

*Vladimir Vladimirovich Kolmakov**
*Aleksandra Grigorievna Polyakova***
*Vasily Sergeevich Shalaev****

AN ANALYSIS OF THE IMPACT OF VENTURE CAPITAL INVESTMENT ON ECONOMIC GROWTH AND INNOVATION: EVIDENCE FROM THE USA AND RUSSIA

.....

ABSTRACT: *We hear a lot of political declarations stating the importance of developing an innovation economy by fostering venture capital inflows. But it is obvious that the venture capital market makes an extremely low contribution in terms of total R&D spending or gross investment. Thus, theory says venture capital investment (VCI) is important due to its huge impact on modernization, but practitioners note that there is no evidence and VCI constitutes about 1% of total investments. Formal logic foregrounds the thesis that the effect of venture investment is important and significant, but delayed.*

We contribute to the theory and discussion of the problem of choosing between venture and non-venture funding by determining

a specific niche for venture capital investment. We derive lagged regression models for GDP and patent applications for the US and Russia, to test VCI's impact on economic growth and innovation. Comparison of model estimates shows significant VCI influence on GDP at a 4-6-year lag and no synchronous influence, valid for both the US and Russia. We prove the main hypothesis of our research: the effect of venture investment on economic and innovation development parameters is significant and much greater than that of 'conventional' investment.

KEY WORDS: *venture capital investment, economic growth, innovation, comparative studies, R&D spending*

JEL CLASSIFICATION: O43, O31, G24, O33, O57, D83, C53

* Plekhanov Russian University of Economics, Moscow, Russia,
E-mail: vladimirkolmakov@mail.ru

** Plekhanov Russian University of Economics, Moscow, Russia; Tyumen State Oil and Gas University, Russia, E-mail: agpolyakova@mail.ru

*** National Business Institute, Moscow, Russia, E-mail: kolobchadze@gmail.com

1. INTRODUCTION

What is the relation between venture financing and development; e.g., innovation development? It is hard to disagree that “innovations constitute a distinctive attribute of modern economies” (Clancy and Moschini 2013, p. 206), but a multitude of research papers and statistical data demonstrate the insignificant amount of venture investment, especially in relative terms. Nevertheless, this has not resulted in researchers and public officials taking the question off the agenda or relegating it to obscurity. Instead, countries and regions introduce different incentives to support venture-backed businesses, which are integrated into state innovation and investment and industrial development policies, and stimulate the growth and promotion of venture capital market infrastructure. It is notable that declarations about venture investment’s contribution to ‘technological breakthrough’ or ‘instant modernization’ are becoming more frequent. This raises questions as to whether these declarations are plausible, if such a form of investing is really that important, and if the effect of relatively small venture investment is significant.

These reasonable doubts legitimate the following proposal, which can be regarded as the hypothesis of the research: venture investment’s effect on the parameters of economic and innovation development should be (1) significant and notable and (2) much larger than ‘conventional’ investment; e.g., in terms of GDP growth contribution or amount of patent applications. We find it natural that venture investment’s effect is primarily lagged or delayed, which is why we attempt to identify the time horizon in which capital invested in high-risk innovation projects contributes to the forming of post-industrial society by facilitating a gradual shift to new technological modes.

In the mid-term, one should expect the next growth in the demand for capital to be from hi-tech companies, fostered by the dissolution and dissipation of the impact of progressive development and searching for alternative drivers of growth that are based on innovation and advanced technologies and place an emphasis on innovative products.

Thus it is appropriate to carry out an empirical survey of the interrelation between venture financing dynamics and innovation growth, and the parameters of economic development. If we presume the existence of a cause–effect relationship between these indicators, it is necessary to search for the most statistically significant and reliable time lag of the economic development indicators that

constitute the 'effect'. This research models the relationship with different lags in order to find the most appropriate one.

2. THEORETICAL BACKGROUND

Prior to revisiting previous research, we will outline the object and scope of this paper. There is much evidence of methodological pluralism in approaches to determining 'venture investment' and 'venture capital', which originates in the distinction between the functions and roles of different institutional investors and private equity owners.

One of the significant results of the continuous discussion on the specifics and pattern of venture capital participation in financing entrepreneurship can be postulated as follows: there is a distinct and clear criterion that distinguishes venture capital investment from project financing by banks or other private equity holders. Without debating the nature of lending and investing, it is possible to state that a lending bank acts as a passive investor, which is accurate in terms of Balance of Payment statistics methodology. A venture fund involved in project financing provides not only capital inflow but also the additional contribution of increasing project value. According to Brander and de Bettignies (2009, p.3) it can be treated as a "value-added service(s)", the nature of which, as we see it, is analogous to the practice of engineering services, e.g., turnkey or involved engineering.

It is obvious from the experience of venture project implementation that the investor's role includes both funding and taking part in the management of the newly organized enterprise by providing an appropriate level of expertise, consulting, and maintenance, and balancing the risks of all the parties involved (stakeholders). In this case an investor's objective is to guide the project through the process of implementation on the critically optimal development path.

We agree with Brander and de Bettignies (2009) that venture financing is most appropriate when the marginal cost of the investor's effort is high: theoretically, the increase of investor involvement in the administration of a project results in exponential growth of its value and linear growth of the probable positive outcome. This conclusion also has a reverse impact: the more the investor tends to evade the administration process, the greater the chance of the project having a negative outcome. Moreover, in terms of the risk–return combination, it is plausible that an investor's participation in project administration can increase

an initially low probability of high return on investment and maximize a project's termination value in case of its unsuccessful development, which is initially expected to be low.

Given the 'engineering-like' nature of venture financing we find the problem of the choice between venture and non-venture financing, raised in several papers, to be rather obsolete. In most cases entrepreneurs have no alternative when choosing the source of funding. For instance, Da Rin et al (2011) pose and explore the question in detail and come to the conclusion, derived from a broad variety of sources, that there is a little practical evidence of choice between venture capital and bank financing. We agree that to some extent borrowing from a bank and finding investors are mutually exclusive, due to the particular characteristics of the project to be funded. A bank cannot provide a standard loan to finance a project in its early phase, when ideas are vague, the vision is limited, and the money is to be spent on business planning, pre-marketing, research, and investor relations. This particular phase is not intended to generate cash inflows but to develop a saleable business idea and offer it to potential investors. Such a project is inexpedient for bank financing. The same limitations apply to seed and further stages of risky innovation projects.

Conversely, implementation of a 'standard' business project is possible with venture capital funding, but is going to be irrational because of the relatively greater cost of venture investors' equity and the objectively high level of their intervention in management and decision-making. There is an illustrative quotation from Evgueny Chichvarkine (2011), one of the most successful Russian start-up entrepreneurs and the founder of retailer Euroset: "Try not to borrow from private equity holders but go to a bank. If you can do without a partner – do without a partner. A business partner is needed to contribute the things you cannot, otherwise there is no need for a partner". The quotation clearly states that venture financing has a unique niche that does not interfere with other segments of the capital-providing market. So we conclude that the problem of choice is highly exaggerated because in fact there is no alternative: the decision of funding sources is taken not on the basis of standardized criteria but on the basis of a project's characteristics only, which are very specific. Still, one can easily imagine and even recall cases where investment has been requested from a venture fund after a loan has been refused.

The analysis of different financing sources points to the conclusion that venture investing should be treated as a specific type of activity in capital markets, efficiently filling the niche that 'conventional' capital market participants

(investors, contributors, lenders) try to avoid. This niche entails projects that can be described as follows:

- (i) unusually high risk;
- (ii) not subject to standardization and aggregation into a uniform portfolio for further refinancing;
- (iii) it is usually not possible to meet requirements from the provision of own funds;
- (iv) market and project information are asymmetrical;
- (v) project phases tend to be indeterminate and have a low capacity for formalization;
- (vi) there is a need for detailed studies by experts both at the preliminary stages (prior to investment) and during project implementation (expertise);
- (vii) a total lack of analogies makes forecasting project outcomes unreliable;
- (viii) financing of a tranche is dependent on the results and achievements of the previous tranche;
- (ix) the capital cost is higher due to less liquidity;
- (x) due to the multitude of real options in the project, the capacity of traditional financial modelling and planning instruments is limited.

In other words, if a business project does not match most of these conditions, it can and should be financed by a loan. Otherwise, private investment is the only option and opportunity.

