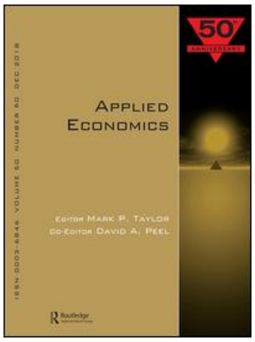


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# Level and dynamics of financial depth: consequences for volatility of GDP

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# Level and dynamics of financial depth: consequences for volatility of GDP

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**ABSTRACT**
The existing literature documents positive but potentially non-linear relationship between financial depth measured as private credit to GDP ratio and volatility of GDP. In this paper, we extend the analysis by considering also the role of financial depth dynamics. We use dynamic spatial panel models to address the issue of cross-sectional dependence of errors obtained from the standard dynamic panel models. We confirm the non-linear impact of the financial depth level but also find that higher growth rates of financial depth are significantly associated with higher volatility of output. The role of the latter factor is considerably more important in terms of explained variance compared to the impact of the private credit level. These results are robust to changes in the sample range, specification of the model, and measurement of the key variables. We also document considerable differences between the estimates obtained from the standard GMM and the spatial models.

**KEYWORDS**
Financial development; credit; economic crisis; GDP volatility; spatial dynamic panels; cross-sectional dependence

**JEL CLASSIFICATION**
C23; E44; G10

## I. Introduction

Although the discussion on the relationship between financial depth (financial development) and real activity focuses primarily on economic growth, two separate strands of research study the impact on volatility of GDP. The first group argues that a high level of financial depth reduces fluctuations of GDP (Dabla-Norris and Srivisal 2013; Islam 2016; Ma and Song 2017). The second one points out that a rapid increase in credit is a financial crisis predictor (Jordà, Schularick, and Taylor 2011; Schularick and Taylor 2012). While the two findings can be viewed basically as complementary it is difficult to assess relative importance of the factors for determining volatility of GDP because none of the studies considers them jointly. Moreover, the two strands of research work with different datasets and econometric methods. The literature focusing on the role of the financial depth level prefers panel data with many countries and few time periods and uses the standard panel data models. On the other hand, the role of financial depth dynamics as a financial crisis predictor is usually investigated using data for several developed countries over more than 100 years and utilizing treatment models.

In this paper, we blend the two approaches and investigate the role of both the level and dynamics of financial depth for GDP fluctuations. Given the fact that financial depth dynamics is a reliable predictor of financial crises – the main source of economic activity volatility – we think that this factor should be characterized with the stronger relationship with the size of GDP fluctuations compared to the financial depth level.

In the paper, we work with a panel data for 77 countries over the period 1970–2014. We apply panel data models but unlike the previous studies we carefully address the issue of cross-sectional dependence of errors. In particular, we start with the standard IV-GMM estimates. Then, we perform the CD test of cross-sectional dependence of errors (Pesaran 2004, 2015). The test does not reject the null of the weak (local) form of cross-sectional dependence which we account for using spatial models. We employ a novel M-estimation method developed recently by Yang (2018) that overcomes the key difficulties associated with the standard quasi-maximum likelihood approaches to dynamic spatial panels.

We find that both the financial depth level and its dynamics are correlated with volatility of GDP and confirm our hypothesis that the latter factor plays the dominant role in terms of the explained variance. The strong impact of financial depth

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dynamics is limited neither to the recent financial crisis period nor to the developed countries but is observed in all the robustness checks performed in the paper. We also document that accounting for cross-sectional dependence of errors using spatial models can result in significantly different estimates compared to the standard IV-GMM models that disregard the dependence.

The paper is organized as follows. Section 2 contains a literature review. The methods and data are discussed in Section 3. The results are presented in Section 4. Section 5 concludes the paper.

## II. Literature review

In line with Beck (2013), we distinguish between financial depth and financial development. Financial depth refers to the volume of financial transactions in an economy measured as a ratio of credit to GDP or bank assets to GDP. Financial development is a broader category that comprise: financial depth, financial breadth (diversity of providers and segments of the financial system, including banks, capital markets, and contractual savings institutions), and financial inclusion (access to and use of financial services by a large share of the household and enterprise population in a society).

The relationship between the level of financial depth and GDP growth has been the subject of numerous empirical studies. It is broadly accepted that this relationship has the shape of an inverted 'U' – financial depth fosters growth but only up to a certain threshold, after which it becomes a drag on economic growth (Cecchetti and Kharroubi 2012; Arcand, Berkes, and Panizza 2015; Beck, Degryse, and Kneer 2014; Stolbov 2017, among others).

The links between the level of financial depth and short-term volatility of GDP has been investigated to a much lesser extent. Theoretical literature relating to financial depth (development) contains mixed results. There is a large strand of models that investigate the mechanisms by which the financial sector amplifies temporary shocks and makes them more persistent. Starting with two classical papers, Bernanke and Gertler (1990) develop the model where asymmetric information in financial markets exacerbates volatility. Kiyotaki and Moore (1997) show that the dynamic interaction between credit limits and asset prices amplifies the magnitude and persistence of temporary productivity shocks. In the recent paper, Pinheiro, Rivadeneyra, and Teignier (2017), based on Kiyotaki (1998), find a hump-shaped relationship between the degree of financial frictions and the amplification of unexpected productivity shocks. Aghion, Banerjee, and Piketty (1999) and the role of financial depth Aghion et al. (2010) argue that economies with less developed financial sectors tend to be more volatile and volatility is more likely in open economies with intermediate levels of financial development. Brunnermeier and Sannikov (2014) study the general equilibrium dynamics of an economy with financial frictions. Due to highly non-linear amplification effects, the economy is prone to instability and occasionally enters volatile crisis episodes. Wang, Wen, and Xu (2017) show that when financial depth increases the variance of output growth is reduced but it does so at the diminishing rate, regardless of the sources of aggregate shocks. At the same time, firm-level volatility is growing.

