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New technologies and diffusion of innovative financial products: evidence on exchange-traded funds in selected emerging and developed economies.

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Abstract

Exchange-traded funds (ETFs) are one of the most rapidly-expanding categories of innovative financial products that have been introduced on many financial markets, in both emerging and developed economies. Our research contributes to the present state of knowledge by examining factors, including information and communication technologies (ICTs), influencing the diffusion of ETFs. In our research, we consider also the impact of other segments of the financial system, such as the banking sector, and changes in the real side of the economy. The main aim of the paper is to provide empirical evidence on relationships between penetration of ICTs and diffusion of ETFs. Using a sample of 32 emerging and developed economies; we analyze all countries for which data on the turnover of ETFs on the local stock exchanges are available. The time span of our analysis is 2004–2014. The methodological framework combines innovation diffusion models, which are applied to characterize the key features of the process of diffusion of ETFs and ICT, with dynamic panel models, panel VAR models with exogenous variables and VAR models with exogenous variables (for country-specific analysis), which are used to examine the relationships between ETFs, ICTs, and other selected factors. Our major findings confirm that adoption of ICTs constitutes an important prerequisite for the diffusion of ETFs due to potential demand- and supply-side linkages. Among the other factors that potentially influence the diffusion of ETFs, we found three variables that demonstrate positive and statistically significant impacts: stock market turnover, financial development, and financial markets. Country-wise VAR models

with selected exogenous variables confirm the influence of ICTs in most of the countries analyzed.
Keywords: exchange-traded funds, financial innovations, information and communication technologies, diffusion.

JEL classification codes: G11, G12, G23, O16.

1. Introduction.

Exchange-traded funds (ETFs) are one of the most rapidly-expanding categories of innovative financial products. The popularity of ETFs has been spurred by the benefits they offer to their users in comparison to those offered by traditional investment companies (Gastineau, 2010; Agapova, 2011; Hill et al., 2015; Lechman & Marszk, 2015). Their spread has been observed on many financial markets, not only in the developed economies but also in some emerging countries. Despite the growth of the ETF markets in many countries, factors influencing the diffusion of these financial innovations (i.e., the growth of the turnover of their shares or assets under management) remain a largely neglected topic in scientific research.

It is claimed that information and communication technologies (ICTs) constitute an important factor contributing to the strengthening of financial systems and financial development [see, for example, Wurgler (2000) and Yartey (2008)]. ICTs may affect financial markets and the spread of financial innovations (including ETFs) in various ways. Undeniably, the unbounded spread of ICTs may effectively facilitate both the emergence and the diffusion of financial innovations and enhance the dynamic development of financial markets as a whole. Broad adoption of ICTs gives rise to a new network, the members of which gain access to financial markets, especially to innovative financial products, on-line banking systems, and many other financial services that enhance their financial inclusion. Arguably, a kind of 'domino effect' (Economides, 1996; Cabral, 2006) occurs as new potential users wish to join the emergent 'financial network', hoping to fulfill their expectations of potential gains. Apparently, the role of ICTs in the diffusion of ETFs can be observed in both the demand and the supply sides of the ETF market. On the one hand, broad usage of ICTs eliminates information asymmetries, enhances in-time trading, and makes trading mechanisms more effective, which boosts demand for transactions on stock markets. Meanwhile, on the other hand, adoption of new communication methods (especially using a broadband connection) allows an increasing supply of various innovative financial products. Bearing the latter in mind, both sides of the financial market develop continuously. In our research, to more accurately evaluate the impact of ICTs on the diffusion of ETFs, we consider also the impact of other segments of the financial system, such as the banking sector. Undeniably, diffusion of ETFs seems to be dependent on a wide variety of other factors, such as the rate of economic growth and capital and labor productivity.

The main aim of this paper is to provide empirical evidence on the relationships between the penetration of ICTs and the diffusion of innovative financial products—ETFs— using a sample of 32 emerging and developed economies. This means that, with some minor exceptions, we analyze all countries for which it is possible to acquire data on the turnover of ETFs on the local stock exchanges. More specifically, our research contributes to the present state of knowledge by:

- Tracing the diffusion trajectories of financial innovations (ETFs) and examining the dynamics of the process across selected emerging and developed economies;
- Verifying the hypothesis regarding the impact of growing penetration of ICTs on the diffusion of ETFs in the countries analyzed;
- Detailed examination of the impact of financial and macroeconomic factors on the diffusion of ETFs in the countries analyzed.

Our methodological framework involves adoption of a combination of innovation diffusion models (Geroski, 2000; Lechman, 2015), which are used to briefly characterize the key features of diffusion of ETFs, with dynamic panel models, panel vector autoregression models with exogenous variables and country-wise VAR models with exogenous variables. These are applied to examine the relationships between ETFs, ICTs, and other factors. We use annual data for 2004–2014 on the turnover of ETFs, the adoption of ICTs, the development of financial markets/banking sector, and economic growth (as well as its components). These are derived from the following databases: World Telecommunication/ICT Indicators Database 2016, World Federation of Exchanges, World Bank's Global Financial Development Database, the International Monetary Fund (IMF) Financial Development Index Database, and The Conference Board's Total Economy Database.

2. Exchange-traded funds and information and communication technologies—theoretical issues.

2.1. ETFs: key concepts.

ETFs are, relatively, the youngest type of investment company (a company that offers financial products linked with investing); more established alternatives are, above all, mutual funds and, in some countries, either closed-end funds or other similar products, depending on the regulatory environment. The first ETFs in Europe and Asia-Pacific were launched in the late 1990s and early 2000s, although only in a few countries; they were introduced on a larger scale a few years later. The rapid growth in the diversity of the ETFs has made them more innovative alternatives to almost all types of mutual funds (apart from, e.g., money market funds). Due to their features, ETFs (discussed below) may also be considered to be financial instruments and can be compared, from the perspective of their investment aims, with stock index futures or options. However, the second approach is still rather rare; therefore, in this section, we will focus on the features of ETFs that distinguish them from the traditional investment companies, i.e., mutual funds. In our empirical research we will consider both approaches. On the one hand, we will use data on the assets of mutual funds as one of the factors potentially explaining the diffusion of ETFs. On the other hand, the analyzed indicator of the diffusion of ETFs will be the turnover of their shares, which is affected directly by the trade in competing instruments, such as stock index futures or options. We label ETFs as 'innovative financial products' to accurately describe their dual features.

ETFs are regarded as hybrid investment companies that share some features of mutual funds and other companies (Investment Company Institute, 2017). The legal and operational structure of ETFs is, to some extent, similar to mutual funds, with financial companies playing various roles in their creation and distribution. However, in contrast with mutual funds, the units (also labeled 'shares') of ETFs are traded on either stock exchanges or similar trading platforms, in a way similar to trading shares of listed companies (IMF, 2011).

The other crucial difference between ETFs and mutual funds applies to the creation and redemption of their units. Mutual funds can buy back previously-issued units from investors at the units' current net asset value, which is calculated by either the fund itself or by cooperating companies. In the case of ETFs, the creation/redemption is significantly different and involves authorized participants who play a central role in this process (it is called 'in-kind' creation/redemption). Based on the observed market demand from investors who wish to buy shares of ETFs, authorized participants exchange a basket of securities (or other assets managed by a particular ETF) for a large block of shares of ETFs (usually 25 thousand or more). Authorized participants can then sell those shares on the market, i.e., through the stock exchange. When demand for shares of ETF declines, authorized participants may conduct reverse transactions and obtain securities in exchange for the shares of ETFs. These actions of authorized participants, undertaken usually when there is a lack of balance between market demand and supply, limit the deviations of the market prices of the ETF's shares (i.e., prices in transactions either between investors or between investors and authorized participants) from their underlying values (which depend on the values of the managed assets and fund liabilities). ETFs that use derivatives to gain exposure to the tracked assets (labeled 'synthetic' ETFs) operate differently (cash is exchanged for units, not baskets of securities), but they represent the minority of ETFs in Europe and Asia-Pacific.

Table 1. Comparison of mutual funds and ETFs.

attribute	mutual funds	ETFs
Creation/redemption of units	conducted by the mutual fund or cooperating entities	'in-kind'—between authorized participants and ETF
Valuation of units	value calculated by the mutual fund, usually once a day	continuous access to prices determined on stock exchanges
Distribution channels	financial institutions cooperating with the mutual fund	stock exchanges or similar trading platforms
Costs for investors	distribution, management, and other similar fees	mostly costs of stock transactions

Source: own compilation, based on Abner (2016), Ben-David et al. (2017), BlackRock (2017), ICI (2017), IMF (2011), Lechman & Marszk (2015), Madhavan (2016).

The most significant differences between ETFs and mutual funds are summarized in Table 1. The unique creation/redemption process of ETFs and the different distribution method lead to lower costs in ETFs. Another relative benefit is the much more frequently updated prices of ETFs, resulting from the interaction between market demand and supply. By using ETFs, investors can also more easily invest in assets from markets with limited accessibility (e.g., markets that are either physically distant or have highly variable local currency).

2.2. ICTs for economy and financial markets.

ICTs are claimed to be one of most important factors shaping today`s economic and social environment. ICTs are argued to be 'pervasive technologies' [see Bresnahan & Trajtenberg (1995)], meaning that new technological solutions are thoroughly implemented, and their socio-economic impact is put in a complex context involving a wide bundle of social norms and attitudes, political regimes, and legal and institutional frameworks, as well as either geographical location or a country`s historical legacy (Kaur et al., 2017; Lechman, 2017).

Undeniably, ICTs allow unrestricted flows of information and knowledge; as a result, they enable the rise of new products and services, in addition to totally new industries and business models. ICTs enforce the emergence of new types of networks (Shapiro & Varian, 1998; Valente, 1996; Castells et al., 2009), and this generates disruption in the entire socio-economic system (Jovanovic & Rousseau, 2005, Lechman, 2018). Helpman and Trajtenberg (1996) state that *'as GPTs appear (...) there is a spell of growth, with rising output, real* *wages, and profits'* (Helpman & Trajtenberg, 1996, p. 4). ICTs drive the emergence of the economies of networks, mainly because ICTs free people and market activities from physical location and, thus, enhance the growth of economic activities in previously marginalized and peripheral regions [see, for instance, works of Bach et al. (2018) or Banaji et al. (2018)]. Society-, and economy-wide adoption of ICTs, if accompanied by massive flows of information, provides solid fundaments for increasing economic activity (Palvia et al. 2017), economic inclusion, and productivity shifts (Billon et al., 2017; Corrado et al., 2017). ICTs foster participation of economic agents, *inter alia,* in the labor market and, in that sense, adoption of ICTs helps to overcome intensive constraints to growth that are experienced by different countries or regions (Niebel, 2018). The significant impact of ICTs on the economy is enabled by the creation of positive links between market agents, providing both opportunities for more flexible work environments and new contacts, which results in the growth of economic activity (Latif et al., 2017; Thomas, 2017; Spiezia, 2018), with potential increases in productivity, firm efficiency, and cost reduction (Nawinna & Venable, 2018).

The impact of the adoption of ICTs may also be considered with regard to the key part of the modern economy—the financial system, either considered as a whole or with a focus on its specific segments, such as financial markets. In the next few paragraphs, we present selected theoretical and empirical aspects of the influence of ICTs on financial development.

Broadly considered, as raised by Sahay et al. (2015), or, more recently, in Paganetto (2017), economic development, technology, and financial markets constitute a complex system with multiple emerging interdependencies. As presented in the preceding paragraphs, ICTs can significantly contribute to strengthening national economies, both in developed and developing countries. Moreover, ICTs are considered to be one of the factors necessary for a strong financial system (Wurgler, 2000; Yartey, 2008).

The impact of ICTs on financial development has been verified empirically, but the results of the research are fragmented and inconclusive (however, they generally confirm the positive effect); moreover, there are almost no studies that address directly the impact of ICTs on financial innovations. Claessens et al. (2002) analyzed a sample of developing and emerging economies and found that adoption of ICTs may positively contribute to financial development. Shamim (2007), using a sample of 61 countries between 1990 and 2002, claims that the relationship between ICTs and financial development is positive. According to Andrianaivo and Kpodar (2011), diffusion of ICTs plays a positive role in both financial development and economic growth in African economies. Sassi and Goaied (2013) state that adoption of ICTs in MENA region economies has had a positive effect on financial development (and economic growth). Sepehrdoust (2018), in his study concerning OPEC countries, finds that, between 2002 and 2015, positive links between ICT deployment and growth of both economic and financial systems may be traced. Some more evidence demonstrating how ICTs may impact broadly defined financial development may be also traced in works of, *inter alia*, Ghezelbash & Keynia (2014), Islam & Dooty (2015), Kia (2016), Salahuddin & Gow (2016), Drummer et al. (2017), and Sekyere et al. (2017).

One of the areas of the financial system that is most strongly influenced by the diffusion of ICTs is financial markets; this influence is evidenced, above all, by the changes in these markets' infrastructure, such as adoption of electronic systems. Diffusion of ICTs in this area leads to new and faster methods of data and information dissemination, decreasing the scale of information asymmetries and time delays (Asongu & Moulin, 2015; Miller & Skinner, 2015), and providing market participants with access to physically distant assets (Morck et al., 2000). Schmiedel et al. (2006) show the impact of new technologies on the improved cost effectiveness of the stock depository and settlement systems. Madhavan (2012) states that financial markets' participants can act swiftly and gain access to the most recent data. Consequently, the activity in financial markets (measured, e.g., in terms of turnover) may increase (Lechman & Marszk, 2015). All the elements—as channels of impact—mentioned above are closely related to one of the fundamental characteristics of financial markets, which may be characterized as 'information markets' (Stigles, 1961). It should be noted, though, that the influence of ICTs on the development of financial markets is not considered to be unequivocally positive—broader adoption of ICTs and linked usage of, e.g., electronic trading systems (allowing for advanced computerized trading mechanisms, such as high frequency trading) may result in increased volatility of financial markets (Diaz-Rainey et al., 2015). Other problematic issues are potentially increasing fragmentation and complexity of the financial markets (Diaz-Rainey & Ibikunle, 2012; Preece, 2012).

Impact of ICTs on the financial markets has been verified empirically in some studies, but the number of such studies is relatively low. Ngassam and Gani (2003) verified the impact of ICTs on the development of stock markets in a group of high-income and emerging economies and claim that it was positive in both categories of countries. Falahaty and Jusoh (2013) found a positive relationship between adoption of ICTs and development of financial markets in MENA countries. Rezaie Dolat Abadi et al. (2013) conducted a study of 60 major equity markets and found a positive impact of ICTs on stock market capitalization and turnover. Janke et al. (2015) found evidence that stock markets in 4 transforming economies (Czech Republic, Hungary, Poland, and Slovakia) have reacted positively to broad deployment of ICTs. Asongu and Moulin (2016), in their study covering 53 African economies between 2004 and 2011, demonstrated that, in these economies, the links between diffusion of ICTs and growing demand for financial services and products, through which development of financial markets is unveiled, are still relatively weak. Gardner et al. (2017) analyzed 81 stock markets and claim that adoption of ICTs positively influences the capitalization of stock markets. As shown in country-specific empirical studies by Bhunia (2011) and Okwu (2015), deployment of ICTs has a positive impact on development of stock markets as it facilitates stock exchange operations and increases overall transactional capacities. It should be emphasized that the results of the above-mentioned studies prove that analyzed relationships have been recognized in countries at different levels of economic development (i.e., not exclusively in advanced economies).

2.3. Identifying links between ICTs and ETFs.

Factors that determine the diffusion of ETFs remain largely unexplored in both empirical and theoretical literature [a brief theoretical outline is available in Hull (2016)]. The most popular approach is to focus on relative advantages of ETFs for their users as the key factor of the development of their markets [see, e.g., either Agapova (2011) or Aggarwal & Schofield (2014)]. However, such an approach ignores the broader context of the introduction and growth of ETFs in financial markets, i.e., which factors precondition the creation of ETFs, and how they affect their spread. Among the large number of such factors, an important role is played by diffusion of new technologies—ICTs and the development of other parts of the financial system (financial markets above all).

