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Diminishing Research Quotient: Does Capital Availability and Labor Productivity Crowd out R&D Productivity?

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Abstract

This research documents the diminishing research quotient proposed by Knott and Vieregger (2018) from 1975 to 2015. In the United States, per dollar increase on the research and development (R&D) activities expenditure generated $0.19 in firm revenue in 1975, and $0.09 in 2015. Presented in this paper is the argument that the decline in R&D elasticity of revenue is due to the crowding out results of ineffectiveness of innovative activities at the low-capital cost stages, but not because of the higher labor productivity at the stages of high unemployment rate. Firm innovative activities are more productive when the cost of capital is high, but easier access to capital brings lower revenue created by the R&D inputs. The function of capital and innovation on a firm's output is mutually substitutable to an extent, but the function of labor productivity cannot be replaced by engaging innovative activities.

1. Introduction

Research Quotient (RQ) is the firm level research elasticity of revenue. It measures the percentage change of firm revenue per 1% of the firm expenditure on research and development (R&D) activities, holding other inputs and their marginal contributions constant. RQ measures the effectiveness of innovative inputs of a firm, and is different from the total factor productivity (TFP) in a commonly used Cobb-Douglas production function. TFP is an inclusive factor that carries all the residuals of firm production after the attributions to the other production factors.

The aim of this research is to investigate the change of the research quotients of firms in the United States in past decades, and the factors that drive such change. Understanding the levels of research quotients, as well as the influential variables on the research elasticity of revenue, is not only meaningful at the individual firm level when making capital budget decisions, but also important for policy makers to decide the quality of innovation input improvement. A caveat for the reader is that this paper is not about how R&D inputs would increase the firm value, but about how changing R&D inputs would affect the firm value.

The need to separately identify the independent impact of R&D is significant. This affects the individual firm decision when making capital budget, and the regulatory and public financial input decisions. However, the R&D impacts direct and indirect spillover effect, suggested by Eeckhout and Jovanovic (2002). In addition, Lentz and Mortensen (2008) document the impact of worker reallocation across firms that carries the transfer of intellectual assets, which is usually regarded as a type of R&D contribution. He and Brahmasrene (2018) find that R&D investments are more affected by infrastructure related TFP conditions. In addition, Oino (2019) indicates the strong capital input function as a growth driver.

Knott and Vieregger (2018) and Cooper et al. (2018) suggest the calculation of RQ by using the Cobb-Douglas function and control for firm's fixed effect, the capital input, the labor input, the lagged spillovers, and the advertising to separately identify the effect of the R&D. These works develop a new dimension of measuring the contribution of R&D that is orthogonal to other endogenous factors. Their development enables the measure of R&D impact independently. More importantly, their research quotient model allows for comparisons across different industries, when the business operations and realization of R&D are highly heterogeneous. The use of research quotient is widely accepted and promoted as a firm capital efficiency measure, such as Knott (2012), and Goldense (2018).

This study uses the WRDS Research Quotient database, which employs each firm-year data and uses rolling 10-year windows of the COMPUSTAT North American Annual database from 1965-2015 to build the research quotient of the U.S. firms from 1975 to 2015. In total, 58,776 annual R&D data from 5,853 firms are investigated. These data represent firms from 358 different industries identified by the four digit SIC code. This paper controls for the firm's fixed effect, the capital input, the labor input, the lagged spillovers, and the advertising, to separately identify the effect of the R&D.

Specifically, the annual average research quotient decreases from 1975 to 2015 across industries in the United States. In 1975, per 1% increase in R&D spending increases the firm average revenue by 0.1875%; however, such research elasticity of revenue decreases to 0.085% in 2015. From the year of 2004 to 2008, the average research quotient recovers to be as high as \$0.1237 increase in revenue per \$1 increase in R&D, yet such increase quickly diminishes to below \$0.10.

This research further explores the reason for such diminishing research quotient. The productivity of R&D competes with the contribution of capital and labor to a firm's revenue. On the one hand, when the cost of capital is lower, the function of R&D is compromised. This is partially due to the redundant R&D projects firms apply that result in negative net present values. Firm managers are incentivized to inflate the firm performance by promoting the R&D projects that might end up without positive capital gains with the easement of low financing cost. Another plausible explanation is that the lower cost of capital increases the revenue and profit of the firm, crowding out the contribution of R&D, by enhancing the quantity of revenue growth, rather than the quality.

Conversely, when the unemployment rate is high, proficient workers with better labor skillset can be recruited at lower cost. This contributes to the revenue and profit increase of the firms. Further, it compromises the revenue increase attribute to the R&D input, as the learn-by-doing effect is substituted with the existing intelligence and expertise of skillful workers. This is evidenced by the highest research quotient (0.3387) of the Sheet Metal Work Manufacture industry, which requires less working skill and no intensive human capital input, and the lowest research quotient (0.0007) of the Apparel Knitting Mills, which requires high working skill and great accumulation of human capital input.

