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WORKING PAPER

Demographics and Business Cycle Volatility
A Spurious Relationship?

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October 2015
2015/914

D/2015/7012/16

Demographics and Business Cycle Volatility: A Spurious Relationship?

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October 29, 2015

Abstract

This paper replicates the estimation results of three studies on the impact of the age composition of the labor force on business cycle volatility and investigates whether they signal a meaningful long-run relationship. We show that both the volatile-age labor force share variable and the business cycle volatility measure exhibit non-stationary behavior but find no robust evidence of cointegration. Hence, the estimation results reported in the literature may be spurious. This conclusion is further supported by the finding that the strong relationship (i) disappears when cross-sectional dependence is accounted for using the CCEP estimator and (ii) is highly sensitive to small changes in the composition of the sample, to data revisions, and to the exact definition of the volatile-age labor share.

1 Introduction

In a well-cited paper Jaimovich and Siu (2009), hereafter Ja&Si, argue that a significant fraction of the run-up of U.S. volatility in the mid-1960s and of the marked decline since the mid-1980s, known as the Great Moderation, is accounted for by long swings in the age composition of the U.S. population induced by the baby boom and subsequent baby bust. Ja&Si start from the empirical observation that, in their sample of G7 countries, there are clear differences in the responsiveness of labor market activity to the business cycle over individuals of different ages. Both 'the young' and 'the old' tend to experience greater sensitivity of employment and hours worked than the prime-aged. Given this alleged U-shaped pattern, Ja&Si define the *volatile-age* labor force share s_{it} as the fraction of the 15-64-year-old labor force accounted for by those aged 15-29 and 60-64. Using an unbalanced panel for the G7 countries covering the period 1963-1999, s_{it} is then linked

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We are thankful for constructive comments by three anonymous referees, Tino Berger, Freddy Heylen, Helmut Herwartz, Steve Lugauer and Gert Peersman. Hauke Vierke acknowledges financial support from Ghent University's Special Research Fund (BOF) and from the National Bank of Belgium (NBB).

to the time-varying standard deviation of output σ_{it} in the following benchmark regression

$$\sigma_{it} = \alpha_i + \beta_t + \gamma s_{it} + \varepsilon_{it}, \tag{1}$$

with α_i a fixed effect for cross-section i and β_t a fixed effect for period t. Using a variety of alternative measures for σ_{it}, Ja&Si show that shifts in the volatile-age share variable s_{it} have a large and significant effect on cyclical volatility in the G7 countries. Relating their results to the recent decline in U.S. macroeconomic volatility shows that demographic change is not the sole factor responsible for this episode but does account for approximately one-fifth to one-third of this moderation. Similar large and significant effects are obtained by Lugauer and Redmond (2012) for a panel of 51 advanced and developing countries and by Lugauer (2012) for a panel of 50 U.S. states.

Although the exact timing and specific evolution has been different, most developed countries have experienced a similar shift in the age distribution of the labor force over the postwar period which seems to coincide with a general decline in macroeconomic volatility. The aim of this replication paper is to investigate whether this signals a meaningful long-run relationship or is merely an artifact of common long swings in the data. In Section 2 we first show that the G7 data used by Ja&Si display non-stationary behavior. Hence, we next test whether estimating equation (1) results in a cointegrating relation or produces spurious results. As adequately accounting for the potential common trend in volatility over countries requires a sufficiently large cross-sectional dimension, in Section 3 we broaden the analysis by using the richer datasets of Lugauer and Redmond (2012) and Lugauer (2012).

