Persistence analysis of research intensity in OECD countries since 1870

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ABSTRACT

This paper analyses the persistence of research intensity in the OECD over the period 1870 to 2018. The goal is to test if the conclusion of the study conducted by Ang and Madsen (2011), namely that the Schumpeterian growth models predict that research intensity is stationary, is correct. Using fractional integration methods on annual research intensity from 16 OECD countries, we observe that all the countries are very persistent. The order of integration is observed to be statistically higher than 1 in all the countries except Spain, rejecting thus the hypothesis of stationarity. When the likelihood of non-linear trends is considered in the analysis, the results are not materially different. An implication of the results is that policies aimed at boosting research activities will have a long-term impact on research intensity.

Keywords: Research intensity; OECD; persistence; fractional integration

JEL Classification: C12; M21; O00; Y10

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1. Introduction

Research intensity - which is measured as the proportion of research and development (R&D) expenditure in the gross domestic product (GDP)- is a vital indicator of the research capabilities of a country. Research intensity is a vital index with which to track the extent of a nation’s R&D investment and to enable comparisons across different countries. It features among the research indicators used to gauge a country’s progress towards Sustainable Development Goal (SDG) 9, which refers to "industry, innovation and infrastructure". Research intensity is thus used to assess a country's commitment to foster innovative activities, a key issue in a country’s economy and development.

Growth in research intensity increases the quantity of patent applications and invention patent applications (Xia et al., 2020). It is also positively associated with firms’ degrees of internationalization, the opening up of new markets, their opportunities and their risk diversification (Purkayastha et al., 2018). In conjunction with demand growth and the existence of growing returns to scale in manufacturing, research intensity is pertinent for productivity growth as well as the growth rate of firms (Del Monte & Papagni, 2003). In the field of agriculture, if expenditure is well utilised, smallholders may benefit from rising research intensity.

R&D facilitates the path along which a product evolves as well as keeping a product competitive in the market. With the technology boom, markets have changed significantly, as have the expectations and needs of consumers. The competition is vast, with many different options to choose from and the difference between them is not always price, so companies as well as countries must be creative and adapt to new needs and situations in order to survive and grow (Thompson, 2018). The amount of investment devoted to R&D by business enterprises, governments and other establishments within countries must be significant in order to be competitive on the global stage (Lo, 2016).

Due to the importance of research intensity in particular and R&D in general in an economy, some studies have been carried out on different aspects of research intensity (Jones, 2002; Hundley et al. 2017). However, we are not aware of any study on the persistence of research intensity. There are many arguments to support the importance of studying the persistence of research intensity. Evidence of persistent research intensity implies that policies aimed at boosting research activities will have a long-term impact on research intensity. This is because shocks to a persistent series (which might have arisen as a result of policies or policies to improve such series) will have permanent impact on such series (Hendry and Juselius, 2000; Inglesi-Lotz et al. 2014).

Moreover, persistent research intensity suggests that a sudden decrease in research intensity (probably due to a decrease in the profitability of businesses or budget reallocations) will continue into the future unless there are drastic steps taken by business enterprises and authorities to curtail such a decline. It is also important to test for persistence because stationarity in research intensity is one of the cardinal pillars of Schumpeterian growth model (Ang and Madsen, 2011). The Schumpeterian model, which is a second-generation endogenous growth model, states that R&D expansion is responsible for economic growth. Hence, the persistence of research intensity suggests that other growth-enhancing factors (such as energy and natural resources) are also responsible for economic growth, beyond R&D expansion.

The aim of this paper is to make a minimum of two additions to the existing literature on research intensity. First, we examine the persistence of research intensity in 16 OECD countries. The other main contribution of this paper is the use of fractional integration in the methodology. Fractional integration is a very appropriate technique to determine if shocks in time series are permanent or not, being more general than the classical methods based on integer differentiation: 0 for stationary series and 1 for nonstationary ones.

We have covered members of OECD due to numerous reasons. OECD nations are the most R&D centric nations in the globe and therefore are an ideal sample for investigation (Churchill et al. 2020). Research intensity has been increasing in many OECD countries, especially in recent years. For instance, average research intensity in the OECD nations grew from 2.37% in 2017 to 2.40% in 2018. The increase in not surprising given that in 2018, real R&D expenditure grew by 3.8%, whereas real GDP expanded by 2.3% (OECD, 2020).