The interactions between the diffusion of ETFs and the development of financial markets are rather straightforward and result from the mechanisms of ETFs' creation/redemption and turnover, as well as their attractiveness in relation to competing investment alternatives, such as mutual funds, closed-end funds, and stock index derivatives. To ensure the proper functioning of ETFs, the markets for the underlying assets (i.e., either assets whose prices are tracked by ETFs, or, more simply, assets in the portfolio of ETFs) should be liquid and large enough to accommodate transactions made by entities involved in the turnover of ETFs. This applies mostly to stock markets and, to a lower degree, to bond markets, and their key considered indicators should be the value of turnover. The reason for this is the structure of the ETF markets—in all countries, the most popular category of ETFs by far are funds based on stock markets. In most cases, the second largest group is bond ETFs, but the size of this category is much smaller. Diffusion of ETFs depends, therefore, on the existence of stock and bond markets. Apart from the impact of the size and turnover, the activity on ETF markets may also be influenced by the volatility and the profitability of investments in stocks that have a direct impact on parallel features of ETFs. Diffusion of ETFs may also indirectly depend on the general trends in the local financial system and economy. A more advanced financial institution may lead to, for instance, easier access to distribution channels of ETFs. Development of the banking sector, particularly in less developed economies, means more frequent usage of the financial services by the local residents (e.g., increasing bank deposits—but also more sophisticated services, such as purchase of the funds' units). The rate of economic growth and its composition (its structure) influences financial markets (e.g., stock market returns) and, as a result, ETF markets. To the best of our knowledge, the above-mentioned potential linkages between the diffusion of ETFs and the development of other parts of the financial and economic system have not been verified empirically.

As discussed above, ETFs are strongly linked to the financial markets, particularly the stock and bond markets. Therefore, diffusion of ETFs is, to a large extent, dependent upon changes occurring in these markets, including those caused by increasing ICT penetration. These effects may be discussed from the perspective of both the demand side and the supply side of the market. Demand-side factors are understood here as factors linked to the relative advantages of ETFs, which result in the occurrence and growth of demand for ETFs. Analogically, supply-side factors are defined here as factors linked to changes in the financial markets that not only facilitate the launch and diffusion of ETFs but also increase the motivation of financial institutions to enter this market due to, e.g., potential profits from becoming either ETF providers or authorized participants. The most important demand- and supply-side factors are presented in Table 2.

The influence of ICTs on the diffusion of ETFs, as outlined in the preceding paragraphs, has not been checked empirically, with the exception of Lechman and Marszk (2015), who confirm the positive impact of ICTs, in most cases, in a group of countries between 2002 and 2012. However, the applied indicator of the ETF diffusion is the value of assets under management—in our study, we improve on that research by focusing on the measure of turnover, due to reasons explained in Section 3.1. Khodayari and Sanoubar (2016), by examining the impact of ICTs on mutual funds markets development across D-8[1] countries during 1999–2014, found that these are positively interrelated. However, they did not study ETFs but the traditional category of investment companies; therefore their conclusions may not be simply transposed to the innovative category.

Table 2. Impact of ICT on the diffusion of ETFs: demand- and supply-sides of the ETF market.

demand side	supply side
higher automation of turnover reduces trading costs and facilitates more efficient risk-sharing; it also improves the liquidity and efficiency of pricing mechanisms	transfer of securities necessary during creation/redemption or trade in ETF shares requires advanced settlement systems based on new technologies, particularly fast broadband Internet connections
electronic trading increases dissemination of information between different markets and participants	in the past, managing index portfolios with hundreds or thousands of constituents was too expensive in relation to more concentrated portfolios of active investment funds; adoption of electronic data delivery and cheaper processing technology facilitates inception and management of passive funds such as ETFs
electronic trading systems lower trading costs, which increases the attractiveness of ETFs	ICTs facilitate timely responses to the latest data and the transfer of funds between physically distant markets—particularly important for emerging market ETFs
broader access to fast Internet connections and electronic trading systems give market participants the possibility to act quickly and conduct transactions based on the latest market data; a linked effect is lower deviations of ETF shares' prices from the prices of tracked assets	cross-listing of ETFs requires adoption of ICTs in the exchanges' trading and settlement systems and access to technologically advanced foreign exchange markets for investors

Source: own compilation, based on Blitz & Huij (2012), Calamia et al. (2013), Hendershott et al. (2011), Lechman & Marszk (2015), Lettau & Madhavan (2018), Nishimura (2010), and Schmiedel et al. (2006).

3. Materials and methods.

3.1. Data explanation.

In our research, we use a database that includes annual data for 2004–2014 on the following indicator of the diffusion of ETFs: value of ETFs' turnover on the stock exchanges in a particular country in relation to GDP (we use turnover indicator to extend the group of countries in our sample, as it can be obtained for more countries than can than the alternative indicator, i.e., assets under management). ETFs' turnover indicators are derived from the reports of the World Federation of Exchanges and of local stock exchanges. Two ICTs diffusion indicators are fixed broadband subscriptions (FBS, hereafter) per 100 inhabitants, defined as the number of fixed broadband Internet subscribers in a particular country per each 100 inhabitants, and Internet users (IU, hereafter), which refers to the 'proportion of

[1] Bangladesh, Egypt, Indonesia, Iran, Malaysia, Nigeria, Pakistan, and Turkey.

individuals who used the Internet from any location in the last three months'. All data on the diffusion of ICTs are derived from the World Telecommunication/ICT Indicators database 2016. To account for changes in other parts of the financial system (financial markets and the banking sector) and the whole economy, we use financial development and economic growth (including its components) indicators that are derived from the reports of the World Federation of Exchanges (WFE) and the most recent editions of the World Bank's Global Financial Development Database, the IMF Financial Development Index Database [methodology of the indexes is presented in Sahay et al. (2015)], and The Conference Board's Total Economy Database.

Our research covers 32 countries, i.e., all countries for which it is possible to acquire data on turnover of ETFs on the local stock exchanges: 15 countries in Europe, the Middle East, and Africa (France, Germany, Greece, Hungary, Iran, Ireland, Italy, Norway, Poland, Saudi Arabia, South Africa, Spain, Switzerland, Turkey, and the United Kingdom), 10 countries in Asia-Pacific (Australia, China (i.e., Mainland China), Hong Kong, India, Japan, Malaysia, New Zealand, Singapore, South Korea, and Thailand), and 7 countries in two Americas (Brazil, Canada, Chile, Colombia, Mexico, Peru, and the United States). It must be emphasized that the presented enumeration is the not the exhaustive list of all global ETF markets, as we have excluded a few countries with the lowest turnover—in all cases they were also characterized by a significant share of missing observations regarding local ETF markets; another exclusion is countries whose stock exchanges operate within the Nasdaq Nordic group, as WFE statistics are provided on a country-wise level.[2]

3.2. Empirical setting.

To reach the main aims of the study, together with standard descriptive statistics, we use innovation diffusion models (Geroski, 2000; Rogers, 2010; Kwasnicki, 2013; Lechman, 2015), which we apply to approximate the trajectories of ETFs' diffusion.

We use the framework of an innovation diffusion model outlined in Mansfield (1961) and Dosi and Nelson (1994), who adopted the evolutionary dynamics concept in analyzing the phenomenon. This idea may be mathematically presented in the form of the logistic growth function. Such a function can be rewritten as following an ordinary differential equation (Meyer et al., 1999):

$$\frac{dY_x(t)}{dt} = \alpha Y_x(t) , \qquad (1)$$

where $Y(t)$ is the level of variable x, (t) denotes time, and α is a constant growth rate. Eq.(1) explains the time path of $Y(t)$, and it can be reformulated by introducing e in the following way (notations analogous to above):

$$Y_x(t) = \beta e^{\alpha t}, \qquad (2)$$

Or, in alternative specification:

$$Y_x(t) = \alpha \exp \beta t, \qquad (3)$$

where β represents the initial value of x. The presented model is pre-defined as exponential, which leads to the problem of infinite growth of x in geometric progression. It may, therefore,

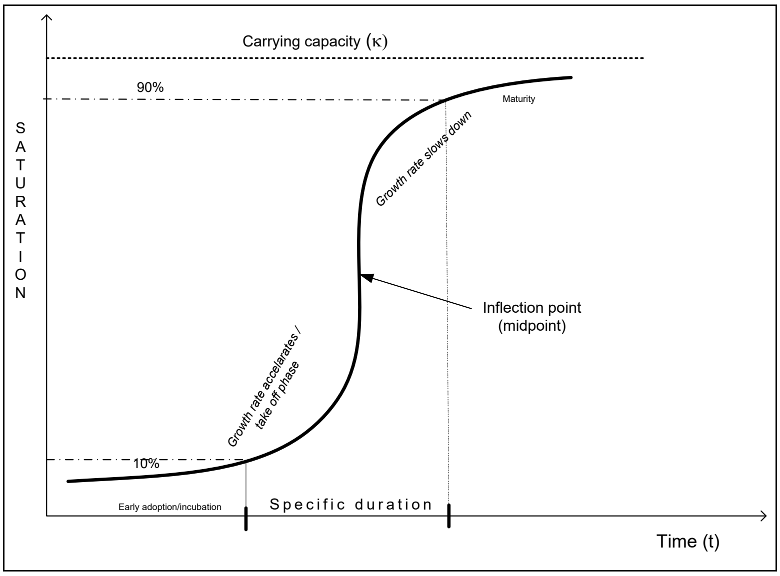
[2] A similar problem applies to the Euronext exchange—in order not to omit this third-largest market in Europe we assigned all Euronext's ETF turnover to France (Euronext Paris represents over 95% of the assets of ETFs primary listed on Euronext).

lead to unrealistic projections, because systems are usually constrained and do not grow infinitely (Meyer, 1994). To solve this problem, Eq.(1) has been expanded by adding the 'resistance' parameter, which introduces an upper 'limit' to the exponential growth model (Kwasnicki, 2013). This also changes the shape of the growth curve, making it sigmoid. Adding the 'resistance' parameter generates an S-shaped trajectory (see Fig. 1). The modified version of Eq.(1) is defined as:

$$\frac{dY(t)}{dt} = \alpha Y(t)\left(1 - \frac{Y(t)}{\kappa}\right), \tag{4}$$

where κ is the imposed upper asymptote that limits the growth of Y.

Fig. 1. Theoretical specification of S-shaped diffusion trajectory.



Source: Lechman (2015).

The 3-parameter logistic differential equation [see Eq.(4)] can be re-written as a logistic growth function that takes only non-negative values throughout its whole path:

$$N_x(t) = \frac{\kappa}{1 + e^{-\alpha t - \beta}}, \tag{5}$$

or, using alternative specification:

$$N_x(t) = \frac{\kappa}{1+\exp(-\alpha(t-\beta))}, \tag{6}$$

where $N_x(t)$ denotes the value of variable x in time period t. The parameters in Eqs.(5–6) can be interpreted as:

κ - upper asymptote, which determines the limit of growth;

α - growth rate, which determines the speed of diffusion;

β - midpoint, which determines the exact time (T_m) when x reaches 0.5κ; it indicates the inflection point of the logistic curve.

To facilitate interpretation of the diffusion pattern, a 'specific duration' parameter may be calculated, which is defined as $\Delta t = \frac{\ln(81)}{\alpha}$. Δt shows the time needed for x to grow from 10%κ to 90%κ. Incorporating parameters Δt and T_m into Eq.(6) entails:

$$N_x(t) = \frac{\kappa}{1+exp\left[-\frac{\ln(81)}{\Delta t}(t-T_m)\right]}. \tag{7}$$

The parameters in Eq.(7) can be estimated using, for instance, ordinary least squares (OLS), maximum likelihood, algebraic estimation, or nonlinear least squares (NLS). According to Satoh (2001), NLS yields relatively better predictions than do other methods—the estimates of standard errors (of parameters in Eq.(7)) are more valid than in other methods. Moreover, using NLS allows avoidance of time-interval biases, which are problematic in the case of OLS (Srinivasan & Mason, 1986). The key disadvantage of NLS is sensitivity of the parameters to the initial values in the time-series.

In our research, we assume that ETFs are innovations, which, due to 'word of mouth' (Geroski, 2000) and emerging network effects, are gradually being adopted by an increasing number of investors; the underlying reason for this is their benefits in comparison to either mutual funds, other competing funds, or financial instruments.

To examine the statistical associations between the diffusion of ETFs and ICTs, as well as other potential determinants, we use dynamic panel models. We adopt a one-step Arellano-Bond difference GMM estimator (Holtz-Eakin et al., 1988; Arellano & Bond, 1991) and we estimate following a dynamic panel regression model:

$$\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{y}} = \alpha(\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{y}-\boldsymbol{1}}) + \boldsymbol{\beta}_{\boldsymbol{1}}\boldsymbol{X}_{\boldsymbol{iy}} + \boldsymbol{\beta}_{\boldsymbol{2}}\boldsymbol{X}_{\boldsymbol{iy}} + \ldots. + \boldsymbol{\beta}_{\boldsymbol{n}}\boldsymbol{X}_{\boldsymbol{iy}} + \boldsymbol{u}_{\boldsymbol{i},\boldsymbol{y}}, \tag{8}$$

where $\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{y}-\boldsymbol{1}}$ denotes the lagged value of $ETF_{i,y}$, i stands for country and y – time. α stands for the $\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{y}-\boldsymbol{1}}$ coefficient, while $\boldsymbol{\beta}_{\boldsymbol{1}}$ to $\boldsymbol{\beta}_{\boldsymbol{n}}$ represent coefficients for consecutive explanatory variables included in the model. For the model specified in Eq.(8), we assume that $\boldsymbol{u}_{\boldsymbol{i},\boldsymbol{y}}=\boldsymbol{\mu}_{\boldsymbol{i}} + \boldsymbol{\nu}_{\boldsymbol{i},\boldsymbol{y}}$, if $\boldsymbol{\mu}_{\boldsymbol{i}} \sim \boldsymbol{IID}\ (\boldsymbol{0}, \boldsymbol{\sigma}_{\boldsymbol{\mu}}^{\boldsymbol{2}})$ and $\boldsymbol{\nu}_{\boldsymbol{i},\boldsymbol{y}} \sim \boldsymbol{IID}(\boldsymbol{0}, \boldsymbol{\sigma}_{\boldsymbol{\nu}}^{\boldsymbol{2}})$ (Baltagi 2008b); $\boldsymbol{\mu}_{\boldsymbol{i}}$is the unobservable, fixed-time, and individual-specific effect, while $\boldsymbol{\nu}_{\boldsymbol{i},\boldsymbol{y}}$ represents the error term.

Additionally, we use panel vector autoregression (PVAR) (Holtz-Eakin et al., 1988), recently commonly applied in macroeconomics and finance (Canova & Ciccarelli, 2013). Such an approach allows us to capture both static and dynamic interdependencies present in the data examined, in addition to cross-country heterogeneity (Canova & Ciccarelli, 2013). By convention, PVAR models include several countries and variables; thus, lagged foreign variables can impact changes in domestic variables, which would suggest existing dynamic interdependencies across analyzed units (countries, for instance) (Canova & Ciccarelli, 2009). The fact that PVAR models account for interdependencies and cross-country heterogeneity simultaneously is claimed one of its major strength.

Technically, panel VAR model is built with the same logic as a standard VAR but with added cross sectional dimension. Suppose we have a cross-section of Y set of units (which may be countries or regions), and we presume that these are linked to each other. For each individual y-unit, a set of X economic variables are being considered over time.

