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The Impact of Process and Object Digital Transformation on the Moscow Exchange Index: A Textual Analysis of Patents

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ABSTRACT

The purpose of the study is to assess the association of process and object digital transformation with daily returns of the broad and sectoral Moscow Exchange indices using textual patent analysis. The subject is the short-run response of the Russian stock market to patent-based digital technology indicators. We propose a research method that separates object transformation (material components) from process transformation (management and information technologies). The empirical base contains 850,784 patent records covering the period from 1977 to 2025; the estimates use ARX-EGARCH models. Conclusions: The association is heterogeneous across technology blocks and sectors: after multiple-testing correction, robust negative short-run coefficients remain for process indicators in energy and finance. The applied and empirical-methodological novelty of this study is a reproducible patent indicator of object and process digital transformation for the Russian stock market.

Keywords: patents; innovation; digital transformation; company capitalization; text analysis; time series models

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INTRODUCTION

Digital transformation is changing costs, business processes, and market positions of companies, and patents serve as an observable indicator of technological change. Russian research examines the impact of macrofinancial policy and investment on innovation activity [1–5], stock market scenarios [6], and patent indexes [7]. However, the relationship between digital patent activity and the profitability of general and industry indices on the Moscow Stock Exchange has not been sufficiently studied, which determines the relevance of this work.

The aim of this study is to investigate the relationship between digital transformation in processes and objects and the daily performance of general and industry indexes on the Moscow Stock Exchange. This will be achieved through a textual analysis of patent documents. The research sample includes 850,784 patents from the period 1977–2025.

The scientific novelty of this work is both applied and empirical in nature. It consists of several original elements, including an applied dictionary for digital transformation, a division of patent indicators into object and process blocks, and their verification using data from the Russian stock market. While the short-term negative coefficients obtained are not a direct test of E. Brynjolfsson's J-shaped productivity curve of E. Brynjolfsson et al. [8], they are consistent with the logic of its initial costs associated with implementing digital technologies.

LITERATURE REVIEW AND RESEARCH HYPOTHESES

Digitalization is a process that involves the use of digital technologies and digitized data to transform business processes, business models, and business operations [9]. S. Nambisan et al. [10] define digital innovation as “the use of digital technologies in the innovation process”, “the creation (and subsequent change) of market proposals, business processes or models that result from the use of digital technologies”. And digital

innovation management includes practices, processes, and principles underlying effective coordination of digital innovation.

In our study, we will conditionally divide digital transformation into two classes: process and object. By process digital transformation, we mean a fundamental change in business models, operational processes, management practices and organizational culture of a company based on digital technologies. The process approach focuses on the role of technology as a catalyst for structural change within a company, rather than on technology itself. Digital transformation is a set of technological artifacts, systems, and solutions implemented within a company as part of the digitalization process. This includes software, information systems, equipment, digital platforms, and other technological solutions. The analysis of publications on the problem under study allowed us to identify three groups of studies. **The first group of studies** concerns technological progress as a source of growth, as well as the relationship of patent statistics with the pace of technological change, the competitive position of specific companies, countries, etc. Technological progress occupies a special place in economic growth models, as it explains the part of GDP output that goes beyond the mechanical increase in labor and capital.

In the classic work on assessing the impact of technology on economic growth, R. Solow [11] was one of the first to set the task of dividing the growth of production per capita into two components: one is associated with technical changes; the other is due to changes in the availability of capital per capita.¹

In the 1950s, economists attributed almost all changes in labor productivity to technological changes [11]. Subsequently, P. Romer proposed a model of endogenous rather than exogenous technological changes;

¹ When describing the production function, R. Solow understands technical changes as acceleration associated with an increase in the level of education of the workforce and all sorts of other things (for example, technical innovations, although he does not name them directly).

he considered economic growth caused by technological changes as a result of targeted investment decisions [12]. According to P. Romer: “Technological progress stimulates further capital accumulation, and together, capital accumulation and technological progress largely lead to an increase in production per hour worked”; “technological changes occur largely due to the purposeful actions of people who respond to market incentives”. P. Romer points out the peculiarity of technology. (Once the cost of creating a new set of instructions has been incurred, they can be used over and over again at no additional cost. Developing new and more advanced instructions is equivalent to incurring fixed costs. This property is considered a defining characteristic). In addition, P. Romer “emphasizes the role of market incentives, which are essential in the process of transforming new knowledge into goods with added value” [12].

“General purpose” technologies, most of which play the role of “assistive technologies”, and economic growth are also discussed in [8, 13]. The central idea of T. Bresnahan and M. Trajtenberg [13] is that as “general purpose technologies” are developed and improved, they spread across various sectors of the economy, providing an overall increase in labor productivity in the economy as a whole. E. Brynjolfsson et al. The impact of “general purpose technologies” such as AI in the first and subsequent years of implementation on productivity is being investigated. The authors note the paradox of R. Solow’s productivity, which grows unevenly, calling it a J-shaped curve. In the early years, productivity is underestimated because investments in capital and labor occur, and in subsequent years it is overestimated due to the emergence of new side effects, including intangible assets. Flows of capital services from these hidden intangible reserves generate a measurable volume of production [8].

The second group of studies evaluates the impact of patents on economic growth. Z. Griliches, when analyzing economic growth,

considers patents as an economic indicator, observable but heterogeneous. The author points out that there is a problem in economic analysis related to the use and interpretation of patent statistics [14]. They serve as indicators of technological change and are dependent on R&D costs. For financial applications, it is necessary to identify technological features within a patent case that can be linked to the market’s industry logic. Kogan et al., analyzing data on patents granted to American companies between 1926 and 2010, and the stock market reaction to news about patents, found differences in the returns on R&D investments in different industries and the redistribution of resources between them after waves of technological innovation [15]. B. Hall et al. The relationship between patent citations as an indicator of the “importance” of a firm’s patents was investigated using data on patents and citations for 1963–1995. Using the Tobin equation, the authors measured the ratios of R&D to assets, patents to R&D, and citations to patents. It has been proven that each ratio significantly affects the market value: an additional citation per patent increases the market value by 3% [16].

The third group of studies focuses on the text analysis, and its use in various studies, including the analysis of patent texts. M. Gentzkow et al. They consider the text as an independent data source for conducting various kinds of research. The authors note the features that distinguish the text from other forms of data, review the relevant statistical methods and consider various areas of its application. They note that it is extremely important to correctly translate words into variables. They also emphasize the dependence of the result on the corpus, vocabulary, model, and aggregation procedure [17]. W. Antweiler and M. Frank explore how financial press reports on stocks for investors can influence markets. The authors investigate the impact of 1.5 million messages posted on Yahoo! Finance and Raging Bull, regarding 45 companies included in the Dow Jones index. Using computational linguistics, they prove that stock reports

can be used to predict market volatility [18]. S. Baker et al. Textual analysis of business publications is used to investigate the impact of economic policy uncertainty on economic growth and recession. The authors analyzed articles from six American newspapers over a long period of US history, starting in 1900, examining 12,000 newspaper articles. They found that uncertainty in economic policy as reported in these publications can be used to predict economic downturns [19]. B. Kelly et al. The quality of patents and their potential are analyzed through textual analysis of multidimensional data from patent documents on technological innovations, and by comparing them with previous and subsequent patents. The authors point out that the textual similarity of patents can be used to create long sequences of technological cycles [20]. Thus, the experience of analyzing financial and macroeconomic text data shows that words can only become regular economic indicators with a clear selection criterion. A text index should have a verifiable corpus, a stable unit of observation, and economically meaningful aggregation. In addition, textual analysis has not previously been used to assess the dynamics of the Russian stock market.

Based on a review of scientific papers, a research hypothesis is put forward.

Hypothesis: the registration of patents related to digital transformation affects the market value of companies, but this growth manifests itself over time and has industry specifics.

DATA ANALYSIS AND RESEARCH METHODOLOGY

Empirical Research Base

To solve this problem, the authors consulted the patent registry, *Table 1* presents the main characteristics of the original patent array.