The phenomenon of investment in different notations and paradigms – direct and portfolio, private and public, domestic and foreign, national and overseas, risky and risk-free, etc. – has been sufficiently explored in economic and finance literature. There are many studies and surveys on the theory of investing, feasibility and efficiency assessment, investment capacity limits, productivity breakpoint, marginal efficiency, and measurement and evaluation of the impact on economic growth and innovation. We assume that the regularities and interrelations of ‘broader investments’ apply to venture investments, which, due to their relatively low development level and absolute values close to statistical error, require additional study to prove or refute such a conclusion.

Considering the fact that venture capital investment is a rather insignificant part of total investments, it would be incorrect to say that social and economic development has no reliable and robust interrelation with the dynamics of venture capital market development. Da Rin, Hellmann, & Puri note that “the global VC industry is a relatively young industry that is still undergoing major

growing pains and significant structural changes” (Da Rin et al 2011, p. 100). This certainly means that analytical procedures need to be more sophisticated in terms of deriving conclusions that are sustainable over time. This reasoning lies behind the controversy surrounding the assessment of venture capital investment dynamics and their contribution to economic growth and innovation development. Puri and Zarutskie (2012), for instance, analysed 25-year data on newly organized enterprises in the USA and found that only 0.11% of all the companies founded in a particular period were venture-based, and their conclusion is proved in other data subsets. Some studies show more significant values of this indicator (up to 1% of all start-ups), but it still does not drastically change the conclusion that the share of venture capital recipients is insufficient. Other indicators of venture capital recipients’ relative quantity provide much larger estimates; e.g., the number of job offers (5.3% to 7.3% according to Puri and Zarutskie (2012), share in total amount of fixed capital investments (up to 2% according to Berger and Udell (1998)¹, or in the number of Initial Public Offerings (IPOs) held (up to 35% according to Ritter (2011)².

On the level of theoretical assumptions, we tend to treat venture investments as the ‘cause’ rather than the ‘effect’ of the development process. Due to its delayed effect, venture investment introduces the possibility of progressive growth in the short- and long-term by creating the basis of competitiveness and shaping the innovation-based economy.

3. METHODS AND TECHNIQUES

Considering the lack of reliable and official statistical data on venture capital investment in the Russian Federation as well as the relatively short history of both the Russian capital market and the relevant data collection, it is difficult to form statistically reliable analytical constructions. Given these constraints, we employ the method of analogy, by taking US market data on venture capital as the basis for further comparison, as the most developed market with the longest history and experience.

The survey uses correlation and regression analysis techniques. All the estimates were obtained using the multiple regression model and assuming the linear nature of the phenomena in focus. We also presumed and found proof of the

¹ To be exact, 1.89% (Berger and Udell 1998, p. 916)

² Cited in (Da Rin, Hellmann & Puri 2011, p. 21)

hypothesis of data series normality. Regression model coefficients were estimated by least squares function implemented by several alternative algorithms: Gauss-Newton, quasi-Newtonian, and Levenberg-Marquardt.

Regression model results were verified both in levels and in stationary representation. We used data in levels to build-up the 'Executive' model, which has greater explanatory power in terms of practical decision-making implementation because it deals with data in its 'natural' measures and scales. 'Executive' model results were then spurious-tested by applying the same modelling algorithm to the data in stationary representation (the 'Authentic' model). Matching statistically significant lags in 'Executive' and 'Authentic' models, we found the lags that prove the hypothesis of existing VCI to GDP delayed causality.

The next step dealt with appropriate lag estimates that were used for polynomial distributed lag (PDL) model specification. The model allowed for cumulative long-term impact estimates and verification of the paper's hypothesis. We ran several PDL algorithms to find the matching patterns and get more reliable proof of the hypothesis, using the data in levels and stationary representation as well as quarterly and annual data.

We used linear models (as opposed to non-linear) due to the immanently linear nature of the function and arguments. Our preliminary studies show that the dynamics of US GDP, despite its general exponential growth pattern since 1959, have tended to linearization over the past several decades. The same notations are relevant to Russian Federation GDP dynamics. We also find it improbable that GDP will grow exponentially in the near and more distant future, due to worldwide economic growth slowdown and other externalities that decrease the impact of progressive development.

There is also a rational argument in support of linear models, the same we used to postulate the 'Executive' model. It deals with standardization requirements, which are usually not applicable in the case of linear models, which is why the interpretation of results would be more instrumental and the results themselves rather obvious and comparable between the two countries.

4. DATA SOURCES AND MANIPULATIONS

Our research required reliable and prolonged datasets that contained comparable, non-discreet, actual, and verifiable time series. The analytical survey was based on statistical data published by:

- Market Line Country Statistics (gross domestic expenditure on R&D in the US and Russia, amount of patents granted in the US and Russia);
- PricewaterhouseCoopers / National Venture Capital Association (NVCA) ‘Money Tree Report’ from Thomson Reuters (Venture capital investment in the US: totals, deals);
- OECD.Stat (Industrial production in the US);
- US Department of Commerce Bureau of Economic Analysis (GDP in the US);
- Russian Venture Company, Russian Venture Investors Association (Venture capital investment in the US: totals, deals).

The datasets contained cases starting from 1995 (or earlier in the case of US GDP), fixed annually or quarterly where available, and represented by the following indicators:

- venture capital investment (seasonally adjusted), \$ billion;
- current GDP (seasonally adjusted), \$ billion;
- industrial production index;
- stock market index (NASDAQ, Moscow Exchange);
- amount of venture investment deals;
- venture investment average per deal, \$ million.

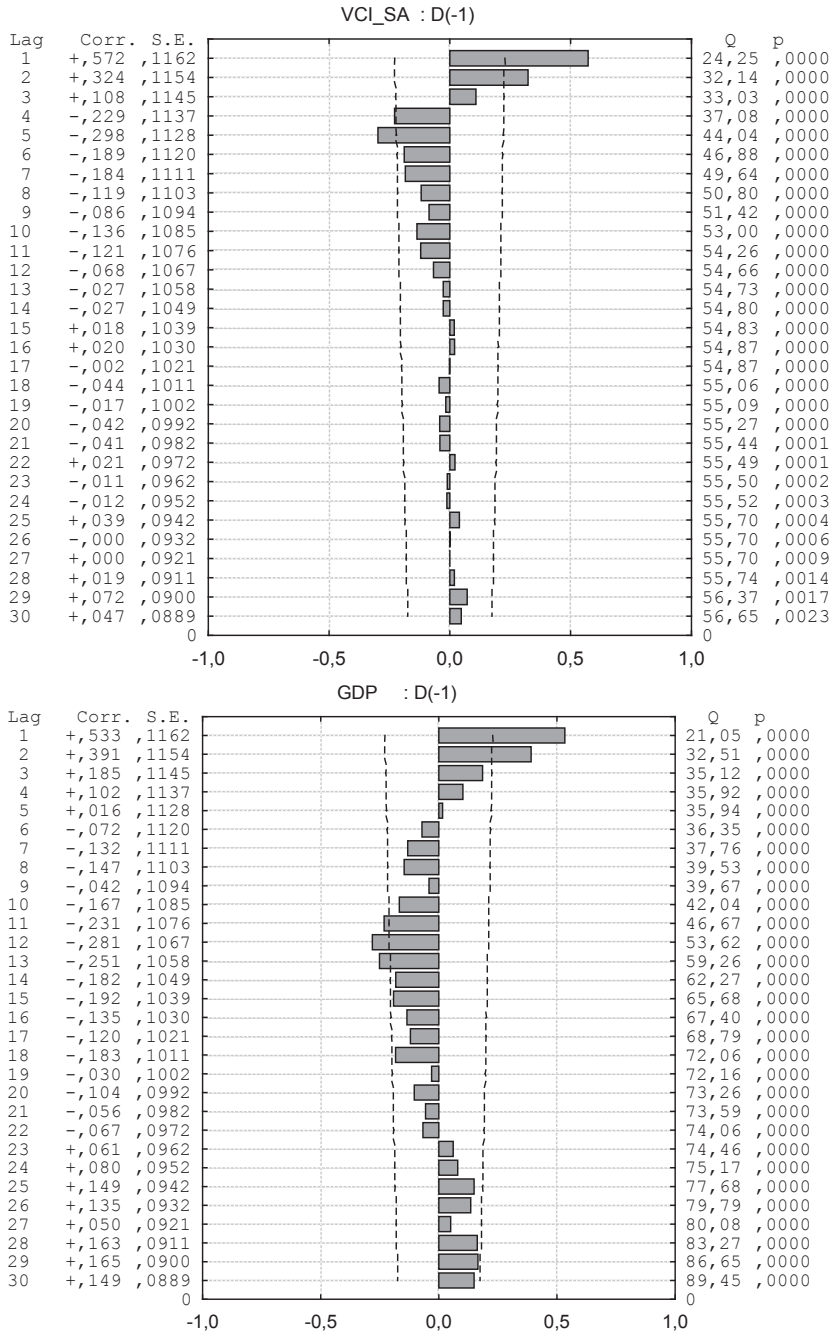
The data were aggregated into time series. The normality problem required several transformations to exclude the influence of the ‘dotcom boom’ (1st quarter of 1999 to 4th quarter of 2001) by censoring the dataset. All the time series were subject to unit root tests.