2. Review of the literature

There are several papers available in the existing literature that have examined different aspects of R&D. For instance, Jaffe (1988) demonstrated that technological opportunity and market demand have significant effects on R&D demand. Gao and Jefferson (2007) analysed the trend of technology and science take-off. The results confirmed that government R&D investment is a crucial factor in the expansion of energy innovation.

Garrone and Grilli (2010) conducted an empirical analysis of public energy R&D and its relationship with carbon emissions per GDP. The results revealed that there is a need to take into account further variables beyond R&D spending in the process of promoting energy innovation. Ejermo et al. (2011) analysed the Swedish economy. They showed that R&D expenditure generated value-added growth in fast-expanding sectors but not in slow-expanding sectors.

Coccia (2012) examined the relationship between labour productivity and R&D expenditure. The empirical findings suggested that R&D expenditure promoted productivity. Wong et al. (2013) analysed the determinants of economic growth. The result showed that research activities drove economic development more than fossil fuel consumption. Ziesemer (2020) showed that research activities promoted both total factor productivity and real GDP in Japan.

There are specific studies on different dimensions of research intensity. Pakes and Schankerman (1984) explored the economic factors determining research intensity. The results revealed that past industry growth generated more research intensity. Angelmar (1985) showed that market concentration has a positive and significant impact on research intensity, whenever uncertainty and the cost of R&D were high and conditions favour rapid imitation by competitors. However, the impact of market concentration on research intensity was negative and significant, whenever uncertainty and the cost of R&D were low and there were substantial barriers to imitation in the market.

Jones (2002) considered the link between research intensity, educational attainment and economic growth in the U.S. The conclusion was that expansion in research intensity and educational attainment generated positive economic growth in the country. Hundley et al. (2017) compared research intensity in different economies such as Japan and the U.S. The results suggested that in Japan, profitability decreases were a driver of higher R&D intensity.

Falk (2007) studied the influence of investment in research activities on long-term economic development. The result revealed that research intensity has strong positive impacts on GDP per hour worked and per capita GDP in the long run. Churchill et al. (2020) studied the convergence of research intensity in OECD countries covering 14.5 decades and observed evidence in favour of full convergence.

There are also several papers in the literature that have used the same method as ours-fractional integration, but these papers focussed mostly on different variables. Using fractional integration, Gaffeo et al. (2005) rejected the supposition of long term temporal homogeneity of GDP per capita. Cunado et al. (2007) also applied this method to analyse the order of integration of the series of real GDP per capita for emerging countries.

Gil-Alana et al. (2021) has used it to analyse the long-run equilibrium relationship between population and GDP. Ahmed et al. (2021) has used the same fractional integration methods to investigate the determinants of carbon dioxide emissions. As far as we are aware, the only study that has used fractional integration methods to examine research intensity is the paper of Altuzarra (2016). The results suggested that there was convergence of research intensity in 21 countries in Europe.

Finally, there are also studies that have looked at different dimensions of the Schumpeterian growth model. Cheng and Dinopoulos (1992) considered the relationship between international business cycles and the Schumpeterian growth model. Venturini (2012) evaluated the role of research activities within the Schumpeterian growth framework. Chu and Ji (2016) used the Schumpeterian growth framework to evaluate the role of monetary policy. It was shown that monetary policy has no long-run growth effect, but the nominal interest rate increases perpetually brought down the levels of consumption, output and employment.

Jones and Kim (2018) used the Schumpeterian growth framework to explain the impact of innovation on income inequality. It was shown that creative destruction reduces income inequality. Using a Schumpeterian growth framework, Oikawa and Ueda (2018) showed that the optimal inflation rate is about −2%. Aghion and Festré (2017) showed that the Schumpeterian growth framework provided a suitable guide in the process of designing growth policies.

3. Methodology

As far as the methodology is concerned we use linear and non-linear models with fractional integration. Starting with the linear approach, the model under estimation is:

$$y(t) \;=\; \alpha \;+\; \beta t \;+\; x(t), \qquad (1 - B)^{d}\, x(t) \;=\; u(t), \qquad t \;=\; 1, 2, \ldots \tag{1}$$

where y(t) refers to the data involved, β and α are unknown parameters referring to a linear time trend and an intercept, and x(t) is presumed to be an integrated of order d process, or I(d), so that u(t) is I(0) or follows a short-memory pattern. Therefore, x(t) exhibits a long memory when d > 0. Note that values of d smaller than 0.5 imply covariance stationarity while d ≥ 0.5 signposts a lack of it and the greater the value of d is, the bigger the level of nonstationary is, following the logic that the partial sums variance increases in magnitude with d. Here, we estimate the differencing parameter d utilizing the frequency domain variant of the Whittle function by utilizing a testing approach introduced initially in Robinson (1994) for the linear case.

