price index (three years prior to T_m)

Duration of the (largest) mortgage

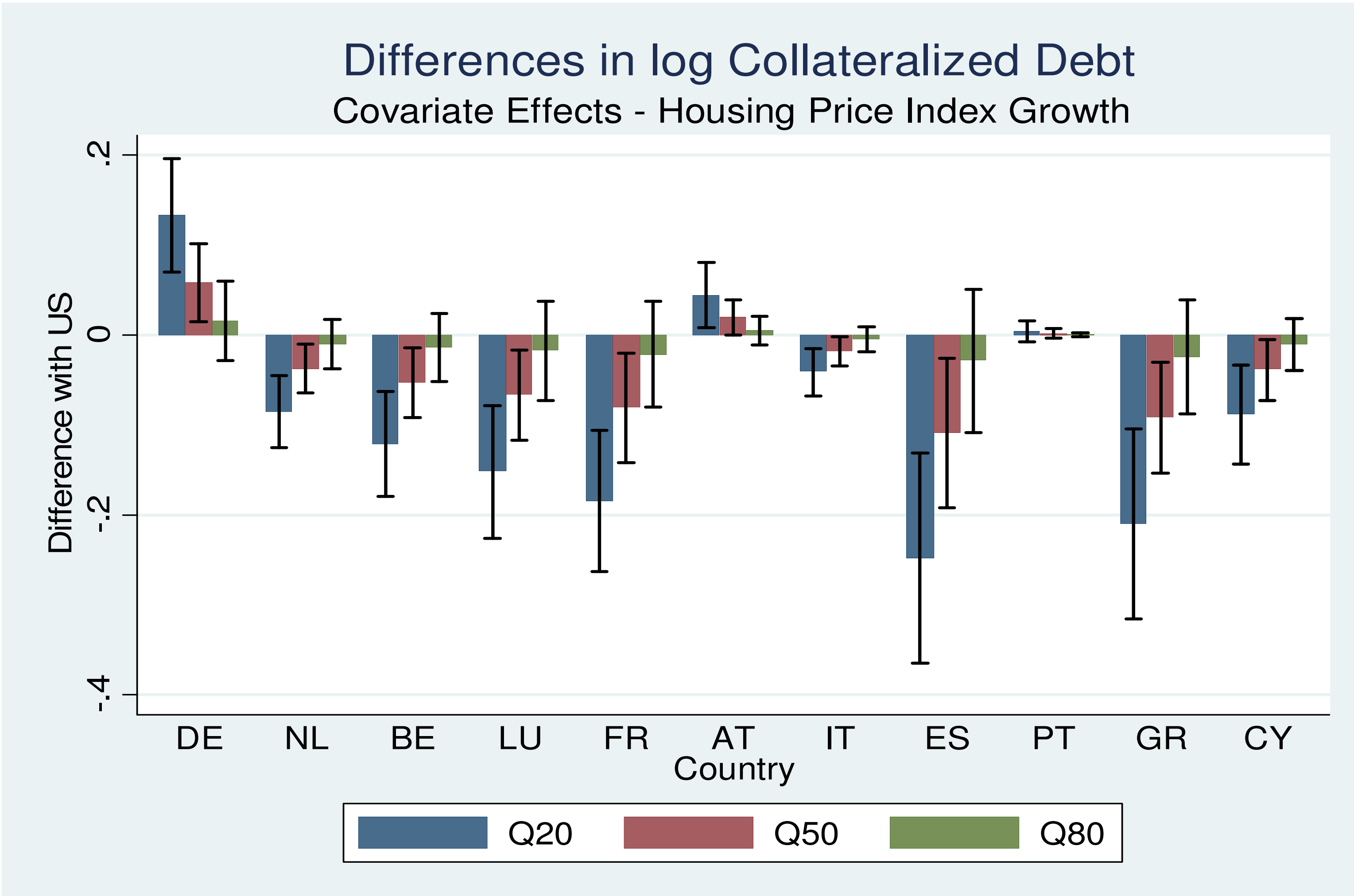
Time elapsed between t - T_m