5. RESULTS AND DISCUSSION

We ran the analysis of US venture capital investment time series in its levels and derived several notable conclusions.

First, there is a strong pattern of 6-month and 18-month cycles in the dynamics of venture capital investment. This is evident in the high values of autocorrelation at

Figure 1. Autocorrelation function graph of quarterly venture capital investments (top chart) and GDP (bottom chart) in USA, 1995-2012



Source: Authors' calculation

lag 5 (quarterly) as well as from alternating and descending fluctuations on even and odd lags respectively (see Fig. 1). The cycles harmonically interfere with 3-year cycles of GDP (high autocorrelation on lag 12 in quarterly representation). There is an obvious link to Kleinknecht's conclusion on Schumpeterian innovation waves that explains the causes of economic expansion (Kleinknecht 1990, p.90).

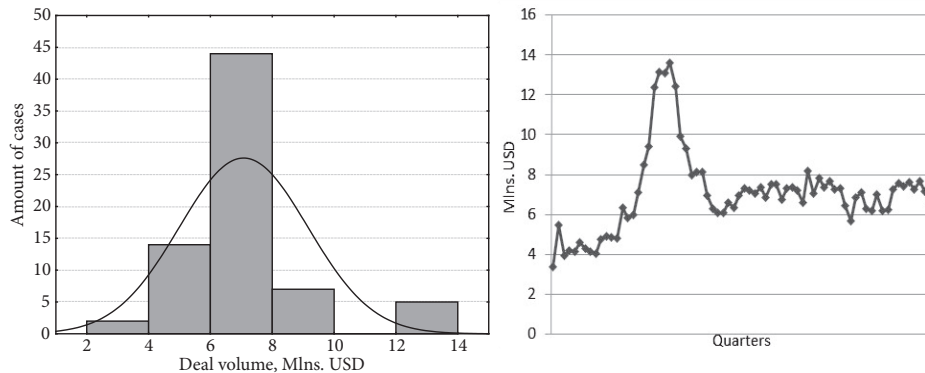
The nature of venture capital investment fluctuations requires additional research in relation to the fluctuations of global economic conditions and particular events and occasions in the national or global economy. As a hypothetical assumption, we note that one of the reasons for the existence of the described waves is the relatively permanent set of investors who exit projects after implementing seed or start-up stages, which usually take about 6 months or a year and a half, respectively.

Second, although the dynamics pattern of GDP and venture capital investment interfere and match sufficiently, we found that in half of the cases in the same time-interval the indicators do not copy each other's direction in terms of ascending or descending vectors but move reciprocally. To be exact: 34 of 72 cases show asymmetric change – growth of one variable meets decline of the other in the same period, or vice versa. The variance of fluctuations is also different. It is notable that negative growth rate of GDP is achieved only in four successive periods of 3-4 quarters of 2008 and 1-2 quarters of 2009, but venture capital investments are highly volatile. Nevertheless, the two parameters in the long-run perspective grow according to a linear trend waving around it according to the found fluctuation cycles.

Average growth rates of the parameters in focus are different if compared to each other relatively: venture capital investment, although extremely volatile, grows 4.1% per annum, which is 3.7 times greater than GDP (1.1% per annum).

The third conclusion derived from VCI dynamics analysis is that the growth of the venture capital market is extensive rather than intensive. We see an increase in investment followed by a growing number of venture capital placement deals. Thus we can determine the empiric upper limit of funds invested in a project of about 6-8 million USD. Theoretically, this can be treated as the venture capital productivity margin. Except for in the dotcom boom, the average volume of deals stayed within 6-8 million dollars and has shown no growing or declining trend since then. We see from the distribution chart in Fig. 2 that venture investments of 12-14 million dollars are outside the normal distribution pattern and can be considered as outliers, as long as 6-8 million USD investments predominate.

Figure 2. Average venture capital investment per deal distribution (left chart) and quarterly dynamics (right chart) in USA, 1998-2011



Source: PricewaterhouseCoopers / NVCA raw data, Authors' calculation

We also studied dependencies between changes in venture capital investment and changes in several other parameters by searching pair correlations. We found strong correlation to GDP, which is described above, but no correlation to the industrial production index (see Table 1).

Table 1. Correlation coefficients matrix ante and post censoring

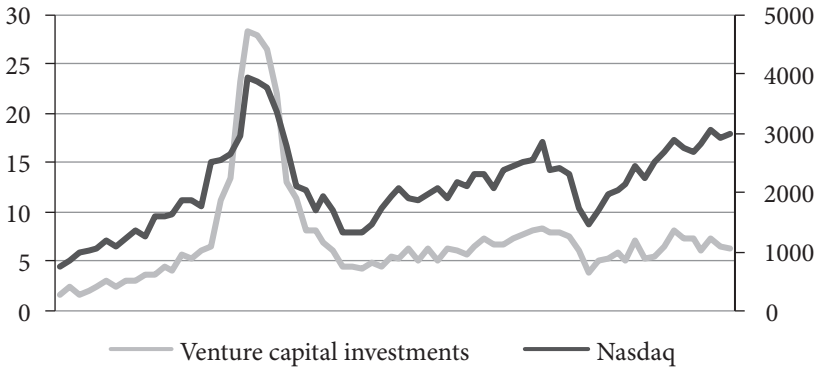
| Parameters | Ante censoring | | | | | | Post censoring | | | | | |
|--------------------------------|----------------|-------|-------|-------|-------|-------|----------------|-------|-------|-------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 |
| 1. Venture capital investment | 1.00 | -0.01 | -0.04 | 0.79 | 0.97 | 0.94 | 1.00 | 0.78 | -0.15 | 0.88 | 0.91 | 0.90 |
| 2. GDP | -0.01 | 1.00 | -0.25 | 0.49 | 0.05 | 0.18 | 0.78 | 1.00 | -0.31 | 0.85 | 0.65 | 0.77 |
| 3. Industrial production index | -0.04 | -0.25 | 1.00 | -0.00 | -0.03 | -0.13 | -0.15 | -0.31 | 1.00 | -0.02 | -0.07 | -0.20 |
| 4. NASDAQ index | 0.79 | 0.49 | -0.00 | 1.00 | 0.82 | 0.83 | 0.88 | 0.85 | -0.02 | 1.00 | 0.81 | 0.79 |
| 5. Number of VCI deals | 0.97 | 0.05 | -0.03 | 0.82 | 1.00 | 0.91 | 0.91 | 0.65 | -0.07 | 0.81 | 1.00 | 0.67 |
| 6. Average VCI per deal | 0.94 | 0.18 | -0.13 | 0.83 | 0.91 | 1.00 | 0.90 | 0.77 | -0.20 | 0.79 | 0.67 | 1.00 |

Source: Authors' calculation

An illustrative finding that has not been yet described in literature is the high correlation between VCI and the stock market index NASDAQ, which is obvious in normalized time series graphs that match synchronously (see Fig. 3).

The illustrated duplication of parameter development patterns can be partially explained by Ritter's study, mentioned previously, because about 35% of IPOs on the stock exchange are held by venture-based companies. An important conclusion derived from the found analogy is that the stock market indices of hi-tech companies can be used as a real-time indicator of actual trends and intentions on the venture capital investment market at a moment in time.