Let's analyze *Table 1* in more detail. 600 names are marked up for manual configuration and verification: 426 are included in the digital class, 174 are excluded; this means that, at the selected threshold, the classifier gives an accuracy of 0.986, a completeness of 0.812, and an F1-measure of 0.890. For financial models,

Table 1

The Main Characteristics of the Initial Patent Array and the Final Text Corpus

Indicator	Meaning
Entries in the original patent registry	850 784
Lines with a non-empty name of the invention	847 518
The application period in the final digital case	1977-01-26-2025-11-17
Marked up patent names	600
Positive manual labels	426
Negative manual labels	174
Classifier accuracy at the selected threshold	0.986
Completeness of the classifier at the selected threshold	0.812
F1 is the measure at the selected threshold	0.890
The final digital patent Case	14 972
Observations in the final daily database	4088

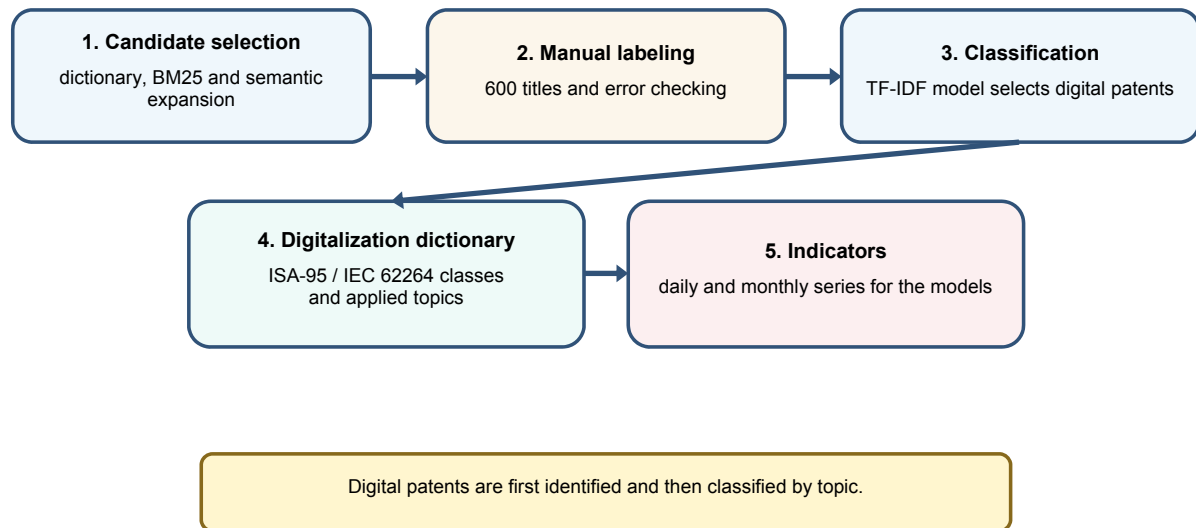
Source: Calculations by the authors.

a calendar database with 4,088 dates is used, in which patent indicators are combined with stock market time series.

The allocation of digital transformation classes took place in several stages. At the first level, 600 patent titles receive manual labels indicating which applications are considered digital. At the second level, logistic regression uses verbal and symbolic TF-IDF features along with additional vocabulary indicators; at the third level, cleared digital patents are divided into thematic subclasses related to ISA-95/IEC 62264-1 and GOST R IEC 62264-1-2010 as sources of terms for distinguishing equipment, networks, sensors, controls, data, and software methods.

The final algorithm is shown in *Fig. 1*.

The original patent records were uploaded on February 2, 2026 from the open register

Steps in constructing the patent index**Fig. 1. Methodology for Building a Patent Digitalization Index Based on the Names of Inventions***Source:* Calculations by the authors.*Table 2***The Main Stages of the Textual Methodology of the Patent Index**

Stage	The extended stage	A brief illustration	Methodological significance
Marked up selection	The expert markup of 600 patent titles provides examples of digital applications and typical inclusion errors	"COMPUTER SYSTEM", "Public computer" are included in the digital circuit; "BULLDOZER" and "EXPLOSIVE COMPOSITION" are excluded from the case	The stage creates a reference sample for configuring the model and for subsequent quality control of the automatic selection
Trained classifier	Logistic regression based on verbal and symbolic TF-IDF features, along with additional dictionary indicators, transfers the logic of manual markup to the entire candidate array	Of the 600 marked-up names, 120 were postponed as stratified validation according to the 80/20 scheme; accuracy is 0.986, completeness 0.812, F1 0.890	The classifier scales the manual examination to the full registry; the selected threshold is fixed during validation and then applied equally to the entire patent array
Classical Dictionary	The cleaned corpus is divided into six thematic subclasses; on this basis, object and process orientations are built	Computing equipment: server, terminal; communication and network infrastructure: switchboard, network Object-based block: computing equipment, measurement and sensors, communications and network infrastructure. Process unit: automation and control, data management and processing, software and AI methods	Dictionary decomposition translates binary selection into interpretable indicators for graphs and regression tables, and two orientations make it possible to read digitalization through a type of technological restructuring

Source: Calculations by the authors.

Table 3

Applied Dictionary of Digitalization by Patent Names

Subclass	Orientation	Vocabulary features	Coverage of the digital body	Formation of the daily indicator
Computing equipment	object	Server, terminal, hardware and software, electronic device, integrated controller	2 420 patents (0.162)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag
Communications and network infrastructure	object	Switchboard, network, telecommunications, wireless, local link	3 353 patents (0.224)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag
Measurement and sensors	object	Telemetry, phasometer, detector, measuring transducer, telemetry system	181 patents (0.012)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag
	the aggregated indicator	Computing equipment, measurement and sensors, communications and network infrastructure	Non-zero total score for an object-based block	Daily average of the total estimate, followed by a 30-day smoothing with a 1-day lag
Object orientation	process	Status control, management system	733 patents (0.049)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag
Automation and control	process	Status control, management system, information processing, storage, data carrier, array of data	3 201 patents (0.214)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag
Data management and processing	process	Intellectual, optimization, predicted data, machine learning model, expert system	722 patents (0.048)	The average for patents on a single date, followed by a 30-day smoothing with a 1-day lag

Source: Calculations by the authors.

of FIPS/Rospatent (RUPAT database; https://www1.fips.ru/fips_serv1/fips_servlet?DB=RUPAT) and saved in the file data-2026 0202-structure-20180828.csv. After deleting entries without names and duplicates, the names are normalized by case, spaces, and technical symbols. The series of general and industry indexes are obtained through the ISS of the Moscow Stock Exchange (<https://iss.moex.com/iss/>), Brent — Yahoo Finance quotes, ticker BZ = F, official USD/RUB exchange rate — Bank of Russia

(https://cbr.ru/currency_base/dynamics/). The rows are synchronized on the calendar grid for 01.01.2014–03.11.2025; the models include only patents with a date no later than 03.11.2025. The last available market value was postponed to non-working dates, so the profitability on such dates is zero.

