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Finance and growth: Time series evidence on causality☆

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ABSTRACT

This paper re-examines the empirical relationship between financial and economic development while (i) taking into account their dynamics and (ii) differentiating between stock market and banking sector development. We study the cointegration and causality between finance and growth for 22 advanced economies. Our time series analysis suggests that causality patterns depend on whether countries' financial development stems from the stock market or the banking sector. We show that stock market development tends to cause economic development, while a reverse causality is mostly present between banking sector development and output growth. These findings indicate that the direction of causality between finance and growth is likely to be different at high levels of development.

1. Introduction

The importance of the relationship between financial development and economic growth is well recognized in the growth and financial literature alike. Economic theory predicts that well-functioning financial intermediaries and markets reduce information asymmetries, facilitate risk sharing and mobilize savings, which leads to a more efficient resource allocation and, thus, may foster long-term growth.[1] A large empirical literature provides evidence that financial development matters for growth. However, there is less consensus as to whether the effect is mainly due to banks, stock markets or both. The "finance-led growth" hypothesis, according to which financial development exerts a positive and causal effect on real output is mainly supported in cross-country studies that focus on *bank* development proxies (King and Levine, 1993; Levine et al., 2000; Calderon and Liu, 2003; Christopoulos and Tsionas, 2004; Rioja and Valev, 2004; Loayza and Ranciere, 2006). Evidence when *stock market* development is also considered is more scarce or leads to less consistent results (Harris, 1997; Arestis et al., 2001).

This study provides new evidence that strengthens the notion that finance and growth co-move in a more complex way than previously thought. For this purpose, we investigate the relationship

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[1] Theoretical models that capture the different channels through which financial intermediaries have a positive impact on real output, have been developed, among others, by Greenwood and Jovanovic (1990), Levine (1991), Bencivenga and Smith (1991), Greenwood and Smith (1997), Blackburn and Hung (1998). Together with a positive finance-growth nexus, the destabilizing effect of stock market crashes and financial crises is also recognized (Minsky, 1974; Kindleberger, 1978), however its impact on long-term growth is less clear (Cerra and Saxena, 2008; Ranciere et al., 2008).

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between economic and financial sector - banking and stock markets - development for 22 advanced economies during the period 1973–2011. Our empirical strategy is motivated by recent theoretical contributions that stress how banks and stock markets may relate differently to economic development. These studies argue that, because banks and stock markets affect economic outcomes through different channels, their effectiveness depends on a host of country-specific factors such as the legal and contractual environment (Deidda and Fattouh, 2008; Song and Thakor, 2010), stage of development (Boot and Thakor, 1997) or new technologies available (Allen and Gale, 1999). Thus, the role of finance in real sector outcomes may differ depending on whether financial development stems from securities markets or the banking sector. To capture these different causality patterns, we explore the link between finance and economic development for each country in our sample, over time, by employing a framework in which both financial and economic development are treated as endogenous variables.

Our results show that causality patterns indeed differ across countries and, in particular, with the type of financial institution considered. We find that, among advanced economies, stock market development generally causes economic development, while the causality between banking sector development and growth goes in the reverse direction, most of the time. These results suggest that the extensive empirical evidence that finance causes growth is sensitive to the type and dominance of a particular financial institution. Our findings are robust to different estimations techniques and proxies for financial development. We use time series unit root and cointegration tests, as well as recent panel cointegration techniques, and distinguish between several notions of causality including long- and short-run causality. We find that the strong causal link between stock market development and GDP is present both in the short- and the long-term, while the reverse causality from real economic growth to banking sector development generally has a delayed effect.

Our research contributes to the finance-growth literature in several ways. First, we show that, among countries with relatively high levels of development, a finance-led growth hypothesis is supported only when financial development stems from security markets. Thus, the strong causal link between banking sector development and growth appears to vanish when we consider a time period in which financial sectors have developed intensively. Second, our results suggest that finance and growth might relate differently in advanced economies. Empirical evidence generally shows that both stock markets and banks tend to become more developed as economies grow and that securities markets tend to develop more rapidly than banks (Demirguc-Kunt and Levine, 2004). However, there is less consensus whether this financial system evolution matters for growth (Beck and Levine, 2002; Levine, 2002). Our findings show that, at higher levels of development, stock market development tends to have a causal impact on growth, while banking sector does not. Thus, the evolution of financial systems towards a more market-based structure does have an impact on real sector outcomes. These findings complement recent research that argues that not just the size, but also the structure of financial systems may matter for growth (Fecht et al., 2008; Luintel et al., 2008; Ergungor, 2008; Arestis et al., 2010; Demirguc-Kunt et al., 2012).

The remainder of this paper is organized as follows. Section 2 reviews theoretical and empirical contributions on this topic. Section 3 presents the variables and data used. Section 4 discusses the cointegration and causality tests employed and presents our main results and robustness checks performed. Section 5 concludes.

2. Motivation and previous research

Economists hold different opinions of the role of finance on economic growth and the developed theoretical literature mirrors these divisions. The theoretical underpinnings of this role can be traced back to Schumpeter (1934), who saw financial intermediaries as playing a pivotal role in output growth by channeling savings to the most productive investments. The alternative view is held by Robinson (1952), who argued that financial development simply follows economic growth which is generated elsewhere. Patrick (1966) characterizes these two possible relationships as the “supply-leading” and “demand-following” hypotheses. Both of his hypotheses, as well as possible interactions between them, have been further developed by, among others, Greenwood and Jovanovic (1990), Levine (1991), Bencivenga and Smith (1991), Greenwood and Smith (1997), Blackburn and Hung (1998).

While both banks and stock markets perform important functions which affect real sector outcomes, their relative effectiveness might not be the same depending on the economic and contractual environment of a country. A recent theoretical literature analyses how banks and financial markets can affect economic outcomes through different channels and how this impact might depend on structural characteristics of the economy. For example, the well-functioning of stock markets depends on how important is the value of market information in real sector outcomes. Boot and Thakor (1997) argue that severe moral hazard attenuates the value of this information feedback through prices. They show that, in economies prone to such severe information asymmetries, banks can actually provide a better resolution of post-lending moral hazard and improve real sector decisions. The technological characteristics of an economy or the degree of agency problems it faces can also influence the comparative importance of banks and stock markets. In particular, Allen and Gale (1999) show that securities markets are better at financing new industries and technologies in economies characterized by high information uncertainty and diversity of opinion. Furthermore, in Dewatripont and Maskin (1995), a more market-based system provides better financial discipline in the presence of adverse selection by not committing to fund unprofitable projects.

The relative merits of banks and stock markets also depend on the stage of economic development and, in particular, on the legal and institutional framework of a country. Rajan and Zingales (1998) argue that banks are more effective in weak legal systems with poor institutional infrastructure, whereas the well-functioning of stock markets relies on strong contractual environments and legal enforceability. This implies that market-based systems might prevail only at higher levels of development. Finally, the distribution of risk in the economy can also impact the link between finance and the real economy. Bolton and Freixas (2000) develop a model in which more mature and safe firms rely on equity markets, while small, riskier firms are better served by banks. Stock markets are also better at providing cross-sectional risk sharing, while banks allow for more inter-temporal risk-sharing (Allen and Gale, 1997). Fecht et al. (2008) show how this risk-sharing trade-off can lead to less investment in productive assets in bank-dominated economies and hence lower growth, as compared to market-based economies.

The arguments articulated in these theoretical models imply that the services provided by banks and stock markets should exert a different impact on economic activity at different levels of development or depending on a host of country-specific characteristics. Empirical research however, has mainly investigated the overall role of financial development in real sector outcomes, and is less precise on the relative importance of either type of financial institution.

A large body of cross-sectional and panel studies generally supports a positive link between finance and growth and mainly addresses the issue of causality using IV and GMM techniques (see King and Levine, 1993; Levine and Zervos, 1998; Levine et al., 2000; Beck et al., 2000; Beck and Levine, 2004). This cross-country literature finds evidence in line with a "financial-service" view in which the overall size of the financial sector, and not necessarily its structure, matters for growth (Levine, 2002; Beck and Levine, 2002). Time-series studies, however, show that these causality patterns may reflect only one side of the causal link (see Demetriades and Hussein, 1996; Arestis et al., 2001; Christopoulos and Tsionas, 2004; Ang, 2008; Luintel et al., 2008). Their results suggests that exploring the role of finance in economic development for a specific country, over time, may reveal causality patterns that cannot be inferred from pooled cross-sectional studies. One important caveat of pooling countries together in cross-sections is pointed out by Rioja and Valev (2004) who show that the link between finance and growth depends on the stage of economic development: highly and low developed economies are characterized by a weak link, while for developing countries, finance exerts a stronger influence on growth.