2 The Jaimovich and Siu (AER, 2009) regression

Time series properties

As a first step in the empirical analysis, Table 1 reports unit root tests on the cyclical volatility σ_{it} and the volatile-age labor share variable s_{it} taken from the Ja&Si dataset. This is an unbalanced panel of G7 countries over the period 1993-1999. As proxies for σ_{it} we consider the two baseline measures used by Ja&Si: the standard deviation of HP filtered real GDP over a 10-year window, hereafter HP, and the instantaneous standard deviation of real output growth calculated using the stochastic volatility model of Stock and Watson (2003, 2005), hereafter SW. More details on the construction of these variables can be found in Ja&Si.[1]

The top left panel of Table 1 reports Maddala and Wu (1999) (MW) panel unit root tests calculated by combining the p-values from country-specific Augmented Dickey and Fuller (1979) (ADF) tests for a specification including a constant. The main advantages of the MW test are that (i) it does not require a balanced panel such that it can be applied to the unbalanced panel of G7 countries at hand and (ii) it can combine p-values from any individual test such that it can

[1] The data are available at the AER website: *https://www.aeaweb.org/aer/data/june09/20070168_data.zip*. Note that while HP and SW are their baseline measures, Ja&Si also consider alternative de-trending methods (such as first differencing, calculating four-quarter growth rates, and using the Baxter and King bandpass filter) as robustness checks. We do not consider these measures as data for these measures are not publicly available.

not only be used as a panel unit root here but also as a panel cointegration test below. Since a rejection of the null hypothesis of a unit root based on the MW panel test would not qualify as evidence that the panel as a whole is stationary, we also report the underlying country-specific ADF statistics. This allows for a more careful analysis of the time series properties of the panel (see also Karlsson and Löthgren, 2000). The results show that the null hypothesis of a unit root in the HP and SW volatility measures cannot be rejected at the 5% level of significance for any of the individual countries nor for the panel as a whole. For the labor share variable s_{it} the unit root hypothesis is rejected for only 2 out of 7 countries, i.e. for Canada and Japan, while not being rejected using the panel MW test.

Insert Table 1 about here

The bottom left panel of Table 1 reports the average cross-sectional correlation $\overline{\hat{\rho}}$ in the first-differenced error terms of the ADF regressions together with the Pesaran (2004) cross-sectional dependence (CD) test.[2] For each of the variables significant positive cross-sectional dependence is found. This is in line with the graphs in Ja&Si which show quite some similarities in the long-run pattern in σ_{it} and s_{it} over countries. O'Connell (1998) shows that ignoring significant cross-sectional dependence leads to incorrectly sized panel unit root tests, i.e. they are biased towards finding stationarity. Therefore, the fact that from the MW tests reported in Table 1 we are not able to reject the null hypothesis of a unit root even reinforces the argument that the data exhibit non-stationary behavior.

To control for time-varying factors affecting volatility that are common across countries, Ja&Si include a full set of time dummies. The top right panel of Table 1 therefore also reports unit root tests after projecting out time effects (model = constant + time dummies). This does not change the main conclusion with respect to the non-stationary behavior in the data. The null hypothesis of a unit root can still not be rejected for the HP and SW volatility measures using either the country-specific ADF tests or the MW panel test. For the labor share s_{it} the unit root hypothesis is again rejected for Canada and Japan, although here only at the 10% level, while now also rejected for Germany at the 2% level. As a result the MW panel test also rejects the unit root hypothesis at the 2% level of significance. The bottom right part of Table 1 shows that the time dummies are able to remove most of the positive cross-sectional dependence in the data. The small number of countries available to estimate the time effects even induces significant negative cross-sectional dependence. Clear positive cross-sectional dependence only remains in the error terms of the ADF test on the labor share variable. This implies that, given the resulting size bias referred to above, the rejection of the unit root hypothesis for this variable by the MW panel unit root test should be treated with caution.

Taking stock, the unit root tests show that the data used in Ja&Si exhibit non-stationary behavior. This is especially the case for the volatility measures but also the labor share variable is found to be non-stationary in some countries. Although this is in line with the permanent shifts

[2] We take first differences to avoid spurious non-zero correlation due to non-stationarity in the error terms when there is no cointegration. As the Pesaran (2004) CD test relies on the assumption of serial independence, an additional advantage of taking first differences is that it removes most of the serial correlation from the level error terms.