Figure 3. Quarterly dynamics of VCI and NASDAQ index normalized

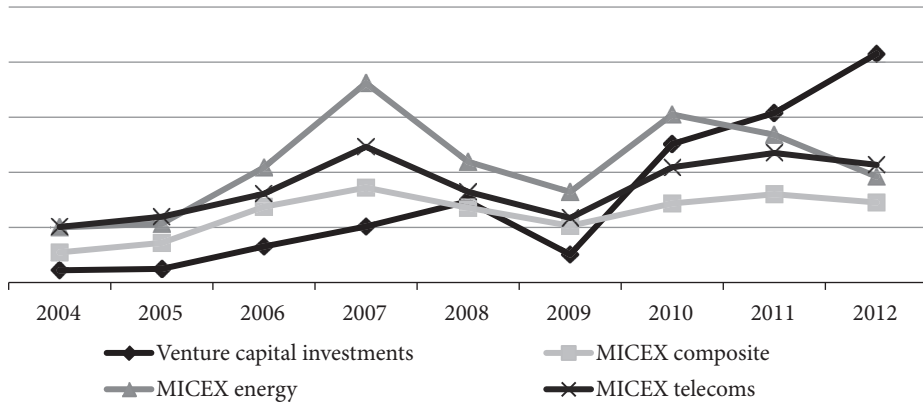


Source: NVCA, NASDAQ raw data, Authors' calculation

We looked at the Russian stock market to prove the thesis of interrelation between hi-tech indices and venture capital investment and found that the conclusions for the American market also apply to the Russian market. We took annual averages of Moscow Exchange indices such as the MICEX composite index for general comparison as well as the MICEX-energy and MICEX-telecoms indices, where most high-tech enterprises are represented³ (see Fig. 4).

³ The Moscow Exchange's innovation economy index (MICEXINNOV) has only been quoted since 2010.

Figure 4. Russian VCI and annual averages of Russian stock indices normalized



Source: Moscow Exchange raw data, Authors' calculation

It is notable that general trends of the four parameters shown in Figure 4 matched until the year 2011, and starting from 2012 the stock market began moving reciprocally with the venture capital market, which kept on growing. Consequently, the derived observations allow for extrapolation of stock market hi-tech indices for current and prospective estimates of national venture capital investments, considering their cyclic nature.

The survey of the interrelation between venture capital investment and GDP, aimed at proving the hypothesis of the influence of VCI on economic growth, employed quarterly GDP data for the USA during 1995-2012. Taking into account the probable delayed or lagged effect of venture capital investment on GDP, the research objective was not only to estimate the quantitative extent of the interrelation between the two parameters at different lags but also to determine the exact lag at which previous investment most influences current GDP.

Shift of the function along the argument was done iteratively for each consecutive lag (3 months) up to the significant decrease of the multiple determination coefficient (R-squared) after its peak, according to the following notation:

$$GDP_{i+lag} = bVC_{(i)} + const; i \in [1; n]; lag \in [0; 28] \quad (1)$$

Prior to the analysis, we made several theoretical assumptions concerning the nature and specifics of the time series in focus. We agree that VCI and GDP series

have to be tested for the presence of unit root and probably modified according to the results in order to avoid spurious regression. Time series modification techniques, used to achieve stationarity, usually imply differencing, which leads to rescaling the series. The problem with rescaling is further difficult interpretation of regression coefficients in terms of hands-on implementation in policymaking or administration: it takes an effort to make them manageable. By contrast, modelling the series in their levels, even rescaled by natural logarithm, allows for easily interpreting the regression coefficients as the measure of function and argument relation in the ‘cause – effect’ manner. This assumption is valid only if this effect is statistically verified by modelling the stationary series.

Using the Augmented Dickey and Fuller test (ADF-test), we found that both VCI and GDP are non-stationary. As for the GDP series, it is difference-stationary: ADF-testing it in GRETl interface proved the presence of unit root ante differencing and no unit root post differencing (see Table 2).

Table 2. Augmented Dickey-Fuller unit root test results for the US GDP and VCI

| | Ante differencing | Post differencing |
|---------------------|--|--|
| GDP series testing | | |
| Series | GDP levels | GDP 1 st difference at lag 1 |
| Model type | $(1-L)y = b_0 + b_1*t + (a-1)*y(-1) + \dots + e$ | $(1-L)y = b_0 + b_1*t + (a-1)*y(-1) + e$ |
| Sample size | 70 | 70 |
| Max lag (criterion) | 20 (AIC) | 20 (AIC) |
| Actual lag | One | Zero |
| tau_ct(1) | -2.62003 > 1% critical value* | -4.49766 < 1% critical value |
| asymptotic p-value | 0.2712 | 0.003044 |
| Unit root | Present | Not present |
| VCI series testing | | |
| Series | VCI levels | VCI 1 st difference at lag 1 |
| Model type | $(1-L)y = b_0 + b_1*t + (a-1)*y(-1) + \dots + e$ | $(1-L)y = b_0 + b_1*t + (a-1)*y(-1) + e$ |
| Sample size | 70 | 70 |
| Max lag (criterion) | 20 (AIC) | 20 (AIC) |
| Actual lag | One | Zero |

| | | |
|--------------------|------------------------------|------------------------------|
| tau_ct(1) | -3.18354 > 1% critical value | -4.27951 < 1% critical value |
| asymptotic p-value | 0.08768 | 0.005867 |
| Unit root | Present | Not present |
| Critical values | 1% critical value (-3.9996) | |
| | 5% critical value (-3.4298) | |
| | 10% critical value (-3.1381) | |

Source: Authors' calculation

The same results were obtained for VCI series. This means we have to deal with differenced series in order to avoid spurious regressions. Considering the stationarity, we ran our survey in the following sequence:

- a) Modelling GDP and VCI series in their levels to obtain an 'Executive model', which is regression coefficients and model parameters that can be used for short-run and long-term policy implications and administration purposes, including forecasting, goal-setting, and planning;
- b) If the 'Executive model' results are statistically significant; i.e., the regression model characteristics match the described criteria, we are to verify or reject the spurious regression hypothesis. This requires modelling the series of GDP and VCI using the same algorithm but in stationary representation; i.e., differenced ('Authentic model');
- c) If the 'Executive' and 'Authentic' models simultaneously exhibit appropriate goodness of fit, the spurious regression hypothesis is rejected and the 'Executive' results are further interpreted. If not, the model is considered to be insignificant for policy implementation.

Executive model

Table 3 represents several characteristics of the 'Executive' regression models obtained as the result of multiple regression at selective lags: regression coefficient value (b), its normalized value (beta), and multiple determination coefficient of a model (R^2).

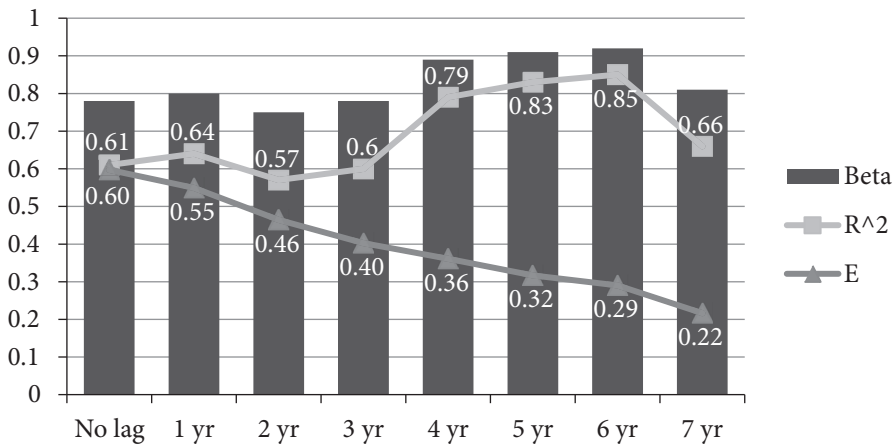
Table 3. Linear regression summary for GDP (dependent variable) and VCI (independent variable) at selected lags ('Executive model')

| Lag | b | Beta | R ² | Lag | b | Beta | R ² |
|-----------|--------|------|----------------|-----------|--------|------|----------------|
| No lag | 1220.3 | 0.78 | 0.61 | 21 months | 1023.9 | 0.76 | 0.57 |
| 3 months | 1215.0 | 0.79 | 0.63 | 2 years | 986.9 | 0.75 | 0.57 |
| 6 months | 10.8 | 0.66 | 0.44 | 3 years | 872.1 | 0.78 | 0.60 |
| 9 months | 10.5 | 0.66 | 0.43 | 4 years | 796.4 | 0.89 | 0.79 |
| 1 year | 1138.2 | 0.80 | 0.64 | 5 years | 717.4 | 0.91 | 0.83 |
| 15 months | 1097.5 | 0.79 | 0.62 | 6 years | 677.2 | 0.92 | 0.85 |
| 18 months | 1059.3 | 0.77 | 0.60 | 7 years | 509.1 | 0.81 | 0.66 |

Source: Authors' calculation

Although the 'Executive' regression coefficients (b) decline as the lag grows, thus indicating a decrease of interrelation between the parameters, it is impossible to state that this interrelation is significant at smaller lags. For instance, at the interval of lags up to 3 years, the multiple determination coefficient scores 0.64 or less, which is traditionally treated as insufficient in terms of regression model reliability assessment. The latter shows insufficient influence of venture capital investment on GDP dynamics at lags up to 3 years. This means that GDP growth was not enabled by venture capital investment but by other factors beyond the model, as can be derived from the beta-coefficients analysis, whose values keep growing up to 6-year lag (see Fig. 5).