The prevailing view in the finance – volatility of growth nexus empirical literature is that the higher level of financial depth reduces fluctuations of economic activity. For example, Denizer, Iyigun, and Owen (2002) analyse 70 countries between 1956 and 1998 and find that greater financial depth is associated with the lower amplitude of fluctuations in GDP, consumption, and investments. Cecchetti, Flores-Lagunes, and Krause (2006), among others, reach similar conclusions. Beck, Lundberg, and Majnoni (2006) find that the role of financial depth depends on the type of shock. Well-developed financial intermediaries dampen the effect of real shocks, while magnifying monetary shocks. They conclude that the overall impact of financial intermediaries on volatility of GDP is ambiguous.

It is usually assumed that this positive impact on the reduction of volatility of GDP is due to the fact that a developed financial system facilitates risk-sharing and provides more liquidity thereby enhancing the economy's ability to absorb shocks (Dabla-Norris and Srivisal 2013). Wang, Wen, and Xu (2017) argue that decisions of firms become less dependent on internal cash flows. Moreover, financial deepening enables agents to make an optimal investment decision based on their own idiosyncratic needs rather than on aggregate shocks.

Most studies emphasize the non-linear nature of the relationship between the level of financial depth and volatility of GDP. Easterly, Islam, and Stiglitz (2000) maintain that a financial sector may increase the volatility of GDP if the ratio of credit to GDP exceeds 100%. Generally, an increase in corporate debt, including increased dependence of companies on external financing, makes the real sector more susceptible to shocks from the financial sector. While Dabla-Norris and Srivisal (2013) support the conclusion drawn in earlier studies, i.e. that a developed financial system allows to absorb shocks and thus helps to reduce the amplitude of GDP fluctuations, they claim that this holds true only up to a certain ratio of the financial sector size to GDP. Upon exceeding 106–132% (depending on the analysed variable) of GDP, this effect declines, and the larger size of the financial sector may contribute to the increase of macroeconomic volatility. At the very high levels, financial depth amplifies consumption and investment volatility. Mallick (2014) decomposes growth volatility into business-cycle and long-run components and finds that higher private credit dampens business cycle volatility but does not affect long-run volatility. Islam (2016) shows that financial development smooths growth in gross domestic product and consumption per capita, but only up to a point. At the high levels of credit, its further increase is positively associated with volatility even after controlling for the quality of institutions and periods of financial crises.

Recent papers confirm the non-linear relationship between financial depth and GDP volatility. Ma and Song (2017) using GMM estimators and overlapping time-averaged variables over the period 1996–2012 present evidence that the relationship between financial depth and GDP volatility is U-shaped. They find that the threshold value is higher than those reported in the previous studies. Wang, Wen, and Xu (2017) show that higher financial depth is associated with lower volatility but this volatility reduction effect diminishes with further financial deepening. In other words, the financial depth and GDP volatility curve is L-shaped. Da Silva et al. (2017) also find the similar U-shaped relationship between the ratio of GDP volatility to the growth rate and financial depth. However, none of these studies directly assess the impact of financial depth dynamics on macroeconomic stability.

Another stream of research documents that rapid growth in credit is a financial crisis predictor. Jordà, Schularick, and Taylor (2011) suggest that credit growth is the single best predictor of financial instability. Furthermore, high credit growth makes financial crises more likely (Schularick and Taylor 2012) and economic recessions tend to be longer and deeper when accompanied by financial distress (Jordà, Schularick, and Taylor 2013; Claessens, Kose, and Terrones 2012). Jordà, Schularick, and Taylor (2013) study the role of credit in the business cycle, with a focus on private credit overhang. Based on a study of over 200 recession episodes in 14 advanced countries between 1870 and 2008, they document that more credit-intensive expansions tend to be followed by deeper recessions and slower recoveries.

To sum up: the previous studies confirm the positive but potentially non-linear relationship between the level of financial depth and volatility of GDP using IV or system GMM approach. Our goal is to extend the analysis by including dynamics of financial depth. Contrary to the previous studies, we also account for cross-sectional dependence of errors in the panel data models. Thereby, we contribute to the finance – volatility of GDP nexus literature using spatial econometric methods and testing simultaneously the effects of both the financial depth level and its dynamics for volatility of GDP.

## III. Methodology and data

### *Data*

Our panel comprises data over the period 1970–2014 for 77 countries. In contrast to the previous studies and due to the requirements of spatial models, the panel is balanced where few missing observations are interpolated. As a standard practice (Dabla-Norris and Srivisal 2013; Islam 2016), we transform the time series data into five-year, non-overlapping periods.

We measure financial depth by the aggregate private credit by deposit money in banks and other financial institutions as a share of GDP. Volatility of GDP is measured by standard deviations of GDP (expressed in constant local currencies) growth rates in the five-year periods. As controls, we include a number of variables considered in the literature. Our dataset includes: GDP per capita, GDP growth rate, change of the nominal exchange rate versus USD, current account balance, inflation, trade and financial openness. We also include the indexes of the political regime and political stability. The latter is measured as the number of the years without major changes in the polity index from the Polity IV database. Volatility of world GDP is used as a proxy for the time-specific effects. All the variables and their sources are described in Table 1.

### Methods

Following the literature (Dabla-Norris and Srivisal 2013), we start with the standard dynamic panel data model with fixed effects:

**Table 1.** Data sources.

| Variable | Description | Source |
|---|---|---|
| $\sigma(GDP)$ | Volatility (standard deviation) of GDP growth rate | World Bank, World Development Indicators |
| $FD$ | Private credit by deposit money banks and other financial institutions to GDP (%), | World Bank, Global Financial Development |
| $GDP$ | GDP per capita (constant 2010 US$) | World Bank, World Development Indicators |
| $\Delta GDP$ | $\log GDP_t - \log GDP_{t-1}$ | World Bank, World Development Indicators |
| $\sigma(GDP_w)$ | Volatility of world GDP | World Bank, World Development Indicators |
| $INFL$ | Inflation, GDP deflator (annual change %) | World Bank, World Development Indicators |
| $\Delta USD$ | Change of nominal exchange rate against USD (Official exchange rate – LCU per US$, period average) | Fund, International Financial Statistics. |
| $POLIT$ | Polity 2: unified polity scale +10 (strongly democratic) to −10 (strongly autocratic) | Polity IV Project: Political Regime Characteristics and Transitions |
| $STAB$ | Political Stability – number of the years without major changes in polity index | Polity IV; own calculation |
| $OPEN$ | Economic openness; total exports and imports as % of GDP | World Bank, World Development Indicators |
| $NFA$ | Net financial assets (% of GDP) | External Wealth of Nations Mark II database (see Lane and Milesi-Ferretti 2007) |
| $GFA$ | Gross financial assets (% of GDP) | External Wealth of Nations Mark II database |
| $CA$ | Current account balance (% of GDP) | World Bank, World Development Indicators |