in these variables as documented by the plots in Ja&Si, theoretically both the labor share variable and the volatility measures cannot be pure random walk processes as they are bounded series while a random walk is unbounded. However, boundedness does not preclude non-stationary behavior. Nicolau (2002) for instance proposes a bounded random walk, whose path is indistinguishable from a pure random walk but is stochastically bounded. Moreover, even if the labor share variable and the volatility measures are truly stationary, but the unit root tests lack power to detect this, spurious regression results may still be obtained when there is strong persistence in the data induced by either near unit root behavior (see e.g. Cavanagh et al., 1995; Granger et al., 2001; Deng, 2013) or one or more permanent shifts in the mean of the otherwise stationary data generating process (see e.g. Noriega and Ventosa-Santaularia, 2006, 2007; Chu and Kozhan, 2011). The main message of the unit root tests is therefore that due to the strong persistence in the data one should be careful when interpreting the results of a regression of volatility on the labor share variable. Below we analyze the consequences of this finding for the estimation results in Ja&Si.

Regression results

The top left panel of Table 2 replicates the baseline coefficient estimates of 4.02 when using the HP volatility measure and 3.34 when using the SW measure reported by Ja&Si in their Table 4.[3] These results show that the volatile-age workforce participants have a strong and significant positive impact on business cycle volatility. In addition to results for a model with both individual and time fixed effects (FETE), as used by Ja&Si, we also report fixed effects (FE) estimation results to signify the difference. For the full G7 sample, excluding the time effects does not result in fundamentally different results, i.e. this only leads to slightly higher point estimates and slightly lower standard errors.

Insert Table 2 about here

Cointegration tests and spurious regression

Given the non-stationary behavior of the data detected above, Table 2 also includes country-specific ADF and MW panel cointegration tests using the estimated error terms $\widehat{\varepsilon}_{it}$ (see note to Table 2 for technical details). These results show that equation (1) is not a cointegrating relation as the null hypothesis of a unit root in ε_{it} cannot be rejected using either the country-specific ADF or the panel MW tests. This raises the question whether the strong correlation between demographics and volatility is spurious. Ja&Si do suggest themselves that the observed strong positive correlation could be spurious because of omitted non-stationary factors such as unstable oil prices and monetary policy in the 1970s. They argue however that the different evolution in demographics and volatility over countries, most markedly in Japan compared to the other countries, should avoid spurious correlation.

[3] Ja&Si also report results using an IV instead of a LS estimator to account for the possible endogeneity of the labor share variable. We experimented with the IV approach but this did not change the qualitative results.

The importance of a large number of independent cross-sections

Phillips and Moon (1999) indeed show that pooling over a *large number* of *independent* cross-sections attenuates the strong noise in the non-stationary residuals while retaining the strength of the signal. When using panel data, a consistent estimate of the long-run relation can thus be obtained even if there is no cointegration. Besides a sufficiently large cross-sectional dimension, an important condition for this asymptotic result to hold is that the error terms are independent over cross-sections (see also Urbain and Westerlund, 2011). The bottom left panel of Table 2 shows that although there are signs of cross-sectional dependence in the error terms this is not overwhelming especially when using the SW volatility measure. However, given the small cross-sectional dimension of the G7 panel dataset and some cross-sectional dependence the question remains whether the Phillips and Moon asymptotic result holds or whether the results are in fact spurious. In this respect, it is informative to see that the positive correlation disappears, and even becomes negative, when Japan is excluded from a model with both individual and time fixed effects. As the Phillips and Moon result builds on the fact that asymptotically the impact of a single country on the pooled panel estimates is negligibly small, the sensitivity of the results to the inclusion of Japan further suggests that the cross-sectional dimension of the panel is not large enough to cancel out the strong noise in the non-stationary error terms of the individual cross-sections.