Figure 5. Changes in parameter estimates of the US GDP regression by VCI at different lags ('Executive model')



Source: Authors' calculation

It is rational that the strong influence of venture capital investment on GDP, synchronously or at 1-year lag (in terms of b-coefficient), should be interpreted as a mostly unreliable or even probabilistic result that does not allow for deriving significant conclusions or proving the hypotheses. By contrast, high estimates of beta-coefficients and determination coefficients at 4-6-year lags indicate a strong interrelation between the two variables. This proves the thesis of venture capital investment's delayed influence on GDP dynamics.

Analysis of GDP elasticity to venture capital investment change at different lags helped prove the unreliability of the models at lags 0 to 16 by comparing elasticity estimates, derived from the models, to actual data. Calculations were made using the following GDP elasticity function:

$$\eta(VC) = \frac{D'(VC)}{D(VC)} \times VC = \frac{VC(bVC + c)'}{(bVC + c)} = \frac{bVC}{bVC + c} \quad (2)$$

Actual average GDP to VCI elasticity, estimated as a proportion of their respective average growth rates (see above), scored 0.27, which most fits the model estimate at a 6-year lag (as shown in Fig. 5). The rational interpretation is that every percentage of venture capital growth in a given period causes 0.29% GDP growth in a 6-year perspective with 85.2% probability, and 0.32% in a 5-year perspective with 83.1% probability. Venture capital investment's influence on GDP in the present period or in the short-run is statistically insignificant.

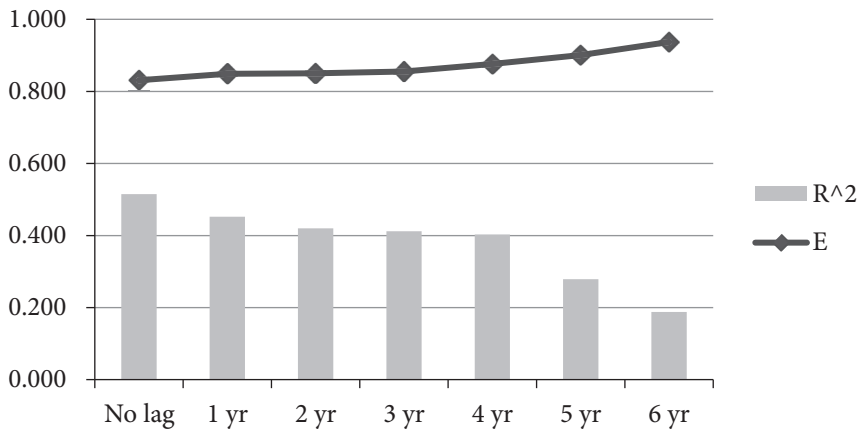
This is the effect and measurable result anticipated by algorithms and mechanisms described in numerous papers. J. Lerner and J. Tåg are right when saying that “an active venture capital market can boost economic growth” (Lerner and Tåg 2013, p. 154), but in a 4-6-year perspective.

Differences in the level of development of the Russian and US economies are foregrounded if we try to clone the described study algorithm on the data on the Russian Federation venture capital market. There is one obvious limitation: raw data on venture capital investment in Russia is only available annually, despite the fact that GDP is measured quarterly. The time series is not very long, so we could only test year lags.

The results are drastically different. They show that the Russian innovation system employs different knowledge-capital-product transfer mechanisms to the USA, and those mechanisms are sub-optimal. This is neither good nor bad but different, and requires explanation.

As we see it, according to the ‘Executive model’, Russian GDP to VCI elasticity grows from 0.844 to 0.967 as the lag rises, but the interrelation is statistically insignificant on all lags and declines as the lag grows. The reason for this may be found in the deficit of growth resources, as the impact of progressive economic development is slightly dependent on venture capital investment but is not driven by it. A decrease or even a total ban on venture capital investment in Russia would not affect GDP growth because it is very small (see Fig. 6).

Figure 6. Changes in parameter estimates of Russian GDP regression by VCI at different lags (‘Executive model’)



Source: Authors’ calculation

Determination coefficients declining as the lag increases can be interpreted as the distribution of venture project implementation periods from the moment of financing to exit: slightly more than 20% of venture capital investment gives the desired effect in a six-year perspective, and the effect is less but more probable at smaller lags. Alternatively, the obtained ‘Executive’ result correlates strongly to venture projects’ survival statistics in an appropriate time horizon: six years after start-up, only 20% of projects are making a feasible or tangible contribution to GDP, which, up to that moment, is ‘washed out’ by less efficient projects.

Authentic model

As seen from the ‘Executive model’, the influence of US venture capital investment on GDP is manageable only at greater lags of four to six years. Despite the dependencies derived from data in its levels, we have only to verify several

conclusions about the 6-year lag of the VCI causal effect to GDP growth, as well as prove or reject the significance of dependency between them at zero lag representation.

We ran the same linear regression algorithm using VCI and GDP series brought to stationarity by differencing. Compared to the ‘Executive’ model, the dependencies do not stand out and seem implausible. Quarterly representation of data provided no significant evidence of any causality of VCI to GDP, with several exceptions. We turned to annual data to finalize the ‘Authentic model’ approximation, which was more fruitful as regards statistically significant results that support our basic hypothesis.

Thus, in terms of parameters, the ‘Authentic’ model characteristics strive to reject the hypothesis of VCI causal effect on GDP at most lags, but not all: R-squared values do not exceed 0.55 (zero lag) and regression coefficients are statistically unreliable according to t-statistics and p-level values.

As seen in Table 4, the maximum Beta (0.74) stands for zero lag regression of annual GDP by annual VCI, as the determination coefficient scored 0.55. These actually reject the spurious regression hypothesis in the ‘Executive’ model, which demonstrates nearly the same values for R-squared (0.61) and Beta (0.78).

Table 4. Linear regression summary for GDP (dependent variable) and VCI (independent variable) at selected lags (‘Authentic model’)*

| Lag | b | Beta | R ² |
|---------------------------|----------|----------|----------------|
| No lag (quarterly data) | 24.9595 | 0.256537 | 0.0658 |
| No lag (annual data) | 0.003914 | 0.741584 | 0.55 |
| 3 months (quarterly data) | 40.5287 | 0.419820 | 0.1762 |
| 6 years (annual data) | 0.005147 | 0.618584 | 0.383 |

* - insignificant values omitted

Source: Authors’ calculation

The economic interpretation of such an impact is obvious: the invested funds push up spending directly and involve several known multiplier effects, which increase collateral spending and other side effects. That is why the found interrelation cannot be treated as the measure of VCI ‘results’ being consumed and/or employed by the economy. The impact of VCI momentum is still to be investigated, but this problem lies beyond the scope and objectives of this paper

and also requires a larger dataset of venture-backed projects and their ‘economics’ from several countries.

The second largest Beta (0.62) in the ‘Authentic’ model stands for a 6-year lag (annual data) and is verified by the appropriate t-value. Since the R-squared value is only 0.383, we note that the lagged effect of VCI on GDP growth is not spurious, although its extent is not very good. The elasticity coefficient of GDP in the ‘executive’ model (0.27 at 0.85 R-sq.) was close to that estimated from the data (0.29). At the same lag the ‘Authentic’ model demonstrates an average 0.16% GDP growth resulting from 1% growth of VCI at 38.3% probability. The discrepancy may be explained by the existence of other determinants of GDP growth, as well as by distraction factors that wash away the impact of VCI, both direct and collateral.