Building Digital Transformation Indexes

After applying the proposed methodology, we create a digital patent corpus. The result is daily and monthly indicators. The main stages

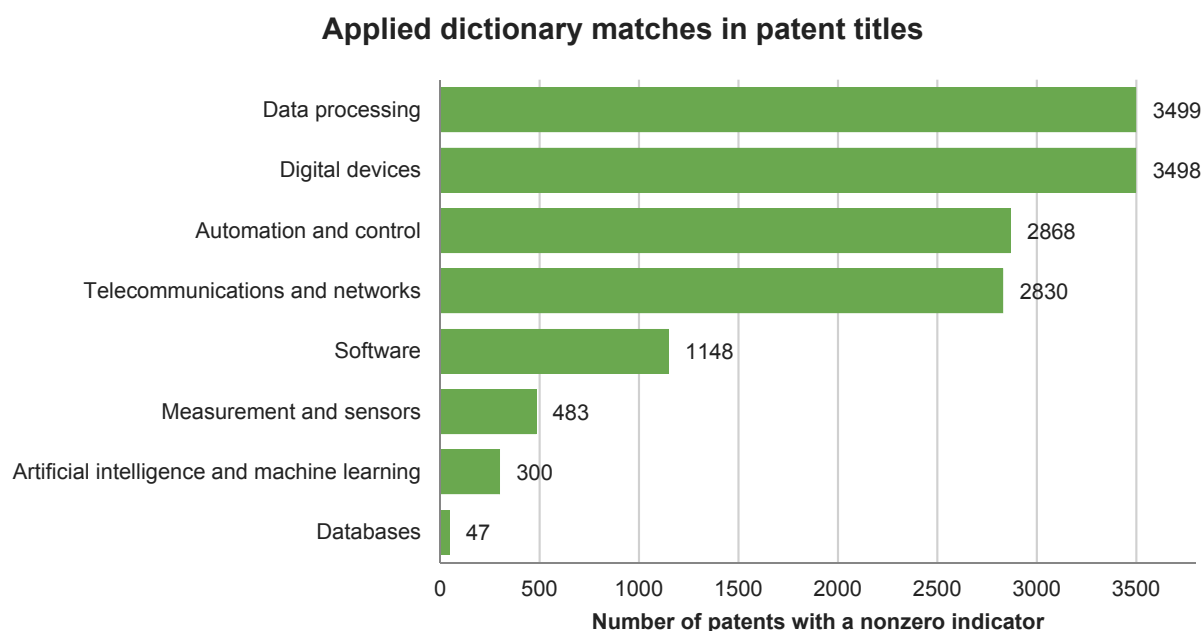


Fig. 2. The Number of Digital Patents According to the Developed Thematic Dictionary

Source: Calculations by the authors.

of the textual methodology of the patent index are presented in more detail in *Table 2*.

After selecting the text corpus of patents related to digitalization, we calculate the frequency of words in the names according to the dictionary, which uses six subclasses: computing equipment, communications and network infrastructure, measurement and sensors, automation and control, data management and processing, software and AI methods. This grouping is consistent with the literature on the digital economy and intangible capital, in which digitalization is associated with data, computing, communication, and organizational change [10, 21]. The final version of the dictionary is presented in *Table 3*.

Patents were divided into six categories based on their technological focus. For the purpose of this analysis, they were grouped into two broader categories: “object-oriented” and “process-oriented”. Object orientation combines computing equipment, sensors, and network infrastructure: the material and communication layer. Process orientation combines automation, data processing, and software/AI methods: management, information, and analytical functions. This grouping is correlated with ISA-95/IEC 62264-1

and GOST R IEC 62264-1-2010. A time series was calculated for each subclass. At the first stage, the average value of the indicator was calculated for all patents published on the same day. At the second stage, a 30-day moving average with a one-day lag was used to eliminate short-term fluctuations and highlight long-term trends. This structure allowed us to form a set of independent variables reflecting the intensity of innovation activity in various segments of digitalization, for their subsequent inclusion in the model of analysis of the impact on the Moscow Stock Exchange index. *Figure 2* shows the number of digital patents.

In *Fig. 2*, data processing and digital devices are the largest categories, while AI and machine learning are less common. This distribution confirms the need for a separate accounting of the hardware, network, sensors, management, information, and software areas.

Analysis of the Dynamics of Digital Transformation Indices

The smoothed time series of digital transformation indices calculated above are shown in *Fig. 3*.

The graph below illustrates the dynamics of the distribution of the shares of scientific

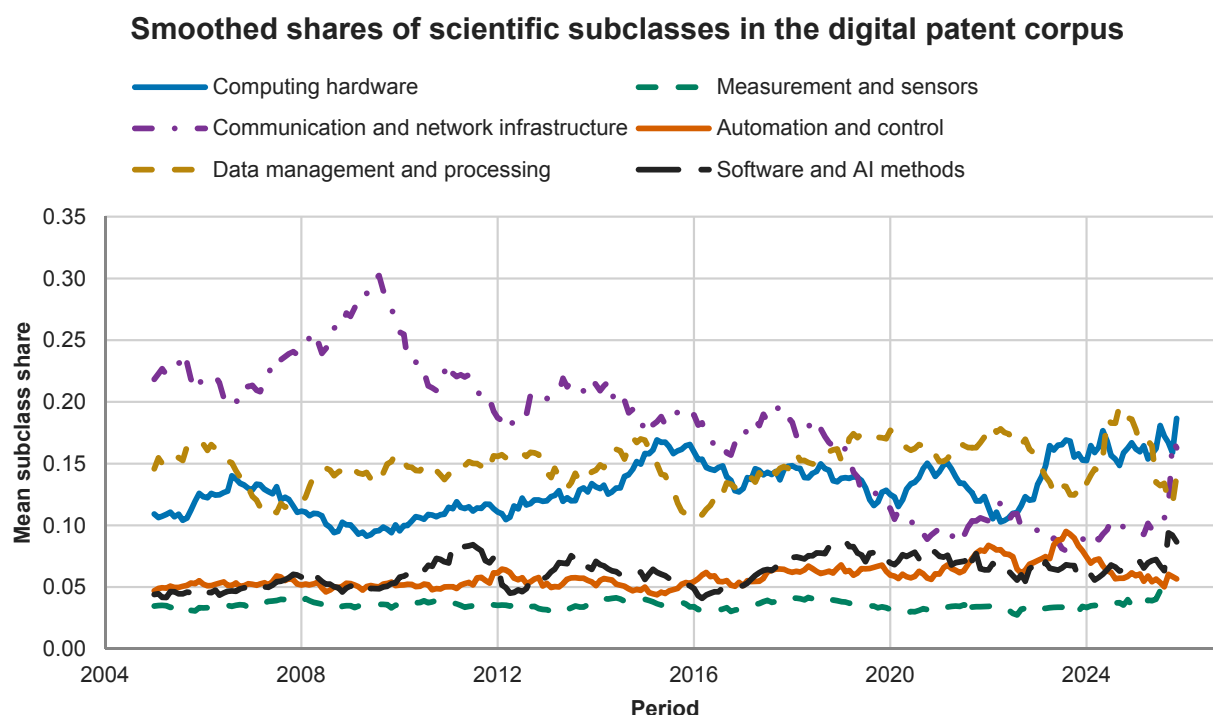


Fig. 3. Smoothed Shares of Thematic Subclasses in the Digital Patent Corpus

Source: Calculations by the authors.

subclasses in the digital patent corpus for the period from 2004 to 2024. This visualization is based on the use of exponential smoothing of time series. For each category of scientific subclasses, a smoothed average share is calculated, representing the share of the corresponding class in the total volume of patent applications in the period under review. At the initial stage, we observe the dominance of two categories of subclasses: “computing equipment”, “communications and network infrastructure”. Their high share (up to 0.25 and 0.15, respectively) reflects the natural stage of the digital economy’s formation, when the main focus was on building the material basis for information and communication technologies. However, since the mid-2010s, there has been a downward trend in the relative significance of these subcategories. This is because we are gradually moving into the next stage of technological development, commonly referred to as the era of software and artificial intelligence. The most notable result is a sharp increase in the share of the “software and AI methods” subclass. Starting from about 0.05 in the first half of the study period, this

category demonstrates an exponential increase, reaching an average value of about 0.15 by 2024. This phenomenon is explained by the widespread use of the Industry 4.0 concept, the growing popularity of cloud services and the widespread digitalization of business. The “data management and processing” subclass demonstrates a similar trajectory to software methods, but reaches its peak somewhat earlier (around 2018). The subsequent decline in patent activity is likely due to the integration of individual data management solutions into complex software products. This has led to a shift in patent activity towards broader categories. Although the average number of patents in the “automation and control” subclass is relatively low, it has shown a steady upward trend.

This can be explained by the increasing use of cyber-physical systems and robotic complexes in industrial enterprises. These systems have become an essential part of modern production processes. The patterns indicate a shift in technological development from investments in tangible assets towards investments in software and intelligent systems.