To address these issues of country-specific effects, time series research identifies causality on a country-by-country basis, while accounting for the dynamics and cointegration properties of data (Christopoulos and Tsionas, 2004). Among the first to explore causality in this framework were Demetriades and Hussein (1996) and Luintel and Khan (1999) who mainly find a bi-directional relationship between banking sector development and growth in a sample of developing countries. Their results suggest that pooling countries with different levels of financial development in cross-sectional regressions may well suggest simpler than actual dynamics between finance and growth. Arestis et al. (2001), recognizing the low power of the Johansen cointegration test in small samples, limit their research to five developed nations, but find significantly different causality patterns among them. Christopoulos and Tsionas (2004) try to overcome the issues of low availability of data over long periods of time using panel cointegration techniques. Their findings are restricted to banking sector development and support a unidirectional causality going from financial depth to growth. Generally, the low data availability of measures of stock market development has restricted most of the time-series research to bank development proxies (Demetriades and Hussein, 1996; Luintel and Khan, 1999; Rousseau and Wachtel, 1998; Rousseau and Vuthipadadorn, 2005; Ang and McKibbin, 2007).[2]

At the same time, when country-specific characteristics are taken into account, financial architecture also seems to matter (Arestis et al., 2001; Tadesse, 2002; Luintel et al., 2008). Luintel et al. (2008) show how, in assessing the role of financial structure on growth, cross-country data cannot be pooled due to significant cross-country heterogeneity. Tadesse (2002) finds that bank-based systems appear to be more effective in financially underdeveloped countries and in countries dominated by smaller firms, whereas market-based systems are more effective in financially developed countries and in economies dominated by larger firms. Furthermore, Demirguc-Kunt et al. (2012) find that, as economies grow, the marginal increase in economic activity associated with an increase in bank development falls, while the one associated with stock market development rises. Thus, as economies develop, stock markets generate more growth than banking sector development.

The foregoing evidence implies that banks and stock markets might relate differently to the real economy depending on the level of development. Since advanced economies are more likely to have a strong legal and institutional framework, be less prone to severe agency problems and value more the information feedback coming from securities markets, we expect the impact of stock markets to be stronger in economies with highly developed financial sectors. The setting of our analysis allows us to test this hypothesis. First, by looking at both types of intermediaries, we can test whether causality patterns between the two financial sectors and economic development differ. Second, since our sample includes a set of countries with relative high levels of stock market development, we can examine whether, indeed, the services provided by financial markets tend to contribute more to real outcomes at higher levels of development.

3. Data

Consistent with theoretical specifications and previous studies (Demetriades and Hussein, 1996; Levine and Zervos, 1998; Arestis et al., 2001; Beck and Levine, 2004), we define *economic development* as the logarithm of real GDP per capita (GDP). We measure *stock market development* by the logarithm of the *ratio of stock market capitalization to nominal GDP* (STOCK) in line with Rousseau and Wachtel (2000), Arestis et al. (2001) and Shen and Lee (2006). Stock market capitalization, which measures the overall size of stock market activity, ought to capture the importance of financing through equity issues in the capital mobilization and resource allocation process. However, measures of stock market activity and liquidity have also been found to be closely connected with economic activity (see, for example, Rousseau and Wachtel, 2000). As a result, we check the robustness of our findings using the *turnover ratio* defined as the value of the trades of shares divided by the total value of listed shares (market capitalization) (as in Beck and Levine, 2004).[3] The *development of the banking sector* is captured by the logarithm of *domestic bank credit to the private sector divided by nominal GDP* (CRED). Several other measures of bank development are used in the literature.[4] However, domestic credit is argued to be more robustly linked to output growth and is more widely used in recent studies (Arestis et al., 2001; Loayza and Ranciere, 2006; Luintel et al., 2008). Appendix Table A.1 provides additional details on the construction of variables and data sources, while Appendix Table A.2 provides some basic descriptive statistics.

The theoretical arguments put forward in the previous section suggested that banks tend to be more closely related to economic outcomes at lower levels of development, while stock markets should exert a higher impact in more economically developed countries. As a result, we focus our analysis on a large sample of advanced economies for which data on both bank and stock market development is available for long periods of time. We follow the 2013 FTSE Global Equity Index Series Country Classification which splits countries in four groups according to their level of stock market development. We limit our research to the first group, i.e. Developed Capital Markets, which contains 25 countries. These countries are assessed to have (i) a free and well-functioning

[2] Recent evidence that benefits from the availability of longer time series, in particular with regards to stock market data, has cast some doubts on the stylized positive relationship between financial development and growth. Shen and Lee (2006) find a negative relationship between bank development and growth, when controlling for the development of stock markets. Arcand et al. (2012) show that the relationship between financial development and economic growth turns negative for high levels of credit to GDP.

[3] We thank an anonymous referee for suggesting this robustness.

[4] These include the ratios of broad money (M2) and stock of liquid liabilities (M3) to GDP as measures of intermediary activity able to capture the notion of "financial depth".

equity market with formal stock market regulatory authorities that actively monitor it, (ii) no legal impediments to trading, (iii) sufficient liquidity and (iv) reasonable transaction costs. We eliminate three countries from this sample due to a lack of sufficiently long time series of data and we are left with a sample of 22 countries.[5] Our empirical strategy follows the country-by-country approach of time series studies such as Demetriades and Hussein (1996), Luintel and Khan (1999) and Arestis et al. (2001) who study developing and advanced economies using either annual or quarterly data. Our variables are measured quarterly in line with Arestis et al. (2001) and cover a time span of around 40 years (1973–2011).

4. Empirical analysis

In this section, we briefly present the econometric methods we use and the results we obtain. The empirical literature on finance and growth builds on three econometric approaches: pure cross-sectional OLS studies, time series estimations and panel data analysis employing GMM (see Ang, 2008; Beck, 2008; Valickova et al., 2014, for an overview). We perform a country-by-country time series analysis which enables us to take into account country specific conditions and the cointegration properties of data. This also allows us to disentangle causality patterns between different types of financial intermediaries and real output across countries.

4.1. Cointegration between financial and economic development

Time series research on the finance-growth nexus has centered around cointegration (Demetriades and Hussein, 1996; Luintel and Khan, 1999; Arestis et al., 2001; Christopoulos and Tsionas, 2004). Consistent with this literature, we use the Johansen (1988, 1992) maximum likelihood procedures to test for the presence of cointegration in a vector autoregression with n variables integrated of order one, of the form:

$$y_t = b_1 y_{t-1} + b_2 y_{t-2} + \ldots + b_k y_{t-k} + \Phi D_t + \varepsilon_t. \quad (1)$$

The *VAR(k)* in (1) can be rewritten as a vector error correction model:

$$\Delta y_t = \pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_{k-1} \Delta y_{t-(k-1)} + \Phi D_t + \varepsilon_t, \quad (2)$$

where y, in our case, is a vector with the three variables capturing economic development, stock market and banking sector development, i.e., y=(GDP STOCK CRED)', $\pi = \left(\sum_{i=1}^{k} b_i\right) - I_n$, $\Gamma_i = -(b_{i+1} - \ldots - b_k)$, (i=1,...,k-1), D_t is a set of deterministic variables such as a constant, trend and dummies, and ε_t is a vector of normally distributed errors with zero mean and constant variance.

We test for cointegration through the rank r of the π matrix using Johansen's (1988) maximum likelihood statistics: the trace statistic $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i)$ and the maximal-eigenvalue statistic: $\lambda_{\max}(r, r+1) = -Tln(1-\hat{\lambda}_{r+1})$, where $\hat{\lambda}$ is the estimated value of the i^{th} ordered eigenvalue of π. We test sequentially for the presence of an increasing number of cointegrating vectors r, in favor of the alternative that there are $r+1$ (for λ_{trace}) or more than r (for λ_{max}), until we cannot reject the null hypothesis.

We carry out a number of standard steps prior to testing for cointegration in this framework. These include verifying the integration properties of each variable, setting the optimal number of lags, parameterizing the deterministic component D_t and testing for structural breaks in the cointegrating relationship. We refer the reader to Appendix B for a more detailed account of these steps. Allowing for all these specifications assures us that the estimated VAR models are correctly specified. We thus check whether errors are independently, identically, and normally distributed, which allows us to derive the likelihood function for testing cointegration under the Johansen (1988) procedure. These diagnostics tests are presented in Appendix Table C. Generally, the estimated VAR for each country is well-specified and residuals are i.i.d. with a few cases in which the normality assumption is rejected, due to excess kurtosis. However, Hendry and Juselius (2001) argue that statistical inference is less sensitive to fat-tail distributions, under which parameter estimates are still consistent, but they may not be efficient.

Given all these specifications, we test for cointegration. The results are presented in Table 1. For brevity, we present only the trace statistic since the results of the maximum eigenvalue are qualitatively the same. When they differ, however, we put more weight on the trace statistic, which is more robust than the maximal eigenvalue in finite samples (Cheung and Lai, 1993). We find evidence of one cointegrating vector in all countries.[6]

Having established the presence of cointegration, the matrix π in Eq. (2) can be written as a product of two full rank matrices $\alpha \cdot \beta$', with the β matrix containing the cointegrating vectors and the coefficients of α representing the speed of adjustment to the equilibrium relationship. We just-identify the cointegrating vector by normalizing it on GDP. However, when the coefficients of CRED or STOCK are not statistically significant, we impose over-identifying restrictions on the coefficients in β, to test whether all variables enter the cointegrating relationship (Pesaran and Shin, 2002). When such restrictions are imposed, we verify whether they are supported by the data. Column 3 in Table 2 presents the log-likelihood statistic (LR) of these tests. All imposed restrictions are accepted by the data. As a result, not both measures of financial development enter the cointegrating vectors. More precisely, we find a stable long-term relationship between both measures of financial development and GDP in only six of the countries (see Table 2). Stock market development is positively related to GDP in 14 of them, while a positive stable relationship between CRED and GDP is present in 13 of the countries. Overall, this evidence is consistent with the cross-country literature and points towards a positive finance-growth nexus.[7]

Having established the stable, long-run relationship between our variables of interest, we proceed to testing the direction of causality among them.