The estimates of betas for GDP regression on different VCI lags (quarterly and annually) provide access to dynamic model specification, which could estimate the total impact of VCI, both immediate and delayed. Polynomial distributed lag (PDL) models can be used for this. Among the practical limitations of PDL models is lag-length determination, which often has to be tested empirically: although there are several calculation techniques, none of them is 100% precise and informative.

We tested the following distributed lag models and algorithms:

- Almon 2nd order polynomial lags model (annual data in levels and first order differences) with lag length of 6 – “DLM1”;
- Cochrane-Orcutt autoregressive model (annual data in levels and first order differences) for consecutive (non-discrete) lags [0; 6] – “DLM2”;
- Cochrane-Orcutt autoregressive model (quarterly data in levels and first order differences) for selected (discrete) lags – “DLM3”.

Zero-intercept models were excluded.

DLM1 converged to the model with statistically significant R-squared (0.97), but 1st and 2nd order polynomial coefficients lack significance according to p-level values (see Table 5). However, we consider it possible to continue estimating lag parameters.

Table 5. Almon model of distributed lags VCI influence on GDP (DLM1), annual data in levels

| | Beta | Std.Err. | B | Std.Err. | t(8) | p-level |
|-----------|----------|----------|----------|----------|----------|----------|
| Intercept | | | -4371.54 | 1446.725 | -3.02168 | 0.016517 |
| c0 | 1.46577 | 0.210145 | 148.95 | 21.354 | 6.97505 | 0.000115 |
| c1 | -1.33602 | 0.634791 | -31.16 | 14.806 | -2.10466 | 0.068439 |
| c2 | 0.83845 | 0.522353 | 3.77 | 2.349 | 1.60515 | 0.147129 |

| Coefficient | b_{lag} | Beta | Coefficient | b_{lag} | Beta |
|----------------------------------|-----------|----------|-------------|-----------|----------|
| Intercept | -4371.54 | | b3 | 89,39179 | 0,122237 |
| b0 (short-term) | 148.9479 | 0.203676 | b4 | 84,61908 | 0,115711 |
| b1 | 121.5562 | 0.16622 | b5 | 87,38602 | 0,119494 |
| b2 | 101.7042 | 0.139074 | b6 | 97,69263 | 0,133588 |
| Cumulative long-term effect | | | | | 731.30 |
| Average estimated effect per lag | | | | | 104.47 |

Source: Authors' calculation

The Almon polynomial model of lagged VCI influence on GDP in levels demonstrates almost evenly spread impacts, except for short-term effect, which is greater compared to the following lags: about 20% of cumulative impact (731.3 or an average of 104.5 per lag) take place with no delay due to the reasons described above. Then the VCI cumulative long-term impact on GDP at different lags reads as follows: 1 billion USD growth of VCI will result in 731.3 billion USD GDP growth during the following 6 years, which looks implausible. However, elasticity interpretation accounts for only 0.063% of GDP growth per 1% of VCI growth. Such a decrease can be explained by the extremely large value (6:1) of the intercept compared to the cumulative impact estimate that accounts for the effect of other factors beyond the model.

As we found using the 'Executive' model, the differences in the impact were slight, which is verified by the distributed lags model. The 6-year lagged impact is thus not rejected, but requires deeper investigation within the distributed lags framework.

With DLM2 approximation of levels at consecutive lags we derived a model that indicates the strongest and statistically significant VCI impact at 6-year lag (159.9), followed by zero-lag (129.8). This result (see Table 6) makes no radical difference to DLM1, but it helps to get rid of the doubts concerning the existence

and statistical significance of the delayed impact of VCI. Table 7 demonstrates the strongest VCI impact at 6-year lag on stationary data.

Table 6. Cochrane-Orcutt autoregressive model of annual data (DLM2)
Data in levels; consecutive lags [0; 6] (the asterisk-marked values are significant)

| Lag, years | Coefficient | Std. Error | t-ratio | p-value |
|----------------------------------|-------------|------------|---------|----------|
| Intercept | -6649.25 | 2159.6 | -3.0789 | 0.0542 * |
| No lag | 129.818 | 49.1005 | 2.6439 | 0.0774 * |
| One | 113.863 | 38.3112 | 2.9721 | 0.0590 * |
| Two | 126.942 | 47.1982 | 2.6895 | 0.0744 * |
| Three | 106.481 | 46.7977 | 2.2754 | 0.1074 |
| Four | 77.1372 | 54.6912 | 1.4104 | 0.2532 |
| Five | 114.001 | 70.7947 | 1.6103 | 0.2057 |
| Six | 159.903 | 67.5348 | 2.3677 | 0.0987 * |
| Cumulative long-term effect | 828.14 | | | |
| Average estimated effect per lag | 118.3 | | | |

Statistics based on the rho-differenced data:

| | | | |
|---------------------|-----------|---------------------|----------|
| Mean dependent var. | 13381.03 | S.D. dependent var. | 1626.351 |
| Sum squared resid. | 295840.1 | S.E. of regression | 314.0277 |
| R-squared | 0.988840 | Adjusted R-squared | 0.962801 |
| F(7, 3) | 17.13503 | P-value(F) | 0.019959 |
| rho | -0.054773 | Durbin-Watson | 2.086921 |

Source: Authors' calculation

Table 7. Cochrane-Orcutt autoregressive model of annual data (DLM2)
Data in 1st order differences; consecutive lags [0; 6] (The asterisk-
marked values are significant)

| Lag, years | Coefficient | Std. Error | t-ratio | p-value | |
|---|-------------|------------|---------|---------|-----|
| Intercept | 355.917 | 33.697 | 10.5623 | 0.0018 | *** |
| No lag | 77.4413 | 15.0457 | 5.1471 | 0.0142 | ** |
| One | 7.97728 | 13.4954 | 0.5911 | 0.5960 | |
| Two | 50.4936 | 24.922 | 2.0261 | 0.1359 | |
| Three | -18.0261 | 20.0519 | -0.8990 | 0.4349 | |
| Four | 13.0222 | 20.9592 | 0.6213 | 0.5784 | |
| Five (omitted due to model limitations) | - | - | - | - | |
| Six | 62.4324 | 11.2134 | 5.5677 | 0.0114 | ** |
| Cumulative long-term effect | 211.37 | | | | |
| Average estimated effect per lag | 35.23 | | | | |

Statistics based on the rho-differenced data:

| | | | |
|---------------------|-----------|---------------------|----------|
| Mean dependent var. | 504.2500 | S.D. dependent var. | 324.5830 |
| Sum squared resid. | 28577.04 | S.E. of regression | 97.59959 |
| R-squared | 0.970025 | Adjusted R-squared | 0.910075 |
| F(6, 3) | 41.03726 | P-value(F) | 0.005695 |
| rho | -0.336132 | Durbin-Watson | 2.502899 |

Source: Authors' calculation

Using DLM3 on quarterly data in levels, we found a more precise measure for ‘within-a-year’ impact lag. We took only selected lags for the model (see Table 8). The results demonstrate statistically significant VCI impact at a 3-month lag, as well as at 4-6-year lags. This means that the impact of synchronous lags found in DLM1 is not distributed within a year, but takes place during the 3 months following investment. The more interesting result in terms of the paper’s objective is that the largest regression coefficient (as well as the largest t-ratio) stands for a 6-year lag (352.6) and is twice as big as 4-year or 3-month lag impact. Again, we face an even greater value of the intercept, which compared to the largest “b” is 25:1 and compared to cumulative impact estimate is 8.5:1.