3 Two datasets with a richer cross-sectional dimension

Accounting for cross-sectional dependence using the CCEP estimator

Banerjee and Carrion–i–Silvestre (2015) show that consistent estimation is again possible once cross-sectional dependence is controlled for using the pooled common correlated effects (CCEP) estimator of Pesaran (2006) and Kapetanios et al. (2011). In this approach, cross-sectional averages of the data are included to proxy for the unobserved (stationary and non-stationary) common factors. As such, the CCEP estimator is not only able to account for more general heterogeneous cross-sectional dependence, compared to the homogeneous pattern when using time fixed effects, but also allows for consistent estimation under very general integration properties of both the idiosyncratic errors and the unobserved common factors that generate the cross-sectional dependence. More specifically, both the idiosyncratic error terms and the common factors are allowed to be non-stationary. As consistency of the CCEP estimator requires the number of cross-sections to grow to infinity, in this section we look at two panels with a larger cross-sectional dimension than the G7 panel considered by Ja&Si.[4]

[4]We have also considered the more general mean group version of the CCE estimator. Across all specifications and datasets used below, the CCEMG estimates were found to vary substantially with very large standard errors. As such, we did not find a robust statistically significant relationship using the CCEMG. Results are available upon request.

The Lugauer and Redmond (EconLet, 2012) dataset for 51 countries

Lugauer and Redmond (2012) collect a balanced panel dataset for 51 countries over the period 1957-2000. GDP data from the Penn World Table (2009, version 6.3) are used to calculate output volatility, which is defined as the 9-year rolling standard deviation of log annual GDP, de-trended using the HP filter. Demographic data are taken from the United Nations World Population Prospects (2008). Following Ja&Si, the volatile-age labor share variable is defined as the fraction of the working age population aged 15 to 29 plus those aged 60 to 64.[5] Country-specific ADF unit root tests (not reported) after projecting out time fixed effects show that the null hypothesis of a unit root is rejected at the 5% level of significance in 3 countries for the volatility measure and in 14 countries for the age share variable. A MW panel unit root test rejects the unit root hypothesis for the age share variable but not for the volatility measure. This marked difference in time series behavior already suggests that demographics alone can probably not explain the stochastic trend in volatility in all of the included countries.

The FETE column in the upper left panel of Table 3 replicates the result in Lugauer and Redmond that the age distribution has an economically large impact on volatility, i.e. a 10% points increase in the share variable raises the standard deviation of cyclical output by 0.38, although the effect is only significant at the 10% level. The CCEP estimator yields an even larger estimate which is moreover significant at the 5% level. Cointegration tests (see note to Table 3 for technical details) show that only for a small number of countries this constitutes a cointegration relation while the panel MW test does not reject the null hypothesis of no cointegration. Despite the finding of no cointegration but given that the error terms of the FETE and CCEP regressions are found to be independent over cross-sections, the result in Banerjee and Carrion–i–Silvestre (2015) implies that these estimators should still yield consistent estimates. In this respect, only the FE estimate is not trustworthy as there is significant cross-sectional dependence left in the error terms.

Insert Table 3 about here

However, having a closer look at the data reveals that the estimates are driven by only a small number of countries. After removing 5 outlying countries (i.e. the Democratic Republic of the Congo, Nicaragua, Ethiopia, Nigeria and Mauritius) that exhibit very large swings in volatility, the relation between demographics and volatility completely disappears. More specifically, the FETE and CCEP estimates drop to 0.25 and 0.28 respectively and are no longer significant (more detailed results are available on request). As dropping specific countries is a somewhat ad hoc choice, Table 3 reports results of two alternative robustness checks. First, the middle panel shows that demographics also have no significant impact on volatility when using only the more homogeneous panel of OECD countries.[6] As a further robustness check, we use a more recent version of the Penn World Table (2012, version 7.1) and the 2012 revision of the World Population Prospects, but leave the sample period unchanged (1957 - 2000). The estimation results in the right panel

[5] Although these data are publicly available, we thank Steven Lugauer for kindly providing the original data.

[6] Note that the MW test on the error terms of the FE and FETE regressions rejects the null of no cointegration. This is due to the fact that for the OECD sample the MW test also rejects the null of a unit root in the HP volatility measure.

of Table 3 show that also data revisions remove the alleged strong relation between demographics and volatility. When looking at the countries that are subject to data revisions[7], among the 5 outlying countries that are argued above to drive the strong effect in the original dataset, 4 are also subject to substantial revisions to either the volatile-age share variable (Ethiopia and Nigeria) or the volatility measure (Mauritius) or both (the Democratic Republic of the Congo). This further strengthens the argument that the alleged signal in the large swings in the original data for these outlying countries may very well be noise resulting in a spurious relationship between volatility and demographics.