4.2. Causality between financial and economic development

We test for a causal link between finance and growth in a simultaneous equation framework which allows us to uncover not only unidirectional causality, but also any potential bidirectional causality in which there is a feedback relationship between finance and economic development.[8] Time series evidence on causality between finance and growth generally focuses on long-term causal

[5] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, The Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, UK, USA.

[6] We discuss in Appendix B further robustness tests performed, as well as the specification of the cointegration tests when structural breaks are present.

[7] One exception is Singapore, where private credit enters negatively the cointegrating vector. This is surprising given the extensive financial liberalization undertaken in this country. However, stock market capitalization is positively related to GDP.

[8] Christopoulos and Tsionas (2004) use a different approach to test for a bi-directional causality with a FMOLS framework by regressing both economic growth

Table 1
Johansen cointegration test.

Johansen cointegration test for the VAR in Eq. (2). Variables included in the VAR: logarithm of real GDP per capita (GDP), logarithm of the ratio of stock market capitalization to nominal GDP (STOCK), logarithm of the ratio of private credit to nominal GDP (CRED). Lags refers to the number of lags of the VAR model in Eq. (1). *SB* denotes the presence of structural breaks in: Germany (1991Q1), Ireland (1996Q3, 2003Q1), Italy (1992Q4, 1996Q4), the Netherlands (1988Q4), Sweden (1989Q4, 2004Q2) and USA(1984Q3, 1994Q3). For these countries estimations are performed using the Johansen et al. (2000) methodology detailed in the Appendix B.

Country	Trace statistic under H_0= r			Lags	Sample
	r=0	r≤1	r≤2		
Australia	53.67**	10.61	3.17	2	1984–2011
Austria	30.57*	11.51	3.72	2	1973–2011
Belgium	45.29**	8.61	0.55	2	1980–2011
Canada	36.67*	17.29	6.75	3	1973–2007
Denmark	41.60**	14.38	2.48	3	1977–2011
Finland	37.39**	14.51	2.26	2	1988–2011
France	31.38*	12.70	3.52	1	1973–2011
Germany^{SB}	49.54**	19.40	7.20	3	1973–2011
Greece	29.82*	10.41	1.10	2	1988–2007
Ireland^{SB}	72.22**	25.39	5.20	2	1973–2011
Italy^{SB}	78.41**	38.07	17.90	2	1976–2011
Japan	52.63**	5.54	1.16	2	1979–2011
Netherlands^{SB}	67.09**	21.97	8.49	2	1977–2011
New Zealand	32.72*	12.78	2.16	3	1988–2011
Norway	35.80**	14.43	2.21	3	1981–2011
Singapore	39.08**	14.72	1.12	2	1975–2011
South Korea	66.44**	18.61	5.41	2	1987–2011
Spain	36.19**	14.99	4.85	3	1987–2007
Sweden^{SB}	80.42**	30.02	11.57	2	1982–2011
Switzerland	39.65**	10.35	2.57	2	1975–2011
UK	38.06**	8.69	2.41	2	1965–2011
USA^{SB}	51.73**	23.64	7.70	2	1973–2011

Critical values for the cointegration test are provided by Mackinnon et al. (1999).
* Rejection of the hypothesis at the 5% level.
** Rejection of the hypothesis at the 1% level.

links (Luintel and Khan, 1999; Arestis et al., 2001). However, short-term dynamics may also be important, as pointed out by recent evidence (see Loayza and Ranciere, 2006). In order to uncover the potential complex dynamics behind our variables of interest we perform a wide breadth of causality tests.

We first test for weak exogeneity. In the vector error correction model in (2), the equation determining ΔGDP_t when considering, for example, one cointegrating relationship and two lags, is written as:

$$\Delta GDP_t = \alpha_{11}ECT_{t-1} + \gamma_{11}\Delta GDP_{t-1} + \gamma_{12}\Delta STOCK_{t-1} + \gamma_{13}\Delta CRED_{t-1} + \varepsilon_{1t}, \quad (3)$$

where $ECT_{t-1} = \beta_{11}GDP_{t-1} + \beta_{12}STOCK_{t-1} + \beta_{13}CRED_{t-1}$ is the error correction term, i.e. the cointegration relationship between the variables. A test of the null hypothesis $H_0 : \alpha_{11} = 0$ is a test of weak exogeneity since a non-rejection of the null means the lags of the variables in the error correction term do not enter in the equation determining GDP, i.e. GDP is exogenous to the system.

Rejection of the null hypothesis means there is evidence of long run causality going from the variables in the ECT to GDP. Toda and Phillips (1993) propose testing weak exogeneity as a joint test on both the α and β coefficients. We follow this approach and impose restrictions on the β coefficients to identify the cointegrating relationships as well as on the α coefficients to test whether the variables in the cointegrating vectors also enter each of the error-correction equation. Thus, a test of long-run causality going from STOCK to GDP is a joint test $H_0 : \beta_{12} = \alpha_{11} = 0$. Rejection of the null hypothesis implies that there is a causal link going from stock market capitalization to GDP in the long run. However, long-run causality does not mean causality in the Granger sense since it does not take into account the short-run dynamics. Therefore, we perform a second causality test: a short-run Granger non-causality test on the γ coefficients in equation (3). In this case, a test of short-run causality going from stock market capitalization to GDP is a test of the null hypothesis: $H_0 : \gamma_{12} = 0$.

The third causality test we perform is a stronger notion of exogeneity which involves testing the joint hypothesis of short-run and long-run causality (Charemza and Deadman, 1992). Hence the null hypothesis is $H_0 : \gamma_{12} = \alpha_{11} = 0$. The rejection of the null hypothesis implies an overall causality from STOCK to GDP without distinguishing between long-term and short-term causality.

All previous tests are based on likelihood ratios that follow a χ^2 distribution as long as all the parameters of equation (3) can be rearranged as coefficients of I(0) variables at the same time. However, rearranging all the parameters as coefficients of I(0) variables assumes the cointegration rank has been accurately estimated. Toda and Yamamoto (1995) derive a causality test which does not require any prior knowledge of the order of cointegration of the variables. Their methodology proposes testing for causality in the level VAR equation, by fitting an augmented *VAR(p+d)* to the data, where d is the order of integration of the variables in the VAR with p lags. Toda and Yamamoto (1995) show that tests on the coefficients of the first p lags of such a model have standard asymptotic inferences which are assured by the additional lags added.

Our fourth causality test is the Toda and Yamamoto (1995) test on the augmented level VAR in Eq. (1) by one lag, since our variables are I(1). The equation determining GDP, for example, in a VAR(2) becomes:

$$GDP_t = b_{11}^{(1)}GDP_{t-1} + b_{12}^{(1)}STOCK_{t-1} + b_{13}^{(1)}CRED_{t-1} + b_{11}^{(2)}GDP_{t-2} + b_{12}^{(2)}STOCK_{t-2} + b_{13}^{(2)}CRED_{t-2} + b_{11}^{(3)}GDP_{t-3} + b_{12}^{(3)}STOCK_{t-3} + b_{13}^{(3)}CRED_{t-3} + \varepsilon_{1t}$$

and financial development on each other. In their study a unidirectional causality from financial depth to growth is found for a sample of developing countries.

Table 2
Cointegrating vectors.

Normalized cointegrating relationships based on the number of cointegration vectors in Table 1. Variables included in the VAR: logarithm of real GDP per capita (GDP), logarithm of the ratio of stock market capitalization to nominal GDP (STOCK), logarithm of the ratio of private credit to nominal GDP (CRED). LR test presents the p-value of a log-likelihood test under the null: H_0:β_{ij}=0, i.e. that variable *j* enters cointegrating relationship *i*. Non-rejection of this test means restrictions on the variables entering each cointegrating vector are binding.