Table 8. Cochrane-Orcutt autoregressive model of quarterly data (DLM3)
Data in levels; selected lags (The asterisk-marked values are significant)

| Lag, quarters | Coefficient | Std. Error | t-ratio | p-value | |
|----------------------------------|-------------|------------|---------|---------|-----|
| Intercept | 9041.86 | 571.354 | 15.8253 | <0.0001 | *** |
| No lag | -127.637 | 53.6871 | -2.3774 | 0.0257 | ** |
| 1 | 187.359 | 65.0794 | 2.8789 | 0.0083 | *** |
| 2 | 8.44904 | 66.1609 | 0.1277 | 0.8994 | |
| 3 | 23.997 | 65.5919 | 0.3659 | 0.7177 | |
| 4 (1 year) | 38.7863 | 52.0215 | 0.7456 | 0.4632 | |
| 8 (2 years) | -39.7853 | 35.7803 | -1.1119 | 0.2772 | |
| 12 (3 years) | 48.9649 | 33.403 | 1.4659 | 0.1557 | |
| 16 (4 years) | 170.296 | 37.5021 | 4.5410 | 0.0001 | *** |
| 20 (5 years) | 236.396 | 40.2339 | 5.8755 | <0.0001 | *** |
| 24 (6 years) | 352.612 | 54.7506 | 6.4403 | <0.0001 | *** |
| Cumulative long-term effect | 1066.9 | - | - | - | |
| Average estimated effect per lag | 42.7 | - | - | - | - |

Statistics based on the rho-differenced data:

| | | | |
|---------------------|-----------|---------------------|----------|
| Mean dependent var. | 14001.05 | S.D. dependent var. | 1086.221 |
| Sum squared resid. | 1404083 | S.E. of regression | 241.8749 |
| R-squared | 0.965110 | Adjusted R-squared | 0.950572 |
| F(10, 24) | 133.0420 | P-value(F) | 1.63e-18 |
| rho | -0.154292 | Durbin-Watson | 2.125928 |

Source: Authors' calculation

DLM3 on stationary data series with the same selected lags (see Table 9) indicates a less determinant model (R-squared = 0.55) with a statistically significant impact at 3-month lag and quasi-significant impact at 6-year lag due to a p-value exceeding 0.05. Thus, in the given representation GDP is influenced by VCI only at 3-, 6-, and 9-month lags, as well as 6-year lags. These lags accumulate for the total long-term effect, estimated at 171.5, which is greater than the intercept and in terms of elasticity derives 0.35% of GDP growth per 1% of VCI growth. This measure is relatively close to the actual data estimates that were mentioned before (0.27). We consider this result to be a reliable verification of the 'Executive' model 'results' measuring the VCI causality of GDP.

Table 9. Cochrane-Orcutt autoregressive model of quarterly data (DLM3)
Data in 1st order differences; selected lags (The asterisk-marked values are significant)

| Lag. quarters | Coefficient | Std. Error | t-ratio | p-value | |
|----------------------------------|-------------|------------|---------|---------|-----|
| Intercept | 122.209 | 18.042 | 6.7736 | <0.0001 | *** |
| No lag | 28.5108 | 14.9549 | 1.9065 | 0.0686 | * |
| 1 | 50.8223 | 16.7067 | 3.0420 | 0.0056 | *** |
| 2 | 25.1875 | 16.9807 | 1.4833 | 0.1510 | |
| 3 | 27.024 | 17.5861 | 1.5367 | 0.1375 | |
| 4 (1 year) | -5.85729 | 16.4036 | -0.3571 | 0.7242 | |
| 8 (2 years) | -3.47308 | 16.3034 | -0.2130 | 0.8331 | |
| 12 (3 years) | 10.5663 | 17.0178 | 0.6209 | 0.5405 | |
| 16 (4 years) | -1.42444 | 19.856 | -0.0717 | 0.9434 | |
| 20 (5 years) | -1.47262 | 20.4598 | -0.0720 | 0.9432 | |
| 24 (6 years) | 29.4016 | 22.4322 | 1.3107 | 0.2024 | |
| Cumulative long-term effect | 171.5125 | | | | |
| Average estimated effect per lag | 6.8605 | | | | |

Statistics based on the rho-differenced data:

| | | | |
|--------------------|----------|--------------------|----------|
| Mean dependent var | 131.2257 | S.D. dependent var | 84.25508 |
| Sum squared resid | 108508.8 | S.E. of regression | 67.23988 |
| R-squared | 0.550439 | Adjusted R-squared | 0.363122 |
| F(10, 24) | 1.485024 | P-value(F) | 0.205269 |
| rho | 0.002218 | Durbin-Watson | 1.948359 |

Source: Authors' calculation

VCI impact on innovation: the basis for further research

We agree that venture capital investment's "powerful multiplier effects" (Kleinknecht 1990, p.90) are obtained not directly but through the process of commercialization of investments' tangible result. This requires further study of the interrelation between investments and number of innovations, which, according to Kleinknecht, is one of the growth function arguments.

There is a discussion on the matter of identifying the 'product' of the innovation process and investment in research and development; i.e., on measuring the results. Most researchers believe that patent activity is most appropriate for measuring innovation needs. However, there is growing "dissatisfaction with the

actual performance of the patent system” (Clancy and Moschini 2013, p.214) due to the growing trend of the destruction of the ‘cause–effect’ link between R&D expenditure and patents granted because of the marketing and other business strategies involved. An enterprise can ‘inflate’ its patent portfolio to look more technology-driven and creative, thus raising more funds or preventing legal challenges from competitors. Still, the share of genuine result-backed patents is large enough to be able to state that patents are more a consequence of and less a reason for venture capital investment.

According to Kortum and Lerner (1998), venture capital investment’s influence on the number of patents granted is much more significant than the influence of other corporate (non-venture) R&D expenditures. Hirukawa and Ueda (2008) positively tested this thesis on different samples and time series, so we see no point in retesting them. However, it seems rational to measure the results of venture capital investment’s influence on patent dynamics and activity by number of patent applications filed in a particular period, and not by number of patents. This arises from the discrepancy between the amount of patent applications and number of patents granted: an annual average of only 29% of patent applications was upheld in the USA in 1998-2011. Nevertheless, venture capital investment quite often results in intellectual property, not all of which is eligible for patent protection.

Therefore we ran a survey of US venture capital investment’s influence on amount of patent applications in comparison to estimates of the influence of gross domestic expenditure on R&D. The time series entailed annual data from 1995 to 2011. Considering the stationarity problem of time series, we ran ‘Executive’ and ‘Authentic’ algorithms, as noted above. Still, we assume that positive results of ‘Executive’ modelling will just determine the further research needed to verify more precisely the extent of VCI impact on innovation dynamics. It will require the employment of several binary variables, derived from the investigation of deeper series, including some ‘natural’ characteristics of VCI and of patent applications.

The derived regression models of the amount of patent application dependency on venture capital investment and gross R&D expenditure, akin to the above mentioned ‘Executive’ models, resulted in the following conclusions.

1. The amount of patent application elasticity is the greatest to R&D expenditure if taken unweighted, both synchronously and at 1-year lag (see Table 10).

Table 10. Estimates of USA patent application regression by VCI and gross domestic R&D expenditure ('Executive model')

| Lag, yrs. | VCI | | R&D expenditure | |
|-----------|-------|----------------|-----------------|----------------|
| | E | R ² | E | R ² |
| 0 | 0.891 | 73.2 | 1.075 | 96.3 |
| 1 | 0.800 | 64.2 | 1.031 | 93.1 |
| 2 | 0.678 | 57.5 | 0.951 | 86.9 |
| 3 | 0.626 | 63.7 | 0.890 | 83.2 |
| 4 | 0.570 | 58.7 | 0.855 | 81.2 |
| 5 | 0.581 | 60.1 | 0.885 | 84.8 |
| 6 | 0.619 | 75.5 | 0.910 | 88.1 |

Source: Authors' calculation

2. The influence of venture capital investment on the amount of patent applications can be treated as statistically significant only with synchronous data and at 6-year lag, since the determination coefficient varies from 57.5% to 73.2%. It is notable that R&D expenditure data may entail venture funds, so probably the influence of venture investment is dissipated in total R&D.
3. Using an alternative computation approach, less sophisticated than the one by Kortum and Lerner (1998), we normalized the scales of venture capital investment and gross domestic R&D expenditure and came to weighted influence estimates that are very different and need explaining. Being relatively equal in absolute figures, estimates of patents applications' number elasticity to the two arguments show a different value of 1% in dollars. The absolute of 1% R&D is many times greater than the absolute of 1% of venture capital investment. That is why they are incomparable. Normalization allows for comparison that shows 10 times greater influence of venture capital investment than of R&D expenditure in terms of amount of patent applications growth (see Table 11).