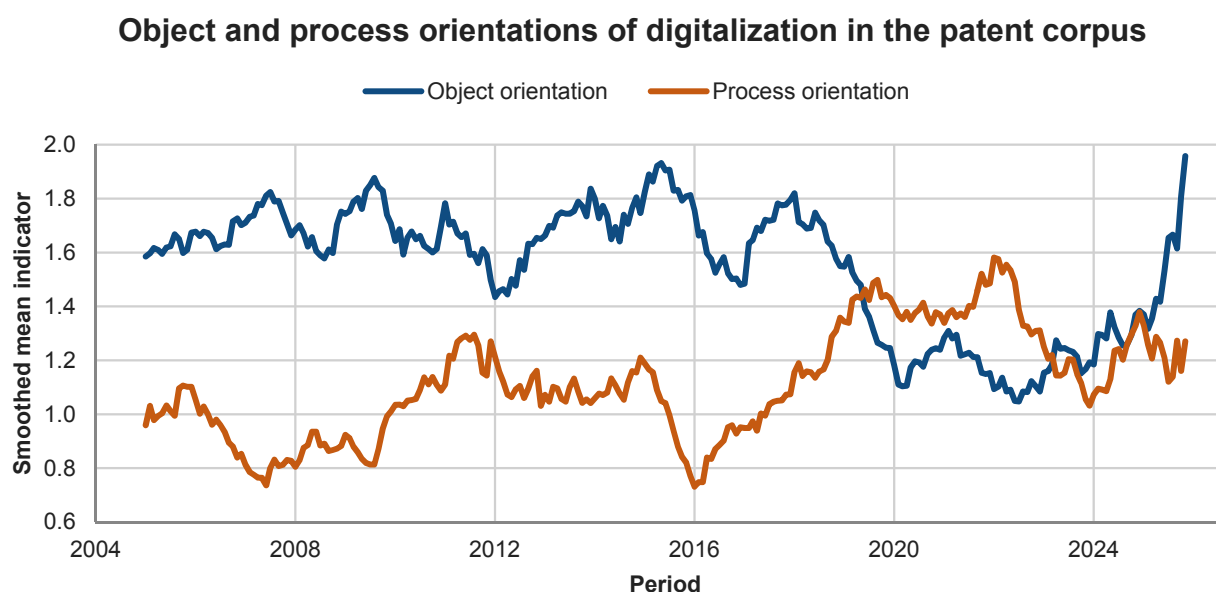


Fig. 4. Object and Process Orientations of Digitalization in the Patent Array

Source: Calculations by the authors.

To support this transformation, educational standards need to be adapted, government science support programs need to be restructured, and private corporations need to review their strategies for allocating resources for research and development.

Figure 4 shows the object and process digitalization in the patent array.

In Fig. 4 the object orientation shows a wave-like trend with peaks in 2008, 2012 and 2020 and new growth by 2024. The process orientation has been steadily increasing since 2010 and reaches a maximum around 2022. The combined growth at the end of the period indicates a combination of updating the material digital infrastructure with the development of management and information solutions.

The Econometric Model

Next, let's take a look at how the patent sample was created. The final set of daily patents was divided into three groups. The first group contains the daily returns of the general MOEX index and its industry sub-indexes. The second group includes macroeconomic variables, such as the returns of Brent crude oil and the USD/RUB exchange rate. The third group combines standardized indicators of

digitalization, which were described in the previous section. The basic specification of the estimates is the ARX (1)–EGARCH (1,1) model with a conditional Student distribution. The average equation (2) contains one yield lag, the yield lags of Brent and USD/RUB, as well as one patent regressor. Equation of variance (4) describes conditional volatility with an asymmetric response to shocks of different signs. All patent regressors are pre-smoothed by a 30-day moving average and lagged for one trading day. The daily logarithmic return is calculated using the standard formula:

$$r_t = \ln(P_t) - \ln(P_{t-1}), \quad (1)$$

where r_t — index profitability; $\ln(P_t)$ — the logarithm of the index value on day t ; $\ln(P_{t-1})$ — the logarithm of the index value on day $t-1$.

Converting the level of the industry index to daily logarithmic returns allows you to work with short-term market revaluation, rather than with the trend of the index itself.

The average equation (2) sets the conditional mathematical expectation of the daily logarithmic return of the i index. It includes a constant, its own first yield lag, the yield lags of Brent and USD/RUB pairs, as well as one

patent regressor. The shock distribution of the average equation is described by the relation (3). The conditional variance equation (4) is constructed in the EGARCH form (1,1) and allows for an asymmetric volatility response to shocks of opposite signs.

$$r_{i,t} = c_i + \phi_{i,1}r_{i,t-1} + \beta_{i,1}r_{t-1}^{USD} + \beta_{i,2}r_{t-1}^{Brent} + \beta_{i,3}DP_{t-1}^k + \varepsilon_{i,t}, \quad (2)$$

where c_i — the constant; $r_{i,t-1}$ — the lag of the index yield; $\phi_{i,1}$ — AR coefficients; r_{t-1}^{USD} — the lag of the USD yield; r_{t-1}^{Brent} — the lag of the Brent yield; DP_{t-1}^k — the lag of the proportion of digital patents of category k ; $\beta_{i,1}, \dots, \beta_{i,3}$ — regression coefficients; $\varepsilon_{i,t}$ — the error of the mean equation.

$$\varepsilon_{i,t} = \sigma_{i,t} \cdot z_{i,t}, z_{i,t} \sim Student-t(v_i), v_i > 2, \quad (3)$$

where $\varepsilon_{\{i,t\}}$ — the error of the equation of the average for asset i at time t ; $\sigma_{\{i,t\}}$ — the conditional standard deviation of asset i ; $z_{\{i,t\}}$ — the standardized remainder with zero mean and unit variance; $Student-t(v_i)$ — the standardized distribution of the Student with v_i degrees of freedom.

$$\ln(\sigma_{i,t}^2) = \omega_i + \beta_i \ln(\sigma_{i,t-1}^2) + \alpha_i \left(|z_{i,t-1}| - E|z_{i,t-1}| \right) + \gamma_i z_{i,t-1}, \quad (4)$$

where $\sigma_{i,t}^2$ — the conditional variance; ω — the variance constant; $\ln(\sigma_{i,t-1}^2)$ — the logarithm of variance lag; $z_{i,t-1}$ — the lag of the standardized remainder, $z_t = \varepsilon_{i,t} / \sigma_{i,t}$; $E|z_{i,t-1}|$ — the expected shock modulus; α_i — the shock magnitude effect; γ_i — the shock sign effect.

The i index designates a group of instruments: the general MOEX index and its industry sub-indexes (oil and gas, energy, finance, consumer sector, chemicals, telecommunications, metals and mining). The value of $r_{i,t}$ is the daily logarithmic yield of index i , calculated by equation (1). The lag daily logarithmic yields of Brent crude oil and the USD/RUB currency pair are denoted as r_{t-1}^{Brent} and $r_{t-1}^{USD/RUB}$ respectively. The $DP_{t-1}^{(k)}$ patent regressor is a 30-day moving

average of the proportion of digital patents of category k , standardized across the entire sample to zero mean and single standard deviation and then lagged by one trading day. The coefficients of the average equation $c_i, \phi_i, \beta_{1,i}, \beta_{2,i}, \gamma_i$ are estimated together. The parameters of the dispersion equation include the free term ω_i , the coefficient for the absolute value of the standardized shock α_i , the asymmetric coefficient δ_i (the negative value of which corresponds to the effect of the “leverage”) and the coefficient of inertia b_i . The number of degrees of freedom of the conditional t -distribution v_i is also estimated together with other parameters; a restriction $v_i > 2$ is imposed on it, which guarantees the finiteness of the unconditional variance. The specific composition of the $DP_{t-1}^{(k)}$ regressor is determined by the specification number. The Basic Model 1 does not contain a patent variable. In Models 2–8: total digital flow (Model 2), computing equipment (Model 3), measurement and sensors (Model 4), communication and network infrastructure (Model 5), automation and control (Model 6), data management and processing (Model 7), software and AI methods (Model 8). Models 9 and 10 use aggregated indicators of object and process orientations, respectively. Each patent indicator is included in the specification in isolation. This eliminates multicollinearity between similar subclasses, and a single standardization scale ensures direct comparability of estimates between specifications. The estimation of parameters (2)–(4) is performed by the maximum likelihood method with a conditional Student t -distribution. The robust standard errors of the coefficients are calculated using the Boyle-Sleva and Wooldridge formulas. For each specification and each industry index, a standard set of diagnostic residue tests is performed: ARCH-LM for residual ARCH dependence, Ljung and Box for levels and squares of residues for autocorrelation, as well as Jarque and Bera for the normality of the distribution. The length of the time series after calculating the lags and the 30-day smoothing of the patent indicators is 4,077 calendar