By definition in panel VAR all variables are endogenous, and thus each endogenous variable is assumed to depend on the lagged values of itself and of all other endogenous variables included in the model (Dées & Guntner, 2014). Considering the fact that the panel VAR model accounts additionally for cross-sectional dimension, its equation holds a general form (Dées & Guntner, 2014):

$$\gamma_{y,t} = \nu_y + \Omega_{1,y}\Gamma_{t-1} + \cdots + \Omega_{p,y}\Gamma_{t-p} + e_{y,t}, \quad \text{if } y = 1, \ldots \ldots, Y \tag{9}$$

In Eq.(9), $\gamma_{y,t}$ denotes the $(X \times 1)$ vector of endogenous variables for y-unit examined; t is time and p – lags of endogenous variables. $\Gamma_t = \left(\grave{\gamma}_{1,t}, \dots, \grave{\gamma}_{N,t}\right)$ stands for the $(Y \cdot X \times 1)$ vector of $\gamma_{y,t}$ if $y = 1, \dots \dots, Y$. $\Omega_{j,y}, j = 1, \dots \dots, p, y = 1, \dots \dots, Y,$ represents $(X \times Y \cdot X)$ matrices of slope coefficients of endogenous variables, ν_y is the $(X \times 1)$ vector of intercepts, and $e_{y,t}$ stands for the $(X \times 1)$ vector of contemporaneously correlated reduced-form coefficients (Dées & Guntner, 2014; Abrigo & Love, 2016).
However, Γ_t representing the vector of $(Y \cdot X \times 1)$, can potentially depend on the selected exogenous variables defined as $(Z \times 1)$ vector – see, for instance, in the pioneering work of Ramey and Shapiro (1998). The exogenous variables which, as additional determinants of Γ_t, may be included in the model, are – by definition – independent of lagged values of Γ_t.
The panel VAR model augmented by a set of exogenous variables (PVARX) holds the general form:

$$\gamma_{y,t} = \nu_{1y} + \sum_{l=1}^{p} \Omega_{l,y} \Gamma_{t-l} + \sum_{\grave{l}=0}^{q} \Psi_{\grave{l},y} \Phi_{t-\grave{l}} + e_{1y,t}, \tag{10}$$

$$\text{where:} \Phi_t = \nu_2 + \sum_{l=1}^{p^x} \vartheta_l \Phi_{t-l} + e_{2,t}, \tag{11}$$

In Eq.(10) $\Psi_{\grave{l},y}, \grave{l} = 0, \dots \dots,$, are $(Y \cdot X \times Z)$ matrices of coefficients of exogenous variables, and q represents potential lags of exogenous variables, while $e_{1y,t}$ and $e_{2,t}$ should be uncorrelated.
By estimating Eqs. (10-11), we generate a system of simultaneous equations, where each consecutive equation contains $W = Y \cdot X \cdot p + Z \cdot (q + 1) + 1$ of estimated coefficients including intercept; while the total number of coefficients generated by all equations in the system amounts to $Y \cdot X \cdot W$.
To enrich the picture, we additionally estimate country-specific VAR models with exogenous variables included (VARX), assuming that in that case the system has a set of predefined endogenous and exogenous variables. Keeping the notation as in Eqs.(10-11), the country-specific VAR is following (Ocampo & Rodríguez, 2012):

$$\Gamma_t = \nu + \Omega_1 \Gamma_{t-1} + \dots . + \Omega_p \Gamma_{t-p} + \Theta_o X_t + \dots + \Theta_q X_{t-q} + e_t, \tag{12}$$

where Γ_t represents the $(Y \cdot X \times 1)$ vector of endogenous variables, ν is the $(Y \cdot X \times 1)$ vector of intercepts, $\Omega_j,\ j = 1, \dots \dots, p$ are $(Y \cdot X \times Y \cdot X)$ matrices of slope coefficients; X_t and Θ_q stand for corresponding vector and matrices as Γ_t and Ω_p respectively.
In our research we deal with strongly balanced panel, hence to estimate the panel VARX models we use GMM estimator (Canova & Ciccarelli, 2013), and within this procedure we estimate consecutive equations of the system by instrumenting lagged differences with differences and levels of $\gamma_{y,t}$ from the past periods (Anderson & Hsiao, 1982; Hayakawa 2016). Based on GMM estimates, Wald tests may be implemented verifying the null hypothesis that each variable does not Granger-cause the other (Granger, 1980; Green, 2008).
Typically, before consecutive panel VARX models` estimations, the analysis is preceded by optimal lag order specification (Abrigo & Love, 2016). As suggested by Andrews and Lu (2001) the model selection criteria (MSC) are based on commonly used criteria like the Akaike information criteria (AIC) (Akaike, 1969), the Bayesian information criteria (BIC)

(Akaike, 1977; Schwarz, 1978) and the Hannan-Quinn information criteria (HQIC) (Hannan & Quinn, 1979).
To selected the appropriate number of lags in our panel VARX models, we follow the Moment and Model Selection Criteria (MMSC) suggested by Andrews and Lu (2001). It is assumed that we have x-variate panel VARX of order p, n sample size, and q lags of dependent variables, where $J_n(x,p,q)$ is the Hansen`s J statistic of over-identifying restrictions (Hansen, 1982). We choose the pair of vectors (p,q) that minimizes the following:

$$MMSC_{AIC,n}(x,p,q) = J_n(x^2p, x^2q) - 2k^2(|q| - |p|), \quad (13)$$

$$MMSC_{BIC,n}(x,p,q) = J_n(x^2p, x^2q) - (|q| - |p|)k^2 \ln n, \quad (14)$$

$$MMSC_{HQIC,n}(x,p,q) = J_n(x^2p, x^2q) - Rk^2(|q| - |p|) \ln \ln n\,, \quad (15)$$

Note that the pair of vectors vectors (p,q) that minimizes criteria defined in Eqs.(13-15) is available only if $q > p$. These information criteria [Eqs.(13-15)] consist of a vector that minimizes the modified Akaike information criteria (MAIC), the modified Bayesian information criteria (MBIC) and the modified Hannan-Quinn information criteria (MQIC), which conversely to the conventional information criteria, based on normal likelihood function, are calculated using quasi-likelihood function (McCullagh & Nelder, 1989).
Additionally, the CD—coefficient of determination may be used, which captures the proportion of the total variation explained by specific panel VARX model (Abrigo & Love, 2016). In contrast with the information criteria, maximum value of CD is considered to indicate the optimum number of lags.
To conclude, the lag length of panel VARX model should be chosen by maximizing CD and minimizing MAIC, MBIC and MQIC; if the results are inconclusive, then, as suggested in Ng and Perron (2001), the MAIC criterion should be considered.
In our research, to stay in line with the main aims and scopes of the paper, we assume that ETF, IU and FBS variables are treated as endogenous variables, while the other variables are defined as exogenous, which applies both to PVARX and VARX models. In the next Sections we present results of our empirical analysis, interpretations and discussion.

4. Empirical research: results.

4.1. Diffusion of ETFs and ICTs.

Our analysis begins with evaluation of the diffusion paths of ETFs and ICT to determine the key trends in their dynamics. In this Section, we analyze exclusively 14 countries with the highest ETFs' turnover values in relation to GDP reached as of 2014 (Canada, China, France, Germany, Hong Kong, Italy, Japan, Mexico, Norway, South Africa, South Korea, Switzerland, the United Kingdom, and the United States)—in the remaining economies, ETF markets have remained underdeveloped; therefore, it is clear that no diffusion of ETFs has taken place.
The diffusion trajectories of ETFs (in terms of turnover in relation to GDP) in the selected countries displayed considerable between-country heterogeneity and in-time variability, whereas the diffusion of ICTs (measured using the IU indicator) was much more stable (declines were very rare), even though the minimum and maximum levels of ICTs' adoption differed significantly between countries—see Fig. 2. However, in all countries, the value of

IU in 2014 was much higher than in 2004. The highest levels were reached in Norway (96.3), the United Kingdom (91.6), Japan (90.5), and Switzerland (87.4). Countries that lagged behind were Mexico (34.4), South Africa (44.2), and China (47.9), which may be attributed to the lower level of their economic development. However, this may not be regarded as the only factor explaining the lower diffusion of ETFs—see the example of Italy, with an IU value of 61.9, which is much lower than in other advanced economies in the sample.

Figure 2. Diffusion paths of ETFs and ICTs in selected countries. 2004–2014.

Source: Authors' elaboration. Note: red line—ETFs, dash black line—IU; for the United States incomplete ETFs dataset for 2004–2007 (understated values).

Two countries where diffusion of ETFs reached the highest level in the considered time period were the United States and Hong Kong (see Fig. 2). However, it should be borne in mind that both countries may be regarded as outliers in the analyzed group of economies: the United States is the largest ETF market globally, with much higher assets and turnover than all the remaining countries combined, and Hong Kong is a specific case of a country (now part of the People's Republic of China) with very large financial markets in a small economy. Switzerland is also among the countries with the highest turnover of ETFs, with a mean value of 8.7 and a maximum value of 16.7% of local GDP—to some extent, its case may be regarded as similar to that of Hong Kong, as it has an advanced financial system (one of the global financial centers) in a rather small economy. Among other countries, we may distinguish two groups based on the turnover of ETFs between 2004 and 2014: countries where ETFs have become a noticeable part of the local financial system (with turnover of either a few or several percent of GDP) and countries where their role is still rather insignificant, yet not minimal. The first group includes South Korea (where very rapid diffusion of ETFs was observed after 2010), the United Kingdom (stable growth of the ETF market), Japan (quick growth since 2012), Mexico (rapid growth until 2012, a decline between 2013 and 2014), in addition to France, Germany, and Italy (in all three, the trajectory was similar—growth until 2011, followed by decline, which may be explained by the euro-zone debt crisis). The second group consists of China and South Africa, where turnover of ETFs remained below 2% of GDP. There are also two countries where diffusion of ETFs may be described as reverse U-shaped. These are Canada and Norway, where diffusion reached its highest level around the middle of the analyzed time period and then declined significantly. This shows that the diffusion process is not one- directional and, in some cases, may be reversed.

The diffusion model presented in Section 3.2. was applied to more accurately describe the diffusion trajectories of ETFs (see Table 3). Estimates confirm, to a large extent, results of the preliminary analysis based on descriptive statistics (see preceding paragraphs). Starting from the countries with the highest diffusion of ETFs, the largest growth limits were estimated for the United States, Hong Kong, and Switzerland (67.7, 39.2, and 14.9, respectively: all values are in % of local GDP). A lower value of Δt (time needed to grow from 10% to 90% of the growth limit) in the case of the United States suggests a higher speed of diffusion. High R^2 for all three countries suggests that the trajectory is, to a large degree, S-shaped (Fig. 2 confirms this conclusion). The limit for South Korea was estimated at 13.2; T_m at 2010.6 (ca. June 2010—when 50% of the growth limit was reached), the highest in the whole sample, which proves that fast diffusion began later than in all other countries, but a low Δt, at 4.2, shows the high speed of the process. Estimates for the United Kingdom confirm the stability of ETFs' diffusion in this country. Results for France and Germany are rather similar (with faster diffusion in France)—for both countries, the R^2 of estimated models was lower than, for instance, for Switzerland, which was caused by the trajectory of the diffusion: after reaching the maximum level, the turnover of ETFs declined significantly. In Italy, the decrease in this period was less substantial; therefore, there was a higher R^2 (and higher T_m). Growth limits were similar for those three countries—at ca. 5, and the estimated speed of diffusion for Italy was relatively the lowest. In China and South Africa, estimated growth limits were the lowest in the whole sample. Interestingly, the Δt for China is one of the lowest in the whole sample, which proves that the growth limit was achieved very quickly. Results obtained for Mexico, with a growth limit of ca. 4.86%, place this country above China and South Africa, yet below all others mentioned previously.

Table 3. Estimates of diffusion models of ETFs in selected countries. 2004–2014.

Country	κ	β (T_m)	Δt	α	R^2
Canada	6.84	2005.9	2.6	1.6	0.41
China	1.52	2007.3	2.2	2.1	0.69
France	4.87	2005.9	2.9	1.5	0.72
Germany	5.83	2005.4	4.4	0.99	0.70
Hong Kong	39.2	2007.8	5.3	0.83	0.84
Italy	4.71	2007.5	6.0	0.73	0.87
Japan	*4 547 907*	*2039*	*8.2*	*0.53*	*0.89*
Mexico	4.86	2008.3	3.4	1.28	0.84
Norway	2.73	2007.9	0.27	16.4	0.51
South Africa	1.26	2005.6	4.84	0.91	0.69
South Korea	13.2	2010.6	4.2	1.06	0.94
Switzerland	14.9	2008.1	6.5	0.67	0.93
United Kingdom	8.36	2008.4	5.4	0.8	0.96
United States	67.7	2007.2	2.5	1.7	0.92
Average values of estimated parameters (Hong Kong, Japan, and United States – excluded)	6.28	2007.3	3.9	2.54	0.78

Source: Authors' estimations. Note: in italics—misspecifications (unrealistic values of estimated parameters); Hong Kong and the United States excluded from calculations of average values due to their specific character ('outliers').

Taking into account the mean values, it seems that the growth limit of ETFs (as % of local GDP) in the selected countries was ca. 6.3, and 50% of this value was reached, on average, in the first half of 2007; this applies exclusively to countries with the most active ETF markets.

The results for other countries will not be discussed. In one case (Japan), estimations yielded obvious misspecifications, as the diffusion trajectories were not S-shaped—ETFs seem to be still in the stage of rapid logistic growth, which precludes using the diffusion model. For two countries (Canada and Norway—where diffusion was described as reverse U-shaped) the R^2 was rather low (0.41 and 0.51 respectively), and the estimated parameters may not be regarded as highly reliable—they will not be interpreted.

4.2. Factors influencing the diffusion of ETFs.

In the second step of our research, we investigate factors that potentially influence the diffusion of ETFs; unless stated otherwise, in this Section, we use data for 30 countries (i.e., all in our sample, except for the 'outliers'—Hong Kong and the United States) to cover both the economies in which the diffusion of ETFs was observed (at least to some extent—see the previous Section) and those that lag behind. We start by examining correlations between selected indicators (see Table 4). The correlation between turnover of ETFs (as % of local GDP) and two ICTs' adoption indicators is the highest among all potential determinants of the diffusion of ETFs (0.64 and 0.46), which proves that spread of ICTs may play some role in the increasing turnover of these financial innovations. Fig. 3 proves that, while the relationship between FBS and ETFs is positive at almost all levels, the relationship between IU and ETFs is more complicated—at very high levels of the IU variable, it becomes negative. Another variable that is rather highly correlated with the turnover of ETFs is the mutual funds' assets in relation to GDP (the correlation coefficient is, however, statistically insignificant). This result should not be surprising—the relationship between ETFs and mutual funds was discussed in detail in Section 2.1. However, in both the theoretical literature and previous research those two types of investment companies have been considered to be substitutes, therefore the expected correlation coefficient has been negative; for our sample it is positive. This shows that the investment company industry can accommodate both innovative and conventional investment companies.