The Lugauer (ReStat, 2012) dataset for 50 U.S. states

Lugauer (2012) uses a panel of 50 U.S. states over the period 1981-2004. Output volatility is defined as in Lugauer and Redmond (2012), with state-level GDP data taken from the Bureau of Economic Analysis. Demographic variables are based on U.S. Census data. The age share variable used in the baseline regression is the *youth share*, defined as the fraction of the population aged 20 to 54 under the age of 35.[8] State-specific ADF unit root tests (not reported) after projecting out time fixed effects show that the null hypothesis of a unit root is rejected at the 5% level of significance in 1 state for the HP volatility measure and in 3 states for the youth share variable. For both variables, the null hypothesis of a unit root is not rejected using a MW panel unit root test.

Table 4 replicates the FETE estimate of 3.13 reported by Lugauer. Again this is not a cointegrating relation as the null hypothesis of a unit root in the error terms is rejected in only 1 out of the 50 states while the MW panel test does not reject the null hypothesis. Also note that the time dummies are now no longer able to remove all of the cross-sectional dependence. The CCEP estimate of 1.20 is much smaller but still significant at the 5% level. Interestingly, this estimator is able to remove all of the cross-sectional dependence with the MW test on the idiosyncratic part of the error term rejecting the null of no cointegration.

Insert Table 4 about here

Important to note is that the youth share used by Lugauer as demographic variable is different from the volatile-age share variable suggested by Ja&Si. As such, this variable does not capture the alleged U-shaped pattern of employment volatility as it excludes the youngest (15-19) and oldest (60-64) workers. As a first robustness check, in columns 5-7 of Table 4 we therefore present regression results when the demographic variable is defined as in Ja&Si.[9] The coefficient turns negative and, in the case of the FETE estimator, is even statistically significant. The CCEP regression is now no longer a cointegrating relation. In fact, the youth share used by Lugauer

[7]For the volatile-age share variable, data revisions are most pronounced for Bolivia, the Democratic Republic of Congo, Egypt, El Salvador, Ethiopia, Morocco, Nigeria, Pakistan and Turkey. For the volatility measure, the largest revisions occur for Australia, Colombia, the Democratic Republic of Congo, Mauritius, Morocco, South Africa, and Trinidad & Tobago.

[8]The data are available at the Review of Economics and Statistics Database: *http://hdl.handle.net/1902.1/19663*.

[9]To construct the volatile-age share variable we had to make us of the most recent Census revision. Replacing the original with the revised data but keeping the youth share definition did not notably change the results reported in columns 2-4 of Table 4.

is more in line with the theoretical model in Jaimovich et al. (2013), which only distinguishes between young and old workers. This distinction is motivated by the empirical observation that in the U.S., unlike in the other G7 countries, the cyclical volatility of the labor market activity of 60-64-years-old workers is not higher than that of 40-49-year-olds. For the 15-19 and 20-24-year-old workers, this sensitivity is five and two times that of 40-49-year-olds, respectively. For 25-29 and 30-39-year-olds volatility is only 1.6 and 1.4 times as large. Although for the U.S. this motivates the use of a youth share instead of the original volatile-age share, there is no clear motivation for why Lugauer excludes the 15-19-years-olds from his definition of the youth share. As a second robustness check, in columns 8-10 of Table 4 we therefore present regression results when the youth share is redefined as the fraction of the working age population accounted for by the 15-24-years-olds. Again a significant negative impact is found using the FETE estimator, while the CCEP estimator produces insignificant results. This finding is robust over alternative specifications of the youth share variable whenever this includes the 15-19-years-old workers.

4 Conclusion

This paper has replicated three important studies that find a large and significant impact of the age distribution of the workforce on cyclical output volatility. As each of these studies largely ignores the time series properties of the data, the aim of this replication paper is to investigate whether the reported strong impact signals a meaningful long-run relationship or is in fact spurious. We first show that the volatility measures and the labor share variable used by Ja&Si for the G7 countries exhibit non-stationary behavior. This is most pronounced for the volatility measures. We then argue that the reported long-run relationship between these variables in Ja&Si is not a cointegrating relation. This does not automatically imply that the results are not meaningful, though, as Phillips and Moon (1999) have shown that a spurious regression can be avoided when pooling over a large number of independent cross-sections. However, the small cross-sectional dimension of the G7 panel dataset in combination with the presence of some cross-sectional dependence raises doubts about whether this asymptotic result applies.