$$Y_{it} = \phi_i + \rho Y_{it-1} + \beta_1 FD_{it} + \beta_2 FD_{it}^2 + \beta_3 \Delta FD_{it} + \sum_{l=1}^{k} \gamma_l X_{lit} + \varepsilon_{it}, \qquad (1)$$

where $Y$ represents our measure of GDP volatility, $FD$ and $\Delta FD$ stand for the financial depth level and volatility, respectively, $X_l$ denote the controls, $\varepsilon_{it}$ are iid error terms, indices $i$ and $j$ represent countries, and $t$ corresponds to periods. The coefficients $\phi_i$ capture the country-specific effects while $\rho$ measures persistence of the endogenous variable. The parameters are estimated using the difference GMM (Arellano and Bond 1991).

These standard GMM estimates are valid unless the error terms are cross-sectionally independent which means that individual units of the panel are independent (Sarafidis and Wansbeek 2012; Sarafidis 2016). If the errors are dependent two forms of cross-sectional dependence are distinguished: weak (local) and strong (global). In the former case, the exponent $\alpha$ of cross-sectional dependence is positive but lower than 0.5 (Bailey, Kapetanios, and Pesaran 2016). In other words, the impact of a unit is limited to several neighbourhood units or vanishes quickly as a distance between the units grows. Under weakly cross-sectionally dependent errors, the GMM estimates remain consistent but are biased and inefficient (Sarafidis and Wansbeek 2012; Sarafidis 2016). In this case, spatial models can be used to account for the dependence between the units (Elhorst, Gross, and Tereanu 2018). As far as the strong dependence is considered, the exponent is equal or higher than 0.5. It means that links between distant units are non-negligible and the GMM estimates become inconsistent. This form of cross-sectional dependence can be accommodated by a factor structure of the error term or by global VAR models (Elhorst, Gross, and Tereanu 2018).

The existence of cross-sectional dependence of errors can be signalled by the non-zero values of the correlation coefficients between the units. In our case, the mean correlation exceeds 0.3. To check the form of the dependence, we apply the CD test (Pesaran 2004, 2015; De Hoyos and Sarafidis 2006). The test verifies the null hypothesis of the weak form of cross-sectional dependence against the alternative of strong dependence. Because the test does not reject the null we use spatial models to account for cross-sectional dependence of errors. As a baseline specification, we employ the spatial autocorrelation model (SAR) which takes the form (1) but allows for spatial dependence in the error term (Elhorst 2014; Baltagi 2013):

$$Y_{it} = \phi_i + \rho Y_{it-1} + \beta_1 FD_{it} + \beta_2 FD_{it}^2 + \beta_3 \Delta FD_{it} + \sum_{l=1}^{k} \gamma_l X_{lit} + \tilde{\varepsilon}_{it}, \tag{2}$$

$$\tilde{\varepsilon}_{it} = \rho_s \sum_{j=1}^{N} w_{ij} \varepsilon_{jt}, \tag{3}$$

where $w_{ij}$ represent elements of the spatial weighting matrix and $\rho_s$ measures spatial autocorrelation.

In the baseline version of the study, we use the row-normalized inverse of geographical distances between countries' capitals as the elements of the spatial weighting matrix:

$$w_{ij} = \begin{cases} \frac{d_{ij}^{-1}}{\sum_{j=1}^{N} d_{ij}^{-1}} & \text{if} \quad i \neq j, \\ 0 & \text{if} \quad i = j, \end{cases} \tag{4}$$
$$i, j = 1, 2, \ldots, N,$$

where $d_{ij}$ denotes the geographical distance between the capitals of countries $i$ and $j$.

The model is estimated using a novel, unified M-estimation method (Yang 2018). This is a modified quasi-maximum likelihood algorithm for fixed-effects dynamic spatial panel data with the short time dimension. It overcomes the problem of the assumption on initial values of the data generating process that plagues the standard QML estimators (Elhorst 2005; Yu, de Jong, and Lee 2008; Lee and Yu 2010) in the case of short samples. If the assumption is incorrect, it can result in inconsistency and a serious bias of the estimates. The M-estimators are also robust to non-normality of errors. As an alternative, one can apply the neighbourhood GMM (Sarafidis 2016), which uses additional non-redundant moment restrictions that account for spatial dependence. However, GMM is usually thought as less efficient than the ML-based estimators. Moreover, the estimates are sensitive to the choice of instruments and small changes to the sets of instruments can change the results considerably.

## IV. Results

In this section, the estimation results are presented. First, the baseline model and the dataset described in the previous section are considered. Subsequently, the results of several robustness checks are shown.

### The baseline model

In Table 2, the results for our baseline econometric specification are presented. The first column contains IV-GMM estimates and the CD test statistics.