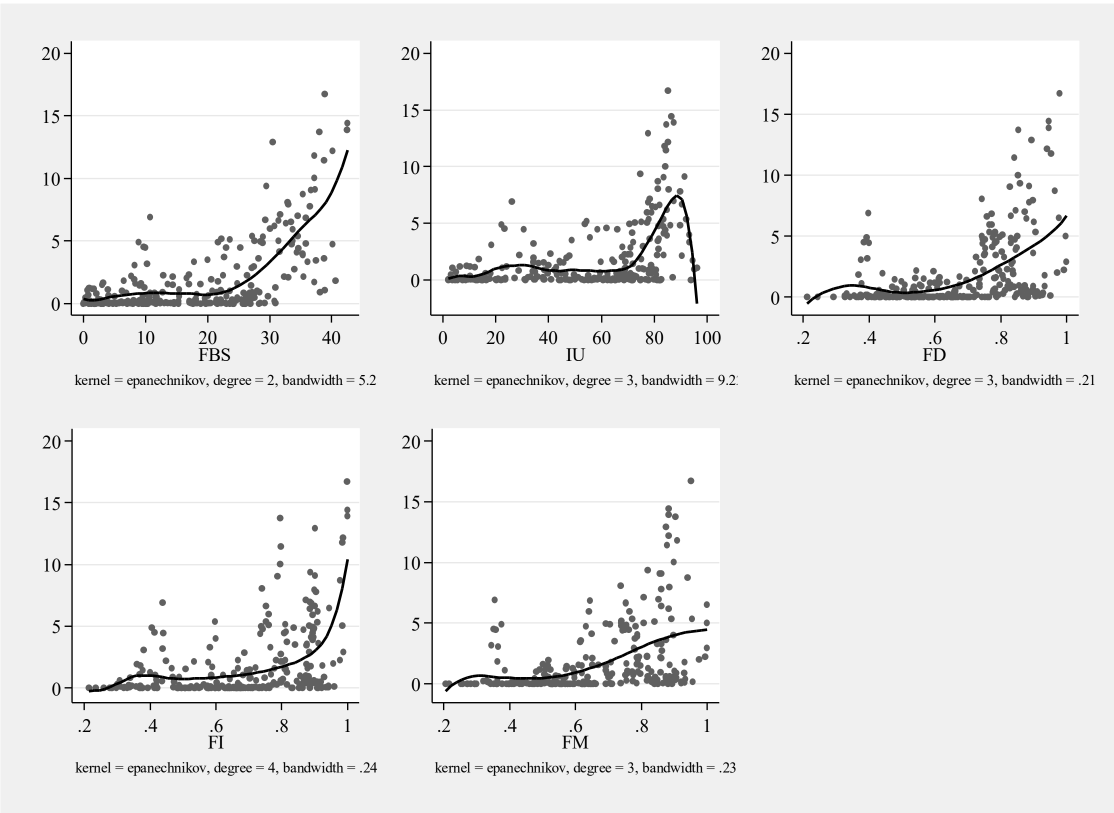
Table 4. ETFs, ICTs, and selected financial and economic determinants—correlation matrix. 2004–2014.

	ETFs	FBS	IU	BD_ GDP	MFA_ GDP	SMC_ GDP	SMR	SMT_ GDP	SPV	FD	FI	FM	GDP _gr
ETFs	1.0												
FBS	**0.64**	1.0											
IU	**0.46**	**0.91**	1.0										
BD_ GDP	**0.41**	**0.49**	**0.48**	1.0									
MFA_GDP	0.39	**0.39**	**0.39**	**0.44**	1.0								
SMC_GDP	**0.23**	**0.05**	**0.07**	**0.50**	**0.45**	1.0							
SMR	**-0.12**	**-0.28**	**-0.26**	**-0.21**	0.01	0.08	1.0						
SMT_GDP	**0.43**	**0.45**	**0.38**	**0.44**	**0.36**	**0.46**	**-0.09**	1.0					
SPV	-0.06	0.00	**-0.15**	**-0.21**	-0.22	**-0.35**	**-0.23**	-0.01	1.0				
FD	**0.45**	**0.71**	**0.73**	**0.71**	**0.62**	**0.43**	**-0.18**	**0.65**	**-0.18**	1.0			
FI	**0.41**	**0.67**	**0.71**	**0.66**	**0.67**	**0.43**	**-0.25**	**0.48**	**-0.21**	**0.93**	1.0		
FM	**0.43**	**0.65**	**0.65**	**0.65**	0.45	**0.35**	**-0.09**	**0.72**	-0.11	**0.92**	**0.72**	1.0	
GDP_gr	**-0.18**	**-0.42**	**-0.36**	**-0.21**	-0.12	**0.19**	**0.54**	0.05	**-0.3**	**-0.31**	**-0.36**	**-0.21**	1.0

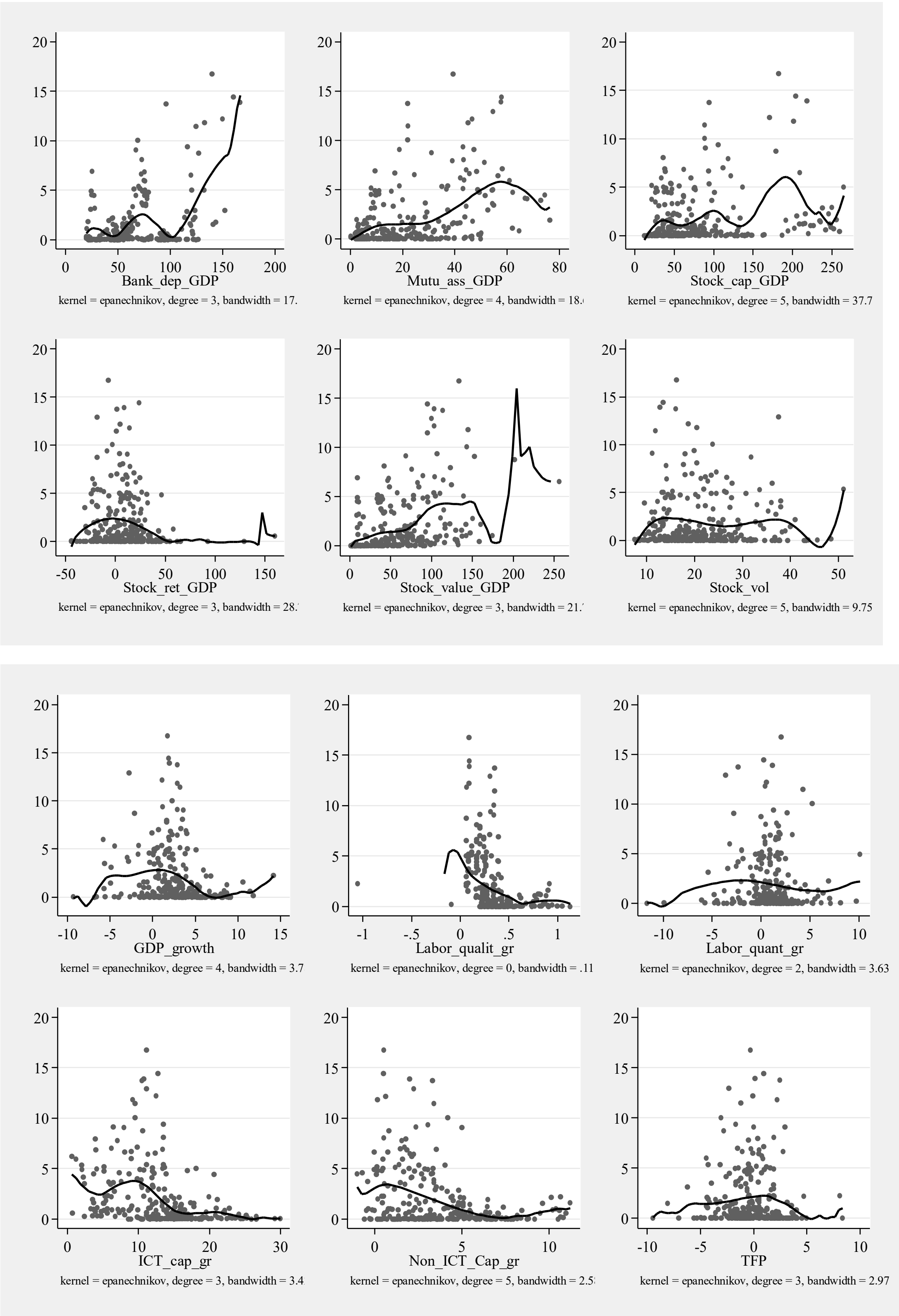
Source: Authors' calculations. Note: ETFs—turnover of ETFs as % of local GDP; BD_GDP—bank deposits (as % of GDP), MFA_GDP—mutual fund assets (as % of GDP), SMC_GDP—stock market capitalization (as % of GDP), SMR—stock market return (%, year-to-year), SMT_GDP—stock market total value traded (as % of GDP), SPV—stock price volatility (average of the 360-day volatility of the national stock market index), FD—IMF financial development index, FI—IMF financial institutions index, FM—IMF financial markets' index, GDP_gr—GDP growth (%, year-to-year). Hong Kong, the United States—excluded (outliers in terms of ETFs' diffusion – see Section 4.1.). MFA_GDP for Ireland and BD_GDP for Japan are excluded, as they are substantially higher than for the remaining countries. Results in bold are statistically significant at the 5% level of significance.

Correlation between turnover of ETFs and the key indicator of the stock market development in the context of the innovative products—stock market turnover in relation to GDP—is also positive, as expected. A negative correlation between diffusion of ETFs and stock market returns, as well as stock price volatility, suggests that turnover of ETFs declines in the case of high rate of changes on the stock markets; however, this correlation is very low. Diffusion of ETFs also exhibits a positive correlation with all other financial system development indicators (three IMF indicators and bank deposits in relation to GDP).[3] Finally, diffusion of ETFs is negatively correlated with the rate of economic growth (measured here as annual GDP growth) and all its components (not included in Table 4—see the third part of Fig. 3); the only exception is total factor productivity (TFP), for which correlation is close to 0. These results may be explained by referring to the general trend in the economic growth process—less developed countries tend to grow faster but, at the same time, their financial systems are less advanced, with a lower level of diffusion of ETFs (see, for instance, the results in Section 4.1.). However, the estimates of the dynamic panel models (see the remainder of the current Section) suggest that the role of economic factors in the diffusion of ETFs is highly limited in comparison to other determinants.

Figure 3. ETFs' diffusion versus selected ICT, financial, and economic determinants. 2004–2014.



[3] Bond market indicators are not presented – their correlation with ETFs is close to 0; they are not used in further analysis, as the market share of bond-tracking or similar ETFs in most of the discussed countries remains low (equity ETFs are the biggest category).



Source: Authors' elaboration. Note: on Y-axis—turnover of ETFs as % of local GDP; on X-axis—selected indicators. Hong Kong, the United States—excluded (outliers in terms of ETFs' diffusion—see Section 4.1.). Data on mutual fund assets (as % of GDP) for Ireland and bank deposits (as % of GDP) for Japan are excluded, as they are substantially higher than for the remaining countries. Stock_value_GDP— stock market total value traded (as % of GDP).

In the remainder of this Section, using linear dynamic panel models and PVARX models, we examine the relationships between diffusion of ETFs and ICTs, in addition to other potential factors that may affect the process of ETFs' propagation across financial markets. In our research, aside from broadly-adopted dynamic panel models, we propose to use a PVARX model to capture dynamic cross-country interdependencies and heterogeneity between diffusion of ETFs and its selected determinants. We argue that, bearing in mind the nature of the examined variables and the existing interdependencies among national financial markets, it can be hypothesized that lagged foreign variables in country i_1 may impact changes in other domestic variables in country i_2. Intensification of information, knowledge, and technology flows leads to significantly increasing interdependencies among economies (Koop & Korobilis, 2016). These inter-linkages may arise as essential factors propagating two-directional causal effects, demonstrating global dependencies and transmission channels.

Tables 5 and 6 demonstrate results of dynamic panel regression estimates explaining determinants of ETFs' diffusion. The choice of explanatory variables was made based on their correlation with ETFs and other variables (to avoid the problem of multicollinearity).

Table 5 summarizes the outcomes of regressing ETFs on its lagged value (ETFs_1-year-lag),[4] FBS, and other financial and economic factors. We estimated 15 different specifications, and in each case both ETFs_1-year-lag and FBS variables were included in the model. The results are striking and enable us to confirm our preliminary supposition that broader access to fixed-broadband networks enhances rapid diffusion of ETFs on examined financial markets. In each specification, regardless of which and how many other explanatory variables were included in the model, the FBS variable coefficient holds a positive sign and is statistically significant [with the exception of DPD(12) and DPD(14)]. Moreover, the value of respective FBS coefficients oscillates around 0.6 to 0.8 (in 10 out of 15 models estimated); hence, we may claim that the statistical association between ETFs and FBS is positive, statistically significant, and robust. Regardless of whether the FBS variable is entered solely with the ETFs_1-year-lag, or jointly, with other control variables, it remains statistically significant, and its coefficient is positive. Another important observation is that the ETFs_1-year-lag variable also, in most cases, holds a positive sign and is statistically significant, irrespective of whether other variables are included in the model. It may be thus concluded that the diffusion of ETFs is, to a large extent, a self-perpetuating and endogenously strong process, due to, for instance, growing awareness of investors of the increasingly popular financial products, which may result in their decisions to buy the shares of ETFs. Analogical processes can be observed on the supply-side, where new providers enter the ETFs market (or offer new ETFs) to match the competing financial institutions (both processes are currently observed on most major ETFs' markets). In the case of decline of the local ETFs' market reverse processes can be expected.

Regarding the other regressors, which potentially may impact the process of ETFs' diffusion, we have uncovered that only 2 of them (out of 15 considered) were statistically significant in more than one specification (3 more were statistically significant in only one specification). The former two are SMT_GDP—stock market turnover, and FD—IMF financial development

[4] We have tested models with different ETFs-lags included—in each case only the 1-year-lag was statistically significant. Results of other estimates are available upon request.

index [it covers development of all segments of the financial system, including banks, capital markets, mutual funds, insurance companies etc. (Sahay et al., 2015)]. Their coefficients hold the expected positive sign. The former variable merits particular attention, as it exhibited statistical significance in all 4 tested specifications in which it was included. These results fully comply with the theoretical outline presented in Section 2.3., in which the development of the stock markets (in particular in terms of turnover) is listed as the key determinant of the ETFs' diffusion.

No other tested variables have shown a statistically significant relationship versus ETFs' diffusion across the examined economies. Surprisingly, this applies also to the assets of mutual funds, even though this indicator could be expected to influence the diffusion of ETFs, as suggested by the theoretical concepts and evaluation of correlation (see Table 4). Thus, it may be stated that the interactions between the ETFs and mutual funds' industries are less significant than is either the role of the stock market or the overall financial development. Moreover, it may be seen that stock market capitalization was also statistically insignificant, which proves that the turnover on the equity markets is more important for the diffusion of ETFs than is their size.

Next, Table 6 summarizes results of dynamic panel models' estimates with the IU variable (approximating the share of individuals having access to the Internet network). The remaining set of regressors is analogous, as in the case of the models presented in Table 5. According to our estimates, the impact of ICTs (here – IU) was confirmed, although these results are slightly 'weaker' than in the case of models shown in Table 5. In only 7 (out of 15) cases, the coefficients of the IU variable are statistically significant and hold the expected positive sign; suggesting that broader usage of the Internet network positively impacts the diffusion of ETFs. Analogous to previous cases (compare Table 5), the ETFs_1-year-lag is reported as having a relatively strong, positive, and statistically significant impact on the dependent variable. Interestingly, in different models, the ETFs_1-year-lag variable holds coefficients that are very close in value (around 0.3–0.45), demonstrating that the influence of past values of ETFs' diffusion drives its further expansion during consecutive periods. Similar to the estimates summarized in Table 5, out of 15 potential ETFs' diffusion determinants examined, only 3 had a statistically significant positive impact on the diffusion of ETFs: these were SMT_GDP, and FD, supplemented by the FM—IMF financial markets' index. These results confirm again the crucial role of the stock markets in the diffusion of ETFs as well as the importance of general financial development, including that of the financial markets. FM covers not only the development of the stock markets (in terms of, *inter alia*, capitalization and turnover) but also various types of debt securities issued in particular countries (Sahay et al., 2015)—therefore it confirms to some extent the impact of segments of the financial markets other than just stock markets on the diffusion of ETFs (however, exact evaluation is impossible due to the index's construction). The outcomes in Table 6 also prove the relative insignificance of the remaining financial and macroeconomic determinants.