To shed further light on whether there is a stable long-run relation between business cycle volatility and demographics, we consider the richer datasets of Lugauer and Redmond (2012) and Lugauer (2012), including 51 countries and 50 U.S. states respectively. After replicating their results, we still find no clear evidence in favor of cointegration. Although the richer panel dimension allows the authors to pool over a larger number of cross-sections, cross-sectional dependence can still render their estimation results spurious (see Urbain and Westerlund, 2011). However, Banerjee and Carrion–i–Silvestre (2015) show that consistent estimation is possible once cross-sectional dependence is controlled for using the CCEP approach of Pesaran (2006). Remarkably, most of the CCEP estimation results do no longer show a significant relationship. This reinforces our argument that the strong correlation between demographics and business cycle volatility reported in the literature may be spurious rather than signaling a meaningful long-run relationship. This argument is further supported by the finding that, for each of the three datasets used in this replication, the estimation results are very sensitive to small changes in the composition of the sample, to data revisions, and to the exact definition of the volatile-age labor share variable.

Our finding that there is no cointegrating relation does not imply that demographics do not affect business cycle volatility. However, it does show that the current set-up of using a composite demographic change variable as the sole explanatory variable is probably too restrictive and more work is needed to come up with a satisfactory explanation for the Great Moderation and for shifts in volatility more in general.

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Table 1: Time series properties of the Jaimovich and Siu (AER, 2009) data

	Sample period: 1963-1999, unbalanced panel of G7 countries					
Model:	constant			constant + time dummies		
	σ_{it}		s_{it}	σ_{it}		s_{it}
	HP	SW		HP	SW	
Country-specific ADF unit root tests						
Canada	−0.88	−2.44	−3.87	−1.28	−2.33	−2.82
	[0.79]	[0.14]	[0.01]	[0.63]	[0.17]	[0.07]
France	−2.76	−2.38	1.40	−0.31	−0.56	−0.01
	[0.08]	[0.16]	[0.99]	[0.91]	[0.87]	[0.95]
Germany	−0.17	−1.45	0.41	−2.14	−1.27	−3.40
	[0.94]	[0.55]	[0.98]	[0.23]	[0.63]	[0.02]
Italy	−0.48	−1.28	−0.60	−0.54	−0.73	−1.80
	[0.88]	[0.63]	[0.84]	[0.85]	[0.81]	[0.37]
Japan	−1.26	−1.60	−4.64	−1.37	−1.43	−2.88
	[0.64]	[0.48]	[0.00]	[0.59]	[0.56]	[0.06]
U.K.	−0.34	−0.99	2.34	1.17	−1.57	−1.85
	[0.91]	[0.75]	[0.99]	[0.99]	[0.48]	[0.35]
U.S.	−0.42	−0.92	−1.63	−1.69	−2.02	−2.30
	[0.90]	[0.77]	[0.45]	[0.44]	[0.28]	[0.18]
Panel unit root tests						
MW	7.36	12.40	20.45	7.13	10.37	26.45
	[0.92]	[0.57]	[0.12]	[0.93]	[0.74]	[0.02]
Cross-sectional dependence in the error terms of the ADF regressions						
$\overline{\widehat{\rho}}$	0.11	0.13	0.21	−0.11	0.03	0.20
CD	2.92	3.28	4.94	−2.63	0.50	4.24
	[0.00]	[0.00]	[0.00]	[0.00]	[0.61]	[0.00]

Notes: 'Model = constant' refers to results for projecting out fixed effects while 'Model = constant + time dummies' refers to projecting out both fixed effects and time effects.