Table 4

Descriptive Statistics of the Final Patent Sample

Variable	N	Average	Std. dev.	Median	Min	Max
MOEX Yield, %	4078	0.019	1.279	0.000	-40.467	18.262
Brent Yield, %	4078	-0.010	2.039	0.000	-27.976	19.077
USD/RUB Yield, %	4078	0.024	1.068	0.000	-12.864	11.812
Yield: MOEX Oil and Gas index	4078	0.023	1.336	0.000	-38.305	23.128
Yield: MOEX Energy index	4078	0.012	1.321	0.000	-36.181	18.399
Yield: MOEX Financial index	4078	0.018	1.491	0.000	-44.423	12.383
Yield: MOEX Consumer Sector Index	4078	0.007	1.152	0.000	-33.186	14.002
Yield: MOEX Chemical Sector Index	4078	0.040	1.253	0.000	-25.466	35.288
Yield: MOEX telecommunication Index	4078	-0.008	1.338	0.000	-21.093	20.491
Yield: MOEX Metals and Mining Index	4078	0.030	1.231	0.000	-32.425	16.075
Number of digital patents per day	4078	1.50	2.10	1.00	0.00	70.00
Communications and network infrastructure	4078	0.0829	0.1704	0.0000	0.0000	0.8626
Software and AI methods	4078	0.0410	0.1083	0.0000	0.0000	0.8750
Object orientation	4078	0.8602	1.4723	0.0000	0.0000	12.6000
Process orientation	4078	0.7088	1.3083	0.0000	0.0000	9.4000
Computing equipment	4078	0.0834	0.1699	0.0000	0.0000	0.8798
Measurement and sensors	4078	0.0211	0.0489	0.0000	0.0000	0.8798
Automation and control	4078	0.0366	0.0910	0.0000	0.0000	0.8563
Data management and processing	4078	0.0877	0.1661	0.0000	0.0000	0.8832

Source: Calculations by the authors.

observations; this series is common to all evaluated specifications (see Table 4).

The formal correction of multiple testing is not applied: within each index, nine theory-defined indicators are checked, which are positively dependent on construction, and standard procedures in this configuration overestimate the effective number of

independent tests and unreasonably reduce power. Robust Boyle-Sleva-Wooldridge standard errors and the consistency of the marks of the estimates within the technological blocks serve as protection against accidental triggers.

Descriptive statistics of the variable models (2)–(4) are given in Table 4. After the formation of

Table 5

Full Regression Table: MOEX Index

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macrocontrols)	Patents: total Volume of digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: communications and network infrastructure	Patents: automation and control	Patents: management and data processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
Constant	0.0315*** (0.0073)	0.0321*** (0.0073)	0.0314*** (0.0081)	0.0326*** (0.0070)	0.0322*** (0.0072)	0.0321*** (0.0073)	0.0320*** (0.0073)	0.0327*** (0.0073)	0.0327*** (0.0050)	0.0320*** (0.0073)
AR(1)	-0.0079 (0.0118)	-0.0085 (0.0122)	-0.0084 (0.0149)	-0.0081 (0.0077)	-0.0086 (0.0120)	-0.0082 (0.0122)	-0.0087 (0.0122)	-0.0082 (0.0122)	-0.0082 (0.0122)	-0.0084 (0.0122)
Brent Yield (t-1)	0.0110 (0.0117)	0.0109 (0.0119)	0.0116 (0.0088)	0.0108 (0.0139)	0.0111 (0.0118)	0.0117 (0.0118)	0.0114 (0.0118)	0.0114 (0.0119)	0.0108 (0.0118)	0.0115 (0.0119)
USD/RUB Yield (t-1)	0.0018 (0.0065)	0.0013 (0.0066)	0.0016 (0.0066)	0.0016 (0.0065)	0.0015 (0.0066)	0.0020 (0.0066)	0.0015 (0.0066)	0.0013 (0.0066)	0.0016 (0.0041)	0.0015 (0.0066)
Patents: total volume digital stream		-0.0096 (0.0075)								
Patents: computing equipment			0.0043 (0.0073)							
Patents: measurement and sensors				-0.0073* (0.0039)						
Patents: communications and network infrastructure					-0.0146** (0.0074)					
Patents: automation and control						-0.0062 (0.0073)				
Patents: data management and processing							-0.0047 (0.0079)			
Patents: software and AI methods								-0.0121 (0.0075)		

Table 5 (continued)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macrocontrols)	Patents: total Volume of digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: communications and network infrastructure	Patents: automation and control	Patents: management and data processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
Patents: object orientation									-0.0101*	
Patents: process orientation									(0.0052)	
										-0.0047
The omega parameter	0.1583 (0.1563)	0.1307*** (0.0507)	0.1300** (0.0514)	0.1295** (0.0506)	0.1308** (0.0516)	0.1300** (0.0510)	0.1292** (0.0509)	0.1299** (0.0509)	0.1316** (0.0517)	0.1300** (0.0510)
The alpha parameter [1]	0.2218 (0.1769)	0.1941*** (0.0628)	0.1931*** (0.0636)	0.1923*** (0.0626)	0.1941*** (0.0637)	0.1930*** (0.0631)	0.1919*** (0.0631)	0.1923*** (0.0628)	0.1951*** (0.0638)	0.1929*** (0.0631)
The gamma parameter [1]	-0.1307 (0.1112)	-0.1071** (0.0441)	-0.1054** (0.0439)	-0.1077** (0.0441)	-0.1072** (0.0443)	-0.1065** (0.0439)	-0.1065** (0.0438)	-0.1101** (0.0447)	-0.1077** (0.0445)	-0.1065** (0.0440)
The beta parameter [1]	0.9880*** (0.0043)	0.9877*** (0.0043)	0.9879*** (0.0043)	0.9877*** (0.0043)	0.9878*** (0.0042)	0.9877*** (0.0043)	0.9878*** (0.0043)	0.9876*** (0.0043)	0.9875*** (0.0044)	0.9877*** (0.0043)
The nu parameter	2.0500*** (0.0721)	2.0726*** (0.0317)	2.0725*** (0.0323)	2.0733*** (0.0321)	2.0722*** (0.0327)	2.0727*** (0.0318)	2.0730*** (0.0322)	2.0725*** (0.0320)	2.0726*** (0.0323)	2.0726*** (0.0320)
Observations	4085	4077	4077	4077	4077	4077	4077	4077	4077	4077
AIC	9890.91	9889.26	9890.32	9889.85	9887.49	9889.93	9890.34	9888.50	9889.19	9890.28
BIC	9947.74	9952.39	9953.45	9952.98	9950.62	9953.06	9953.47	9951.64	9952.32	9953.41
Logarithm of likelihood	-4936.45	-4934.63	-4935.16	-4934.93	-4933.75	-4934.97	-4935.17	-4934.25	-4934.59	-4935.14

Source: Calculations by the authors.

Note: *, **, *** – $p < 0.10$, $p < 0.05$ и $p < 0.01$ / $p < 0.10$, $p < 0.05$ and $p < 0.01$.