In other words, innovation activity in venture-backed companies is 10 times greater than in other companies. *Ceteris paribus*, every additional one million USD of venture investment is as 'powerful' as 12.23 million USD of gross R&D expenditure in terms of contribution to patent application growth. To be exact, a million dollars invested as venture capital results in an average of 13.1 additional applications; gross R&D expenditure provides only 1.3 applications per million dollars spent.

Table 11. Standardized elasticity coefficients of the US model
(no lag; ‘Executive model’)

| Parameters | Variables | |
|--|-----------|-----------------|
| | VCI | R&D expenditure |
| Annual average in 1995-2011, USD billion | 21.9 | 268.0 |
| The absolute of 1 percent, USD billion | 0.22 | 2.68 |
| The absolute 1 percent scaled to 1 percent of R&D expenditure, USD billion | 12.23 | 2.68 |
| Scaled patent applications amount elasticity | 10.9 | 1.075 |

Source: Authors’ calculation

Patent applications and grants are collinear through the period 1959-2011, so our results prove the achievements of Kortum and Lerner (1998). The time series we explored represents an average venture capital investment to gross domestic R&D expenditure ratio equal to 8.2%, whereas VCI provides up to 61.8% of patent applications in the USA in a given period.

We tested the latter result on Russian data by analogy. The time series was not that long as that of the USA: it entailed cases since 1996 because previous data are not officially available. We found that, just as in the case of VCI influence on GDP, the growth of lag in the patent applications regression model provides a decrease of the determination coefficient within boundaries of 0.515 (highest, no lag) to 0.188 (6-year lag). At the same time, patent application amount elasticity grows permanently, which can be treated as the dependency of efficiency on prolonged projects.

Venture investment in Russia is 10.3 times less than gross R&D spending. If scaled to R&D spending, elasticity of patent applications number to VCI can be estimated at 8.1: a million-dollar-growth of venture capital investment in Russia results, *ceteris paribus*, in 23.1 patent applications on average, and, for R&D spending, only 2.9 applications per million dollars spent. J. Lerner and J. Tåg’s⁴ paper provides valuable verification.

The results demonstrate a significant difference between the US and Russian venture capital markets in terms of growth potential. Using the same algorithm, we can calculate that up to 95% of all product innovation in Russia is venture-

⁴ “There is also less consistent evidence that taxes, labor market regulations, and public R&D spending are of importance” (Lerner and Tåg 2013, p.175).

backed. The difference is clearly explained by J. Lerner and J. Tåg, who found “ample empirical support for the view that the legal environment and financial market development matter for the development of active venture capital markets” (Lerner and Tåg 2013, p. 175). Many Russian researchers and industry experts note the legislative problems and low level of financial market development in Russia. The Russian innovation sector is in its early growth stage, which is why additional capital inflow results in much more innovation in terms of patent applications.

As can be seen, ‘Executive’ regression models exhibit the causal effect of VCI to amount of patent applications at several lags, and it has a rational explanation. In order to verify this we also ran the ‘Authentic’ model, but faced several limitations in data that had to be managed prior to analysis. They included twin-counts both in R&D spending (it has to describe venture-free capital inflows, which is why data modification is needed) and in the amount of patent applications (it is true that not all applications represent ‘brand new’ discoveries, and not all of them are venture-backed, or even funded). Taken broadly, EBIT or its growth rate, lagged from the period of start-up, is a better indicator of VCI influence on innovation.

6. CONCLUSION

The research results allow constituting several time-stable theorems, which are proven above but are still open to argumentation, probing, and criticism:

1. Venture financing is widely discussed as an alternative to borrowing funds from a bank or finding some other non-venture investment. We consider such an approach to be outdated because rational sense and empirical evidence show that the choice itself is highly opportunistic: high-risk projects in the field of innovation and research leave no space for any other capital-granting mechanism, thus creating a specific niche for venture financing.
2. The regression models of US GDP by venture capital investment helped to validate the main research hypothesis, that VCI does affect economic growth and this effect is much stronger from a 4-6-year perspective. The lagged regression model estimates show that the most statistically significant elasticity coefficients are reached at distant lags and verified by retrospective data.
3. Extrapolation of USA parameters as an analogy for Russian data brought interesting results. We took US data as the most reliable and illustrative sample of venture capital market development in order to test results based on Russian statistics. Elasticity growth dependency is repeated on Russian data,

but model determination coefficients decline strongly and consecutively to an unreliable 20%. We explain this by the different transfer mechanism and the less-than-effective capital market structure, which has been studied in detail outside this research. The situation in Russian GDP-to-VCI dependency, as we see from the model, can be treated as an insufficient absolute volume of venture capital investment that vanishes when compared to total investment and R&D spending, without any feasible effect. If statistical reliability criteria are set aside, we see distinctly and clearly the 6-year survival pattern of venture projects in the market: 20% of start-ups reach their goal and contribute to GDP growth substantially (GDP elasticity ratio of 0.967) and this contribution is quite long-lasting.

4. We found no substantial difference in the statistically strong correlation between number of patent applications and venture capital investment, both in the USA and Russia. The respective regression models verified the hypothesis that the innovation development dynamic depends on VCI rather than on conventional investment. In both the USA and Russia, venture capital investment, scaled to absolute R&D spending, continues to foster the growth of the number of patent applications over regular investment: American VCI was estimated to be 10 times more effective and Russian VCI 8 times more effective in terms of patent applications. The dominant role of venture capital investment, widely described in theory, was empirically validated.

The collateral results, which are not in the scope of our research but are worth mentioning, include:

1. US GDP and venture capital investment dynamics show distinct and clear 6-month and 18-month cycles that harmonically interfere and link our findings to the explanation of innovation waves theory.
2. We found a reliable VCI forecasting and analysis instrument that can be derived from numerous reliable stock exchange index forecasts available from industry professionals. Normalized time series of VCI and NASDAQ (VCI and MICEX in Russia) almost match during the whole period surveyed. This matching also provides retro-forecasting opportunities in the case of missing data and statistics backlog.
3. We discovered that average venture capital investment per project in the US, except for the dotcom boom period, never exceeded 8 million dollars and has stayed within the boundary of 6-8 million dollars for the last decade. This can be interpreted as the empirical productivity margin or venture project capacity. Further investment growth is only going to be extended by the number of deals. Such an option is affordable in all economies, both growing and static.

REFERENCES

Berger, A. N. & Udell, G. F. (1998). The economics of small business finance: the roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, 22, pp. 613-673.

Brander, J. A. & de Bettignies, J.-E. (2009). Venture capital investment: the role of predator-prey dynamics with learning by doing. *Economics of Innovation and New Technology*, 18, pp. 1-19.

Chichvarkine, E. (2011). Advice to beginner entrepreneurs from Evgueny Chichvarkine. *Forbes Russia*. Retrieved from <http://www.forbes.ru/svoi-biznes-column/predprinimateli/69891-sovety-nachinayushchim-predprinimatelyam-ot-evgeniya-chichv> [in Russian. Title translated by authors.]

Clancy, M. S. & Moschini, G.-C. (2013). Incentives for innovation: patents, prizes, and research contracts. *Applied Economic Perspectives and Policy*, 35, pp. 206-241.

Da Rin, M., Hellman, T. & Puri, M. (2011). *A survey of venture capital research*. (TILEC Discussion Paper No. 2011-044), Tilburg: Tilburg Law and Economics Center

Hirukawa, M. & Ueda, M. (2008). *Venture capital and industrial innovation*. (CEPR Discussion Paper No 7089), London: Center for Economic Policy Research.

Kleinknecht, A. (1990). Are there Schumpeterian waves of innovation? *Cambridge Journal of Economics*, 14, pp. 81-92.

Kortum, S. & Lerner, J. (1998). *Does venture capital spur innovation?* (NBER Working Paper No. 6846), Cambridge, MA: National Bureau of Economic Research.

Lerner, J. & Tåg, J. (2013). Institutions and venture capital. *Industrial and Corporate Change*, 22, pp. 153-182.

Puri, M. & Zarutskie, R. (2012). On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms. *The Journal of Finance*, 67, pp. 2247-2293.

Ritter, J.R. (2011). Initial public offerings: tables updated through 2010. Retrieved from <http://bear.warrington.ufl.edu/ritter/IPOs2010underpricing.pdf>

Received: November 01, 2014

Accepted: December 01, 2015