This paper is organized as follows: section 2 explains the research quotient model and how it is computed; section 3 describes the data and methods of exploring the crowding out effect of the diminishing research quotient; section 4 presents the results and the industry rankings of research quotient; and section 5 provides clues for the further research.

2. The Research Quotient Model

According to Knott and Vieregger (2018), the variation of firm level output is decomposed into different components:

$$\mathrm{Y} = A_i K_{i,t}^{\alpha} L_{i,t}^{\beta} R_{i,t-1}^{\gamma} S_{i,t-1}^{\delta} D_{i,t}^{\phi} e_{i,t} \qquad (1)$$

where $Y_{i,t}$ is output, A_i is a firm fixed effect, $K_{i,t}$ is capital, $L_{i,t}$ is labor, $R_{i,t-1}$ is the lagged R&D, $S_{i,t-1}$ is lagged spillovers, and $D_{i,t}$ is advertising.

Again, according to Knott and Vieregger (2018), Equation (1) is estimated using a random coefficients model (Longford, 1993). The model includes heterogeneity in the output elasticity for R&D and treats coefficients as non-fixed and potentially correlated with the error term. Equation (1) is estimated as the regression function described in Equation (2):

$$\ln Y_{i,t} = (\beta_0 + \beta_{0,i}) + (\beta_1 + \beta_{1,i}) \ln K_{i,t} + (\beta_2 + \beta_{2,i}) \ln L_{i,t} + (\beta_3 + \beta_{3,i}) \ln R_{i,t-1} + (\beta_4 + \beta_{4,i}) \ln S_{i,t-1} + (\beta_5 + \beta_{5,i}) \ln D_{i,t} + \varepsilon_{i,t} \quad (2)$$

The β_3 and the $\beta_{3,i}$ represent the direct effect and the firm-specific error of the lagged impact of R&D to firm revenue. The research quotient that we report in this study is the sum of the β_3 and the $\beta_{3,i}$ coefficients, which are the joint effect of the change of R&D input to the change of the firm output. Specifically, the research quotients by selected industry, from 1975 to 2015, are presented in Table 1. The full list is provided in Appendix A. The industries with high research quotients need intensive capital input, infrastructure input, or high human intelligence capital input. Our study distinguishes the two types of human capital: intelligence and labor. The former is regarded as capital intensive as it needs long-time training, experience, and more advanced education degrees. The latter is labor intensive that demands more inputs of man-hours and a higher degree of labor strength. The industries with low research quotients need intensive inputs from labor force hiring and longer labor hours that cannot be replaced by capital, artificial intelligence, or standard assembly procedure.

Table 1: Research Quotients of the Firms in the United States by Selected Industry, 1975 to 2015

Industry	RQ
Sheet Metal Work manufacture	0.3387
Direct Life Insurance Carriers	0.2902
Publishers	0.2358
Hobby, Toy, and Game Stores	0.2340
Radio Stations	0.2336
Casino Hotels, Bed-and-Breakfast Inns, Motels, and other Traveler Accommodations	0.2217
Cable and Other Subscription Programming	0.2210
Investment Advice	0.2209
Home Health Care Services	0.2063
CPA and Other Accounting Services	0.1974
Computer and Peripheral Equipment manufacture	0.1867
Petroleum Refineries	0.1654
Tobacco manufacture	0.1637
Paint and Coating manufacture	0.1589
Office Supplies (Except Paper) manufacture	0.1550
Advertising Agencies	0.1477
Plastics Material and Resin manufacture	0.1468

Analytical Laboratory Instrument manufacture	0.1443
Electric Power Distribution	0.1434
Breweries	0.1294
Airplane manufacture	0.1273
Mining Machinery and Equipment manufacture	0.1138
Cookie and Cracker manufacture	0.1135
Full- and Limited-Service Restaurants, Drinking Place, Pharmacies and Drug Stores, Liquor Stores	0.1018
Engineering Services	0.0930
Soft Drink manufacture, Bottled Water manufacture	0.0818
Recyclable Material Merchant Wholesalers	0.0666
Medicinal and Botanical manufacture	0.0447
General Medical and Surgical Hospitals	0.0299
Meat Processed from Carcasses	0.0204
Waste Treatment and Disposal, Solid Waste Landfill, Materials Recovery Facilities,	0.0025
Apparel Knitting Mills	0.0007

3. Data and Methodology

This study uses the WRDS Research Quotient database, which employs each firm-year data and uses rolling 10-year windows of the COMPUSTAT North American Annual database from 1965-2015 to build the research quotient of the U.S. firms from 1975 to 2015. In total, 58,776 annual R&D data from 5,853 firms are investigated. These data represents firms from 358 different industries identified by the four digit SIC code.

The annual average research quotient across industries decreases over the past decades, as presented in Figure 1. We collect the money supply, interest rate, and unemployment rate to explore the reason. Such collection is valid based on the evidence of the Principal Components Analysis presented in Table 2. The first four components account for 100% of the total variation.