Table 6

Full Regression Table: MOEX Energy Sector Index

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro- controls)	Patents: total vol- ume digital stream	Patents: computing equipment	Patents: measure- ment and sensors	Patents: com- munications and network infrastructure	Patents: automa- tion and control	Patents: .data man- agement and processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
The constant	0.0232*** (0.0080)	0.0231*** (0.0051)	0.0233*** (0.0057)	0.0242* (0.0138)	0.0232*** (0.0050)	0.0232*** (0.0053)	0.0257*** (0.0065)	0.0238*** (0.0069)	0.0234*** (0.0051)	0.0252*** (0.0063)
AR(1)	-0.0011 (0.0312)	-0.0013* (0.0007)	-0.0015** (0.0007)	-0.0024 (0.0037)	-0.0014** (0.0007)	-0.0014** (0.0007)	-0.0024 (0.0127)	-0.0017 (0.0122)	-0.0019*** (0.0007)	-0.0022 (0.0091)
Brent Yield (t-1)	-0.0007 (0.0106)	-0.0010 (0.0073)	-0.0010 (0.0094)	-0.0005 (0.0172)	-0.0010 (0.0072)	-0.0010 (0.0077)	-0.0003 (0.0088)	-0.0008 (0.0106)	-0.0010 (0.0074)	-0.0003 (0.0085)
USD/RUB Yield (t-1)	0.0001 (0.0066)	0.0003 (0.0013)	0.0003 (0.0015)	-0.0002 (0.0136)	0.0003 (0.0012)	0.0003 (0.0013)	-0.0003 (0.0063)	0.0001 (0.0062)	0.0003 (0.0013)	0.0001 (0.0050)
Patents: total volume digital stream		0.0015 (0.0040)								
Patents: computing equipment			-0.0010 (0.0040)							
Patents: measurement and sensors				-0.0130 (0.0166)						
Patents: communications and network infrastructure					0.0004 (0.0055)					
Patents: automation and control						-0.0002 (0.0045)				
Patents: management and processing data							-0.0161*** (0.0054)			

Table 6 (continued)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro-controls)	Patents: total volume digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: communications and network infrastructure	Patents: automation and control	Patents: data management and processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
Patents: software and AI methods								-0.0077		
								(0.0066)		
Patents: object orientation									-0.0050	
									(0.0039)	
Patents: process orientation										-0.0152***
										(0.0057)
The omega parameter	0.2389 (4.4634)	0.2045 (0.2580)	0.2044 (0.2575)	0.2015 (0.2372)	0.2045 (0.2547)	0.2042 (0.2545)	0.2100 (0.3062)	0.2030 (0.2437)	0.2049 (0.2545)	0.2064 (0.2600)
The alpha parameter [1]	0.3102 (4.6876)	0.2734 (0.2850)	0.2733 (0.2843)	0.2696 (0.2622)	0.2733 (0.2814)	0.2730 (0.2812)	0.2786 (0.3343)	0.2714 (0.2694)	0.2738 (0.2809)	0.2750 (0.2858)
The gamma parameter [1]	-0.0563 (1.2736)	-0.0426 (0.0942)	-0.0429 (0.0945)	-0.0445 (0.0912)	-0.0428 (0.0937)	-0.0428 (0.0936)	-0.0528 (0.1200)	-0.0438 (0.0913)	-0.0437 (0.0945)	-0.0499 (0.1019)
The beta parameter [1]	0.9734** (0.4177)	0.9794*** (0.0279)	0.9794*** (0.0279)	0.9798*** (0.0257)	0.9794*** (0.0277)	0.9794*** (0.0276)	0.9782*** (0.0345)	0.9795*** (0.0264)	0.9793*** (0.0278)	0.9789*** (0.0287)
The nu parameter	2.0500*** (0.7327)	2.0500*** (0.0414)	2.0500*** (0.0414)	2.0500*** (0.0395)	2.0500*** (0.0407)	2.0500*** (0.0408)	2.0500*** (0.0449)	2.0500*** (0.0398)	2.0500*** (0.0403)	2.0500*** (0.0406)
Observations	4085	4077	4077	4077	4077	4077	4077	4077	4077	4077
AIC	10044.79	10034.21	10034.24	10031.72	10034.27	10034.24	10029.98	10033.21	10033.92	10030.70
BIC	10101.63	10097.35	10097.37	10094.85	10097.40	10097.37	10093.11	10096.34	10097.05	10093.83
Logarithm of likelihood	-5013.39	-5007.11	-5007.12	-5005.86	-5007.14	-5007.12	-5004.99	-5006.60	-5006.96	-5005.35

Source: Calculations by the authors.

Note: *, **, *** – $p < 0.10$, $p < 0.05$ и $p < 0.01$ / $p < 0.10$, $p < 0.05$ and $p < 0.01$.

Table 7

Full Regression Table: MOEX Financial Sector Index

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro- controls)	Patents: total volume digital stream	Patents: computing equipment	Patents: measure- ment and sensors	Patents: com- munications and network infrastructure	Patents: automation and control	Patents: data management and processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
The constant	0.0335*** (0.0084)	0.0338*** (0.0085)	0.0329*** (0.0085)	0.0333*** (0.0085)	0.0335*** (0.0085)	0.0336*** (0.0085)	0.0335*** (0.0050)	0.0342*** (0.0065)	0.0337*** (0.0085)	0.0333*** (0.0085)
AR(1)	-0.0075 (0.0109)	-0.0084 (0.0110)	-0.0083 (0.0110)	-0.0083 (0.0110)	-0.0085 (0.0110)	-0.0080 (0.0110)	-0.0087 (0.0109)	-0.0079 (0.0073)	-0.0084 (0.0110)	-0.0083 (0.0082)
Brent Yield (t-1)	0.0028 (0.0122)	0.0027 (0.0123)	0.0030 (0.0122)	0.0027 (0.0123)	0.0026 (0.0123)	0.0034 (0.0122)	0.0035 (0.0121)	0.0031 (0.0092)	0.0028 (0.0123)	0.0033 (0.0120)
USD/RUB Yield (t-1)	-0.0009 (0.0079)	-0.0010 (0.0079)	-0.0008 (0.0079)	-0.0013 (0.0079)	-0.0011 (0.0079)	-0.0004 (0.0079)	-0.0009 (0.0077)	-0.0015 (0.0059)	-0.0010 (0.0079)	-0.0010 (0.0080)
Patents: total volume digital stream		-0.0120 (0.0089)								
Patents: computing equipment			-0.0000 (0.0087)							
Patents: measurement and sensors				-0.0108 (0.0089)						
Patents: communications and network infrastructure					-0.0120 (0.0086)					
Patents: automation and control						-0.0087 (0.0085)				