The lag length of the country-specific ADF unit root tests is selected using the Akaike information criterion with a maximum lag length of $\text{int}\{12\,(T\,/100\,)^{0.25}\}$. The ADF tests for the model with constant include a constant while for the model with constant and time dummies the data are first regressed on fixed and time effects and the residuals are next used to calculate the ADF statistics. The p-values are calculated from ADF distributions obtained from Monte Carlo simulations that take into account the number of observations available for each cross-section and the deterministic terms present in the model.

The MW panel unit root test is defined as $-2\sum_{i=1}^{N}\ln(p_i)$ where p_i is the p-value corresponding to the unit root test of the ith country.

The average cross-correlation coefficient $\overline{\widehat{\rho}} = (2\,/N\,(N-1)\,)\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}$ is the average of the country-by-country cross-correlation coefficients $\widehat{\rho}_{ij}$ (for $i \neq j$). The cross-sectional dependence CD test is defined as $\sqrt{2T\,/N\,(N-1)}\,\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}$, which is asymptotically standard normal under the null of cross-sectional independence.

p-values are in square brackets.

Table 2: The Jaimovich and Siu (AER, 2009) regression

	Sample period: 1963-1999, unbalanced panel of G7 countries							
	Full G7 sample				G7 sample excl. Japan			
	HP		SW		HP		SW	
	FE	FETE	FE	FETE	FE	FETE	FE	FETE
Estimation results								
γ	4.70	4.02	4.89	3.34	4.39	−0.34	4.24	−3.09
	(0.79)	(1.13)	(0.70)	(1.17)	(0.95)	(1.64)	(0.82)	(1.78)
Country-specific ADF cointegration tests								
Canada	−1.22	−1.15	−2.78	−2.35	−1.25	−1.31	−2.92	−2.35
	[0.70]	[0.73]	[0.09]	[0.19]	[0.69]	[0.66]	[0.07]	[0.19]
France	−1.01	0.11	1.40	−0.40	−1.11	−0.44	1.21	−0.72
	[0.78]	[0.98]	[0.99]	[0.93]	[0.74]	[0.92]	[0.99]	[0.86]
Germany	−1.62	−1.67	−0.92	−1.37	−1.60	−2.69	−0.77	−1.93
	[0.51]	[0.48]	[0.81]	[0.63]	[0.52]	[0.11]	[0.85]	[0.35]
Italy	−1.62	−2.21	−0.48	−1.82	−1.59	−0.50	−0.66	−1.33
	[0.51]	[0.25]	[0.91]	[0.41]	[0.53]	[0.91]	[0.88]	[0.65]
Japan	−2.15	−1.93	−2.11	−1.82				
	[0.26]	[0.35]	[0.27]	[0.41]				
U.K.	1.55	0.88	−2.68	−2.34	−0.17	0.40	−2.45	−1.90
	[0.99]	[0.99]	[0.12]	[0.21]	[0.96]	[0.99]	[0.17]	[0.38]
U.S.	−1.05	−1.48	−1.54	−1.84	−1.00	−1.52	−1.42	−1.82
	[0.76]	[0.58]	[0.55]	[0.39]	[0.78]	[0.56]	[0.61]	[0.40]
Panel cointegration test								
MW	7.26	8.16	13.73	13.06	4.56	6.90	10.69	10.38
	[0.92]	[0.88]	[0.47]	[0.52]	[0.97]	[0.86]	[0.56]	[0.58]
Cross-sectional dependence in the first-differenced error terms								
$\bar{\hat{\rho}}$	0.10	−0.15	0.06	−0.03	0.14	−0.17	0.08	−0.04
CD	2.35	−3.42	1.16	−0.93	2.65	−3.08	1.32	−1.12
	[0.02]	[0.00]	[0.25]	[0.35]	[0.01]	[0.00]	[0.19]	[0.26]

Notes: Newey-West standard errors in parentheses, p-values in square brackets.

The cointegration tests are ADF unit root tests on the estimated error terms $\widehat{\varepsilon}_{it}$ of the FE and FETE model. The p-values are calculated from ADF distributions obtained from Monte Carlo simulations that take into account the number of observations available for each cross-section, the deterministic terms present in the model, and the fact that this is a unit root test on error terms obtained from estimating a homogeneous panel data model instead of raw data.