In the non-linear context, we replace the first equation in (1) by a non-linear trend that uses Chebyshev polynomials in time, i.e.,

$$y(t) \;=\; \sum_{i=1}^{m} \theta_i \, P_{iT}(t) \;+\; x(t), \tag{2}$$

where T is the size of the sample, and *m* suggests the Chebyshev polynomials order, which is specified as:

$$P_{0,T}(t) \;=\; 1, \tag{3}$$

$$P_{i,T}(t) \;=\; \sqrt{2}\cos\left(i\,\pi\,(t - 0.5)/T\right), \qquad t \;=\; 1, 2, \ldots, T; \quad i \;=\; 1, 2, \ldots \tag{4}$$

This model described in (2) was utilized in a fractionally integrated context by Cuestas and Gil-Alana (2016) applying a modified version of Robinson’s (1994) test to jointly investigate persistence and non-linearities. Thus, if m = 1 the model comprises only a constant; if m =2, it comprises a constant and a linear trend as in equation (1), and if m >

2 non-linearities exist, a greater m demonstrating a greater level of non-linearity. In Section 5, where the empirical investigation is conducted, we set m = 4, and thus θ_3 and θ_4 being the coefficients capturing potential non-linearities in the data.

4. Data

The data for research intensity of all the countries for the period 1870-2009 has been extracted from the paper of Madsen and Ang (2016). The data for research intensity for Ireland (for the period, 2010-2016) and of the other countries (for the period 2010-2018) have been taken from World Bank (2021). The descriptive statistics of the series are contained in Table 1. It has been demonstrated that, for the period 1870-2018, the Netherlands has the highest average research intensity while Spain has the lowest average research intensity. The largest standard deviations in the data set are observed for France, followed by the Netherlands and Finland.

5. Results

All series are highly persistent. Table 2 displays the estimates of d in equation (1) under the assumption of white noise errors. Thus, all the time dependence is then captured with the differencing parameter d. Mean reversion evidence i.e., significant evidence of d smaller than 1 is only observed for Spain, with an estimated value of d of 0.83. For the other cases, the values of d are within the I(1) interval, in nine countries: Austria, Canada, Germany, Ireland, Japan, Norway, the Netherlands and Sweden; or significantly higher than 1, in the remaining seven cases: Belgium, Denmark, France, Finland, Greece, Italy and Portugal. Finally, the time trend is significant in five countries and with a significantly positive time trend coefficient in all of them (see Table 3).

Insert Tables 2 and 3 about here

If we focus now on the results for the model with autocorrelated errors, in Tables 4 and 5, the first thing we notice is that the figures of d are substantially lower than in the previous case. Thus, mean reversion evidence is found in three countries: Germany, Norway and Spain. The unit root null hypothesis cannot be rejected in Austria, Belgium, Canada, Denmark, France, Italy, Ireland, Japan, the Netherlands, Portugal or Sweden, and evidence of $d > 1$ is only found in the case of Greece. However, time trends are found in a higher number of cases than in the white noise case, in particular in ten nations: Belgium, Austria, Denmark, Finland, Italy, Japan, Portugal, Norway, Sweden and Spain, in each case with a positive coefficient and with the highest figures corresponding to Austria (0.0210), Japan (0.0213) and Sweden (0.0218).

Insert Tables 4 and 5 about here

Finally, the likelihood of non-linear trends is also considered. Focussing first on the estimated values of d, Spain appears as the only country showing mean reversion, and significant support of non-linear trends is only found in the cases of Japan, the Netherlands and Sweden, in the three scenarios with a significant θ_3-coefficient.

A likely justification for the foregoing empirical results of persistence of research intensity is the persistence of the macroeconomic variables by which it is determined, notably the persistence of the number of researchers, patents trade-openness and GDP. Persistence in GDP causes persistence in other variables that are determined by GDP including income inequality. Pradhan et al. (2018) has shown that the number of researchers and patents are persistent variables in developed economies. Tudor and Sova (2022) have shown that the number of researchers and patents are variables that determine research intensity. According to Narayan and Smyth (2007), a variable that is reliant on another variable that is persistent will absorb such persistence, and transfer it to numerous other variables in the economy.