**Table 2.** The results for the baseline econometric specification.

| Coefficient | IV-GMM | SAR I | SAR II | SAR III | SAR IV |
|---|---|---|---|---|---|
| $\rho$ | 0.135 | 0.231*** | 0.208*** | 0.2*** | 0.202*** |
| | (0.111) | (0.054) | (0.058) | (0.056) | (0.055) |
| $\rho_s$ | | 0.576*** | 0.524*** | 0.534*** | 0.511*** |
| | | (0.084) | (0.15) | (0.147) | (0.149) |
| $FD$ | −0.411*** | | | −0.191* | −0.315*** |
| | (0.15) | | | (0.114) | (0.118) |
| $FD^2$ | 0.002*** | | | 0.001* | 0.001** |
| | (0.001) | | | (0.001) | (0.001) |
| $\Delta FD$ | 0.249*** | | | | 0.204*** |
| | (0.069) | | | | (0.059) |
| $\log GDP$ | −32.609*** | | 0.305 | 2.25 | 2.976 |
| | (9.107) | | (6.417) | (6.245) | (6.039) |
| $\Delta GDP$ | −3.049*** | | −1.224** | −1.21** | −1.119* |
| | (0.619) | | (0.6) | (0.614) | (0.601) |
| $INFL$ | 0.003*** | | 0.001 | 0.001 | −0.001 |
| | (0.001) | | (0.005) | (0.005) | (0.005) |
| $\Delta USD$ | 0 | | 0 | 0 | 0 |
| | (0) | | (0) | (0) | (0) |
| $POLIT$ | 0.082 | | −0.302 | −0.284 | −0.286 |
| | (0.279) | | (0.228) | (0.225) | (0.223) |
| $STAB$ | 0.183 | | −0.034 | −0.03 | −0.03 |
| | (0.156) | | (0.091) | (0.089) | (0.089) |
| $OPEN$ | 0.199** | | 0.054 | 0.059 | 0.065 |
| | (0.089) | | (0.051) | (0.05) | (0.053) |
| $NFA$ | 5.359*** | | −1.526 | −1.786 | −2.271 |
| | (2.564) | | (3.791) | (3.788) | (3.929) |
| $GFA$ | 0.719 | | 0.503 | 0.464 | 0.526 |
| | (0.468) | | (0.342) | (0.336) | (0.332) |
| $CA$ | 0.562 | | 0.093 | 0.067 | 0.135 |
| | (0.534) | | (0.25) | (0.25) | (0.255) |
| $\sigma(GDP_w)$ | 0.905 | | 1.846 | 1.693 | 1.635 |
| | (1.089) | | (1.912) | (1.941) | (1.857) |
| CD test | 0.32 [0.359] | | | | |
| $R^2_{AR}$ | | 0.340 | | | |
| $R^2_{CONT}$ | | | 0.377 | | |
| $R^2_{FD}$ | | | | 0.380 | |
| $R^2$ | | | | | 0.390 |

In parentheses, the standard errors are reported. Bolded are the estimates that are significant at 0.1(*), 0.05(**), or 0.01(***) significance level. All the values but the autocorrelations and $R^2$ are multiplied by 10. The row 'CD test' contains the value of the CD test of cross-sectional dependence statistic with the one-sided $p$ value in brackets. In the rows '$R^2$', the overall $R^2$ coefficients are reported for the models with the autocorrelation terms only ($R^2_{AR}$), autocorrelations and the controls ($R^2_{CONT}$), autocorrelations, the controls, and the $FD$ terms in levels ($R^2_{FD}$), and all the considered variables ($R^2$).

The IV-GMM estimates are obtained using the two-step difference estimator of Arellano and Bond (1991) (Stata's xtabond2 function is used; Roodman (2009)); variable $\Delta GDP$ is used as a GMM-style instrument; the remaining variables are treated as the standard IV-style instruments.

[1]This number can be calculated as $\frac{-\hat{\beta}_1}{2\hat{\beta}_2}$.

In the next columns, the results of the SAR model are shown. In order to assess the impact of the different financial depth measures in terms of explained variance, we sequentially extend the set of explanatory variables starting with the autocorrelations and the country-specific effects only.

The value of the CD test statistic equal to 0.32 suggests that the null hypothesis of weak cross-section dependence of errors from the IV-GMM model should not be rejected. Therefore, the SAR model is applied to account for the error dependence. The results for the full set of the explanatory variables (SAR IV) indicate that both the level and dynamics of financial depth play the important role in explaining volatility of GDP. The impact of the financial depth level is non-linear. Initially, the higher values of financial depth are associated with lower fluctuations of GDP. However, once the private credit exceeds 117%[1] of GDP, further rise in financial depth has a destabilizing effect on an economy. The relationship between dynamics of private credit and GDP volatility is positive in the sense that higher growth rates of financial depth are associated with higher volatility of output. The role of financial depth dynamics is considerably more important in terms of explained variance compared to the private credit level. Adding the two variables related to the financial depth level ($FD$ and $FD^2$) rises $R^2$ only marginally, from 37.7% to 38.0%. The increase of explained variance after inclusion of the financial depth growth rates reaches 1 p.p.

The dependent variable is characterized by statistically significant autocorrelations in both space and time. While the latter is relatively weak, the spatial dependence is considerable and must not be neglected. The significance of the autocorrelation coefficients supports our choice of the spatial models.

The spatial autocorrelation may be interpreted in the vein that volatility of GDP is partially regional in the nature, e.g. in the line with regional synchronization of the shocks due to the financial and real linkages between neighbourhood countries. Common shocks are rather regional than global as volatility of world GDP is not statistically significant.

Finally, one can notice the large differences between the IV-GMM and the SAR estimates. For example, logarithm of the GDP level has a large negative impact on volatility of GDP in the case of the IV-GMM model but the positive, though insignificant, coefficient in the SAR case. Similar differences exist, for example, for inflation, economy openness, and net foreign assets. On the other hand, the disparities are small in the case of the financial depth variables.

## Discussion

The nature of the non-linear impact of financial depth on volatility of GDP, together with the positive relationship between dynamics of financial depth and GDP fluctuations needs further studies but in line with the existing literature we can suppose that while financial systems, when functioning well, promote productivity and help smoothing GDP, they can also increase volatility in an economy. At the narrative level, we can argue that with financial deepening firms become less dependent on internal financing (and less sensitive to real shocks) but more dependent on external financing. As a consequence, sensitivity of an economy to financial shocks grows. Moreover, relaxing the borrowing constrains means more credit risk and less productive investments e.g. more risky and less productive projects are financed. There is a considerably diversified research strand including both theoretical and empirical works that support our findings. For example, financial deepening can lead to more risk-taking by entrepreneurs and banks or facilitate over-leverage, both of which could potentially drive up volatility (Rajan 2005). A few papers, like Jordà, Schularick, and Taylor (2013), discuss the amplification effect of rising leverage preceding economic downturns.

We also find that the GDP growth rate is the only control variable significantly affecting volatility of GDP. The negative sign of coefficient is also reported in the previous studies (Ma and Song 2017) but the direction of causality is open. Ramey and Ramey (1995) and the subsequent literature find that countries with higher volatility have lower growth. The weak relationship between the controls and volatility of GDP is also confirmed by Dabla-Norris and Srivisal (2013).