Country	Cointegrating relationship	LR test
Australia	$C = GDP - \underset{[-27.4]}{0.53}\,CRED - 8.80$	0.99
Austria	$C = GDP - \underset{[-15.3]}{1.17}\,CRED - 7.46$	0.88
Belgium	$C = GDP - \underset{[-21.4]}{0.21}\,STOCK - 8.68$	0.64
Canada	$C = GDP - \underset{[-6.75]}{0.20}\,STOCK - 7.99$	0.69
Denmark	$C = GDP - \underset{[-10.7]}{0.11}\,STOCK - \underset{[-2.85]}{0.13}\,CRED - 10.81$	–
Finland	$C = GDP - \underset{[-10.3]}{0.29}\,STOCK - \underset{[-3.92]}{0.30}\,CRED - 9.84$	–
France	$C = GDP - \underset{[-8.79]}{0.09}\,STOCK - 8.67$	0.52
Germany	$C = GDP - \underset{[-3.33]}{3.26}\,CRED - 3.38$	0.08
Greece	$C = GDP - \underset{[-3.98]}{1.19}\,CRED - 7.66$	0.16
Ireland	$C = GDP - \underset{[-5.49]}{2.33}\,CRED - 10.52$	0.52
Italy	$C = GDP - \underset{[-3.75]}{0.09}\,STOCK - 8.50$	0.31
Japan	$C = GDP - \underset{[-8.31]}{0.30}\,STOCK - 8.26$	0.07
Netherlands	$C = GDP - \underset{[-33.5]}{0.61}\,CRED - 8.04$	0.06
New Zealand	$C = GDP - \underset{[-3.83]}{7.50}\,STOCK - 7.86$	0.65
Norway	$C = GDP - \underset{[-8.54]}{0.89}\,CRED - 10.62$	0.07
Singapore	$C = GDP - \underset{[-7.33]}{1.21}\,STOCK + \underset{[4.06]}{1.16}CRED - 8.56$	–
South Korea	$C = GDP - \underset{[-2.85]}{0.21}\,STOCK - \underset{[-2.37]}{0.67}\,CRED - 14.47$	–
Spain	$C = GDP - \underset{[-7.31]}{0.23}\,STOCK - 8.39$	0.99
Sweden	$C = GDP - \underset{[-6.58]}{0.10}\,STOCK - \underset{[-4.40]}{0.49}\,CRED - 10.34$	–
Switzerland	$C = GDP - \underset{[-15.8]}{0.78}\,CRED - 8.22$	0.40
UK	$C = GDP - \underset{[-5.80]}{0.36}\,STOCK - 8.13$	0.16
USA	$C = GDP - \underset{[-12.9]}{0.34}\,STOCK - \underset{[-3.27]}{0.70}\,CRED - 11.32$	–

t-Statistics in [].

Toda and Yamamoto (1995) show that a F-test with the null that the first two lags of STOCK are zero: $H_0 : b_{12}^{(1)} = b_{12}^{(2)} = 0$ is asymptotically distributed as $\chi^2(2)$. Again, rejection of the null hypothesis points to causality going from STOCK to GDP, in the Granger sense.

All the causality tests performed are presented in Appendix Table D. Given that the four tests capture different types of causality, results are not always consistent among them. We present a summary of all the causality tests in Table 3, where two (one) stars represents strong (weak) evidence of causality. We report a weak evidence of causality if half of the tests performed for a particular coefficient are significant at 5%. A higher number of significant tests and/or a stronger precision is reported as strong evidence of causality.

A clear pattern of causality can be observed in our sample of 22 advanced economies. On the one hand, evidence that bank development has an exogenous effect on GDP is present in only one country. On the other hand, we find strong evidence of reverse causality going from GDP to CRED in 16 of the countries. Looking at the causality patterns between stock market development and GDP, results are considerably different. Evidence of reverse causality is very scarce, with GDP causing STOCK in only three countries. The most compelling evidence points to a causal link going from stock market development to GDP, which is the case in 11 countries. Our results thus suggest a very weak support for a finance-led growth hypothesis, since *both* measures of financial development cause long-run economic development in only one country in our sample.

While most of the tests support a uni-directional causal link beween our two measures of financial development and GDP, we do find some evidence of a bi-directional link. This is consistent with the theoretical predictions of Greenwood and Jovanovic (1990) which model a feedback relationship in which the growth of economies leads to the development of a financial structure, which then leads to more efficient investment that will generate even further growth. We find a two-way causality between GDP and STOCK in four countries and between GDP and CRED in three. While a bi-directional link does not refute our overall conclusion, it does point to more complex dynamics than previously considered. For example, our conclusion of a bi-directional causality between GDP and CRED is mainly the result of a short-term causal impact of CRED on GDP, while GDP causes CRED mainly in the long-run. On the other hand, the bi-directional causality between GDP and STOCK appears stronger since it is supported by both short- and long-run dynamics (see Appendix Table D).

Overall, our results show an interesting pattern. The first notable implication is that countries experience rather different causality patterns and that these differences mainly stem from the type of financial institution considered. These results confirm previous time series research that stresses the significant heterogeneity in the finance-growth link, such as Demetriades and Hussein (1996), Luintel and Khan (1999), Arestis et al. (2001) or Luintel et al. (2008).

However, most of these findings are limited to proxies of banking sector development in developing countries (for example, Ang and McKibbin, 2007; Christopoulos and Tsionas, 2004; Luintel and Khan, 1999; Demetriades and Hussein, 1996). We show here that, among countries with relatively high levels of development, a supply-leading hypothesis is supported only when financial development stems from security markets. One exception is Arestis et al. (2001), who test for long-run causality in a sample of five advanced economies. Their weak exogeneity tests yields similar results to ours (for example in the case of US, UK or Germany), however our general conclusion is slightly different, due to the fact that our evidence of causality rests on a wider breath of tests that imply both short- and long-run causality.

The second implication of our results, i.e. that stock markets contribute more to economic growth at higher levels of financial development is echoed in several theoretical models (see Section 2). One particular channel through which securities markets may matter more for growth is through the financing of novel, innovative investments that rely more on intangible inputs. For example, Brown et al. (2009) and Brown et al. (2012) highlight the importance of equity finance for US and European firms' research and development spending.

Given the undeniable role of R&D investments in endogenous growth models, stock markets may be an important driver of growth, especially at higher levels of development. While our findings do not shed light on the particular channels through which market-based financial systems might contribute to higher growth, they provide empirical support for an increasing importance of stock markets. Indeed, our results suggest that, at higher levels of development, stock market development plays a causal

Table 3
Summary of causality tests.

Country	GDP→CRED	CRED→GDP	GDP→STOCK	STOCK→GDP	GDP↔CRED	GDP↔STOCK
Australia	**					
Austria	**		*			
Belgium	**					**
Canada				**		
Denmark	**			**		
Finland		**		**		
France	**			*		
Germany	*					
Greece				*	*	
Ireland	*					
Italy	**			**		
Japan	*			**		
Netherlands					*	**
New Zealand				*		
Norway			**		*	
Singapore	**		**			
South Korea	**					
Spain	**			**		
Sweden	**			**		
Switzerland	**					**
UK	**			**		
USA	**					**

Tables present the summary of the four causality tests shown in Appendix Table D.
"→"/"↔" symbolizes a unidirectional/bidirectional causality.
*/** represent a weak/strong evidence of causality. We consider the threshold for weak evidence of causality as half of the tests performed for a particular direction of causality being significant at 5%. A higher number of significant tests and/or a stronger precision is reported as strong evidence of causality.
GDP is the log of real GDP/capita, STOCK is the log of the ratio of stock market capitalization to nominal GDP, CRED is the log of the ratio of private credit to nominal GDP.

role in the growth of economies, while the banking sector does not. These findings complement those of Tadesse (2002) and Demirguc-Kunt et al. (2012), but bring a new perspective on how the finance-growth nexus is sensitive to the type of financial institution considered. Tadesse (2002) examines how industry-level performance varies in a cross-section of countries with different financial architectures. He finds that, depending on a set of country characteristics such as level of development or average firm size, market- or bank-based financial systems can disproportionately impact growth. We instead focus on the dynamics of financial development and its association with real economic performance over a long period of time. Demirguc-Kunt et al. (2012) also look at the evolving contribution of banks and markets to real sector outcomes, however they do not explicitly identify a causal impact.

Finally, since we find very little evidence that both measures of financial development have a causal impact on GDP, our findings suggest that the finance led-growth hypothesis requires modification. In particular, the strong causal link between banking sector development and growth appears to vanish when we consider a time period in which financial sectors have developed intensively. Rousseau and Wachtel (1998) document a strong causal link going from financial intermediaries to growth before the 1930's. We show that, at higher levels of financial development, this strong causality seems to vanish, and banking sector development simply follows that of the real economy. A theoretical intuition for this reversed effect is provided in Deidda (2006). He shows how, at high stages of development, financial intermediaries tend to become "too big" and their consumption of real resources offsets their contribution to economic growth.