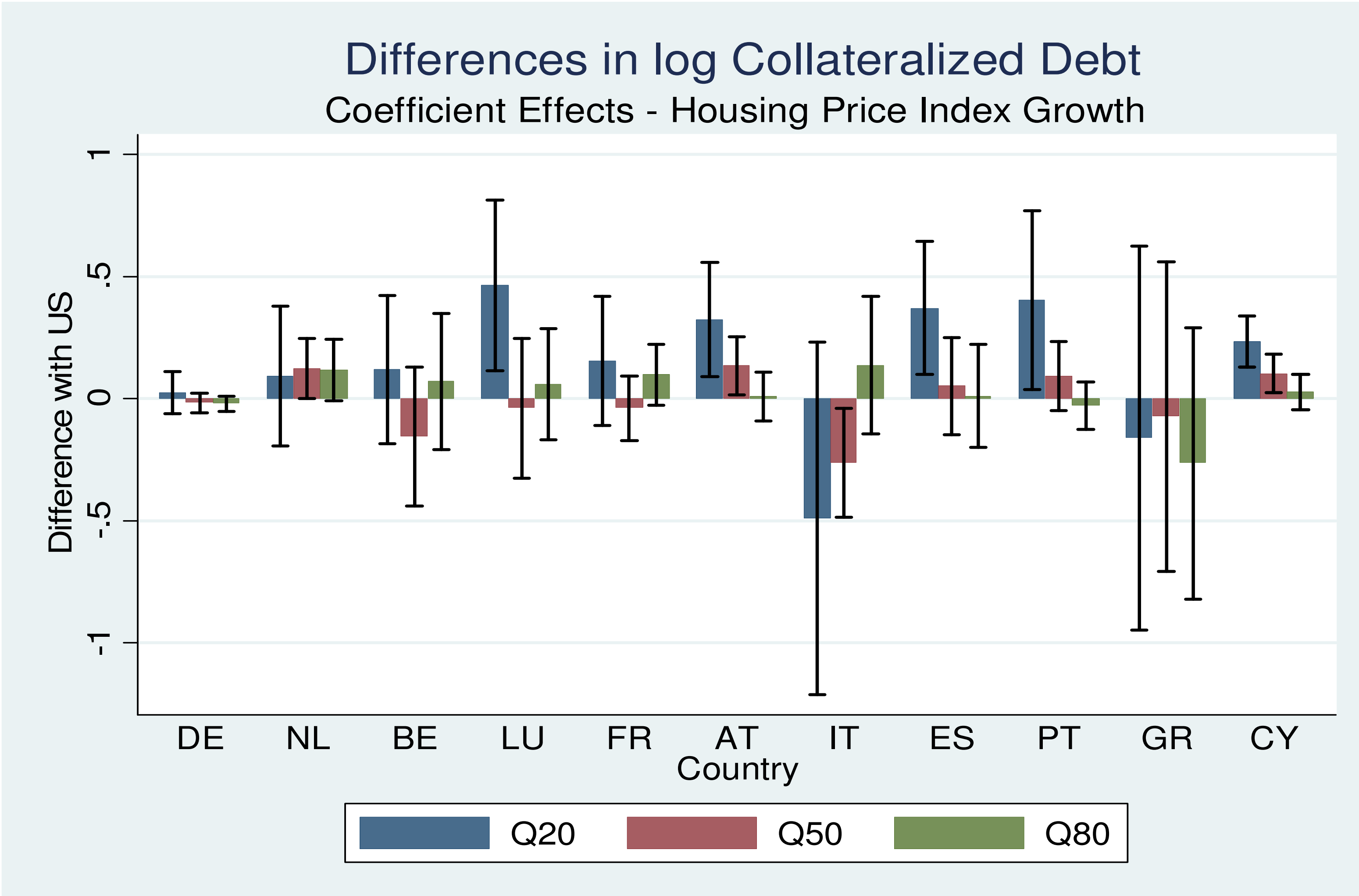

Differences in log(Collateralized Debt): Q20
Difference with US
1.5
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect

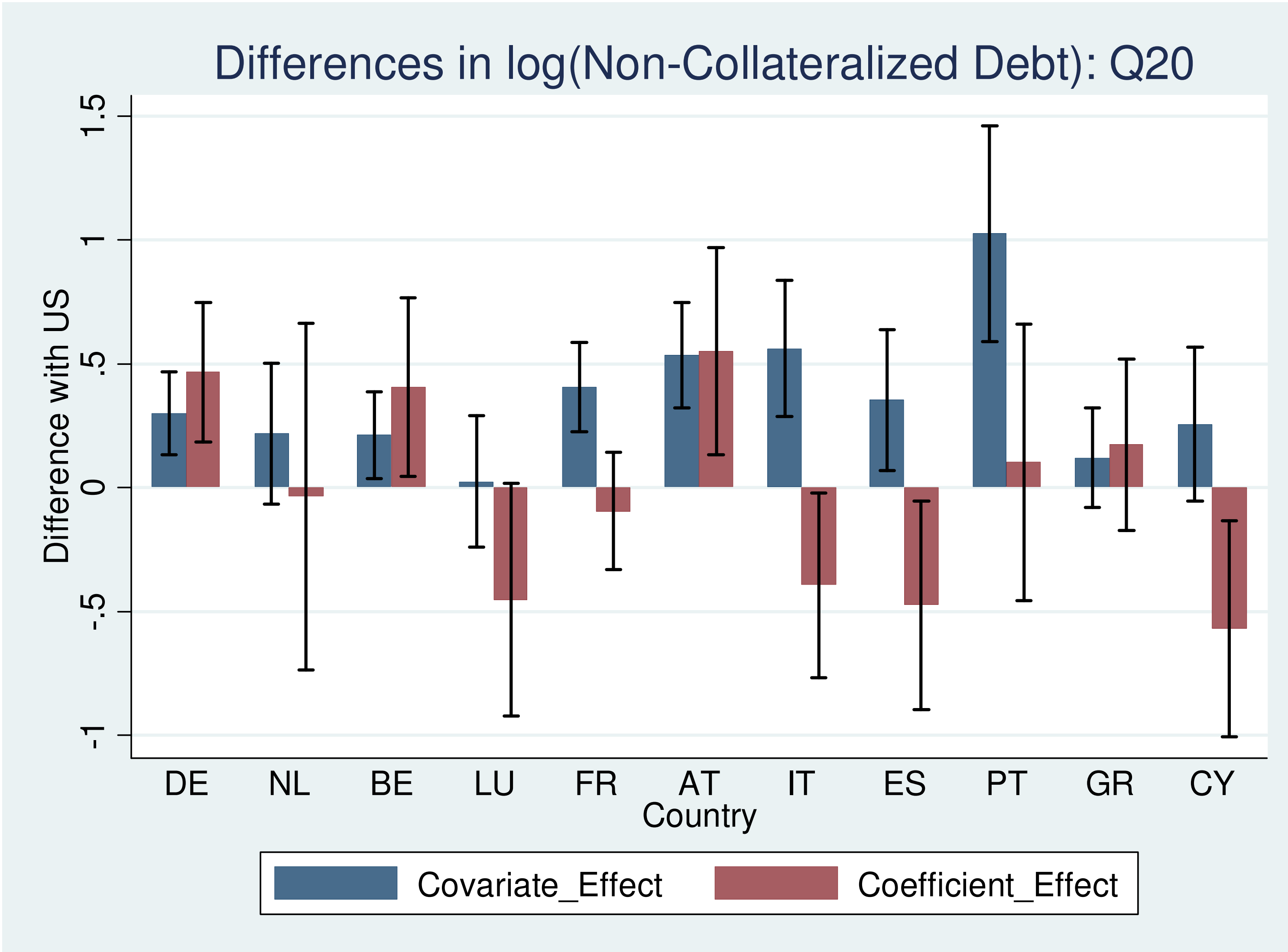

Differences in log(Collateralized Debt): Q50
Difference with US
1
.5
0
-.5
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect



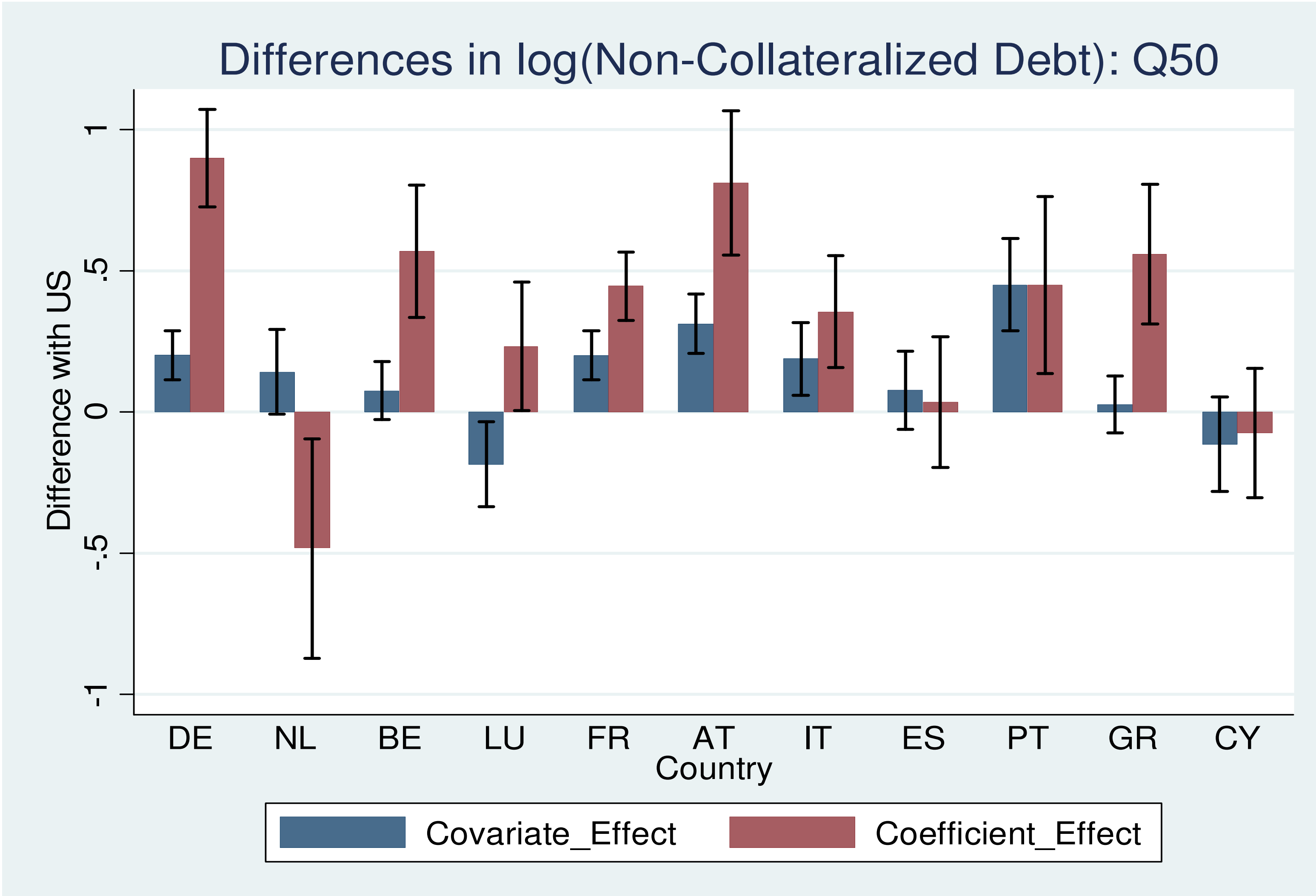
Differences in log(Collateralized Debt): Q80
Difference with US
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect


Differences in log Collateralized Debt
Covariate Effects - Housing Price Index Growth
Difference with US
.2
0
-.2
-.4
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Q20
Q50
Q80