## Alternative specifications of spatial dependence

In Table 3, the results of the numerous robustness checks are presented. First, we analyse changes to the

**Table 3.** The results for the different models and samples.

| Variable | baseline SAR | SL | $W_{4NN}$ | year < 2005 | low inc. | medium inc. | high inc. | SL-QML |
|---|---|---|---|---|---|---|---|---|
| $\rho$ | **0.202*** ** | **0.198*** ** | **0.229*** ** | **0.189*** ** | 0.047 | 0.092 | **0.347*** ** | 0.056 |
| | **(0.055)** | **(0.056)** | **(0.06)** | **(0.07)** | (0.129) | (0.061) | **(0.091)** | (0.052) |
| $\rho_s$ | **0.511*** ** | **0.49*** ** | **0.144*** ** | 0.377 | −0.339 | **0.602*** ** | **0.324*** | **0.523*** ** |
| | **(0.149)** | **(0.118)** | **(0.051)** | (0.234) | (0.279) | **(0.186)** | **(0.182)** | **(0.121)** |
| $FD$ | **−0.315*** ** | **−0.318*** ** | **−0.306** ** | **−0.39** ** | 0.494 | **−0.557*** ** | −0.18 | **−0.343*** ** |
| | **(0.118)** | **(0.117)** | **(0.119)** | **(0.154)** | (1.032) | **(0.194)** | (0.12) | **(0.123)** |
| $FD^2$ | **0.001** ** | **0.001** ** | **0.001** ** | **0.002** ** | −0.011 | **0.004*** ** | 0.001 | **0.001*** ** |
| | **(0.001)** | **(0.001)** | **(0.001)** | **(0.001)** | (0.018) | **(0.001)** | (0.001) | **(0.001)** |
| $\Delta FD$ | **0.204*** ** | **0.228*** ** | **0.209*** ** | **0.24*** ** | **0.944** ** | **0.165*** | **0.177*** ** | **0.212*** ** |
| | **(0.059)** | **(0.057)** | **(0.056)** | **(0.09)** | **(0.41)** | **(0.092)** | **(0.058)** | **(0.057)** |
| $\log GDP$ | 2.976 | 3.335 | −0.903 | 3.536 | −8.681 | 13.475 | −0.553 | 3.973 |
| | (6.039) | (4.912) | (4.743) | (8.364) | (11.967) | (11.167) | (5.589) | (5.416) |
| $\Delta USD$ | **−1.119*** | **−1.067** ** | **−1.183** ** | −0.636 | 0.086 | −0.648 | **−2.041*** ** | **−1.168** ** |
| | **(0.601)** | **(0.525)** | **(0.574)** | (0.619) | (1.577) | (0.668) | **(0.709)** | **(0.56)** |
| $INFL$ | −0.001 | 0 | 0.001 | 0.001 | −0.135 | 0 | 0.208 | 0 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.243) | (0.005) | (0.178) | (0.006) |
| $\Delta GDP$ | 0 | 0 | 0 | 0 | **0.492** ** | 0 | −0.211 | 0 |
| | (0) | (0) | (0) | (0) | **(0.229)** | (0) | (0.18) | (0) |
| $POLIT$ | −0.286 | −0.319 | **−0.489** ** | −0.192 | **−0.785** ** | −0.271 | **−0.66** ** | **−0.414*** |
| | (0.223) | (0.225) | **(0.247)** | (0.253) | **(0.319)** | (0.32) | **(0.284)** | **(0.227)** |
| $STAB$ | −0.03 | −0.029 | −0.047 | 0.079 | **−0.835*** ** | 0.131 | −0.206 | −0.048 |
| | (0.089) | (0.088) | (0.092) | (0.112) | **(0.288)** | (0.103) | (0.178) | (0.089) |
| $OPEN$ | 0.065 | 0.067 | 0.056 | 0.072 | 0.157 | 0.033 | 0.035 | 0.084 |
| | (0.053) | (0.053) | (0.054) | (0.08) | (0.164) | (0.07) | (0.118) | (0.056) |
| $NFA$ | −2.271 | −2.128 | −1.41 | −1.983 | **−40.012** ** | −6.42 | 0.036 | −2.339 |
| | (3.929) | (3.669) | (3.709) | (4.332) | **(15.544)** | (5.453) | (4.246) | (3.91) |
| $GFA$ | 0.526 | 0.426 | 0.445 | 0.215 | **−30.657*** ** | −1.223 | 0.582 | 0.457 |
| | (0.332) | (0.326) | (0.345) | (0.64) | **(8.84)** | (2.32) | (0.31) | (0.347) |
| $CA$ | 0.135 | 0.141 | 0.097 | 0.515 | −0.421 | **0.86*** ** | 0.163 | 0.181 |
| | (0.255) | (0.238) | (0.242) | (0.374) | (0.504) | **(0.283)** | (0.429) | (0.241) |
| $\sigma(GDP_w)$ | 1.635 | 0.593 | **2.334*** | **8.338*** ** | −3.673 | 0.239 | **3.952*** | 1.066 |
| | (1.857) | (0.904) | **(1.21)** | **(3.027)** | (3.341) | (3.105) | **(2.21)** | (1.504) |
| $R^2_{AR}$ | 0.340 | 0.352 | 0.334 | 0.432 | 0.269 | 0.264 | 0.466 | – |
| $R^2_{CONT}$ | 0.377 | 0.391 | 0.382 | 0.475 | 0.430 | 0.299 | 0.627 | – |
| $R^2_{FD}$ | 0.380 | 0.394 | 0.385 | 0.478 | 0.433 | 0.303 | 0.629 | – |
| $R^2$ | 0.390 | 0.406 | 0.394 | 0.485 | 0.447 | 0.306 | 0.647 | 0.311 |

In parentheses, the standard errors are reported. Bolded are the estimates that are significant at 0.1(*), 0.05(**), or 0.01(***) significance level. All the values but the autocorrelations and $R^2$ are multiplied by 10. 'baseline' – baseline specification; 'SL' – spatial lag model of the form (5); '$W_{4NN}$' – baseline specification with the four-nearest-neighbours weighting matrix; 'SL-QML' – spatial lag model of the form (5) estimated with the bias-corrected quasi-maximum likelihood method of Yu, de Jong, and Lee (2008) from Stata's xsmle package of Belotti, Hughes, and Mortari (2013).