The results summarized above reflect both a short- and long-term causal link. We also tested explicitly for short-term causality, given the recent evidence looking at the short-run impact of finance on growth (see Christopoulos and Tsionas, 2004; Loayza and Ranciere, 2006). Short-run Granger causality tests (SRG) are presented in Appendix Table D and support our general conclusion. However, two interesting patterns are worth highlighting. First, evidence of short-run causality between banking sector development and GDP is weak, at best. Thus, the causal link going from GDP to banking sector development highlighted above appears to be present mainly in the long-term.[9] This is in line with the findings in Christopoulos and Tsionas (2004) who look at causality between bank development and GDP in a sample of 10 developing countries. Second, and more interestingly, the strong causal impact of stock market development on GDP is reflected in the short-run, as well. The short-run coefficients of STOCK (not reported) are positive in all the countries, with the exception of two in which the coefficients are negative but not statistically significant. This distinction between short-run and long-run causality allows us to draw interesting policy implications. In particular, we argue that the design of policies that boost stock market development can positively impact output in both the short- and the long-run. On the other hand, the fact that economic growth tends to be followed, in the long-run, by an increase in the size of the banking sector, should also raise policy concerns about the implications of this growth in credit. For example, Greenwood and Scharfstein (2013) document that, in fact, the growth in financial intermediation in the US over the past three decades has mainly been driven by the expansion of household mortgage credit. At the same time, Beck et al. (2013) show that non-intermediation activities such as household credit are less correlated to economic performance. Given the significant social costs associated with excessive credit growth, policies should be designed towards facilitating the evolution of bank development in directions which bring a positive contribution to economic growth.

4.3. Robustness checks

We check the robustness of our results along several lines. First, the Johansen cointegration procedure can be prone to falsely reject the null hypothesis of no cointegration in small samples (Reinsel and Ahn, 1992). We thus check the robustness of the estimated cointegrating relationships using two alternative econometric techniques: the fully modified OLS (FMOLS) estimator and

[9] We thank an anonymous referee for suggesting this discussion.

panel unit roots and cointegration models. Second, we test the robustness of our main estimates using alternative measures of financial development.

4.3.1. FMOLS

We perform an alternative cointegration test proposed by Phillips and Hansen (1990) which corrects for finite-sample biases. The FMOLS procedure estimates cointegrating relationships by modifying the traditional OLS coefficients to account for endogeneity and serial correlation in the regressors. FMOLS is asymptotically equivalent to system methods like Johansen (1988), while it is less sensitive to lag lengths and performs better in small samples (Phillips and Hansen, 1990). We present the FMOLS estimators in Appendix Table E. Using this procedure we identify the same stable long-term relationship as with the Johansen procedure and test for cointegration by examining the stationarity of the error term obtained. The results of the ADF test on the residuals are presented in column 3 of Appendix Table E and generally confirm the stationarity of the residuals and, hence, of the estimated relationships.[10]

4.3.2. Panel cointegration and causality

We further test the robustness of our main results by implementing panel cointegration and causality tests. This methodological approach offers several advantages. First, we can, once again, correct for the Johansen small sample bias. Second, traditional panel techniques such as generalized method-of-moments (GMM) dynamic estimators generally require pooling individual cross-sections and only allow the intercept to differ across cross-sections. However, when dealing with panels where both the number of cross-sections and the time dimension are large, assuming a homogeneous slope may not be appropriate (see Pesaran and Smith, 1995; Im et al., 2003). Indeed, our country-by-country estimations in Section 4.1 suggest that the coefficients of bank and stock market development can be significantly different among countries. Panel cointegration techniques can allow for such heterogeneous cointegrating vectors to be present in each country. Lastly, GMM dynamic estimators would be a valid approach if our data were averaged across large time periods, such that the time dimension of the panel is small (as in, Levine et al., 2000; Beck and Levine, 2004). However, as we argue in Section 2, this may mask important dynamics. As a result, we follow novel estimation techniques for non-stationary heterogeneous panels (Canning and Pedroni, 2008).

The cointegration analysis of panel data consists of four steps which we briefly describe here. The first step rests in testing the integration properties of the panel data. To that end, we implement a panel unit root test proposed by Im et al. (2003) for each variable. This test allows each panel member to have a different autoregressive parameter and short-run dynamics. Appendix Table F1 presents the panel unit root tests. The null hypothesis of a panel unit root cannot be rejected for either of the three time series, while their first difference is stationary.

Having established that all our variables are $I(1)$, we test for panel cointegration. We follow the technique proposed by Pedroni (1999, 2004) which is robust to causality running in both directions, as our individual country tests suggest. Furthermore, this method also allows for both heterogeneous cointegrating vectors and short-run dynamics across countries which is, again, the case in our sample. More specifically, the cointegrating regression we estimate is:

$$GDP_{it} = \alpha_i + \beta_t + \gamma_i CRED_{it} + \delta_i STOCK_{it} + \epsilon_{it},$$

where we allow for country and time fixed effects. The residuals of this equation, ϵ_{it}, are then used to construct panel cointegration tests as proposed by Pedroni (1999, 2004). Pedroni (1999, 2004) develops two distinct tests. The first pools the autoregressive coefficients across countries and includes four statistics, while the second is based on averages of the individually estimated coefficients and includes three statistics (see Appendix Table F1). These tests confirm our previous results, since the null of no cointegration is rejected in six of the seven statistics proposed. Having confirmed the presence of a long-run relationship between the variables, we estimate this cointegrating relationship using the fully modified least square method (FMOLS) of Pedroni (2001). Using this method, we construct the error correction term: $\hat{\epsilon}_{it} = GDP_{it} - \hat{\alpha}_i - \hat{\beta}_t - \hat{\gamma}_i CRED_{it} - \hat{\delta}_i STOCK_{it}$. As a final step, following Canning and Pedroni (2008), we estimate the following error correction mechanisms:

$$\begin{aligned}
\Delta GDP_{it} &= c_{1i} + \lambda_{1i}\hat{\epsilon}_{it-1} + \gamma_{11i}\Delta GDP_{i,t-1} \\
&\quad + \gamma_{12i}\Delta STOCK_{i,t-1} + \gamma_{13i}\Delta CRED_{i,t-1} + \varepsilon_{1it} \\
\Delta CRED_{it} &= c_{2i} + \lambda_{2i}\hat{\epsilon}_{it-1} + \gamma_{21i}\Delta GDP_{i,t-1} \\
&\quad + \gamma_{22i}\Delta STOCK_{i,t-1} + \gamma_{23i}\Delta CRED_{i,t-1} + \varepsilon_{2it} \\
\Delta STOCK_{it} &= c_{3i} + \lambda_{3i}\hat{\epsilon}_{it-1} + \gamma_{31i}\Delta GDP_{i,t-1} \\
&\quad + \gamma_{32ij}\Delta STOCK_{i,t-1} + \gamma_{33i}\Delta CRED_{i,t-1} + \varepsilon_{3it},
\end{aligned} \tag{4}$$

where Δ denotes first difference.[11] Given that all variables in the error correction models in (4) are stationary, we carry out standard hypothesis tests on their coefficients. Evidence of causality in the Granger sense is a joint test on the coefficients of the error terms λ_{1i}, λ_{2i}, λ_{3i} and the short-term dynamics coefficients γ_i in each equation in (4). For example, a test that STOCK Granger causes GDP is the joint test: $\lambda_{1i} = \gamma_{12i} = 0$ for each country in our sample. This test is equivalent to the strong exogeneity test (SET) presented in Appendix Table D.

We present the causality tests for each country in Appendix Table F2. Results show the same patterns of causality: a mostly reverse causality between GDP and CRED, present in eight of the countries. At the same time, the strong evidence of causality going from STOCK to GDP is found in 15 of the countries also under this alternative estimation technique. While our general conclusion is supported under this alternative methodology, it should be noted that individual country causality tests are not always identical. The main reason for this is the manner in which these two tests are constructed. In the causality tests in Appendix Table F2, the error-correction term is constructed by including both financial development variables in the cointegrating relationship in all of the countries. The strong exogeneity tests in Appendix Table D are performed after over-identifying restrictions are imposed on

[10] Overall, the identified cointegrating relationships are similar to the ones estimated under the Johansen procedure. In a few cases, FMOLS coefficients are not significant where the Johansen coefficients were (for example, Greece and New Zealand). This may be caused by the fact that the FMOLS procedure assumes that the variables on the right hand-side of the equation, hence the proxies for financial development, are exogenous. This is not always the case, as the causality tests presented in Appendix Table D show. For this reason, we stress the importance of a simultaneous framework that allows for testing different feedback relationships. However, we estimate the FMOLS relationships using GDP as the explained variable just to allow for a consistent comparison with the Johansen normalized cointegration vectors.

[11] We estimate the error correction term allowing for one lag in the difference. We tested to higher order lags, but these were not significant.

the cointegrating vectors, thus after excluding, in certain countries, either STOCK or CRED from the cointegrating relationship.[12]

4.3.3. Alternative measures of financial development

Lastly, we check the robustness of our results with regards to the proxies for financial development. As discussed in Section 3, measures of stock market liquidity have been found to be more closely related to real sector output. We thus re-test the causality between financial development and GDP, using the turnover ratio as a proxy for financial development. However, this measure is not available for all the countries in our sample for a sufficiently long time span and, as a result, we present the findings for a restricted sample of 17 countries. Results are reported in Appendix Table G and are broadly similar to our baseline tests. We, once again, find significant evidence of reverse causality from CRED to GDP in 12 of the countries. There is less evidence of causality going from the turnover ratio to GDP, which is present in only two of the countries, however we do find stronger evidence in favor of a bi-directional causality, present in six of the countries. Reverse causality is also found in three cases, the same as in our main results. These slight differences can be attributed to the significantly smaller sample size for which the turnover ratio is available (the late 1980s for most countries). Nevertheless, our key findings still hold using this alternative proxy: bank development mostly follows that of the real economy, while stock market development appears to exert a stronger causal impact on GDP.