Another reason for the foregoing results is that research intensity has been increasing in many OECD countries due to the introduction of different national targets at various times. For instance, research intensity surpassed the 3% milestone in the U.S., Denmark reached 3.02% research intensity in 2018 while the target was to reach 3.0% by 2020. Moreover, Germany achieved 3.12% research intensity in 2018 while the target was to achieve 3.0% by 2020 (OECD, 2021)

6. Conclusions

In this study we have studied research intensity persistence in various OECD countries for the time period 1870-2018 using yearly data. Testing the stationarity hypothesis formulated throughout the Schumpeterian growth models and using fractional integration, our results indicate that the 16 OECD countries examined display high levels of persistence. In fact, the orders of integration are found to be statistically higher than 1 in all countries except for Spain, inferring permanency of shocks and absence of mean reversion in most of the countries in the sample. When the likelihood of non-linear trends is considered in the analysis, the empirical results are not substantially different.

One of the implications of the persistence of research intensity is that policies aimed at boosting research activities will have a long-term impact on research intensity. This is not surprising given that OECD countries have more capability to ensure that resources devoted to science and technology yield positive results. Moreover, the private sector accounts for a substantial part of research efforts in these countries. For instance, the business sector was responsible for 66% of the total expenditure on research and development activities of OECD countries in 2019 (OECD, 2021).

Hence, it is recommended that authorities should introduce policies that promote capacity building for those countries such as strengthening human resources and research infrastructure. Moreover, the government in these countries should create an atmosphere that encourages greater private investment in research and development activities. These policies include incentivizing investments on the part of industry and supporting competitiveness among the industry players.

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Table 1: Descriptive statistics: research intensity

Country	Mean	Standard deviation	Maximum value	Mínimum value
AUSTRIA	0.909993	0.799966	3.171770	0.101110
BELGIUM	0.983731	0.743863	2.821190	0.105040
CANADA	1.261725	0.667624	2.544100	0.225660
DENMARK	0.987532	0.846047	3.104010	0.102000
FINLAND	1.676106	1.012157	3.725980	0.285190
FRANCE	2.453868	1.432792	6.282090	0.549280
GERMANY	1.374302	0.933362	3.094150	0.199000
GREECE	0.250760	0.213436	1.177320	0.036670
IRELAND	0.701623	0.425046	1.600000	0.105000
ITALY	0.465947	0.452694	1.399090	0.031480
JAPAN	1.354104	1.161842	3.560000	0.108000
NETHERLANDS	1.853721	1.006130	4.260000	0.366180
NORWAY	0.924379	0.584341	2.093430	0.123000
PORTUGAL	0.283937	0.367256	1.532570	0.016550
SPAIN	0.188531	0.304817	1.349610	0.001070
SWEDEN	1.395980	1.258625	4.240000	0.127000

The raw figures are reported in the Table

Table 2: Estimates of d under the assumption of white noise errors

Country	No terms	An intercept	An intercept and a time trend
AUSTRIA	1.07 (0.99, 1.19)	1.07 (0.99, 1.18)	**1.07 (0.99, 1.19)**
BELGIUM	1.30 (1.13, 1.51)	**1.29 (1.12, 1.51)**	1.29 (1.12, 1.51)
CANADA	0.97 (0.87, 1.11)	**0.99 (0.89, 1.12)**	0.99 (0.88, 1.12)
DENMARK	1.15 (1.03, 1.35)	**1.16 (1.03, 1.36)**	1.17 (1.03, 1.37)
FINLAND	1.13 (1.01, 1.29)	**1.14 (1.02, 1.29)**	1.14 (1.02, 1.29)
FRANCE	1.13 (1.02, 1.28)	**1.13 (1.02, 1.29)**	1.13 (1.02, 1.29)
GERMANY	0.95 (0.80, 1.17)	0.94 (0.80, 1.16)	**0.94 (0.78, 1.17)**
GREECE	**1.24 (1.16, 1.35)**	1.24 (1.15, 1.35)	1.24 (1.15, 1.35)
IRELAND	**1.07 (0.93, 1.22)**	1.10 (0.97, 1.24)	1.10 (0.97, 1.24)
ITALY	**1.27 (1.13, 1.46)**	1.27 (1.13, 1.46)	1.28 (1.13, 1.46)
JAPAN	0.99 (0.90, 1.13)	1.00 (0.90, 1.13)	**1.00 (0.89, 1.14)**
NETHERLANDS	1.08 (0.97, 1.23)	**1.07 (0.96, 1.22)**	1.07 (0.96, 1.22)
NORWAY	0.97 (0.84, 1.14)	0.96 (0.83, 1.14)	**0.96 (0.82, 1.14)**
PORTUGAL	**1.39 (1.23, 1.60)**	1.39 (1.23, 1.59)	1.39 (1.23, 1.59)
SPAIN	0.84 (0.75, 0.97)	0.84 (0.74, 0.97)	**0.83 (0.73, 0.97)**
SWEDEN	**1.06 (0.97, 1.21)**	1.07 (0.97, 1.21)	1.07 (0.97, 1.22)

Values in bold refer to the significant model according to the deterministic terms.