In the rows $R^2$, the overall $R^2$ coefficients are reported for the models with the autocorrelation terms only ($R^2_{AR}$), autocorrelations and the controls ($R^2_{CONT}$), autocorrelations, the controls, and the $FD$ terms in levels ($R^2_{FD}$), and all the considered variables ($R^2$).

spatial dependence structure of the baseline model. In the column 'SL', the estimates of the spatial lag model are shown. The model takes the following form:

$$Y_{it} = \phi_i + \rho Y_{it-1} + \rho_s \sum_{j=1}^{N} w_{ij} Y_{jt} + \beta_1 FD_{it} + \beta_2 FD^2_{it} + \beta_3 \Delta FD_{it} + \sum_{l=1}^{k} \gamma_l X_{lit} + \varepsilon_{it}. \quad (5)$$

Compared to the spatial error specification (2)–(3), the spatial autocorrelation term does not occur in the error term Equation (3), but is directly associated with the dependent variable. As a result, spatial autocorrelation affects not only variance of the dependent variable, but also its mean. However, this modification virtually changes the estimates compared to the baseline specification.

We also replace the inverse-distance weighting matrix with the four-nearest-neighbours one (column '$W_{4NN}$'). This is a sparse matrix with entries $w_{ij}$ taking a value of 0.25 if a country $j$ is one of the four nearest neighbours of a country $i$, and 0, otherwise. Although the spatial autocorrelation estimate is now considerably weaker the estimated impact of the financial depth measures remains unchanged. Volatility of world GDP is now statistically significant which suggests that the economic linkages (in line with intuition) are broader than those defined by the four-nearest-neighbour countries.

## *Different subsamples*

Subsequently, we run the regressions on different subsamples. First, we exclude the periods of the recent financial crisis and consider the series until the year 2004 (column 'year < 2005'). The relationship between volatility of GDP and financial depth dynamics remains statistically significant but the rise in explained variance is now somewhat smaller. This result suggests that the observed dependence between the two analysed variables need not be attributed solely to the negative consequences of the uncontrolled rise in financial depth observed before the recent financial crisis in many countries.

We also divide the whole sample according to the level of income in a country using the most recent classification of countries proposed by the World Bank. We study three separate groups: low-, medium-, and high-income countries. The composition of the groups are reported in Appendix A. Interestingly, the positive relationship between dynamics of financial depth and GDP volatility is observed across all the groups while the impact of the financial depth level is significant only in the middle-income group. Moreover, the role of private credit dynamics in terms of explained variance is much stronger in the low- and high-income countries. For example, in the latter group, $R^2$ rises just by 0.2 p.p. due to inclusion of the level of financial depth measures and by almost 2 p.p. after adding the single indicator of financial depth dynamics. However, it should be noted that a relatively small number of countries included limits our findings for the income-level groups.

### Alternative estimation method

Given the novelty of the estimation method, we reestimate the model using an alternative approach. More specifically, we employ the bias-corrected QML

**Table 4.** The results for the alternative measure of volatility of GDP.

| Variable | baseline SAR | SL | $W_{4NN}$ | year < 2005 | low inc. | medium inc. | high inc. |
|---|---|---|---|---|---|---|---|
| $\rho$ | 0.309*** | 0.289*** | 0.335*** | 0.325*** | 0.218 | 0.211*** | 0.389*** |
| | (0.052) | (0.055) | (0.055) | (0.057) | (0.308) | (0.055) | (0.086) |
| $\rho_s$ | 0.539*** | 0.495*** | 0.153** | 0.425** | −0.355 | 0.605*** | 0.463*** |
| | (0.156) | (0.123) | (0.061) | (0.208) | (0.459) | (0.189) | (0.127) |
| $FD$ | −0.155* | −0.161** | −0.156* | −0.238** | 0.345 | −0.322** | −0.123* |
| | (0.081) | (0.081) | (0.083) | (0.106) | (0.603) | (0.141) | (0.068) |
| $FD^2$ | 0.001* | 0.001* | 0.001 | 0.001** | −0.006 | 0.002*** | 0 |
| | (0) | (0) | (0) | (0.001) | (0.01) | (0.001) | (0) |
| $\Delta FD$ | 0.136*** | 0.158*** | 0.141*** | 0.211*** | 0.594* | 0.123* | 0.097** |
| | (0.045) | (0.043) | (0.043) | (0.07) | (0.309) | (0.064) | (0.041) |
| $\log GDP$ | 1.617 | 2.019 | −1.232 | 2.932 | −8.819 | 9.078 | −1.323 |
| | (4.58) | (3.728) | (3.603) | (5.511) | (9.154) | (8.013) | (4.133) |
| $\Delta GDP$ | −1.165** | −1.05** | −1.209*** | −0.747 | −1.306 | −0.607 | −2.04*** |
| | (0.467) | (0.417) | (0.441) | (0.477) | (1.411) | (0.539) | (0.575) |
| $INFL$ | −0.002 | −0.002 | −0.001 | −0.002 | −0.11 | −0.003 | 0.112 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.229) | (0.004) | (0.096) |
| $\Delta USD$ | 0 | 0 | 0 | 0 | 0.288 | 0 | −0.166 |
| | (0) | (0) | (0) | (0) | (0.201) | (0) | (0.107) |
| $POLIT$ | −0.324** | −0.319** | −0.475*** | −0.273 | −0.668** | −0.25 | −0.814*** |
| | (0.149) | (0.158) | (0.163) | (0.171) | (0.267) | (0.229) | (0.188) |
| $STAB$ | −0.019 | −0.012 | −0.031 | 0.078 | −0.493* | 0.074 | −0.239 |
| | (0.061) | (0.059) | (0.063) | (0.083) | (0.256) | (0.075) | (0.134) |
| $OPEN$ | 0.039 | 0.042 | 0.034 | 0.039 | 0.109 | −0.001 | 0.144** |
| | (0.036) | (0.037) | (0.037) | (0.058) | (0.136) | (0.052) | (0.067) |
| $NFA$ | −1.214 | −1.295 | −0.673 | −1.4 | −12.126 | −4.733 | −2.894 |
| | (2.6) | (2.461) | (2.468) | (2.883) | (19.896) | (3.775) | (1.906) |
| $GFA$ | 0.107 | 0.049 | 0.028 | −0.146 | −12.233 | −1.379 | 0.011 |
| | (0.189) | (0.206) | (0.236) | (0.342) | (11.552) | (1.571) | (0.264) |
| $CA$ | 0.098 | 0.131 | 0.085 | 0.406* | −0.375 | 0.502** | 0.221 |
| | (0.138) | (0.134) | (0.133) | (0.235) | (0.509) | (0.206) | (0.201) |
| $\sigma(GDP_w)$ | 2.245* | 1.119* | 2.677*** | 6.741*** | −1.37 | 1.256 | 2.754* |
| | (1.279) | (0.618) | (0.78) | (2.137) | (2.397) | (2.102) | (1.606) |
| $R^2_{AR}$ | 0.356 | 0.370 | 0.348 | 0.434 | 0.281 | 0.298 | 0.444 |
| $R^2_{CONT}$ | 0.424 | 0.442 | 0.432 | 0.503 | 0.443 | 0.348 | 0.659 |
| $R^2_{FD}$ | 0.425 | 0.443 | 0.432 | 0.504 | 0.457 | 0.349 | 0.659 |
| $R^2$ | 0.435 | 0.454 | 0.440 | 0.515 | 0.466 | 0.352 | 0.674 |