5. Conclusions

The growing importance of financial institutions over the past decades has fueled a large body of research over its effects on economic development. Despite the fact that the finance-growth nexus has been extensively analyzed, recent evidence and events have challenged many of the stylized facts derived during the 1990s.

This paper contributes to the finance-growth literature by presenting evidence that causality patterns between finance and growth differ depending on whether financial development stems from the banking sector or stock markets.

We study the time series properties of economic and financial development for a sample of 22 advanced economies. We find that stock market development exerts a causal impact on GDP in 11 of the countries in our sample, while a reverse causal link is present between economic and bank development in 16 countries. These results suggest that the finance-led growth hypothesis derived from cross-country studies might be different in developed economies, where only stock markets tend to have a causal impact on growth. The impact of banking sector development, on the other hand, appears less strong at high levels development, result which is also echoed in Shen and Lee (2006) and Arcand et al. (2012) who focus on the sign rather than the direction of causality. Our results confirm the need to reassess the causal link between the finance and growth; the general notion that finance causes growth may no longer be empirically valid when looking at advanced economies and both types of financial sectors. These findings complement recent research that suggests that not just the size, but also the structure of financial systems may matter for growth (Fecht et al., 2008; Luintel et al., 2008; Ergungor, 2008; Arestis et al., 2010; Demirguc-Kunt et al., 2012). Further empirical research may be directed towards disentangling the mechanisms through which the two different types of financial institutions impact real sector outcomes. For example, Beck (2008) shows that banks disproportionally help the growth of small firms, Strieborny and Kukenova (2013) argue that they promote growth by facilitating investment in relationship-specific assets, while Brown et al. (2009) and Brown et al. (2012) find evidence that stock markets lead to more funds being directed towards innovative, young companies, as well as, more investment in R&D. Research along these lines can lead to the formulation of policies that shape the development of financial institutions in directions in which their contribution to economic growth is the highest.

[12] Despite these different methodological approaches to testing causality, note that only 22 of the 88 tests performed using the panel causality approach do not match their equivalent strong exogeneity tests presented in Appendix Table D. Nonetheless, we have further checked the robustness of these results by re-estimating the causality tests for several sub-samples. First, we exclude the 2007-2009 financial crisis window from our analysis. Second, we consider a sub-sample in which financial sectors have developed extensively, and include only the period 1990Q1- 2011Q4 in our panel. Finally, we have re-estimated the panel causality tests for a sub-sample between 1973 to 2000. These robustness tests give the same qualitative results and are available from the authors.

Appendix A. Main variables definitions, sources and descriptive statistics

Table A.1
Definitions and sources of data.

Variable	Definition	Source
Real GDP* (GDP)	Logarithm of real GDP per capita (seasonally adjusted)	Authors' calculation based on nominal GDP data extracted from IMF-IFS Database, CPI and population data obtained from Datastream
Stock Market Capitalization (STOCK)	Logarithm of the ratio of stock market value to nominal GDP	Stock market value was obtained from Datastream (code: TOTMK...(MV))
Domestic Bank Credit (CRED)	Logarithm of the ratio of private sector bank credit to nominal GDP	Credit granted by banks to the private sector obtained from Bank of International Settlements Database: Long series on total credit and domestic bank credit to the private non-financial sector

* GDP data is seasonally adjusted, either from source or by the authors using the U.S. Department of Commerce quarterly seasonal adjustment method, X-12.

Table A.2
Descriptive statistics.

Variable	Mean	Std. dev.	Max	Min
Log real GDP/capita	9.543	1.572	15.51	7.858
Private Credit/GDP	3.348	1.668	8.320	0.401
Stock market capitalization/GDP	2.199	2.246	11.88	0.002

Appendix B. Johansen Cointegration

In this appendix, we discuss some of the caveats that the Johansen cointegration method faces in empirical applications and detail the steps we carry out prior to testing cointegration in this framework.

First, we test the integration properties of each variable using the Augmented Dickey-Fuller (ADF) as well as the Kwiatkowski et al. (1992) (KPSS) procedures. The null hypothesis of a unit root, in the presence of an intercept, cannot be rejected for any of variables considered in all the countries. Furthermore, all series are I(0) in the first difference.[13]

Second, since the Johansen method has been shown to be sensitive to the lag length, we determine the proper number of lags using the Akaike (1974) and Schwarz (1978) information criteria. Hendry and Juselius (2001) argue that the lag length ought to be set such that the VAR residuals are free of autocorrelation, even if this implies longer lags than suggested by the information criteria. We follow both approaches to estimate the optimal lag length. However, if the information criteria suggest a lag length for which autocorrelation is still present, we set the number of lags such that the VECM residuals are uncorrelated, as the Johansen method proposes. As a robustness check, we re-test for the number of cointegrating vectors when different lag length are allowed. Generally, results are qualitatively the same.

Next, we parameterize the deterministic component D_t in equation (1). We allow for an unrestricted constant in the VAR which accounts for linear trends in the level data, but not for a trend in the cointegrating relationship. This unrestricted constant can be decomposed to allow for both linear trends in the data generating process and a non-zero intercept in the cointegrating vectors (Hendry and Juselius, 2001). Our data is best represented by this specification since the log variables are trending over time, while the cointegrating relationship does not present a trend in most cases. Exception are in the case of Canada, Korea, Singapore, Spain and UK, where we allow for a more relaxed assumption and restrict the constant term to lie in the cointegrating space, but we assume no linear deterministic trend in the data. Furthermore, D_t can also include unrestricted (innovational) dummies added to whiten the residuals. Following Hendry and Juselius (2001), we detect outliers larger that three standard deviations, for which we introduce unrestricted impulse dummies.[14]. The introduction of impulse dummies leaves the asymptotic distributions of the cointegration model unaffected, while ignored innovational dummies have only minor consequences for small sample inferences of the cointegration rank (Bohn Nielsen, 2004).

Finally, we investigate the presence of structural breaks in the cointegrating relationships since various policy changes and macroeconomic events could have resulted in a structural break in the cointegrating relationship.[15] The presence of structural breaks in the model generally leads to an over-rejection of the null of cointegration. We address this issue by applying the Hansen and Johansen (1999) methodology of identifying structural breaks in the cointegrating relationship based on recursively estimated eigenvalues. The test consists in recursively estimating the eigenvalues of the β matrix and comparing them to the full-sample estimate. This recursive analysis can be regarded as a misspecification test to detect possible instabilities in the parameters when there is no prior knowledge of structural breaks in the parameters (Hansen and Johansen, 1999). Denote by $\lambda_i^{(\tau)}$ the i^{th} eigenvalue based on a sub-sample from the first τ observations only and let $\xi_i^{(\tau)} = \log\left(\frac{\lambda_i^{(\tau)}}{1-\lambda_i^{(\tau)}}\right)$. The test statistic compares $\xi_i^{(\tau)}$ to the full sample $\xi_i^{(T)}$, for every τ. Whenever the two values are significantly different, the null hypothesis of parameter stability is rejected. Using this methodology, we identify breaks in the cointegrating relationship in the following countries (dates): Italy (1992Q4, 1996Q4), Ireland (1996Q3, 2003Q1), Germany (1991Q1), the Netherlands (1988Q4), Sweden (1989Q4, 2004Q2) and USA(1984Q3, 1994Q3). These breaks correspond to major macroeconomic events like the German reunification (1991), Italy's exit from the ERM (1991), Sweden's credit crisis (1990) or important policy measures like the sudden tightening of monetary policy in the US (in 1984 and again in 1994). Furthermore, we tested whether our results are sensitive to including the period of the financial crisis. This is the case for Greece and Spain, for which we exclude the period after 2007Q3.

After breaks in the cointegrating relationship have been identified, we test for cointegration following the Johansen et al. (2000) procedure which restricts step dummies corresponding to these break dates in the contegrating space. Evidence of one cointegrating vector is found in all of the countries where structural breaks are present. However, since these added step dummies should not impact the direction of causality, the estimations for the causality tests presented in Appendix Table D do not include the step dummies.[16]

[13] Results are available upon request.

[14] The list of impulse dummies introduced for each country is not presented here, but can be obtained from the authors.

[15] We thank an anonymous referee for suggesting this robustness.

[16] These tests have been implemented using the JMulti Econometric package. Results are available upon request.

Appendix C. Diagnostics tests

Table C
Diagnostic tests for the vector autoregressive (VAR) models.

The Lagrange Multiplier is a test of residual autocorrelation under the null of no serial correlation at the lag order in Table 1. Columns 2 and 3 present the multivariate extensions of the Jarque-Berra residual normality test, under the null that the third (column 2) and fourth (column 3) moments of the residuals are comparable to those from the normal distribution. The joint test of residual normality for the three vectors in the VAR is presented in the last column, under the null hypothesis that residuals are multivariate normal.