Table 7 (continued)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro-controls)	Patents: total volume digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: communications and network infrastructure	Patents: automation and control	Patents: management and processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
Patents: data.data management and processing processing							-0.0141***			
							(0.0033)			
Patents: software and AI methods								-0.0154***		
								(0.0032)		
Patents: object orientation									-0.0116	
									(0.0092)	
Patents: process orientation										-0.0076
										(0.0095)
The omega parameter	0.1430 (0.1361)	0.1406 (0.1132)	0.1412 (0.1124)	0.1411 (0.1141)	0.1406 (0.1084)	0.1424 (0.1154)	0.1379 (0.1113)	0.1408 (0.1150)	0.1422 (0.1117)	0.1405 (0.1136)
Parameter alpha[1]	0.1972 (0.1552)	0.1935 (0.1299)	0.1950 (0.1294)	0.1945 (0.1312)	0.1937 (0.1248)	0.1963 (0.1325)	0.1902 (0.1282)	0.1935 (0.1315)	0.1957 (0.1282)	0.1938 (0.1306)
Parameter gamma[1]	-0.0897 (0.0789)	-0.0922 (0.0703)	-0.0883 (0.0678)	-0.0895 (0.0692)	-0.0921 (0.0677)	-0.0898 (0.0699)	-0.0915 (0.0695)	-0.0947 (0.0725)	-0.0919 (0.0692)	-0.0903 (0.0698)
The beta parameter[1]	0.9897*** (0.0065)	0.9898*** (0.0062)	0.9899*** (0.0063)	0.9898*** (0.0064)	0.9898*** (0.0062)	0.9897*** (0.0064)	0.9901*** (0.0060)	0.9897*** (0.0063)	0.9896*** (0.0064)	0.9899*** (0.0062)
The nu parameter	2.0500*** (0.0623)	2.0500*** (0.0520)	2.0500*** (0.0506)	2.0500*** (0.0514)	2.0500*** (0.0490)	2.0500*** (0.0521)	2.0500*** (0.0519)	2.0500*** (0.0533)	2.0500*** (0.0503)	2.0500*** (0.0522)
Observations	4085	4077	4077	4077	4077	4077	4077	4077	4077	4077
AIC	11 407.00	11 389.47	11 390.88	11 389.85	11 389.26	11 390.06	11 388.91	11 388.36	11 389.56	11 390.29
BIC	11 463.83	11 452.60	11 454.01	11 452.98	11 452.39	11 453.19	11 452.04	11 451.49	11 452.69	11 453.42
Logarithm of likelihood	-5694.50	-5684.74	-5685.44	-5684.92	-5684.63	-5685.03	-5684.46	-5684.18	-5684.78	-5685.14

Source: Calculations by the authors.

Note: *, **, *** – p < 0.10, p < 0.05 и p < 0.01 / p < 0.10, p < 0.05 and p < 0.01.

Table 8

Full Regression Table: MOEX Chemical Sector Index

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro- controls)	Patents: total volume digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: com- munications and network infrastructure	Patents: automation and control	Patents: .data man- agement and processing processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
The constant	0.0153*** (0.0058)	0.0151*** (0.0052)	0.0166*** (0.0040)	0.0155** (0.0061)	0.0150** (0.0061)	0.0155** (0.0061)	0.0157*** (0.0061)	0.0157 (0.0117)	0.0154*** (0.0057)	0.0157*** (0.0043)
AR(1)	-0.0135 (0.0095)	-0.0141** (0.0056)	-0.0139 (0.0085)	-0.0139 (0.0104)	-0.0142 (0.0104)	-0.0139 (0.0105)	-0.0138 (0.0104)	-0.0137 (0.0105)	-0.0137 (0.0095)	-0.0138 (0.0104)
Brent Yield (t-1)	-0.0008 (0.0061)	-0.0006 (0.0060)	-0.0009 (0.0057)	-0.0008 (0.0093)	-0.0006 (0.0093)	-0.0007 (0.0093)	-0.0006 (0.0094)	-0.0009 (0.0077)	-0.0006 (0.0086)	-0.0006 (0.0094)
USD/RUB Yield (t-1)	0.0047 (0.0053)	0.0047 (0.0051)	0.0052*** (0.0008)	0.0049 (0.0053)	0.0047 (0.0053)	0.0050 (0.0053)	0.0055 (0.0053)	0.0049 (0.0058)	0.0048 (0.0053)	0.0052*** (0.0011)
Patents: total volume digital stream		0.0030 (0.0052)								
Patents: computing equipment			-0.0090** (0.0039)							
Patents: measurement and sensors				-0.0050 (0.0068)						
Patents: communications and network infrastructure					0.0099* (0.0060)					
Patents: automation and control						-0.0027 (0.0060)				
Patents:.data management and processing processing							-0.0130** (0.0064)			

Table 8 (continued)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Specification	Basic model (only macro- controls)	Patents: total volume digital stream	Patents: computing equipment	Patents: measurement and sensors	Patents: com- munications and network infrastructure	Patents: automation and control	Patents: .data man- agement and processing processing	Patents: software and AI methods	Patents: object orientation	Patents: process orientation
Patents: software and AI methods								-0.0034		
Patents: object orientation								(0.0105)	0.0008	
Patents: process orientation									(0.0064)	-0.0068*
										(0.0038)
The omega parameter	0.1814 (0.4193)	0.1783 (0.2750)	0.1772 (0.2782)	0.1775 (0.2766)	0.1795 (0.2712)	0.1785 (0.2696)	0.1737 (0.2577)	0.1789 (0.2773)	0.1782 (0.2813)	0.1776 (0.2656)
Parameter alpha[1]	0.2400 (0.4322)	0.2370 (0.2893)	0.2362 (0.2947)	0.2360 (0.2915)	0.2386 (0.2856)	0.2371 (0.2838)	0.2316 (0.2742)	0.2377 (0.2916)	0.2367 (0.2957)	0.2361 (0.2802)
Parameter gamma[1]	0.0702 (0.1141)	0.0701 (0.0744)	0.0684 (0.0728)	0.0704 (0.0746)	0.0687 (0.0711)	0.0702 (0.0730)	0.0717 (0.0709)	0.0698 (0.0745)	0.0703 (0.0760)	0.0707 (0.0723)
The beta parameter[1]	0.9780*** (0.0258)	0.9787*** (0.0248)	0.9791*** (0.0254)	0.9788*** (0.0251)	0.9786*** (0.0253)	0.9787*** (0.0249)	0.9795*** (0.0246)	0.9786*** (0.0252)	0.9787*** (0.0252)	0.9788*** (0.0248)
The nu parameter	2.0500*** (0.1481)	2.0500*** (0.0834)	2.0500*** (0.0825)	2.0500*** (0.0830)	2.0500*** (0.0801)	2.0500*** (0.0809)	2.0500*** (0.0748)	2.0500*** (0.0835)	2.0500*** (0.0853)	2.0500*** (0.0784)
Observations	4085	4077	4077	4077	4077	4077	4077	4077	4077	4077
AIC	9240.45	9233.41	9231.99	9233.23	9231.77	9233.43	9230.79	9233.35	9233.56	9232.73
BIC	9297.29	9296.54	9295.12	9296.37	9294.90	9296.56	9293.92	9296.48	9296.70	9295.86
Logarithm of likelihood	-4611.22	-4606.71	-4606.00	-4606.62	-4605.89	-4606.72	-4605.39	-4606.67	-4606.78	-4606.37

Source: Calculations by the authors.

Note: *, **, *** – $p < 0.10$, $p < 0.05$ и $p < 0.01$ / $p < 0.10$, $p < 0.05$ and $p < 0.01$.

Table 9

**Residual Diagnostics for Specifications 2–10:
p-value Ranges Across the Nine Patent Specifications Per Index**

Index	Ljung–Box, residuals	Ljung–Box, squared residuals	ARCH-LM	Jarque–Bera
MOEX	0.0005–0.0006	0.036–0.046	0.041–0.050	< 0.001
Energy	0.0001–0.0002	0.0015–0.0028	0.0018–0.0034	< 0.001
Finance	0.0013–0.0017	0.029–0.034	0.040–0.047	< 0.001
Chemicals	0.506–0.526	≥ 0.999	≥ 0.999	< 0.001

Source: Calculations by the authors.

Note: p-value ranges across specifications 2–10; all 36 specifications converge.

lags and smoothed patent factors, 4,077 calendar observations are used. The averages and medians of daily returns are close to zero; the negative lows are modulo higher than the highs, indicating left-sided asymmetry and heavy lower tails.

THE MAIN RESULTS OF THE EMPIRICAL STUDY

Tables 5–8 show the complete evaluation results: patent coefficients, control variables, and EGARCH parameters defined by equations (2) – (4), with robust standard errors. The estimates for the overall MOEX index are presented in Table 5.

For MOEX, significant negative coefficients were obtained for measurement and sensors ($\beta = -0.0073$; $p < 0.10$), communications and network infrastructure ($\beta = -0.0146$; $p < 0.05$) and object orientation in general ($\beta = -0.0101$; $p < 0.10$). All three estimates relate to the object block, and the consistency of their signs supports the interpretation of object patents as an indicator of capital expenditures with deferred returns. In the short term, the market responds to such patents with caution.