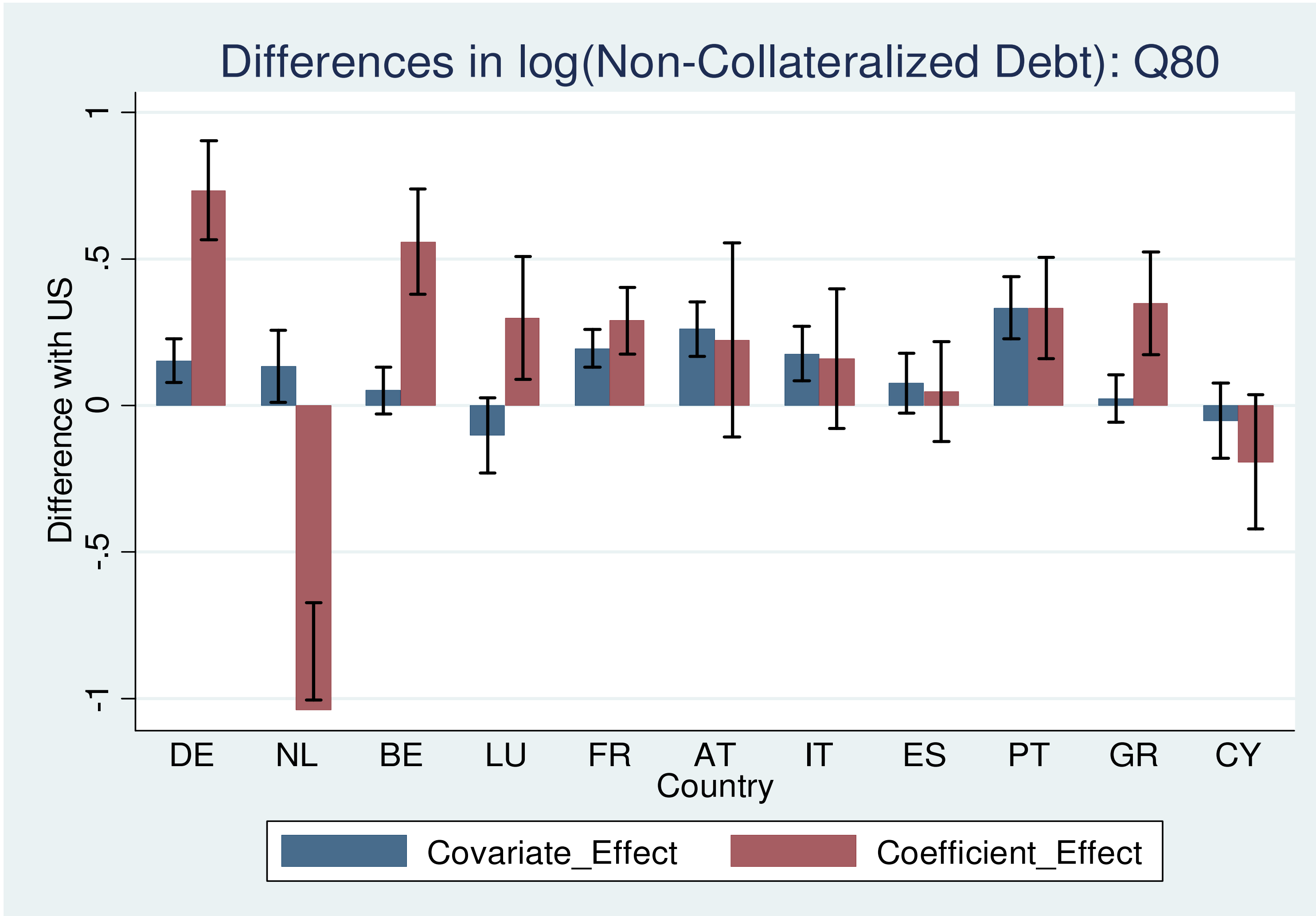

Differences in log Collateralized Debt
Coefficient Effects - Housing Price Index Growth
Difference with US
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Q20
Q50
Q80