Country	Lagrange multiplier test	Skewness	Kurtosis	Jarque-Berra
Australia	7.38 [0.60]	6.96 [0.07]	1.75 [0.62]	8.71 [0.19]
Austria	9.96 [0.35]	6.40 [0.09]	37.5 [0.00]	43.9 [0.00]
Belgium	12.4 [0.19]	8.39 [0.04]	4.16 [0.24]	12.6 [0.06]
Canada	12.6 [0.17]	62.5 [0.00]	215 [0.00]	278 [0.00]
Denmark	6.89 [0.64]	6.70 [0.08]	3.10 [0.37]	9.80 [0.13]
Finland	5.47 [0.79]	0.99 [0.80]	10.1 [0.02]	11.1 [0.08]
France	11.5 [0.24]	28.6 [0.00]	84.2 [0.00]	112 [0.00]
Germany	15.2 [0.08]	14.9 [0.01]	35.3 [0.00]	113 [0.00]
Greece	3.68 [0.93]	7.04 [0.07]	5.67 [0.13]	121 [0.00]
Ireland	9.97 [0.35]	6.46 [0.10]	4.53 [0.21]	11.0 [0.09]
Italy	6.92 [0.64]	7.56 [0.06]	5.18 [0.16]	12.7 [0.05]
Japan	10.4 [0.31]	2.88 [0.41]	4.49 [0.21]	7.38 [0.28]
Netherlands	10.7 [0.29]	4.13 [0.24]	33.5 [0.00]	37.7 [0.00]
New Zealand	14.5 [0.10]	3.42 [0.33]	3.75 [0.28]	7.17 [0.30]
Norway	9.13 [0.43]	3.86 [0.27]	0.39 [0.94]	4.26 [0.64]
Singapore	8.34 [0.50]	6.07 [0.10]	21.4 [0.00]	27.5 [0.00]
South Korea	3.57 [0.93]	1.35 [0.71]	5.95 [0.11]	7.31 [0.29]
Spain	12.1 [0.21]	9.85 [0.02]	22.6 [0.00]	32.5 [0.00]
Switzerland	12.8 [0.16]	8.42 [0.04]	39.9 [0.00]	48.4 [0.00]
Sweden	8.94 [0.43]	4.74 [0.19]	2.73 [0.43]	7.47 [0.27]
UK	11.8 [0.22]	4.33 [0.22]	374 [0.00]	379 [0.00]
USA	8.94 [0.43]	4.74 [0.19]	2.73 [0.43]	7.47 [0.27]

Figures in brackets represent *p*-values associated with the tests.

Appendix D. Main causality tests

Table D
Main causality tests.

Country	GDP→ CRED				CRED→ GDP				GDP→ STOCK				STOCK→ GDP			
	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y
Australia	38.7**	0.53	43.5**	2.65	2.34	0.21	2.47	0.23	1.22	0.07	1.91	1.15	-	3.71	-	5.80
Austria	13.5**	1.85	13.8**	1.71	0.12	0.15	0.30	1.66	5.02*	4.85*	8.01*	4.27	-	5.11*	-	3.57
Belgium	12.2**	3.65	13.1**	9.92**	-	1.65	-	3.34	0.29	7.25**	7.33*	8.19*	9.43**	1.93	14.1**	4.01
Canada	0.39	1.25	1.43	1.26	-	1.51	-	0.99	0.33	4.25	4.26	0.78	11.7**	2.50	18.8**	10.1**
Denmark	9.73**	14.1**	43.6**	30.6**	3.20	0.89	4.77	2.13	4.26*	4.22	5.78	1.89	3.20	6.45*	14.6**	12.5**
Finland	0.24	0.72	0.77	0.10	17.2**	0.07	17.6**	1.28	2.58	1.38	3.06	1.26	17.2**	1.32	28.5**	17.4**
France	8.61**	3.81	10.5**	2.45	-	1.08	-	0.63	1.86	0.02	2.04	0.75	6.88**	1.02	7.93*	2.48
Germany	1.64	6.99*	12.1**	6.74	2.95	2.19	11.8**	6.06	0.00	3.31	6.55	5.32	-	4.74	-	5.84
Greece	2.29	5.39*	5.40	7.06*	12.0**	0.27	22.0**	1.28	0.01	0.89	1.53	2.08	-	9.04**	-	10.6**
Ireland	5.45*	0.01	7.33*	2.70	0.01	2.53	3.21	1.01	5.12*	2.75	5.39	4.89	-	0.32	-	0.22
Italy	17.2**	1.77	23.7**	2.18	-	0.05	-	1.41	0.11	1.74	1.75	4.17	15.2**	0.36	15.5**	2.37
Japan	7.43**	1.17	7.49*	4.80	-	0.03	-	0.05	0.25	2.18	2.23	2.26	13.9**	1.29	18.8**	6.81*
Netherlands	22.2**	0.60	28.6**	5.84	0.57	6.35*	6.53*	3.31	7.80*	10.8**	14.0**	7.29*	-	13.3**	-	13.7**
New Zealand	0.10	0.31	0.40	2.70	-	1.14	-	7.36	1.96	1.76	3.33	1.71	7.54**	1.74	9.39*	7.65
Norway	12.8**	2.43	19.9**	1.98	0.27	8.44*	8.50*	4.91	0.06	9.62**	10.1**	14.3**	-	1.56	-	2.24
Singapore	11.7*	3.37	13.7**	3.45	0.41	0.07	0.52	0.32	9.70**	15.8**	22.6**	15.6**	0.40	0.01	0.42	0.57
South Korea	7.57**	2.08	10.7**	0.64	3.20	0.03	3.21	0.97	2.34	0.01	2.36	1.78	3.20	0.84	5.18	1.85
Spain	4.27*	17.9**	18.2**	10.4**	-	3.32	-	2.41	0.22	1.32	1.34	5.58	18.2**	7.08*	28.8**	10.4*
Sweden	11.7**	5.42*	27.7**	8.31*	0.03	1.59	1.75	1.87	0.06	0.68	0.69	2.36	0.03	6.07*	6.44*	10.0**
Switzerland	8.32**	1.01	8.48*	0.33	0.01	0.01	0.01	4.12	15.4**	7.81**	19.4**	2.55	-	7.41**	0	8.84*
UK	2.56	26.9**	27.8**	5.35	-	7.47**	-	5.69	0.25	2.97	3.30	0.81	22.6**	0.80	25.4**	10.3**
USA	0.01	23.1**	23.2**	22.9**	0.19	2.73	3.15	2.72	14.7**	1.05	15.8**	0.27	0.19	17.6**	19.6**	18.5**

Table presents the log-likelihood statistics of the causality tests distributed $\chi^2(1)$ for the statistics that are not underlined, $\chi^2(2)$ for the statistics underlined with one line and $\chi^2(3)$ for the statistics underlined with two lines.
GDP is the log of real GDP/capita, STOCK is the log of the ratio of stock market capitalization to nominal GDP, CRED is the log of the ratio of domestic credit to nominal GDP.
WEX is the weak exogeneity test under the null: $H_0 : \alpha_{ij} = \beta_{ij} = 0$.
SRG is the short-run Granger causality test under the null: $H_0 : \Gamma_{ij}^p = 0$, distributed $\chi^2(1)$.
SET is the strong exogeneity test under the null: $H_0 : \Gamma_{ij}^p = \alpha_{ij} = 0$.
T&Y is the Toda & Yamamoto(1995) causality test for level VARs.
* Represent significance at 5% level.
** Represent significance at 1% level.

Appendix E. Robustness checks: FMOLS estimation

Table E
FMOLS estimates.

The estimated system is: $x_t = \gamma z_t + u_{1t}$; $z_t = z_{t-1} + u_{2t}$, where x_t is the normalized variable, GDP in the first cointegrating relationship and STOCK\ CRED in the second and z_t is a vector of the other variables. The fully modified OLS estimate of γ is: $\gamma_{FMOLS} = \left(\sum_{t=1}^{T} z_t^2\right)^{-1} \left[\left(\sum_{t=1}^{T} x_t^{+} z_t\right) - T\widehat{\delta^{+}}\right]$, where $x_t^{+} = x_t - \hat{\omega}_{12}\hat{\omega}_{22}^{-1}\Delta z_t$, $\hat{\delta}^{+}$ is the bias correction term: $\hat{\delta}^{+} = \hat{\Lambda}\begin{bmatrix} 1 \\ -\hat{\omega}_{22}^{-1}\hat{\omega}_{21} \end{bmatrix}$, $\hat{\Lambda} = \sum_{k=0}^{\infty} E(u_{20}u'_k)$ and the long-run variance is $\Omega = \left\{\omega_{i,j}\right\}_{i,j=1,2}$. ADF is the Augmented Dickey-Fuller test under the null of a unit root in the FMOLS residuals.