In parentheses, the standard errors are reported. Bolded are the estimates that are significant at 0.1(*), 0.05(**), or 0.01(***) significance level. All the values but the autocorrelations and $R^2$ are multiplied by 10. 'baseline' – baseline specification; 'SL' – spatial lag model of the form (5); '$W_{4NN}$' – baseline specification with the four-nearest-neighbours weighting matrix.

In the rows $R^2$, the overall $R^2$ coefficients are reported for the models with the autocorrelation terms only ($R^2_{AR}$), autocorrelations and the controls ($R^2_{CONT}$), autocorrelations, the controls, and the $FD$ terms in levels ($R^2_{FD}$), and all the considered variables ($R^2$).

method for the spatial lag model (5) proposed by Yu, de Jong, and Lee (2008). For this method, the results are very close to those obtained from the M-estimation approach. The lower and statistically insignificant dynamic autocorrelation coefficient is the only remarkable exception here although the similar behaviour is reported by Yang (2018).

### *Alternative measures of financial depth and volatility of GDP*

In this subsection, we consider alternative measures of volatility of GDP and financial depth. As far as the former is concerned, we use deviations from the Hodrick-Prescott trend. More precisely, first, we extract the trend using the HP filter with the parameter $\lambda = 6.25$ for the log GDP series covering the whole period 1970–2014. Subsequently, volatility of GDP ($Y$) is measured as a root mean squared deviations from the trend for the five-year subperiods:

$$Y_{it} = \sqrt{\frac{1}{5}\sum_{l=0}^{4}\left[100 \cdot \left(\log GDP_{i,t+l} - \log GDP^{*}_{i,t+l}\right)\right]^{2}}, \tag{6}$$

where $\log GDP^{*}$ denotes the trend of log GDP.

Table 4 contains the estimation results for the alternative measure of volatility of GDP. We consider the similar variants as in Subsections 4.3–4.4. The impact of financial depth dynamics is always statistically significant. In most of the cases, the financial depth level also plays an important role although sometimes the relationship is linear only. However, the contribution of this variable is very limited in terms of explained variance. We also find more controls to have a significant impact on

**Table 5.** The results for the alternative measure of financial depth.

| Variable | baseline SAR | SL | $W_{4NN}$ | year < 2005 | low inc. | medium inc. | high inc. |
|---|---|---|---|---|---|---|---|
| $\rho$ | **0.197***** | **0.188***** | **0.222***** | **0.172**** | 0.062 | 0.092 | **0.326***** |
| | **(0.055)** | **(0.055)** | **(0.058)** | **(0.071)** | (0.155) | (0.068) | **(0.085)** |
| $\rho_s$ | **0.515***** | **0.486***** | **0.159***** | **0.4*** | −0.349 | **0.581***** | **0.434***** |
| | **(0.147)** | **(0.124)** | **(0.054)** | **(0.223)** | (0.348) | **(0.19)** | **(0.133)** |
| $FD$ | **−0.15**** | **−0.156**** | **−0.149**** | **−0.204**** | **1.577*** | −0.074 | **−0.16**** |
| | **(0.071)** | **(0.072)** | **(0.075)** | **(0.086)** | **(0.947)** | (0.104) | **(0.067)** |
| $FD^2$ | **0*** | **0*** | 0 | **0**** | −0.024 | 0 | **0***** |
| | **(0)** | **(0)** | (0) | **(0)** | (0.015) | (0) | **(0)** |
| $\Delta FD$ | 0.059 | 0.07 | 0.067 | 0.064 | 0.175 | 0.046 | **0.088**** |
| | (0.047) | (0.049) | (0.048) | (0.059) | (0.281) | (0.059) | **(0.038)** |
| $\log GDP$ | 1.249 | 1.814 | −2.55 | 2.237 | −2.781 | 8.135 | 0.185 |
| | (6.08) | (4.948) | (4.741) | (8.498) | (13.541) | (10.262) | (5.33) |
| $\Delta GDP$ | −1.211 | **−1.153**** | **−1.249**** | −0.706 | 0.244 | −0.766 | **−2.154***** |
| | (0.604) | **(0.535)** | **(0.582)** | (0.622) | (1.58) | (0.723) | **(0.759)** |
| $INFL$ | 0.001 | 0.001 | 0.002 | 0.003 | 0.026 | 0.002 | 0.213 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.283) | (0.006) | (0.179) |
| $\Delta USD$ | 0 | 0 | 0 | 0 | 0.348 | 0 | −0.19 |
| | (0) | (0) | (0) | (0) | (0.291) | (0) | (0.196) |
| $POLIT$ | −0.309 | −0.335 | **−0.497**** | −0.192 | **−0.701**** | −0.408 | **−0.727**** |
| | (0.225) | (0.227) | **(0.247)** | (0.253) | **(0.306)** | (0.341) | **(0.29)** |
| $STAB$ | −0.029 | −0.026 | −0.042 | 0.068 | **−1.03***** | 0.057 | −0.196 |
| | (0.089) | (0.088) | (0.091) | (0.117) | **(0.332)** | (0.104) | (0.229) |
| $OPEN$ | 0.084 | 0.085 | 0.074 | 0.099 | **0.246*** | 0.08 | 0.058 |
| | (0.057) | (0.056) | (0.056) | (0.091) | **(0.143)** | (0.084) | (0.123) |
| $NFA$ | −2.69 | −2.655 | −2.093 | −2.011 | −32.65 | −6.917 | −1.155 |
| | (3.995) | (3.827) | (3.897) | (4.392) | (22.583) | (6.224) | (3.842) |
| $GFA$ | **0.659*** | **0.568*** | **0.599*** | 0.498 | **−25.983*** | −1.126 | **0.59*** |
| | **(0.338)** | **(0.313)** | **(0.328)** | (0.612) | **(14.159)** | (2.054) | **(0.335)** |
| $CA$ | 0.093 | 0.096 | 0.067 | 0.423 | −0.367 | **0.907***** | 0.16 |
| | (0.244) | (0.229) | (0.234) | (0.365) | (0.533) | **(0.252)** | (0.422) |
| $\sigma(GDP_w)$ | 1.654 | 0.646 | **2.402*** | **7.583**** | −2.487 | −0.229 | 3.76 |
| | (1.901) | (0.947) | **(1.237)** | **(3.27)** | (3.084) | (3.109) | (2.602) |
| $R^2_{AR}$ | 0.340 | 0.352 | 0.334 | 0.432 | 0.269 | 0.264 | 0.466 |
| $R^2_{CONT}$ | 0.377 | 0.391 | 0.382 | 0.475 | 0.430 | 0.299 | 0.627 |
| $R^2_{FD}$ | 0.382 | 0.396 | 0.386 | 0.480 | 0.444 | 0.305 | 0.630 |
| $R^2$ | 0.386 | 0.400 | 0.390 | 0.483 | 0.444 | 0.307 | 0.638 |