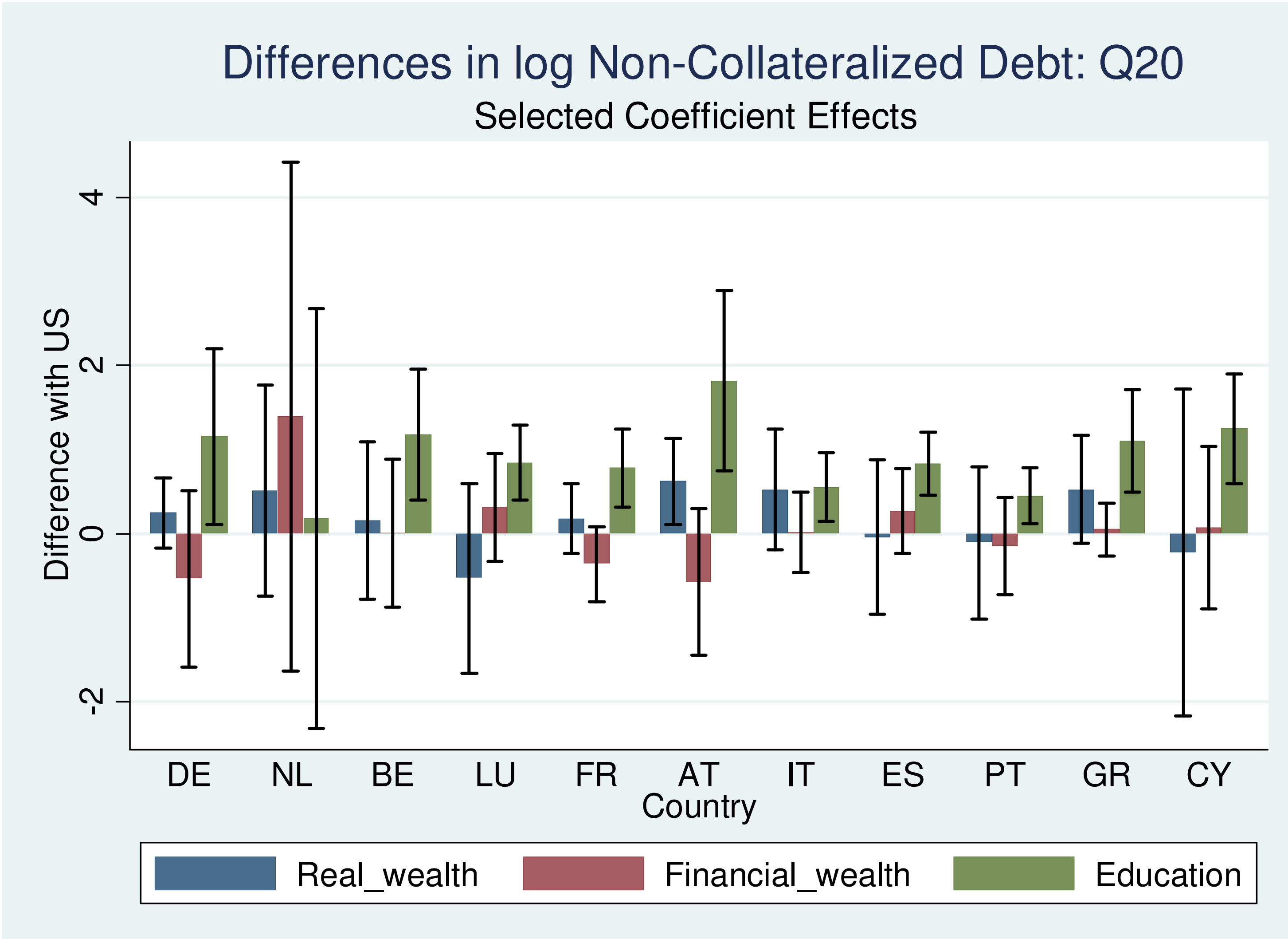


Differences in log(Non-Collateralized Debt): Q20
Difference with US
1.5
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect

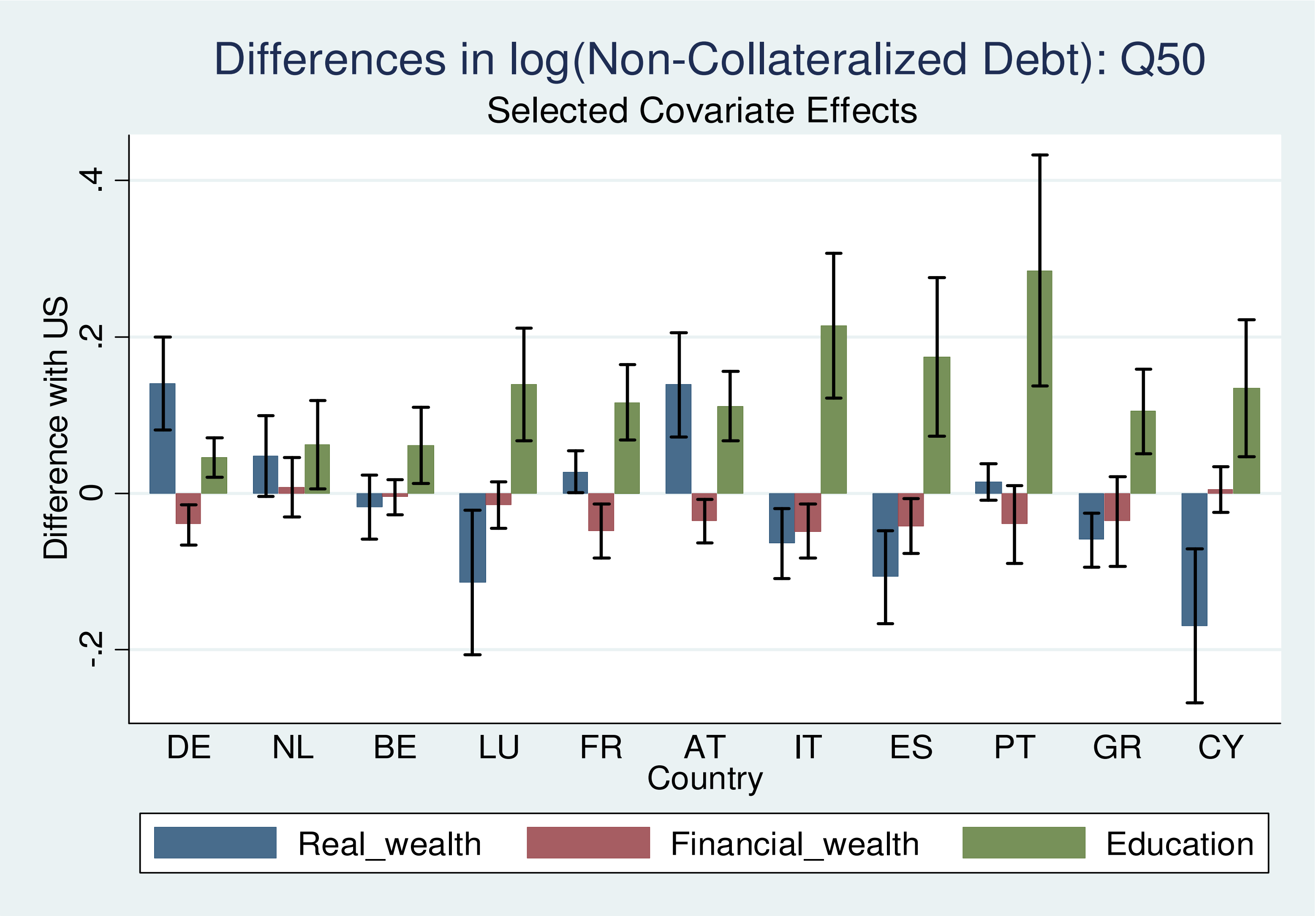


Differences in log(Non-Collateralized Debt): Q50
Difference with US
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect


Differences in log(Non-Collateralized Debt): Q80
Difference with US
1
.5
0
-.5
-1
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Covariate_Effect
Coefficient_Effect



Differences in log Non-Collateralized Debt: Q20
Selected Coefficient Effects
Difference with US
-2
0
2
4
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education


Differences in log(Non-Collateralized Debt): Q50
Selected Covariate Effects
Difference with US
-.2
0
.2
.4
DE
NL
BE
LU
FR
AT
IT
ES
PT
GR
CY
Country
Real_wealth
Financial_wealth
Education

Summary and Conclusions

US: highest prevalence of collateralized and non-collateralized debt

NL, LU, CY: highest (conditional) outstanding amounts of collateralized and non-collateralized debt

US market conditions more conducive to having collateralized/ non-collateralized debt

US market conditions more conducive to higher collateralized/ non-collateralized debt outstanding (exception: the **NL**)

Significant role of:

Real estate for collateralized debt

Education for non-collateralized debt

Extensions:

Explore differences in household financial distress (eg. DSIRs, LTVs)

RIF Regressions

Decomposing proportions is easier than decomposing quantiles

FFL recentered influence function (RIF) regressions. Run LP models (or logit/probit) for being below a given quantile, and divide by density (slope of cumulative) to locally invert.

Dependent variable is dummy $1(Y<Q_\tau)$ divided by density →influence function for the quantile.

RIF approach works for other distributional measures (Gini, variance, etc.)

Chernozhukov et al. (2013): estimate “distributional regressions” (LP, logit or probit) for each value of Y (say at each percentile)

Invert back globally to recover counterfactual quantiles

In the case of quantiles, the RIF is:

$$\text{RIF}(y; Q_\tau) = Q_\tau + \frac{\tau - \mathbb{1}\{y \leq Q_\tau\}}{f_Y(Q_\tau)}$$

Similar RIF can be obtained for other distributional statistics such as a Gini coefficient

Unlike quantile regressions, an important property is that:

$$E(RIF(y,Q_\tau)) = Q_\tau$$

So if we have a regression model like

$$E[RIF(y,Q_\tau)|X] = X\gamma$$

We can do a standard Oaxaca decomposition using the fact that

$$Q_\tau = E(RIF(y,Q_\tau)) = E_X[E[RIF(y,Q_\tau)|X]] = E[X]\gamma$$