Country	Cointegrating relationship	ADF test
Australia	$C = GDP - \underset{[-20.8]}{0.44}\,CRED - 8.90$	0.01
Austria	$C = GDP - \underset{[-24.9]}{0.89}\,CRED - 7.75$	0.02
Belgium	$C = GDP - \underset{[-16.6]}{0.19}\,STOCK - 8.70$	0.09
Canada	$C = GDP - \underset{[-19.7]}{0.18}\,STOCK - 7.88$	0.02
Denmark	$C = GDP - \underset{[-15.8]}{0.12}\,STOCK - \underset{[-3.88]}{0.13}\,CRED - 10.82$	0.01
Finland	$C = GDP - \underset{[-14.6]}{0.19}\,STOCK - \underset{[-11.7]}{0.44}\,CRED - 9.27$	0.01
France	$C = GDP - \underset{[-18.3]}{0.12}\,STOCK - 8.68$	0.01
Germany	$C = GDP - \underset{[-10.1]}{1.37}\,CRED - 6.78$	0.08
Greece	$C = GDP - \underset{[-1.51]}{0.08}\,CRED - 8.09$	0.01
Ireland	$C = GDP - \underset{[-3.07]}{0.86}\,CRED - 10.3$	0.08
Italy	$C = GDP - \underset{[-21.5]}{0.21}\,STOCK - 8.60$	0.01
Japan	$C = GDP - \underset{[-6.62]}{0.34}\,STOCK - 8.28$	0.10
Netherlands	$C = GDP - \underset{[-33.7]}{0.60}\,CRED - 8.05$	0.01
New Zealand	$C = GDP - \underset{[-1.76]}{0.09}\,STOCK - 9.04$	0.65
Norway	$C = GDP - \underset{[-9.85]}{0.58}\,CRED - 10.9$	0.05
Singapore	$C = GDP - \underset{[-12.9]}{0.87}\,STOCK + \underset{[0.31]}{0.04}CRED - 8.04$	0.01
South Korea	$C = GDP - \underset{[-9.97]}{0.32}\,STOCK - \underset{[-7.42]}{0.92}\,CRED - 13.6$	0.01
Spain	$C = GDP - \underset{[-15.0]}{0.28}\,STOCK - 8.33$	0.01
Sweden	$C = GDP - \underset{[-11.0]}{0.12}\,STOCK - \underset{[-3.51]}{0.27}\,CRED - 10.65$	0.15
Switzerland	$C = GDP - \underset{[-15.3]}{0.71}\,CRED - 8.36$	0.02
UK	$C = GDP - \underset{[-11.6]}{0.35}\,STOCK - 7.89$	0.05
USA	$C = GDP - \underset{[-19.5]}{0.31}\,STOCK - \underset{[-3.61]}{0.44}\,CRED - 11.1$	0.01

t-statistics in [].

Appendix F. Robustness checks: panel cointegration

Table F1
Panel unit root and cointegration tests.

Panel unit root test Im et al. (2003)

Variables	Level	First difference
GDP	0.67	−26.4**
STOCK	0.11	−43.4**
CRED	0.74	−15.4**

Table F1 (*Continued*)

Panel cointegration test Pedroni (2004)

Panel v	0.24
Panel ρ	−6.75**
Panel PP	−5.80**
Panel ADF	−4.13*
Group ρ	−2.73**
Group PP	−3.26**
Group ADF	−1.89*

The first panel presents the Im et al. (2003) test under the null that the series presents a unit root. The second panel presents the Pedroni (2004) panel cointegration test under the null of no cointegration. The first four statistics are constructed by pooling the autoregressive coefficients across countries, while the last three are based on the averages of the individually estimated coefficients.

* Represent significance at 5% level.

** Represent significance at 1% level.

Table F2
Panel causality tests.

Country	GDP→ CRED	CRED→ GDP	GDP→ STOCK	STOCK→ GDP
Australia	1.74	1.11	0.65	5.74**
Austria	0.47	0.59	3.10*	2.13
Belgium	2.90	4.40*	1.84	4.47*
Canada	4.64*	2.03	0.99	4.75**
Denmark	8.97**	1.90	2.12	4.04*
Finland	4.01*	1.61	0.33	6.24**
France	0.87	0.32	2.59*	0.22
Germany	0.31	1.87	0.48	0.93
Greece	9.98**	12.5**	1.64	13.7**
Ireland	3.65*	2.19	0.29	1.41
Italy	9.29**	4.18*	3.30	3.26*
Japan	2.35	6.87**	1.24	8.08**
Netherlands	2.35	5.94**	2.47	10.2**
New Zealand	0.18	3.02	0.85	4.12*
Norway	6.97**	5.39**	4.03*	1.67
Singapore	0.89	1.19	5.74**	1.14
South Korea	1.52	2.52	0.26	3.58*
Spain	10.6**	2.20	1.78	2.08
Sweden	14.4**	2.23	0.58	4.75*
Switzerland	3.65*	0.16	2.93	3.87*
UK	1.93	4.25*	0.24	3.67*
US	7.84**	0.79	0.47	6.12**

Table presents a joint test that the coefficient of the error correction term λ_i and short-run dynamics coefficient γ_i enter each of the equations in system (4) for the variables of interest.

* Represent significance at 5% level.

** Represent significance at 1% level.

Appendix G. Robustness checks: turnover ratio

Table G
Causality tests (robustness check using the turnover ratio).

Country	GDP→ CRED				CRED→ GDP				GDP→ TUR				TUR→ GDP			
	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y	WEX	SRG	SET	T&Y
Australia	45.17**	0.30	50.45**	0.90	0.48	0.26	1.28	0.25	7.72**	8.46**	11.6**	5.13	0.48	0.44	0.65	1.81
Austria	11.9**	0.14	12.2**	1.43	2.25	0.10	2.58	2.18	4.31*	0.01	4.73	2.43	-	0.51	-	1.15
Belgium	12.7**	8.21**	15.4**	7.27*	-	4.17*	-	8.61*	5.58*	0.01	6.28*	0.01	2.02	3.01	6.55**	3.30
Canada	0.08	0.13	0.20	0.24	-	1.63	-	1.42	10.1**	0.39	12.6**	1.81	2.27	10.0**	10.0**	9.67*
Denmark	34.1*	0.99	37.7**	2.13	2.20	0.46	2.24	0.01	0.07	0.53	0.01	0.41	2.20	5.19*	6.25*	7.55*
Finland	14.89**	1.26	15.2**	2.41	4.28*	0.94	4.30	0.28	0.26	0.01	0.35	2.38	-	0.01	-	0.58
France	15.5**	0.55	19.1**	2.67	0.28	0.36	0.42	2.26	0.39	1.14	2.07	0.66	0.28	1.03	1.12	2.10
Greece	25.3**	26.2**	58.4**	27.6**	10.8**	11.1**	15.9**	15.5**	0.01	0.56	0.61	0.34	-	3.48	-	5.83
Italy	25.5**	4.97*	32.0**	4.33	27.5**	9.69**	30.3**	5.47	7.07**	0.92	7.71*	1.76	27.5**	10.5**	30.3**	4.13
Japan	3.48	4.24*	7.18**	4.06	-	0.08	-	0.29	11.2**	0.01	11.32**	0.97	7.91**	5.58*	10.3**	0.75
Norway	3.47	4.46*	9.40**	4.06	-	6.53*	-	4.01	17.9**	.67	17.8**	0.29	0.11	0.23	0.36	3.40
Singapore	2.40	3.49	3.92	3.96	14.9**	0.22	15.55**	0.38	1.75	3.56	3.71	6.08*	14.9**	0.11	14.9**	1.14
South Korea	20.1**	0.51	25.6**	0.18	3.71	2.37	4.24	0.09	5.50*	2.39	6.16*	2.66	3.71	0.30	3.72	2.27
Sweden	17.2**	2.95	38.1**	2.80	0.03	0.71	0.82	1.05	3.21	2.18	3.61	0.42	0.03	0.96	0.98	0.88
Switzerland	0.68	1.73	2.18	4.08	2.87	0.06	3.01	7.30*	40.6**	1.62	40.9**	3.40	2.87	7.75**	9.42**	5.70
UK	31.1**	6.88**	31.4**	3.02	0.08	3.65	4.25	5.49	0.01	1.12	1.66	0.84	0.08	0.39	0.57	0.33
USA	3.59	36.9**	41.5**	22.1**	-	0.99	-	2.83	1.04	9.68**	10.5**	1.74	11.4**	0.40	11.6**	1.13

Table presents the log-likelihood statistics of the causality tests distributed $\chi^2(1)$ for the statistics that are not underlined, $\chi^2(2)$ for the statistics underlined with one line and $\chi^2(3)$ for the statistics underlined with two lines.
GDP is the log of real GDP/capita, TUR is the log of the ratio of value traded to stock market capitalization, CRED is the log of the ratio of domestic credit to nominal GDP.
WEX is the weak exogeneity test under the null:$H_0 : \alpha_{ij} = \beta_{ij} = 0$.
SRG is the short-run Granger causality test under the null:$H_0 : \Gamma_{ij}^{p} = 0$, distributed $\chi^2(1)$.
SET is the strong exogeneity test under the null:$H_0 : \Gamma_{ij}^{p} = \alpha_{ij} = 0$.
T&Y is the Toda & Yamamoto(1995) causality test for level VARs.
* Represent significance at 5% level.
** Represent significance at 1% level.

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