To sum up, Tables 5 and 6 demonstrate the results of estimates of dynamic panel regression aiming to identify whether ICTs and other financial and macroeconomic factors influence the diffusion of ETFs across examined financial markets. In the tested models, we have intentionally included either the FBS or the IU variable to check the robustness of ICTs' diffusion in those two dimensions for the ETFs' diffusion. Interestingly, the impact of both

FBS`s and IU`s on ETFs diffusion was stable and robust, which may suggest that expansions of both ICTs and ETFs are closely related and that these two processes are interdependent. By including the ETFs_1-year-lag variable in each specification, we have additionally shown that year-to-year dynamic ETFs' diffusion shows relative stability and path-dependency (due to decisions of the participants on both the demand- and supply-side of the ETFs' market). Apart from the two ICTs' indicators and the ETFs' diffusion lagged variable, the other variables that were identified as statistically significant (at least in some specifications) are SMT_GDP, FD, and FM, which proves the already-discussed importance of both the stock market and the overall financial system's and financial markets' development for the spread of ETFs. The remaining variables were generally statistically insignificant, with exceptions in some specifications. For instance, in the only specification in Table 5 in which it was used, SPV (volatility of the stock market) was statistically significant, and its coefficient was positive, which could imply that turnover of ETFs increases in the turbulent stock market environment (in contrast with the conclusions reached based on the correlation's analysis). However, this result should be regarded with caution, as SPV was in no case significant in specifications in Table 6. In the case of GDP growth, reported coefficients were negative (yet this variable proved to be significant only in one case), whereas, for the components of economic growth (e.g., TFP or ICT capital growth) coefficients were positive but statistically insignificant (compare results in Table 5 and 6). These estimates can be explained, as noted with regard to Table 4, by the slower diffusion of ETFs in the usually more rapidly growing emerging economies. Nevertheless, they prove above all that ETFs' markets are more substantially dependent on the development of the financial systems (particularly development of the stock markets) than on macroeconomic factors. It must also be noted that, in contrast with the relationships discussed in the literature, MFA_GDP—mutual fund assets, was insignificant, which could imply that links between mutual funds and ETFs (resulting from the assumed competition between these two categories of investment companies) are weaker than expected.

Finally, we used PVARX models, aiming to capture potentially arising dynamic cross-country interdependencies and heterogeneity with respect to ETFs' diffusion and determinants of the process. In this case, we limited our analysis by including in consecutive models only those factors that were reported as significant for ETFs' diffusion when using the dynamic panel regression approach; hence, we chose exclusively: FBS, IU (as endogenous variables together with ETFs) and SMT_GDP, FD, and FM (as exogenous variables; see Section 3.2.). Prior to the estimations of the models, we conducted the analysis of the models' lag order using the modified Akaike information criteria, the modified Bayesian information criteria and the modified Hannan-Quinn information criteria. Their results unequivocally suggest using 1-year-lag panel vector autoregression models (see Table A in the Appendix).

In the next step, we estimated 10 different specifications, including in each the 1-year-lags of endogenous variables; FBS and IU were not included jointly in any specification due to the high correlation (0.91) of these two variables. Tables 7 and 8 summarize the results of estimates of PVARX models, as well as a Granger causality Wald tests. The results generated by PVARX models may be interpreted as the average responses of endogenous variables to changes in any variable after controlling for time-invariant characteristics. Considering the returned results, the only valid conclusion concerning the ETFs equations that may be drawn from this analysis is statistical significance of the lagged ETFs variable which shows that ETFs' diffusion is impacted by the past development of the ETF market, thus confirming the results obtained using panel models. Apparently, the coefficients of other variables seem to be random in value; no regularities may be rigidly identified. Moreover, none of the considered variables was statistically significant. The results of Granger causality Wald tests, summarized at the bottom of Tables 7 and 8, lead to the conclusion that the null hypothesis may not be rejected, hence, the examined variables—FBS or IU cannot be used to predict changes in ETFs. Additionally, due to the simultaneous estimation of the FBS and IU equations, we gained some insight into the reverse relationships and hence the determinants of ICTs' diffusion in the examined countries. In case of both ICTs' variables it was demonstrated (like in case of the diffusion of ETFs) that the impact of the past values of FBS or IU drive their further changes during consecutive periods. Moreover, in exclusively two specifications [VAR(7) and VAR(8)] statistical significance of other variables (FD and FM) was identified. However, in the other specifications no such evidence was reported.

To provide more detailed insight into the examined relationships, we additionally deliberately disaggregated the sample and estimated country-specific VARX models, with analogous exogenous variables as in case of panel vector autoregression models. The results of the country-wise VARX models' estimates are summarized in Table B in the Appendix[5]. These results are quite mixed and do not allow for generalizations; however, it is important to note that, in 13 (out of 23 examined) countries, at least one ICTs' variable was reported as being significant for ETFs' diffusion. Few countries were excluded from the analysis, due to insufficiently long time series; this was the case of Chile, China, Colombia, Greece, Iran, Poland and Saudi Arabia. In case of contradictory results for various specifications with a given ICTs' variable, we focused on the one with the lowest value of the information criteria.

The results indicate that ICTs' variable(s) was found significant in 13 out of 23 countries (i.e., 57%): Australia, Brazil, France, Ireland, Italy, New Zealand, Norway, Singapore, South Africa, South Korea, Spain, Thailand and the United Kingdom. These outcomes were also confirmed by Granger causality tests, which showed that, in these 13 countries, changes in the deployment of ICTs may be used to predict the process of diffusion of ETFs. According to our estimates, in the remaining economies, such relationship between ICTs and ETFs is not apparent. It may be noticed that these 13 countries are mostly economies with the highest level of either ETFs' diffusion or adoption of ICTs (except for, for instance, Germany and Japan for which no such relationship was identified)[6]. Therefore it may be concluded that ICTs can be regarded as significant for the diffusion of ETFs in the cases of the most developed ETF markets. Additionally, it can be seen that the group of 13 countries covers most of the largest economies in our sample (however, this set overlaps substantially with the previously-mentioned set of the most developed ETF markets). The results obtained for the FBS and IU equations demonstrate that the reverse relationship is less common, in support of our main conclusions derived from the PVARX models.

In 15 examined countries (Australia, Brazil, Canada, France, Hungary, India, Ireland, Italy, Malaysia, Mexico, New Zealand, Norway, Spain, Thailand and the United Kingdom), at least

[5] In case of country-wise estimates, we decided arbitrary to use 1-year-lag, to stay consistent with panel VAR estimates.

[6] Hong Kong and the United States were not analyzed.

one of the non-ICT variables—SMT_GDP, FD, and FM—was reported as statistically significant driver of ETFs' diffusion (in most cases it was SMT_GDP or FD, or SMT_GDP and FD jointly). Analyzing the values of the estimated coefficients, we may argue that changes in either SMT_GDP, FD, or FM in most of the above-mentioned countries influenced positively changes in the diffusion of ETFs across these highly heterogeneous economies. Another general conclusion that may be derived from country-wise analysis is that, in only 10 out of 23 examined countries, both ICTs and selected financial-type variables impacted the diffusion of ETFs. In the remaining economies, diffusion of ETFs seems to be shaped by other determinants, suggesting that this issue requires further scrutiny, in particular for the countries that lag behind in terms of diffusion of ETFs.

The results from the simultaneous equations that potentially may identify drivers of ICTs` diffusion were highly mixed and to a large extent did not unveil any specific regularities. However, we noticed that in some cases the exogenous variables SMT_GDP and/or FD and/or FM were reported as statistically significant for FBS/IU deployment (see, for instance, India, Ireland, New Zealand, Norway, Spain, Thailand or United Kingdom). Also in some cases (see, for instance, Brazil, Canada, India, or New Zealand) the lagged values of ETFs were unveiled as having statistically significant impact of FBS/IU adoption. These, although highly mixed, results, to some extent may support the hypothesis that ICT deployment is enhanced by dynamic development of financial markets that generate demand for technologically sophisticated solutions.

We may claim that, at least in some countries, ICT deployment enables fast diffusion of financial innovations, and rapidly expanding financial markets drive further development and adoption of new technologies; hence a kind of synergy arises. Undoubtedly these relationships (between ICT and financial markets) are two-directional, and the reverse causal loop exists in this case. Still the country-wise evidence is scattered and lacks robustness—this issue requires further detailed research.

Table 5. Dynamic panel regression estimates—ETFs' diffusion versus fixed broadband subscriptions and selected financial and economic determinants, 2004–2014.

ETFs															
	DPD(1)	DPD(2)	DPD(3)	DPD(4)	DPD(5)	DPD(6)	DPD(7)	DPD(8)	DPD(9)	DPD(10)	DPD(11)	DPD(12)	DPD(13)	DPD(14)	DPD(15)
ETFs_1-year-lag	**0.38 [0.14]**	**0.39 [0.15]**	**0.22 [0.12]**	**0.14 [0.10]**	**0.41 [0.14]**	**0.14 [0.16]**	**0.13 [0.11]**	0.11 [0.11]	**0.35 [0.14]**	**0.41 [0.13]**	**0.35 [0.12]**	**0.38 [0.14]**	**0.38 [0.14]**	-0.43 [0.17]	-0.07 [0.14]
FBS	**0.61 [0.22]**	**0.62 [0.22]**	**0.77 [0.26]**	**0.78 [0.21]**	**0.61 [0.18]**	**1.09 [0.40]**	**1.01 [0.27]**	**0.88 [0.23]**	**0.64 [0.22]**	**0.61 [0.21]**	**0.65 [0.21]**	0.39 [0.23]	**0.62 [0.23]**	2.35 [0.82]	**1.3 [0.30]**
BD_GDP		-0.51 [0.84]	-0.00 [0.95]		-0.36 [0.82]										
MFA_GDP			-0.24 [0.39]					-0.28 [0.36]							
SMC_GDP			0.32 [0.59]												
SMR															0.02 [0.09]
SMT_GDP				**0.61 [0.19]**	**0.54 [0.17]**		**0.58 [0.20]**			**0.62 [0.18]**					
SPV											**0.32 [0.15]**				
FD				0.45 [1.5]		**3.6 [1.4]**						**2.9 [1.31]**			
FI							-1.22 [1.11]								
FM													**2.2 [0.67]**		
GDP_gr				-0.17 [0.11]		**-0.23 [1.02]**	-0.16 [1.1]	-0.16 [0.12]							
Labor_quality_gr														-0.33 [0.28]	
Labor_quantity_gr						0.06 [0.09]									
ICT_cap_gr									0.03 [0.13]						
non_ICT_cap_gr									0.13 [0.15]						
TFP														-0.08 [0.08]	
Wald χ^2 [Prob>χ^2]	63.5 [0.00]	50.7 [0.00]	34.4 [0.00]	63.01 [0.00]	65.8 [0.00]	33.8 [0.00]	56.3 [0.00]	59.6 [0.00]	67.4 [0.00]	80.40 [0.00]	49.6 [0.00]	38.1 [0.00]	59.5 [0.00]	17.7 [0.00]	21.9 [0.00]
# of instruments	47	48	50	50	49	45	50	49	49	48	48	48	48	23	37
Arellano-Bond test for 2^{nd} order	-1.4 [0.15]	-1.2 [0.19]	-1.3 [0.21]	-1.02 [0.31]	-1.4 [0.14]	1.04 [0.29]	-1.04 [0.29]	-1.08 [0.27]	-1.3 [0.19]	-1.6 [0.09]	1.55 [0.12]	-1.51 [0.12]	-1.54 [0.12]	-0.38 [0.70]	0.18 [0.85]

[Prob>z]															
# of obs.	212	181	161	151	181	113	151	139	193	212	212	212	212	39	90

Source: Authors` calculations. Note: BD_GDP—bank deposits (as % of GDP), MFA_GDP—mutual fund assets (as % of GDP), SMC_GDP—stock market capitalization (as % of GDP), SMR—stock market return (%, year-to-year), SMT_GDP—stock market total value traded (as % of GDP), SPV—stock price volatility (average of the 360-day volatility of the national stock market index), FD—IMF financial development index, FI—IMF financial institutions index, FM—IMF financial markets index, GDP_gr—GDP growth (%, year-to-year), Labor_quality_gr—labor quality growth, Labor_quantity_gr—labor quantity growth, ICT_cap_gr—ICT capital growth, non_ICT_cap_gr—non-ICT capital growth, TFP—total factor productivity. Hong Kong and USA—excluded. Results in bold are statistically significant at the 5% level of significance. Constant included—not reported. Arellano-Bond estimator applied. Robust SE below coefficients. All values are logged.

Table 6. Dynamic panel regression estimates—ETFs’ diffusion versus Internet users and selected financial and economic determinants, 2004–2014.

ETFs															
	DPD(1)	DPD(2)	DPD(3)	DPD(4)	DPD(5)	DPD(6)	DPD(7)	DPD(8)	DPD(9)	DPD(10)	DPD(11)	DPD(12)	DPD(13)	DPD(14)	DPD(15)
ETFs_1-year-lag	**0.42 [0.14]**	**0.34 [0.17]**	**0.39 [0.14]**	0.07 [0.11]	**0.41 [0.14]**	**0.42 [0.13]**	**0.42 [0.14]**	**0.36 [014]**	**0.35 [0.16]**	0.09 [0.49]	**0.31 [0.14]**	0.29 [0.16]	-0.13 [0.13]	**0.42 [0.14]**	**0.37 [0.13]**
IU	**0.52 [0.27]**	**0.55 [0.24]**	**0.65 [0.28]**	**0.61 [0.23]**	0.31 [0.26]	0.47 [0.29]	**0.63 [0.30]**	**0.68 [0.29]**	0.40 [0.28]	0.72 [0.67]	0.41 [0.25]	**0.69 [0.28]**	0.18 [0.31]	0.42 [0.27]	0.39 [0.33]
BD_GDP		0.55 [0.79]		0.61 [0.58]					0.35 [0.87]		0.13 [0.85]	0.39 [0.79]			
MFA_GDP															-0.18 [0.38]
SMC_GDP		-0.09 [0.45]							-0.15 [0.42]		-0.32 [0.47]	-0.29 [0.48]			
SMR													-0.04 [0.09]		
SMT_GDP		**0.56 [0.24]**	**0.54 [0.16]**			**0.51 [0.15]**	**0.46 [0.14]**		**0.56 [0.24]**		**0.47 [0.23]**	**0.43 [0.21]**		**0.51 [0.15]**	
SPV			0.19 [0.15]					0.24 [0.16]							
FD					**3.5 [1.3]**	2.5 [1.4]				1.16 [3.2]	**3.5 [1.23]**		**6.9 [2.0]**	2.6 [0.14]	
FI									0.99 [1.2]						1.3 [1.8]
FM							**1.8 [0.68]**	**2.2 [0.62]**				**2.5 [0.57]**			
GDP_gr				-0.07 [0.10]									0.10 [0.07]		
Labor_quality_gr						0.21 [0.29]									
Labor_quantity_gr										0.19 [0.31]					
ICT_cap_gr					0.03 [0.12]					0.22 [0.21]					
non_ICT_cap_gr										0.47 [0.70]					
TFP										0.11 [0.24]					
Wald χ^2 [Prob>χ^2]	51.8 [0.00]	53.2 [0.00]	62.2 [0.00]	43.8 [0.00]	34.2 [0.00]	68.9 [0.00]	62.2 [0.00]	46.1 [0.00]	61.4 [0.00]	74.4 [0.00]	78.6 [0.00]	69.5 [0.00]	70.8 [0.00]	59.0 [0.00]	32.4 [0.00]
# of instruments	47	50	49	49	49	50	49	49	51	22	51	51	39	49	49

Arellano-Bond test for 2nd order [Prob>z]	-1.04 [0.29]	-1.09 [0.27]	-1.2 [0.21]	-0.71 [0.47]	-1.2 [0.23]	-1.2 [0.21]	-1.3 [0.19]	-1.2 [0.20]	-1.08 [0.27]	0.22 [0.82]	-1.2 [0.23]	-1.2 [0.21]	0.18 [0.70]	-1.2 [0.20]	-1.1 [0.26]
# of obs.	211	180	211	133	208	210	211	211	180	24	180	180	86	211	191

Source: Authors` calculations. Note: For explanation of the variables see Table 5. Hong Kong and USA—excluded. Results in bold are statistically significant at the 5% level of significance. Constant included—not reported. Arellano-Bond estimator applied. Robust SE below coefficients. All values are logged.