Table 3: Estimated coefficients in the selected models in Table 2

Country	No terms	An intercept	An intercept and a time trend
AUSTRIA	1.07 (0.99, 1.19)	0.103 (1.31)	0.021 (2.37)
BELGIUM	1.29 (1.12, 1.51)	0.122 (1.64)	---
CANADA	0.99 (0.89, 1.12)	0.270 (2.18)	---
DENMARK	1.16 (1.03, 1.36)	0.118 (1.71)	---
FINLAND	1.14 (1.02, 1.29)	0.332 (2.03)	---
FRANCE	1.13 (1.02, 1.29)	0.642 (2.32)	---
GERMANY	0.94 (0.78, 1.17)	0.213 (1.45)	0.019 (2.09)
GREECE	1.24 (1.16, 1.35)	---	---
IRELAND	1.07 (0.93, 1.22)	---	---
ITALY	1.27 (1.13, 1.46)	---	---
JAPAN	1.00 (0.89, 1.14)	0.107 (0.98)	0.021 (2.37)
NETHERLANDS	1.07 (0.96, 1.22)	0.430 (2.42)	---
NORWAY	0.96 (0.82, 1.14)	0.132 (1.81)	0.013 (2.57)
PORTUGAL	1.39 (1.23, 1.60)	---	---
SPAIN	0.83 (0.73, 0.97)	-0.012 (-0.13)	0.007 (2.07)
SWEDEN	1.06 (0.97, 1.21)	---	---

Table 4: Estimates of d under the assumption of autocorrelated errors

Country	No terms	An intercept	An intercept and a time trend
AUSTRIA	1.08 (0.95, 1.27)	1.08 (0.95, 1.26)	**1.10 (0.95, 1.29)**
BELGIUM	0.90 (0.70, 1.31)	0.86 (0.69, 1.25)	**0.83 (0.62, 1.24)**
CANADA	0.90 (0.74, 1.12)	**0.92 (0.76, 1.13)**	0.92 (0.75, 1.13)
DENMARK	0.93 (0.83, 1.10)	0.94 (0.83, 1.11)	**0.91 (0.79, 1.12)**
FINLAND	0.98 (0.78, 1.27)	**1.02 (0.81, 1.30)**	1.02 (0.80, 1.30)
FRANCE	1.02 (0.84, 1.25)	**1.01 (0.85, 1.25)**	1.01 (0.85, 1.25)
GERMANY	0.65 (0.55, 0.81)	0.67 (0.59, 0.81)	**0.55 (0.40, 0.78)**
GREECE	**1.43 (1.22, 1.64)**	1.39 (1.20, 1.62)	1.37 (1.19, 1.60)
IRELAND	**1.11 (0.43, 1.57)**	1.32 (0.64, 1.67)	1.31 (0.06, 1.67)
ITALY	1.04 (0.86, 1.46)	1.04 (0.86, 1.45)	**1.05 (0.82, 1.45)**
JAPAN	0.97 (0.84, 1.27)	0.99 (0.86, 1.28)	**0.98 (0.81, 1.28)**
NETHERLANDS	0.94 (0.81, 1.15)	**0.94 (0.80, 1.15)**	0.94 (0.81, 1.14)
NORWAY	0.76 (0.62, 1.03)	0.74 (0.63, 0.98)	**0.70 (0.50, 0.99)**
PORTUGAL	1.13 (0.96, 1.51)	1.13 (0.96, 1.51)	**1.14 (0.95, 1.51)**
SPAIN	0.75 (0.62, 0.91)	0.75 (0.62, 0.91)	**0.74 (0.60, 0.90)**
SWEDEN	0.96 (0.83, 0.15)	0.95 (0.84, 0.15)	**0.96 (0.80, 0.16)**

Values in bold refer to the significant model according to the deterministic terms