In parentheses. the standard errors are reported. Bolded are the estimates that are significant at 0.1(*), 0.05(**), or 0.01(***) significance level. All the values but the autocorrelations and $R^2$ are multiplied by 10. 'baseline' – baseline specification; 'SL' – spatial lag model of the form (5); '$W_{4NN}$' – baseline specification with the four-nearest-neighbours weighting matrix.

In the rows $R^2$, the overall $R^2$ coefficients are reported for the models with the autocorrelation terms only ($R^2_{AR}$), autocorrelations and the controls ($R^2_{CONT}$), autocorrelations, the controls, and the $FD$ terms in levels ($R^2_{FD}$), and all the considered variables ($R^2$).

the dependent variable compared to the baseline measure of volatility. These include the political regime index and volatility of global GDP. It should be noted that the values of the autocorrelation coefficients are larger, too.

As the alternative to private credit, we use total domestic credit to GDP series taken from the World Bank's database as the measure of financial depth. Domestic credit provided by the financial sector includes all credit to various sectors and credit to the central government. The results are presented in Table 5. Unlike the previous indicator, growth rates of domestic credit do not exhibit the significant correlation with volatility of GDP. However, its levels still influence the dependent variable although less likely in the nonlinear way. The alternative measure of financial depth includes credit to the central government, which is an instrument of the short-term stabilization policy. It is likely that short-term growth of credit to government dampens volatility of GDP.

## V. Conclusion

We have examined the relationships between the level and dynamics of financial depth measured as private credit to GDP ratio and volatility of GDP. In contrast to the previous studies, we have considered the two financial depth variables jointly and used dynamic spatial panel data models to control for cross-sectional dependence of errors. Our results for the role of the level of financial depth are consistent with the literature. The relationship is non-linear. Higher levels of financial depth are associated with higher volatility once the financial depth measure exceeds 96–124% of GDP.

What is more important, we have presented the evidence that higher dynamics of financial depth, as measured by private credit, increases volatility of GDP in the large panel of countries over the last 45 years. This relationship is observed not only in the whole sample, but also after excluding the period of the recent financial crisis, among the low-, medium-, and high-income countries and are robust to changes in specification of the econometric model and the estimation method. In terms of explained variance, the impact of changes in financial depth is considerably stronger than the role of its level itself, even after accounting for the possible non-linear influence of the latter factor.

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No potential conflict of interest was reported by the authors.

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## Appendix A. List of countries

**Table A1.** The list of the countries.

| Low-income | Medium-income | High-income |
|---|---|---|
| Benin | Argentina | Australia |
| Burkina Faso | Bolivia | Austria |
| Burundi | Botswana | Belgium |
| Central African Republic | Brazil | Chile |
| Chad | Cameroon | Denmark |
| Gambia | Colombia | Finland |
| Madagascar | Costa Rica | France |
| Malawi | Cote D'Ivoire | Germany |
| Mali | Ecuador | Greece |
| Nepal | Egypt | Ireland |
| Niger | El Salvador | Israel |
| Senegal | Fiji | Italy |
| Sierra Leone | Gabon | Japan |
| Togo | Ghana | Korea |
| | Guatemala | Netherlands |
| | Guyana | Oman |
| | Honduras | Portugal |
| | India | Saudi Arabia |
| | Jamaica | Singapore |
| | Kenya | Spain |
| | Malaysia | Sweden |
| | Mexico | Trinidad and Tobago |
| | Morocco | United Kingdom |
| | Nicaragua | United States |
| | Nigeria | Uruguay |
| | Pakistan | |
| | Panama | |
| | Papua New Guinea | |
| | Paraguay | |
| | Peru | |
| | Philippines | |
| | South Africa | |
| | Sri Lanka | |
| | Swaziland | |
| | Thailand | |
| | Tunisia | |
| | Turkey | |
| | Venezuela | |