Table 7. Panel VARX estimates—ETFs' diffusion versus FBS, stock market total value traded (% of GDP), IMF financial development index and IMF financial markets' index, 2004–2014.

	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
	$\gamma_{y.t}$= ETFs equations				
ETFs (t-1)	**0.77 [0.08]**	**0.8 [0.08]**	**0.78 [0.08]**	0.51 [2.6]	**0.75 [0.11]**
FBS (t-1)	-0.07 [0.021]	-0.19 [0.23]	-0.05 [0.02]	1.2 [12.9]	-0.03 [0.21]
SMT_GDP	0.13 [0.31]	-	-	2.05 [19.5]	0.26 [0.80]
FD	-	1.2 [2.7]	-	-18.9 [185.6]	-
FM	-	-	0.99 [1.88]	-	-0.82 [6.3]
	$\gamma_{y.t}$= FBS equations				
ETFs (t-1)	-0.02 [0.02]	-0.01 [0.01]	-0.01 [0.01]	-0.23 [1.8]	0.00 [0.02]
FBS (t-1)	**0.81 [0.07]**	**0.77 [0.04]**	**0.78 [0.04]**	1.88 [8.9]	**0.76 [0.05]**
SMT_GDP	0.02 [0.07]	-	-	1.61 [13.3]	-0.18 [0.23]
FD	-	0.04 [0.52]	-	-15.7 [127.7]	-
FM	-	-	0.02 [0.37]	-	1.3 [1.8]
# obs.	103	103	103	103	103

	Granger causality Wald test - χ^2 [Prob>χ^2]									
Equation	VAR(1)		VAR(2)		VAR(3)		VAR(4)		VAR(5)	
ETFs	0.12 [0.73]	-	0.67 [0.40]	-	0.12 [0.73]	-	0.009 [0.93]	-	0.03 [0.86]	-
FBS	-	1.43 [0.23]	-	1.29 [0.25]	-	1.08 [0.29]	-	0.02 [0.89]	-	0.00 [0.99]

Source: Authors` calculations. Note: GMM estimator applied. First lags of explanatory variables used as instruments. SE below coefficients. Results in bold are statistically significant at the 5% level of significance. Hong Kong and USA—excluded. All values are logged. For explanation of the variables see Table 5.

Table 8. Panel VARX estimates—ETFs' diffusion versus IU, stock market total value traded (% of GDP), IMF financial development index and IMF financial markets' index, 2004–2014.

	VAR(6)	VAR(7)	VAR(8)	VAR(9)	VAR(10)
	$\gamma_{y.t}$= ETFs equations				
ETFs (t-1)	**0.76 [0.08]**	**0.79 [0.07]**	**0.77 [0.07]**	**0.79 [0.13]**	**0.76 [0.08]**
IU (t-1)	-0.06 [0.32]	-0.22 [0.26]	-0.06 [0.18]	-0.27 [0.79]	-0.05 [0.20]
SMT_GDP	0.17 [0.42]	-	-	-0.06 [0.89]	0.18 [0.36]
FD	-	1.23 [0.26]	-	1.78 [9.25]	
FM	-	-	1.05 [1.77]	-	-0.07 [2.92]
	$\gamma_{y.t}$= IU equations				
ETFs (t-1)	-0.01 [0.01]	0.007 [0.01]	0.003 [0.01]	0.01 [0.02]	0.00 [0.01]
IU (t-1)	**0.99 [0.09]**	**0.88 [0.05]**	**0.95 [0.05]**	**0.86 [0.15]**	**0.95 [0.05]**
SMT_GDP	0.12 [0.08]	-	-	-0.03 [0.19]	0.05 [0.07]
FD	-	**0.91 [0.35]**	-	1.2 [1.85]	-
FM	-	-	**0.64 [0.24]**	-	0.29 [0.53]
# obs.	104	104	104	104	104

	Granger causality Wald test - χ^2 [Prob>χ^2]									
Equation	VAR(6)		VAR(7)		VAR(8)		VAR(9)		VAR(10)	
ETFs	0.04 [0.84]	-	0.74 [0.38]	-	0.14 [0.71]	-	0.16 [0.74]	-	0.07 [0.78]	-
IU	-	0.32 [0.56]	-	0.58 [0.44]	-	0.14 [0.71]	-	0.19 [0.66]	-	0.00 [0.99]

Source: Authors` calculations. Note: GMM estimator applied. First lags of explanatory variables used as instruments. Hong Kong and USA—excluded. All values are logged. For explanation of the variables see Table 5.

5. Conclusions.

The major research targets of this study were twofold. First, we intended to determine whether the process of diffusion of information and communication technologies (ICTs) has enhanced the diffusion of innovative financial products, putting special emphasis on the introduction and spread of exchange-traded funds (ETFs) across selected economies between 2004–2014. Additionally, we aimed to detect other financial and economic factors that might determine the diffusion of ETFs. In the preliminary analysis, we checked the diffusion patterns of ETFs and ICTs (approximated by fixed-broadband and Internet users' penetration rates). While the diffusion trajectories of ETFs displayed high in-time variability, the diffusion of ICT was much more stable; considerable between-country heterogeneity was observed for both ETFs and ICTs.

Our major conclusions, reached using dynamic panel models, support the initial supposition that widespread adoption of ICTs constitutes an important prerequisite for diffusion of ETFs due to potential demand- and supply-side linkages. Among the other determinants of the broader usage of these innovative financial products, the stock market turnover seemed to be the most significant due to the structure of the global ETFs' markets (with the domination of equity funds) and the basic mechanisms of the ETFs' shares creation and redemption. We also identified that the development of entire financial systems and of financial markets may influence positively the diffusion of ETFs. Other financial and macroeconomic determinants were mostly insignificant, including the assets of mutual funds, despite the linkages between mutual funds and ETFs discussed in the literature.

To verify the interdependencies with respect to ETFs diffusion and determinants of the process we estimated panel vector autoregression (PVARX) and country-wise VARX models. No valid conclusions could be drawn from the estimates of the PVARX models, as the coefficients of the analyzed variables seemed to be random in value, and no regularities were uncovered. Wald tests of Granger causality showed that the examined variables cannot be used to predict changes in the diffusion of ETFs. The results of the country-wise VARX were mixed, but, in 13 countries, ICTs were reported as significant for diffusion of ETFs, thus supporting the conclusion formulated in the preceding paragraph; this was confirmed by Granger causality tests. In the minority of the analyzed countries, both ICTs and selected financial-type variables were demonstrated as having an impact on the diffusion of ETFs. Moreover, in some countries the impact of ETFs' diffusion on the ICT deployment was identified.

The statistical linkages between ICTs and economic and financial factors are, undeniably, a two-way relationship. It is hardly possible to encapsulate them in one single equation. We wish to emphasize that that all these results should be interpreted very carefully. One should bear in mind that the bundle of ETFs' diffusion determinants have been subject to our subjective view and have been led by general logic and economic intuition. We are fully aware that, first, the statistical relationships that we have reported may be spurious, and, second, that the adoption of innovative financial products is a complex process driven by factors that are hard to either quantify or even capture. It was not our intention to say that diffusion of ETFs is led exclusively by the elements mentioned in this study; however, we wished to contribute to the broad discussion on what factors either foster or, conversely, hinder the process of the spread of financial innovations.

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Appendix

Table A. Order selection criteria for the panel VARX models.

Lag order	CD	Hansen's J [J p-value]	MAIC	MBIC	MQIC
ETFs/FBS					
1	0.999	17.98 [0.32]	-14.01	-46.13	-26.43
2	0.999	11.4 [0.49]	-12.54	-36.63	-21.86
3	0.999	5.99 [0.64]	-10.00	-26.06	-16.21
4	0.999	1.63 [0.80]	-6.36	-14.39	-9.46
ETFs/IU					
1	0.998	15.2 [0.51]	-16.75	-49.15	-29.31
2	0.998	12.9 [0.37]	-11.00	-35.31	-20.43
3	0.998	7.5 [0.48]	-8.47	-24.67	-14.75
4	0.993	3.58 [0.46]	-4.41	-12.51	-7.55

Source: Authors` calculations.

Table B. Country-wise VARX estimates—ETFs diffusion versus selected indicators, 2004–2014.

	Australia				Brazil			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	0.16 [0.22]	0.20 [0.20]	**0.51 [0.13]**	**0.45 [0.14]**	0.23 [0.18]	0.29 [0.18]	0.30 [0.24]	0.30 [0.26]
FBS (t-1)	**2.21 [0.49]**	**2.49 [0.52]**	**-**	**-**	**0.70 [0.35]**	**0.94 [0.36]**	-	-
IU (t-1)	-	-	**7.00 [1.11]**	**6.8 [1.1]**	**-**	**-**	0.82 [0.91]	1.4 [0.82]
SMT_GDP	0.35 [0.35]	0.41 [0.34]	**0.96 [0.31]**	**0.94 [0.31]**	**-1.5 [0.58]**	**-1.2 [0.57]**	-1.2 [0.83]	-0.57 [0.71]
FD	-3.6 [4.1]	-	3.9 [2.9]	-	**7.9 [3.8]**	-	7.6 [5.1]	-
FM	-	**-5.6 [2.8]**	-	2.6 [1.9]	-	2.3 [1.44]	-	1.3 [1.7]
R-square	0.89	0.90	0.93	0.93	0.95	0.94	0.94	0.93
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	-0.006 [0.20]	-0.007 [0.02]	0.0001 [0.03]	-0.03 [0.03]	**0.17 [0.03]**	**0.17 [0.03]**	**0.14 [0.04]**	**0.14 [0.04]**

FBS (t-1)	**0.84** **[0.04]**	**0.85** **[0.04]**	-	-	**0.47** **[0.07]**	**0.49** **[0.06]**	-	-
IU (t-1)	**-**	-	**0.85** **[0.38]**	**0.75** **[0.24]**	**-**	**-**	**0.65** **[0.17]**	**0.57** **[0.14]**
SMT_GDP	**0.08** **[0.03]**	**0.08** **[0.03]**	-0.06 [0.07]	-0.89 [0.06]	**0.28** **[0.12]**	**0.26** **[0.10]**	0.09 [0.15]	0.03 [0.12]
FD	-0.11 [0.37]	-	**2.2** **[0.76]**	-	0.58 [0.79]	-	-1.1 [0.95]	-
FM	-	-0.19 [0.27]	-	**1.6** **[0.42]**	-	0.32 [0.27]	-	-0.29 [0.31]
R-square	0.99	0.99	0.76	0.83	0.99	0.99	0.98	0.98
AIC	-3.37	-3.45	-2.47	-2.82	-1.48	-1.41	-1.2	-0.94
HQIC	-3.71	-3.78	-2.81	-3.15	-1.81	-1.73	-1.5	-1.3
SBIC	-3.07	-3.15	-2.17	-2.52	-1.2	-1.1	-0.86	-0.64
# of obs	10	10	10	10	10	10	10	10

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	20.2 [0.00]	-	22.6 [0.00]	-	39.5 [0.00]	-	39.0 [0.00]	-	3.9 [0.04]	-	6.85 [0.00]	-	0.82 [0.36]	-	3.00 [0.08]	-
FBS	-	0.10 [0.75]	-	0.13 [0.72]		-	-	-	-	20.7 [0.00]	-	24.3 [0.00]	-	-	-	-
IU	-	-	-	-	-	0.00 [0.99]	-	1.08 [0.29]	-	-	-	-	-	10.1 [0.00]	-	9.3 [0.00]

	Canada				**France**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	**0.35** **[0.07]**	**0.35** **[0.09]**	**0.33** **[0.08]**	**0.33** **[0.10]**	0.20 [0.27]	0.24 [0.31]	0.25 [0.31]	0.35 [0.33]
FBS (t-1)	0.12 [0.25]	0.21 [0.31]	-	-	1.01 [0.53]	**1.2** **[0.46]**	-	-
IU (t-1)	-	-	0.38 [0.52]	0.55 [0.65]	-	-	1.4 [0.94]	1.8 [0.97]
SMT_GDP	**1.6** **[0.28]**	**1.6** **[0.38]**	**1.6** **[0.30]**	**1.6** **[0.41]**	0.47 [0.47]	0.46 [0.47]	0.23 [0.44]	0.22 [0.48]
FD	**7.1** **[1.9]**	**-**	**7.0** **[1.8]**	**-**	2.4 [2.7]	-	**5.03** **[2.4]**	-
FM	-	**3.0**	-	**3.03**	-	1.8	-	4.1

		[1.3]		**[1.22]**		[2.1]		[2.2]
R-square	0.97	0.95	0.97	0.95	0.84	0.84	0.82	0.81
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	-0.002 [0.00]	-0.001 [0.00]	**-0.01 [0.00]**	**-0.01 [0.006]**	-0.01 [0.009]	-0.007 [0.009]	0.03 [0.09]	0.04 [0.10]
FBS (t-1)	**0.71 [0.02]**	**0.72 [0.03]**	**-**	**-**	**0.74 [0.02]**	**0.75 [0.01]**	-	-
IU (t-1)	-	-	**0.83 [0.04]**	**0.83 [0.04]**	-	**-**	**0.78 [0.28]**	**0.84 [0.29]**
SMT_GDP	-0.03 [0.03]	-0.02 [0.03]	-0.02 [0.02]	-0.18 [0.02]	-0.02 [0.01]	**-0.02 [0.01]**	0.03 [0.13]	0.05 [0.14]
FD	-0.28 [0.03]	-	**0.36 0.14]**	-	**0.21 [0.09]**	**-**	0.71 [0.73]	0.42 [0.65]
FM	-	-0.17 [0.10]	-	**0.17 [0.08]**	-	**0.2 [0.06]**	-	-
R-square	0.99	0.99	0.99	0.99	0.99	0.99	0.91	0.91
AIC	-6.4	-6.1	-7.2	-6.5	-5.6	-5.9	-1.2	-1.1
HQIC	-6.8	-6.4	-7.5	-6.8	-5.9	-6.3	-1.5	-1.5
SBIC	-6.2	-5.8	-6.9	-6.2	-5.3	-5.6	-0.88	-0.84
# of obs	10	10	10	10	10	10	10	10

Granger causality Wald test – χ^2 [Prob>χ^2]

Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	0.23 [0.63]	-	0.46 [0.49]	-	0.52 [0.47]	-	0.71 [0.39]	-	3.54 [0.06]	-	6.2 [0.01]	-	2.11 [0.14]	-	3.7 [0.05]	-
FBS	-	0.11 [0.73]	-	0.03 [0.85]	-	-	-	-	-	2.3 [0.13]	-	0.56 [0.45]	-	-	-	-
IU	-	-	-	-	-	5.7 [0.01]	-	5.4 [0.02]	-	-	-	-	-	0.12 [0.73]	-	0.15 [0.69]

	Germany				**Hungary**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	0.49 [0.31]	0.46 [0.31]	**0.51 [0.26]**	0.46 [0.25]	-0.26 [0.41]	-0.10 [0.49]	-0.08 [0.41]	0.10 [0.48]
FBS (t-1)	0.25 [0.31]	0.29 [0.31]	-	-	-1.31 [3.2]	-0.92 [3.8]	-	-
IU (t-1)	-	-	2.3 [1.5]	1.8 [1.5]	-	-	0.17 [2.6]	**0.71 [3.1]**