See Table 1 for further notes.

Table 3: The Lugauer and Redmond (EconLet, 2012) regression

	Sample period: 1957-2000, balanced panel of 51 countries								
	Original sample, all ($N = 51$)			Original sample, OECD ($N = 22$)			Revised sample, all ($N = 51$)		
	FE	FETE	CCEP	FE	FETE	CCEP	FE	FETE	CCEP
Estimation results									
γ	7.71	3.84	5.99	4.47	2.19	0.01	5.77	−0.62	0.92
	(1.46)	(1.99)	(2.49)	(1.04)	(1.89)	(2.34)	(1.40)	(1.74)	(2.11)
Cointegration tests									
ADF: # $p_i < 5\%$	4	2	3	3	2	1	4	4	1
Panel MW	112.28	101.58	96.71	68.88	68.32	48.85	111.61	122.27	95.30
	[0.23]	[0.49]	[0.63]	[0.01]	[0.01]	[0.28]	[0.24]	[0.08]	[0.67]
r	–	–	4	–	–	2	–	–	4
Cross-sectional dependence in the first-differenced error terms									
$\bar{\hat{\rho}}$	0.04	0.01	−0.00	0.12	−0.03	−0.04	0.04	−0.00	−0.01
CD	8.72	1.54	−0.34	11.51	−3.43	−3.62	8.66	−0.09	−1.43
	[0.00]	[0.12]	[0.74]	[0.00]	[0.00]	[0.00]	[0.00]	[0.93]	[0.15]

Notes: Newey-West standard errors in parentheses, p-values in square brackets.

For the country-specific ADF cointegration test we report the number of countries for which the unit root hypothesis is rejected, i.e. for which the p-value p_i is smaller than 5%. As in Table 2, the p-values for the country-specific cointegration tests on the residuals of the FE and FETE regressions are calculated from simulated ADF distributions. For the CCEP estimator, the cointegration test is a unit root test on the idiosyncratic part of the error terms. Building on the PANIC approach suggested by Bai and Ng (2004), the idiosyncratic error terms are obtained by removing r common factors from the estimated error terms using principal components. The p-values can be calculated from the standard ADF distribution for the case of no constant (see Bai and Ng, 2004, p. 1135). The value of r is chosen to make sure that the idiosyncratic error terms are cross-sectionally independent. See Everaert (2014) for more details.

See Table 1 for further notes.

Table 4: The Lugauer (ReStat, 2012) regression

	Sample period: 1981-2004, balanced panel of 50 U.S. states								
	s_{it} = youth share $[20-34]/[20-54]$			s_{it} = volatile-age share $([15-29]+[60-64])/[15-64]$			s_{it} = youth share $[15-24]/[15-64]$		
	FE	FETE	CCEP	FE	FETE	CCEP	FE	FETE	CCEP
Estimation results									
γ	4.64	3.13	1.20	6.50	−2.92	−1.01	10.21	−5.10	−0.68
	(0.24)	(1.24)	(0.51)	(0.31)	(1.11)	(0.83)	(0.52)	(1.51)	(0.87)
Cointegration tests									
ADF: # $p_i < 5\%$	1	1	4	1	0	4	7	1	2
Panel MW	77.42	101.27	124.07	101.58	88.76	103.08	161.30	96.72	103.61
	[0.95]	[0.45]	[0.05]	[0.44]	[0.78]	[0.40]	[0.00]	[0.58]	[0.38]
r	-	-	2	-	-	2	-	-	2
Cross-sectional dependence in the first-differenced error terms									
$\bar{\hat{\rho}}$	0.44	0.06	0.00	0.39	0.06	−0.01	0.41	0.05	−0.00
CD	73.32	9.33	0.80	66.04	9.80	−1.30	68.67	8.86	−0.74
	[0.00]	[0.00]	[0.42]	[0.00]	[0.00]	[0.19]	[0.00]	[0.00]	[0.46]

Notes: Newey-West standard errors in parentheses, p-values in square brackets.

See Tables 1, 2 and 3 for further notes.