The energy sector demonstrates a different sensitivity: digital patents here mainly describe production flows, telemetry, and technological infrastructure (see Table 6).

In the energy sector, significant effects are concentrated in the process unit: the coefficients

of control and data processing ($\beta = -0.0161$) and process orientation ($\beta = -0.0152$) are significant at the level of 1%. The remaining patent indicators are statistically insignificant, which is consistent with the process nature of digital patents of energy companies.

In the financial sector, digitalization has traditionally relied on software products, algorithms, and information processing tools rather than on physical infrastructure. Therefore, a significant signal is expected to shift from the financial index to these patent categories (see Table 7).

In finance, the strongest effects are concentrated in the process unit: the coefficients of data management and processing processing ($\beta = -0.0141$), software and AI methods ($\beta = -0.0154$) are significant at the level of 1%. The estimates of the remaining patent indicators are negative, but statistically insignificant, which emphasizes the concentration of the effect in the software and algorithmic categories.

The assessment results for the chemical sector, presented in Table 8, have a number of special features and deserve a separate discussion.

In the chemical sector, significant coefficients are present in both blocks: computing equipment ($\beta = -0.0090$; $p < 0.05$), communications and network infrastructure

($\beta = 0.0099$; $p < 0.10$), data management and processing ($\beta = -0.0130$; $p < 0.05$) and process orientation ($\beta = -0.0068$; $p < 0.10$). A positive sign on the network infrastructure distinguishes the chemical industry from other indexes and is consistent with the role of network solutions in reducing the coordination costs of capital-intensive production. The negative ratings of the process unit repeat the pattern identified for energy and finance.

The overall picture of the estimates is inconsistent with the random nature of individual values. In the absence of effects from 36 patent coefficients in four indexes at the level of 10%, three to four would be expected to be significant, whereas 11 are actually significant, and 10 of them are negative, and 30 out of 36 ratings have a negative sign. The strongest effects, significant at the 1% level, are concentrated in the energy and finance process block; significant estimates for the overall MOEX index and the chemical sector complement this picture at the industry level.

The results of residue diagnostics are shown in Table 9. For the chemical index, the Ljung–Box and ARCH-LM tests do not reveal residual dependence; for MOEX, energy and finance, dependence remains, and the Jarque–Bera test rejects normality in all specifications. Therefore, all models use conditional t -distribution and robust Boyle–Sleva–Wooldridge standard errors.

CONCLUSIONS

The study hypothesized that the registration of patents related to digital transformation affects the market value of companies, but this growth manifests itself after a certain period of time. The hypothesis was partially confirmed for certain categories of digital transformation.

It has been revealed that different sectors of the economy respond to digitalization differently. For example, in the financial sector, which traditionally relies on software products and algorithms for digitalization, there is a more significant impact on process transformation. However, in capital-intensive industries such as chemicals and energy, significant effects can be seen in both the product and process parts of digitalization.

The theoretical contribution of this study is the adaptation of the division of digital transformation into product and process blocks for patent financial indicators. The practical contribution is the development of a reproducible tool for monitoring technological changes and industry market reactions.

The results obtained can be used as a basis for further research into the synchronization of innovation and financial cycles, as well as the development of asset management strategies in the context of digital transformation.

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REFERENCES

1. Tregub I.V., Funtova D.V., Eterskova Ya.S. Economy of the Russian Federation for 2024–2025 and factors of its growth. *Ekonomika. Nalogi. Pravo = Economics, Taxes & Law*. 2024;17(1):44–55. (In Russ.). DOI: 10.26794/1999-849X-2024-17-1-44-55
2. Gospodarchuk G.G., Zeleneva E.S. Consolidation of monetary policy objectives with the goals of financial and economic development. *Zhurnal Sibirskogo federal'nogo universiteta. Seriya: Gumanitarnye nauki = Journal of Siberian Federal University. Humanities and Social Sciences*. 2025;18(6):1091–1103.
3. Abramova M.A., Dubova S.E., Didenko V.Yu., et al. On the main directions of the unified state monetary policy for 2024 and the period 2025 and 2026: Opinion of experts of the Financial University. *Ekonomika. Nalogi. Pravo = Economics, Taxes & Law*. 2024;17(1):6–22. (In Russ.). DOI: 10.26794/1999-849X-2024-17-1-6-22

4. Kireeva E.F., Karaev A.K. Government regulation on economic growth and innovation: The effect of public investment in defence R&D. *Upravlenets = The Manager*. 2025;16(4): 2–18. (In Russ.). DOI: 10.29141/2218-5003-2025-16-4-1
5. Sakharov D.M. Development of the Russian financial market in the context of the structural transformation of the global financial system. *Finance: Theory and Practice*. 2025;29(4):49–70. DOI: 10.26794/2587-5671-2025-29-4-49-70
6. Glebova A.G., Kovaleva A.A. Forecasting the volatility of the Russian stock market in the context of international economic sanctions. *Finance: Theory and Practice*. 2024;28(1):20–29. DOI: 10.26794/2587-5671-2024-28-1-20-29
7. Salnikov M.Yu., Lyskov N.B., Aleksandrova A.V. Methodology for constructing an innovative patent index in the paradigm of state intellectual sovereignty. *Vestnik FIPS = Bulletin of Federal Institute of Industrial Property*. 2026;5(1):40–51. (In Russ.).
8. Brynjolfsson E., Rock D., Syverson C. The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*. 2021;13(1):333–372. DOI: 10.1257/mac.20180386
9. Kudryavtseva T.Yu., Kozhina K.S. Basic concepts of digitalization. *Vestnik Akademii znanii = Bulletin of the Academy of Knowledge*. 2021;(44):149–151. (In Russ.). DOI: 10.24412/2304-6139-2022-11228
10. Nambisan S., Lyytinen K., Majchrzak A., Song M. Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*. 2017;41(1):223–238. DOI: 10.25300/MISQ/2017/41:1.03
11. Solow R.M. Technical change and the aggregate production function. *The Review of Economics and Statistics*. 1957;39(3):312–320. DOI: 10.2307/1926047
12. Romer P.M. Endogenous technological change. *Journal of Political Economy*. 1990;98(5–2): S71–S102. DOI: 10.1086/261725
13. Bresnahan T.F., Trajtenberg M. General purpose technologies: ‘engines of growth’? *Journal of Econometrics*. 1995;65(1):83–108. DOI: 10.1016/0304-4076(94)01598-t
14. Griliches Z. Patent statistics as economic indicators: A survey. *Journal of Economic Literature*. 1990;28(4):1661–1707.
15. Kogan L., Papanikolaou D., Seru A., Stoffman N. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*. 2017;132(2):665–712. DOI: 10.1093/qje/qjw040
16. Hall B.H., Jaffe A.B., Trajtenberg M. Market value and patent citations. *RAND Journal of Economics*. 2005;36(1):16–38. URL: <https://eml.berkeley.edu/~bhhall/papers/HallJaffeTrajtenberg03.pdf>
17. Gentzkow M., Kelly B., Taddy M. Text as data. *Journal of Economic Literature*. 2019;57(3):535–574. DOI: 10.1257/jel.20181020
18. Antweiler W., Frank M.Z. Is all that talk just noise? The information content of Internet stock message boards. *The Journal of Finance*. 2004;59(3):1259–1294. DOI:10.1111/j.1540-6261.2004.00662.x
19. Baker S.R., Bloom N., Davis S.J. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*. 2016;131(4):1593–1636. DOI: 10.1093/qje/qjw024
20. Kelly B., Papanikolaou D., Seru A., Taddy M. Measuring technological innovation over the long run. *American Economic Review: Insights*. 2021;3(3):303–320. DOI: 10.1257/aeri.20190499
21. Goldfarb A., Tucker C. Digital economics. *Journal of Economic Literature*. 2019;57(1):3–43. DOI: 10.1257/jel.20171452

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