SMT_GDP	0.14 [0.18]	0.18 [0.17]	0.18 [0.18]	0.23 [0.17]	**2.9 [0.86]**	**2.5 [1.0]**	**3.1 [0.81]**	**2.6 [0.98]**
FD	3.5 [3.7]	-	4.4 [3.7]	-	**-7.8 [3.2]**	-	**-7.4 [3.3]**	-
FM	-	1.3 [1.8]	-	1.6 [1.8]	-	-3.9 [2.7]	-	-3.5 [2.7]
R-square	0.81	0.80	0.82	0.82	0.90	0.86	0.90	0.86
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	-0.02 [0.02]	-0.03 [0.02]	-0.01 [0.02]	-0.02 [0.02]	**-0.06 [0.02]**	**-0.06 [0.02]**	**-0.02 [0.00]**	**0.02 [0.00]**
FBS (t-1)	**0.77 [0.02]**	**0.76 [0.02]**	-	-	0.26 [0.14]	0.25 [0.16]	**-**	**-**
IU (t-1)	-	-	**0.91 [0.11]**	**0.90 [0.10]**	-	-	**0.50 [0.05]**	**0.49 [0.05]**
SMT_GDP	0.009 [0.01]	0.01 [0.01]	0.00 [0.01]	0.00 [0.01]	0.02 [0.04]	0.02 [0.04]	-0.01 [0.02]	-0.01 [0.02]
FD	**0.83 [0.29]**	-	0.03 [0.27]	-	**-0.46 [0.14]**	-	**-0.20 [0.06]**	-
FM	-	**0.43 [0.13]**	-	0.02 [0.12]	-	**-0.30 [0.11]**	-	**-0.14 [0.04]**
R-square	0.99	0.99	0.97	0.97	0.99	0.99	0.99	0.99
AIC	-5.1	-5.2	-5.5	-5.4	-3.5	-3.3	-5.1	-4.4
HQIC	-5.4	-5.5	-5.8	-5.8	-4.5	-4.3	-5.9	-5.4
SBIC	-4.7	-4.8	-5.2	-5.2	-3.6	-3.4	-5.1	-4.5
# of obs	10	10	10	10	7	7	7	7

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	1.32 [0.25]	-	0.94 [0.33]	-	2.2 [0.13]	-	1.5 [0.21]	-	0.17 [0.67]	-	0.05 [0.81]	-	0.00 [0.95]	-	0.05 [0.82]	-
FBS	-	1.32 [0.25]	-	1.6 [0.20]	-	-	-	-	-	11.9 [0.00]	-	9.04 [0.00]	-	-	-	-
IU	-	-	-	-	-	0.80 [0.37]	-	0.84 [0.36]	-	-	-	-	-	6.3 [0.01]	-	6.4 [0.01]

	India				**Ireland**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	**0.98**	**0.93**	**0.99**	**0.96**	**0.22**	**0.29**	0.06	0.09

	[0.16]	**[0.18]**	**[0.14]**	**[0.16]**	**[0.09]**	**[0.08]**	[0.12]	[0.13]
FBS (t-1)	-0.05 [0.13]	-0.09 [0.14]	-	-	**-0.73 [0.34]**	**-0.88 [0.33]**	-	-
IU (t-1)	-	-	-0.16 [0.29]	-0.32 [0.34]	-	-	**-2.8 [1.3]**	**-3.3 [1.2]**
SMT_GDP	**1.2 [0.21]**	**1.6 [0.24]**	**1.07 [0.22]**	**0.94 [0.24]**	**1.5 [0.33]**	**1.6 [0.33]**	**1.5 [0.33]**	**1.6 [0.33]**
FD	**-4.2 [0.84]**	-	**-4.2 [0.85]**	-	**5.9 [1.24]**	-	**4.6 [1.7]**	-
FM	-	**-2.5 [0.58]**	-	**-2.6 [0.60]**	-	**2.6 [0.55]**	-	**1.9 [0.73]**
R-square	0.97	0.97	0.97	0.97	0.97	0.96	0.97	0.97
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	**0.57 [0.08]**	**0.56 [0.08]**	-0.01 [0.09]	**0.96 [0.16]**	**-0.02 [0.00]**	**-0.02 [0.00]**	**0.02 [0.01]**	**0.03 [0.01]**
FBS (t-1)	**017 [0.07]**	**0.17 [0.07]**	-	-	**0.49 [0.00]**	**0.49 [0.00]**	-	-
IU (t-1)	-	-	**1.07 [0.18]**	-0.32 [0.34]	-	-	**1.2 [0.12]**	**1.1 [0.10]**
SMT_GDP	**0.29 [0.11]**	**0.29 [0.11]**	0.04 [0.14]	**0.94 [0.24]**	**0.06 [0.00]**	**0.06 [0.00]**	-0.02 [0.03]	-0.01 [0.03]
FD	**-0.81 [0.45]**	-	0.10 [0.54]	-	**-0.15 [0.03]**	-	**0.33 [0.16]**	-
FM	-	-0.50 [0.28]	-	**-2.6 [0.60]**	-	**-0.06 [0.01]**	-	**0.14 [0.06]**
R-square	0.99	0.99	0.98	0.98	0.99	0.99	0.98	0.98
AIC	-1.8	-1.6	-1.2	-1.05	-5.5	-5.5	-3.06	-3.1
HQIC	-2.2	-1.9	-1.5	-1.4	-5.9	-5.9	-3.5	-3.6
SBIC	-1.6	-1.3	-0.93	-0.75	-5.3	-5.3	-2.8	-3.8
# of obs	10	10	10	10	9	9	9	9

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	0.15 [0.69]	-	0.69 [0.53]	-	0.30 [0.58]	-	0.93 [0.33]	-	4.6 [0.03]	-	7.2 [0.00]	-	4.4 [0.03]	-	7.4 [0.00]	-
FBS	-	41.2 [0.00]	-	40.8 [0.00]	-	-	-	-	-	54.5 [0.00]	-	76.5 [0.00]	-	-	-	-
IU	-	-	-	-	-	0.01 [0.90]	-	0.005 [0.94]	-	-	-	-	-	5.4 [0.02]	-	6.2 [0.01]

	Italy				Japan			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	-0.10 [0.22]	0.15 [0.25]	**0.42 [0.19]**	**0.41 [0.20]**	**0.79 [0.10]**	0.59 [0.39]	0.68 [0.54]	0.58 [0.50]
FBS (t-1)	**1.9 [0.65]**	**2.1 [0.73**	-	-	0.87 [1.08]	0.68 [1.00]	-	-
IU (t-1)	**-**	-	0.87 [0.95]	0.86 [1.03]	-	-	2.2 [2.9]	1.2 [2.8]
SMT_GDP	**-0.39 [0.20]**	-0.41 [0.22]	-0.27 [0.26]	-0.30 [0.28]	0.27 [0.86]	0.84 [0.85]	0.21 [0.85]	0.75 [0.85]
FD	**4.3 [1.8]**	-	3.9 [2.4]	-	-2.5 [10.7]	-	-1.1 [11.05]	-
FM	-	1.6 [0.94]	-	1.08 [1.2]	-	-6.9 [5.2]	-	-6.7 [5.3]
R-square	0.93	0.92	0.88	0.86	0.57	0.64	0.57	0.63
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	0.01 [0.01]	0.01 [0.01]	0.008 [0.02]	0.005 [0.01]	0.003 [0.00]	-0.001 [0.10]	-0.01 [0.04]	-0.02 [0.04]
FBS (t-1)	**0.62 [0.04]**	**0.61 [0.04]**	-	-	**0.73 [0.02]**	**0.73 [0.02]**	-	-
IU (t-1)	-	-	**0.92 [0.09]**	**0.93 [0.09]**	-	-	**0.97 [0.21]**	**0.89 [0.21]**
SMT_GDP	-0.01 [0.01]	-0.01 [0.01]	0.02 [0.02]	0.02 [0.02]	-0.01 [0.02]	-0.006 [0.02]	0.02 [0.06]	0.06 [0.06]
FD	-0.07 [0.11]	-	-0.19 [0.24]	-	-0.30 [0.26]	-	0.26 [0.79]	-
FM	-	-0.04 [0.05]	-	-0.16 [0.10]	-	-0.20 [0.13]	-	-0.34 [0.40]
R-square	0.99	0.99	0.98	0.98	0.99	0.99	0.86	0.86
AIC	-5.3	-5.1	-3.8	-3.9	-2.7	-2.9	-1.8	-1.8
HQIC	-5.7	-5.6	-4.2	-4.2	-3.01	-3.2	-2.1	-2.2
SBIC	-5.0	-4.9	-3.5	-3.6	2.3	-2.6	-1.5	-1.6
# of obs	9	9	10	10	10	10	10	10
Granger causality Wald test – χ^2 [Prob>χ^2]								
Equation	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs	8.8 -	8.2 -	0.84 -	0.70 -	0.65 -	0.45 -	0.53 -	0.17 -

	[0.00]		[0.00]		[0.36]		[0.40]		[0.42]		[0.49]		[0.46]		[0.67]	
FBS	-	1.06 [0.30]	-	1.3 [0.25]	-	-	-	-	-	0.10 [0.74]		0.01 [0.90]	-	-	-	-
IU	-	-	-	-	-	0.18 [0.67]	-	0.09 [0.76]	-	-	-	-	-	0.20 [0.65]	-	0.33 [0.56]

	Malaysia				Mexico			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	0.18 [0.54]	-0.10 [0.49]	**1.7 [0.44]**	**1.4 [0.31]**	-0.42 [0.31]	0.61 [0.32]	**1.01 [0.20]**	**0.87 [0.14]**
FBS (t-1)	0.10 [0.12]	0.55 [0.50]	**-**	-	**2.03 [0.58]**	0.51 [0.57]	**-**	-
IU (t-1)	-	-	**-2.3 [0.79]**	-0.30 [0.25]	-	-	**-1.6 [0.58]**	0.11 [0.60]
SMT_GDP	**4.8 [1.5]**	**4.6 [1.5]**	**4.7 [0.81]**	**6.2 [0.64]**	-0.86 [0.84]	-0.87 [0.61]	1.03 [0.79]	-0.05 [0.21]
FD	5.4 [10.1]	-	**36.6 [9.4]**	**-**	5.3 [3.1]	-	4.3 [3.5]	-
FM	-	-0.41 [5.4]	-	**16.7 [3.6]**	-	**8.8 [2.5]**	-	**1.3 [0.21]**
R-square	0.56	0.54	0.92	0.94	0.95	0.97	0.94	0.97
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	-0.002 [0.04]	-0.003 [0.04]	0.05 [0.08]	0.07 [0.06]	0.001 [0.11]	0.09 [0.14]	0.06 [0.04]	0.04 [0.03]
FBS (t-1)	**0.78 [0.07]**	**0.78 [0.04]**	-	-	**0.77 [0.20]**	**0.61 [0.25]**	-	-
IU (t-1)	-	-	**1.01 [0.14]**	**0.94 [0.05]**	-	-	**0.71 [0.12]**	**0.91 [0.16]**
SMT_GDP	-0.07 [0.12]	-0.07 [0.12]	**0.34 [0.15]**	**0.29 [0.13]**	0.02 [0.29]	-0.10 [0.25]	0.21 [0.16]	-0.05 [0.21]
FD	0.005 [0.85]	-	-1.11 [1.7]	-	-0.43 [1.08]	-	0.08 [0.74]	-
FM	-	0.001 [0.45]	-	-0.40 [0.76]	-	1.2 [1.1]	-	1.3 [0.78]
R-square	0.98	0.98	0.99	0.99	0.98	0.98	0.98	0.98
AIC	0.54	0.59	-0.75	-1.5	-1.01	-1.2	-0.63	-1.6
HQIC	0.07	0.12	-1.7	-2.5	-1.6	-1.5	-0.96	-1.9

SBIC	0.76		0.81		-0.82		-1.6		-0.71		-0.87		-0.32		-1.3	
# of obs	9		9		7		7		10		10		10		10	
Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	0.01 [0.90]	-	1.2 [0.27]	-	9.01 [0.00]	-	1.4 [0.23]	-	12.1 [0.00]	-	0.79 [0.37]	-	7.4 [0.00]	-	0.03 [0.84]	-
FBS	-	0.00 [0.96]	-	0.00 [0.95]	-	-	-	-	-	0.00 [0.99]	-	0.41 [0.52]	-	-	-	-
IU	-	-	-	-	-	0.41 [0.52]	-	1.2 [0.28]	-	-	-	-	-	2.6 [0.10]	-	1.2 [0.28]

	New Zealand				**Norway**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	-0.20 [0.17]	**0.002 [0.16]**	-0.03 [0.25]	0.12 [0.24]	**0.43 [0.16]**	**0.39 [0.16]**	-0.26 [0.18]	-0.27 [0.17]
FBS (t-1)	**-0.80 [0.11]**	-0.45 [0.08]	-	-	**5.05 [2.3]**	**5.6 [2.3]**	-	-
IU (t-1)	-	-	**-3.2 [0.74]**	**-1.99 [0.70]**	**-**	**-**	**60.1 [10.4]**	**60.7 [9.8]**
SMT_GDP	-0.28 [0.22]	0.07 [0.22]	0.24 [0.29]	0.39 [0.30]	**1.7 [0.51]**	**1.5 [0.56]**	**4.1 [0.52]**	**4.2 [0.54]**
FD	**6.2 [0.79]**	-	**3.6 [0.95]**	-	-1.8 [4.7]	-	-1.22 [2.5]	-
FM	-	**2.5 [0.31]**	-	**1.7 [0.45]**	-	0.52 [3.2]	-	-1.02 [1.7]
R-square	0.97	0.96	0.91	0.91	0.93	0.93	0.94	0.98
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	**0.75 [0.03]**	**0.67 [0.06]**	-0.03 [0.07]	-0.04 [0.07]	**-0.008 [0.00]**	**-0.007 [0.00]**	-0.002 [0.00]	-0.003 [0.00]
FBS (t-1)	**1.15 [0.02]**	**1.04 [0.03]**	-	-	**0.69 [0.04]**	**0.68 [0.04]**	-	-
IU (t-1)	**-**	**-**	**0.62 [0.21]**	**0.56 [0.19]**	**-**	**-**	**1.1 [0.56]**	**1.2 [0.51]**
SMT_GDP	**0.85 [0.04]**	**0.75 [0.09]**	-0.15 [0.08]	**-0.16 [0.08]**	**-0.02 [0.00]**	**-0.01 [0.00]**	0.04 [0.03]	0.05 [0.03]
FD	**-1.8 [0.14]**	**-**	-0.16 [0.26]	-	0.07 [0.08]	**-**	-0.15 [0.13]	-

FM	-	**-0.67 [0.12]**	-	-0.10 [0.12]	-	0.02 [0.05]	-	-0.13 [0.08]
R-square	0.99	0.99	0.89	0.90	0.99	0.99	0.97	0.94
AIC	-7.3	-4.2	-4.8	-4.3	-5.3	-5.2	-4.3	-4.5
HQIC	-8.2	-5.1	-5.8	-5.3	-5.8	-5.7	-4.8	-4.9
SBIC	-7.3	-4.3	-4.9	-4.4	-5.1	-5.0	-4.2	-4.3
# of obs	7	7	7	7	9	9	9	9

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	53.35 [0.00]	-	27.9 [0.00]	-	18.3 [0.00]	-	7.9 [0.00]	-	4.5 [0.03]	-	5.6 [0.02]	-	33.2 [0.00]	-	38.01 [0.00]	-
FBS	-	583.5 [0.00]	-	108.05 [0.00]	-	-	-	-	-	8.6 [0.00]	-	6.6 [0.01]	-	-	-	-
IU	-	-	-	-	-	0.26 [0.60]	-	0.41 [0.52]	-	-	-	-	-	0.07 [0.78]	-	0.16 [0.68]