Table 5: Estimated coefficients in the selected models in Table 4

Country	No terms	An intercept	An intercept and a time trend
AUSTRIA	1.10 (0.95, 1.29)	0.103 (1.33)	0.021 (2.08)
BELGIUM	0.83 (0.62, 1.24)	0.093 (1.23)	0.017 (5.79)
CANADA	0.92 (0.76, 1.13)	0.278 (2.26)	---
DENMARK	0.91 (0.79, 1.12)	0.095 (1.37)	0.019 (5.19)
FINLAND	1.02 (0.81, 1.30)	0.338 (1.99)	---
FRANCE	1.01 (0.85, 1.25)	0.654 (2.34)	---
GERMANY	0.55 (0.40, 0.78)	0.127 (1.06)	0.018 (10.37)
GREECE	1.43 (1.22, 1.64)	---	---
IRELAND	1.11 (0.43, 1.57)	---	---
ITALY	1.05 (0.82, 1.45)	0.029 (0.79)	0.009 (2.39)
JAPAN	0.98 (0.81, 1.28)	0.106 (0.97)	0.021 (2.62)
NETHERLANDS	0.94 (0.80, 1.15)	0.447 (2.53)	---
NORWAY	0.70 (0.50, 0.99)	0.115 (1.70)	0.012 (7.79)
PORTUGAL	1.14 (0.95, 1.51)	0.013 (0.39)	0.009 (1.74)
SPAIN	0.74 (0.60, 0.90)	-0.025 (-0.28)	0.007 (2.86)
SWEDEN	0.96 (0.80, 0.16)	0.127 (1.08)	0.021 (2.73)

Table 6: Estimated coefficients in a nonlinear (Chebyshev) I(d) model

Country					
AUSTRIA	1.06 (0.97, 1.19)	0.968 (1.47)	**-0.659** **(-1.69)**	0.230 (1.23)	-0.177 (-1.46)
BELGIUM	1.29 (1.13, 1.49)	0.266 (0.15)	-0.225 (-0.20)	0.015 (0.03)	0.108 (0.45)
CANADA	0.95 (0.84, 1.10)	**1.235** **(1.91)**	-0.531 (-1.39)	-0.239 (-1.18)	0.090 (0.65)
DENMARK	1.15 (1.00, 1.36)	0.960 (1.11)	-0.696 (-1.29)	0.235 (1.03)	-0.132 (-0.93)
FINLAND	1.13 (1.02, 1.29)	1.822 (0.94)	-0.854 (-0.71)	-0.081 (-0.15)	-0.114 (-0.35)
FRANCE	1.10 (0.98, 1.27)	**2.271** **(1.81)**	-0.468 (-0.28)	-0.981 (-1.29)	0.318 (0.65)
GERMANY	0.92 (0.71, 1.16)	**1.245** **(1.84)**	**-0.917** **(-2.30)**	0.132 (0.60)	0.075 (0.50)
GREECE	1.23 (1.15, 1.32)	**0.009** **(1.88)**	0.063 (0.19)	-0.019 (-0.15)	-0.020 (-0.26)
IRELAND	1.08 (0.94, 1.21)	0.749 (0.74)	-0.468 (-0.71)	-0.015 (-0.05)	-0.010 (0.05)
ITALY	1.27 (1.11, 1.46)	0.324 (0.42)	-0.338 (-0.69)	0.133 (0.74)	0.0004 (0.03)
JAPAN	0.92 (0.77, 1.09)	**1.263** **(2.56)**	**-1.113** **(-3.84)**	**0.278** **(1.75)**	0.035 (0.32)
NETHERLANDS	1.07 (0.88, 1.17)	**1.718** **(1.70)**	-0.597 (-0.87)	**-0.609** **(-1.78)**	0.301 (1.32)
NORWAY	0.96 (0.81, 1.14)	**0.886** **(2.21)**	**-0.578** **(-2.43)**	0.012 (0.10)	0.043 (0.51)
PORTUGAL	1.38 (1.21, 1.59)	0.062 (0.05)	-0.066 (-0.09)	0.110 (0.46)	-0.074 (-0.54)
SPAIN	0.80 (0.69, 0.96)	0.273 (1.05)	**-0.234** **(-1.69)**	0.135 (1.46)	-0.092 (-1.36)
SWEDEN	1.00 (0.88, 1.17)	**1.391** **(1.85)**	**-1.146** **(-2.55)**	**0.407** **(1.81)**	-0.137 (-0.99)

Values in bold refer to the significant coefficients