	Peru				**Singapore**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	0.51 [0.33]	0.15 [0.40]	0.43 [0.42]	0.10 [0.41]	-0.35 [0.30]	-0.26 [0.27]	**0.71 [0.18]**	**0.69 [0.17]**
FBS (t-1)	7.6 [4.2]	0.10 [1.1]	-	-	**7.3 [2.1]**	**6.6 [1.8]**	-	-
IU (t-1)	-	-	3.3 [3.9]	-0.09 [0.83]	-	-	-1.1 [4.7]	0.38 [0.30]
SMT_GDP	1.8 [1.4]	-0.19 [1.7]	1.4 [1.9]	-0.40 [1.8]	**3.6 [1.7]**	1.8 [1.6]	-0.70 [2.8]	0.10 [0.20]
FD	-23.3 [12.9]	-	-13.2 [16.2]	-	-2.1 [7.9]	-	12.7 [13.4]	-
FM	-	3.6 [7.3]	-	4.2 [7.3]	-	3.5 [3.8]	-	-0.32 [5.8]
R-square	0.28	0.07	0.10	0.07	0.92	0.92	0.82	0.83
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	**-0.02 [0.00]**	**-0.02 [0.00]**	0.00 [0.02]	0.02 [0.00]	0.006 [0.01]	0.006 [0.00]	**0.03 [0.01]**	**0.03 [0.01]**
FBS (t-1)	**1.02 [0.08]**	**0.82 [0.02]**	-	-	0.74 [0.08]	**0.75 [0.06]**	-	-

IU (t-1)	-	-	**1.2 [0.19]**	**0.87 [0.02]**	-	-	-1.1 [4.7]	0.38 [0.30]
SMT_GDP	-0.04 [0.02]	-0.0 [0.03]	0.05 [0.09]	**0.11 [0.03]**	0.02 [0.06]	-0.01 [0.06]	-0.70 [2.8]	0.10 [0.20]
FD	**-0.75 [0.26]**	-	-1.4 [0.79]	-	0.33 [0.31]	-	12.7 [13.4]	-
FM	-	**-0.42 [0.11]**	-	**-1.2 [0.16]**	-	**0.28 [0.13]**	-	-0.32 [0.46]
R-square	0.99	0.99	0.98	0.99	0.99	0.99	0.73	0.74
AIC	-1.3	0.87	3.06	1.6	-2.9	-3.0	0.49	0.44
HQIC	-1.6	0.53	2.7	1.2	-3.2	-3.4	0.12	0.11
SBIC	-0.96	1.2	3.4	1.9	-2.6	-2.7	0.76	0.74
# of obs	10	10	10	10	10	10	10	10

Granger causality Wald test – χ^2 [Prob>χ^2]

Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	3.4 [0.06]	-	0.009 [0.92]	-	0.68 [0.41]	-	0.01 [0.91]	-	12.0 [0.00]	-	13.1 [0.00]	-	0.05 [0.82]	-	0.01 [0.91]	-
FBS	-	9.3 [0.00]	-	7.1 [0.00]	-	-	-	-	-	0.28 [0.59]	-	0.36 [0.54]	-	-	-	-
IU	-	-	-	-	-	0.00 [0.97]	-	2.3 [0.13]	-	-	-	-	-	4.8 [0.03]	-	4.1 [0.04]

	South Africa				**South Korea**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	-0.26 [0.27]	-0.24 [0.27]	-0.11 [0.23]	-0.10 [0.23]	-0.20 [0.37]	-0.25 [0.37]	0.03 [0.31]	-0.002 [0.31]
FBS (t-1)	0.34 [0.18]	**0.36 [0.16]**	-	-	**10.5 [3.3]**	**10.9 [3.3]**	-	-
IU (t-1)	-	-	0.22 [0.13]	**0.23 [0.11]**	-	-	**22.7 [7.3]**	**22.9 [7.2]**
SMT_GDP	0.98 [0.65]	0.99 [0.67]	1.2 [0.75]	1.7 [0.75]	-0.50 [0.74]	-0.51 [0.73]	-0.72 [0.81]	-0.73 [0.80]
FD	0.97 [2.8]	-	0.58 [3.03]	-	0.05 [7.5]	-	-0.60 [7.6]	-
FM	-	0.13 [1.7]	-	0.12 [1.8]	-	1.6 [3.8]	-	0.85 [3.9]
R-square	0.65	0.65	0.64	0.64	0.94	0.94	0.94	0.94

	FBS equations		IU equations		FBS equations		IU equations	
ETFs (t-1)	-0.06 [0.14]	-0.04 [0.13]	0.26 [0.19]	0.30 [0.19]	0.004 [0.03]	0.006 [0.03]	0.02 [0.01]	0.02 [0.01]
FBS (t-1)	**0.90 [0.09]**	**0.88 [0.08]**	-	-	**0.78 [0.29]**	**0.77 [0.29]**	-	-
IU (t-1)	-	-	**0.80 [0.10]**	**0.86 [0.09]**	-	-	0.38 [0.27]	0.38 [0.27]
SMT_GDP	**-0.73 [0.34]**	**-0.64 [0.32]**	-0.92 [0.60]	-0.88 [0.67]	0.06 [0.06]	0.06 [0.06]	**0.06 [0.03]**	**0.06 [0.03]**
FD	-0.66 [1.5]	-	2.8 [2.4]	-	0.27 [0.65]	-	-0.09 [0.29]	-
FM	-	-1.2 [0.81]	-	1.3 [1.4]	-	0.09 [0.33]	-	-0.06 [0.15]
R-square	0.97	0.97	0.96	0.96	0.95	0.95	0.92	0.92
AIC	-0.20	-0.49	1.1	1.2	-2.3	-2.3	-3.8	-3.8
HQIC	-0.54	-0.82	0.81	0.85	-2.6	-2.6	-4.2	-4.2
SBIC	0.09	-0.19	1.4	1.5	-1.9	-1.9	-3.5	-3.6
# of obs	10	10	10	10	10	10	10	10

Granger causality Wald test – χ^2 [Prob>χ^2]

Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	3.4 [0.06]	-	4.8 [0.02]	-	2.9 [0.08]	-	4.4 [0.03]	-	10.5 [0.00]	-	10.8 [0.00]	-	9.8 [0.00]	-	10.1 [0.00]	-
FBS		0.17 [0.68]		0.14 [0.71]	-	-		-	-	0.02 [0.89]	-	0.04 [0.85]	-	-	-	-
IU	-	-	-	-	-	1.9 [0.17]	-	2.6 [0.10]	-	-	-	-	-	1.9 [0.16]	-	2.1 [0.15]

	Spain				Switzerland			
	ETFs/FBS		ETFs/IU		ETFs/FBS		ETFs/IU	
	ETFs equations		ETFs equations		ETFs equations		ETFs equations	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	**-1.02 [0.19]**	**-0.98 [0.21]**	**-0.75 [0.21]**	**-0.74 [0.22]**	**0.72 [0.19]**	**0.57 [0.22]**	0.45 [0.28]	0.26 [0.27]
FBS (t-1)	**11.2 [1.5]**	**10.4 [1.6]**	-	-	0.76 [0.54]	0.95 [0.63]	-	-
IU (t-1)	-	-	**16.5 [3.01]**	**15.7 [2.9]**	-	-	4.8 [2.6]	**6.7 [2.9]**
SMT_GDP	**6.5 [0.89]**	**5.7 [0.97]**	**6.4 [1.3]**	**6.2 [1.2]**	0.06 [0.06]	0.04 [0.09]	0.06 [0.06]	0.02 [0.07]

FD	**10.7 [1.9]**	**-**	**10.0 [2.5]**	**-**	7.1 [3.7]	-	6.2 [3.5]	-
FM	-	**6.8 [1.4]**	-	**6.6 [1.7]**	-	1.5 [2.2]	-	1.9 [1.9]
R-square	0.88	0.85	0.81	0.80	0.96	0.96	0.97	0.96
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	**-0.05 [0.00]**	**-0.05 [0.10]**	**-0.03 [0.00]**	**-0.03 [0.00]**	0.002 [0.02]	-0.009 [0.02]	-0.01 [0.03]	-0.01 [0.02]
FBS (t-1)	**1.05 [0.07]**	**1.02 [0.08]**	**-**	**-**	**0.73 [0.06]**	**0.72 [0.06]**	-	-
IU (t-1)	**-**	**-**	**1.3 [0.10]**	**1.3 [0.08]**	**-**	-	**0.98 [0.30]**	**6.7 [2.9]**
SMT_GDP	**0.14 [0.04]**	**1.2 [0.05]**	**0.19 [0.04]**	**0.18 [0.03]**	**-0.01 [0.00]**	-0.01 [0.00]	-0.005 [0.00]	-0.006 [0.00]
FD	**0.32 [0.10]**	**-**	**0.44 [0.08]**	**-**	-0.0006 [0.43]	-	0.08 [0.41]	-
FM	-	**0.19 [0.07]**	-	**0.31 [0.04]**	-	-0.21 [0.21]	-	0.03 [0.21]
R-square	0.99	0.99	0.99	0.99	0.99	0.99	0.96	0.96
AIC	-6.2	-5.9	-6.1	-6.4	-5.4	5.3	-5.6	-5.4
HQIC	-6.8	-6.6	-6.7	-7.1	-5.8	-5.6	-5.9	-5.8
SBIC	-6.0	-5.8	-5.9	-6.4	-5.2	-5.0	-5.3	-5.2
# of obs	8	8	8	8	10	10	10	10

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	55.5 [0.00]	-	41.3 [0.00]	-	29.9 [0.00]	-	28.3 [0.00]	-	1.9 [0.16]	-	2.2 [0.13]	-	3.5 [0.06]	-	5.3 [0.02]	-
FBS	-	32.8 [0.00]	-	24.6 [0.00]	-	-	-	-	-	0.00 [0.92]	-	0.20 [0.65]	-	-	-	-
IU	-	-	-	-	-	17.1 [0.00]	-	25.5 [0.00]	-	-	-	-	-	0.10 [0.74]	-	0.20 [0.65]

	Thailand				**Turkey**			
	ETFs/FBS		**ETFs/IU**		**ETFs/FBS**		**ETFs/IU**	
	ETFs equations		**ETFs equations**		**ETFs equations**		**ETFs equations**	
	VAR[1]	VAR[2]	VAR[3]	VAR[4]	VAR[1]	VAR[2]	VAR[3]	VAR[4]
ETFs (t-1)	**-0.52 [0.18]**	**-0.61 [0.17]**	-0.01 [0.65]	0.15 [0.53]	**1.1 [0.26]**	**0.97 [0.23]**	**1.05 [0.23]**	**0.95 [0.21]**
FBS (t-1)	**4.9**	**3.2**	-	-	-0.64	-0.44	-	-

	[0.86]	**[0.59]**			[0.40]	[0.28]		
IU (t-1)	**-**	**-**	0.21 [2.2]	-0.88 [1.9]	-	-	-0.96 [0.51]	-0.64 [0.34]
SMT_GDP	**-6.1 [1.1]**	**-5.9 [1.01]**	-0.23 [3.9]	0.92 [3.1]	-2.1 [1.8]	-2.8 [1.6]	-2.5 [1.8]	-2.8 [1.5]
FD	**-16.5 [2.5]**	**-**	-4.2 [4.01]	-	0.49 [3.3]	-	1.3 [3.3]	-
FM	-	**-7.06 [0.08]**	-	**-3.9 [1.9]**	-	2.3 [1.9]	-	2.2 [1.7]
R-square	0.89	0.91	0.38	0.54	0.69	0.74	0.76	0.75
	FBS equations		**IU equations**		**FBS equations**		**IU equations**	
ETFs (t-1)	0.009 [0.02]	0.003 [0.02]	**-0.10 [0.04]**	**-0.09 [0.04]**	-0.003 [0.03]	-0.04 [0.03]	-0.004 [0.06]	-0.003 [0.05]
FBS (t-1)	**0.83 [0.11]**	**0.75 [0.08]**	**-**	**-**	**0.54 [0.05]**	**0.64 [0.04]**	-	-
IU (t-1)	-	-	**1.6 [0.13]**	**1.6 [0.14]**	-	-	**0.71 [0.12]**	**0.71 [0.08]**
SMT_GDP	0.05 [0.15]	0.05 [0.14]	**-0.60 [0.25]**	**-0.53 [0.22]**	0.03 [0.23]	0.08 [0.22]	0.35 [0.42]	0.45 [0.38]
FD	**-0.84 [0.33]**	-	**0.74 [0.26]**	**-**	0.77 [0.43]	-	0.16 [0.78]	-
FM	-	**-0.38 [0.13]**	-	**0.43 [0.14]**	-	0.49 [0.25]	-	-0.15 [0.45]
R-square	0.99	0.96	0.99	0.99	0.98	0.98	0.93	0.93
AIC	-4.3	-4.2	-0.93	-1.1	-0.59	-0.72	0.51	0.36
HQIC	-5.2	-5.2	-1.8	-2.1	-1.06	-1.2	0.04	-0.11
SBIC	-4.4	-4.3	-1.0	-1.2	-0.37	-0.49	0.73	0.57
# of obs	7	7	7	7	9	9	9	9

Granger causality Wald test – χ^2 [Prob>χ^2]																
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]		VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	33.7 [0.00]	-	30.9 [0.00]	-	0.009 [0.92]	-	0.21 [0.65]	-	2.5 [0.11]	-	2.5 [0.11]	-	3.6 [0.06]	-	3.4 [0.06]	-
FBS	-	0.13 [0.71]	-	0.02 [0.88]	-	-	-	-	-	0.01 [0.92]	-	1.9 [0.16]	-	-	-	-
IU	-	-	-	-	-	5.8 [0.01]	-	5.6 [0.02]	-	-	-	-	-	0.007 [0.93]	-	0.003 [0.95]

	United Kingdom			
	ETFs/FBS		**ETFs/IU**	

	ETFs equations				**ETFs equations**			
	VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs (t-1)	**0.81 [0.04]**		**0.83 [0.02]**		0.17 [0.27]		0.16 [0.25]	
FBS (t-1)	**0.93 [0.14]**		**1.3 [0.10]**		-		-	
IU (t-1)	-		-		4.6 [2.4]		4.6 [2.4]	
SMT_GDP	0.01 [0.08]		**-0.11 [0.04]**		0.21 [0.22]		0.21 [0.22]	
FD	12.4 [2.4]		**-**		-0.10 [3.3]		-	
FM	-		**12.08 [1.2]**		-		-0.49 [2.1]	
R-square	0.99		0.99		0.99		0.99	
	FBS equations				**IU equations**			
ETFs (t-1)	-0.07 [0.07]		-0.04 [0.07]		**0.07 [0.00]**		**0.07 [0.00]**	
FBS (t-1)	**-0.66 [0.22]**		**-0.65 [0.32]**		-		-	
IU (t-1)	**-**		-		0.00 [0.06]		0.06 [0.08]	
SMT_GDP	**-0.46 [0.12]**		**-0.43 [0.14]**		**-0.09 [0.00]**		**-0.09 [0.00]**	
FD	-4.1 [3.8]		-		**0.48 [0.08]**		**-**	
FM	-		-2.2 [3.4]		-		**0.26 [0.07]**	
R-square	0.70		0.67		0.97		0.97	
AIC	-3.6		-5.4		-9.1		-8.4	
HQIC	-4.3		-6.1		-9.8		-9.1	
SBIC	-3.5		-5.3		-9.0		-8.3	
# of obs	8		8		8		8	
Granger causality Wald test – χ^2 [Prob>χ^2]								
Equation	VAR[1]		VAR[2]		VAR[3]		VAR[4]	
ETFs	39.1 [0.00]	-	151.1 [0.00]	-	3.54 [0.06]	-	3.6 [0.06]	-
FBS		1.08		0.44	-	-	-	-

		[0.29]		[0.51]				
IU	-	-	-	-	-	121.4 [0.00]	-	56.6 [0.00]

Source: Authors` calculations. Note: all values are logged. SE below coefficients. In bold – results statistically significant at 5% level of significance. For explanation of the variables see Table 5. Hong Kong and USA—excluded (for reason see Section 4.2.), Chile, China, Colombia, Greece, Iran, Poland and Saudi Arabia also excluded—too few observations.