Table 2: The Principal Components Analysis of the Research Quotient

Eigenvalues: (Sum = 4, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.040850	1.204596	0.5102	2.040850	0.5102
2	0.836254	0.147190	0.2091	2.877104	0.7193
3	0.689064	0.255232	0.1723	3.566168	0.8915
4	0.433832	---	0.1085	4.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4
RQ	0.559421	-0.378410	0.148439	-0.722371
M3	0.461022	0.401174	-0.791372	-0.015745
INTR	0.541215	-0.484991	0.055810	0.684658
UNEMP	0.426138	0.678711	0.590408	0.095794

Ordinary correlations:

	RQ	M3	INTR	UNEMP
RQ	1.000000			
M3	0.323385	1.000000		
INTR	0.562521	0.311400	1.000000	
UNEMP	0.302112	0.306032	0.246575	1.000000

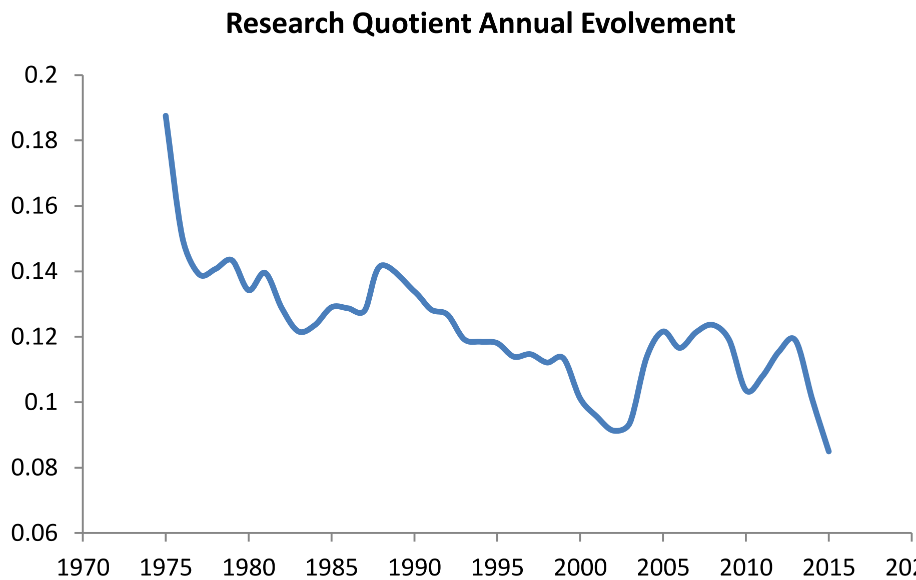

Figure 1: Annual Average Research Quotient from 1975 to 2015

This paper employs the non-seasonally adjusted 10 year U.S. Treasury Note yield as the interest rate and as the cost of financing for company operations and R&D expenses. The unemployment rate and the money supply (M3) are from the Fred database from Federal Reserve Bank of St. Louis.

We conduct a Bayesian vector autoregression (BVAR) model to identify the relationship between the interest rate, money supply, and unemployment rate.

The Bayesian vector autoregression (BVAR) uses Bayesian methods to estimate a vector autoregression model. (VAR). The major difference between a BVAR and a standard VAR, which is also the reason of our model of choice, is that the model parameters are regarded as random variables, and prior probabilities are assigned to them. This research first checks the stationary of the series, by employing the Augmented Dickey-Fuller test. The p value at 5% significance level is -2.9458 in the unit root test, utilizing the MacKinnon (1996) one-sided p value table. The Bayesian information criterion (BIC) is used to select the lag length. At 5% significance level, all the variables, except for the unemployment rate, cannot reject the null hypothesis of having unit root. This justifies the use of the BVAR against the standard VAR. The results are reported in Table 3.

Table 3: Unit Root Tests of the Crowding Out Effect Variables to Research Quotients

Variable	t-Statistic	P Value
Research Quotient	-1.108546	0.7018
10 year U.S. Treasury Note yield	-0.268861	0.9194
Money Supply (M3)	-2.490698	0.1256
Unemployment Rate	-3.241333	0.0256

In addition, as the research quotient data is only available at the annual average level, incorporating 40 years of data in our study likely creates the over-parameterization problem introduced normally by the standard VAR model. A BVAR uses informative priors to shrink the unrestricted model towards a parsimonious naïve benchmark, thereby reducing parameter uncertainty and improving forecast accuracy (Karlsson and Sune, 2015).

4. Results

The Bayesian VAR model output is presented in Table 4, with 2 lags selected.The main findings of the BVAR are:

Firstly, the research quotient is a time series that has positive memory from its lagged value. This implies that the firm revenue elasticity of demand is not a random process with no impact being carried forward from the past. The research quotient of a firm and an industry is relatively stable, at least in the short run. The means by which R&D expenditure impacts the firm's revenue in the current period is similar to the previous period. This is intuitively reasonable, as the R&D productivity of a firm or industry is determined by the industry's production nature and the operational process. It is less possible to observe a an industry's significant gap of research quotient unless an important new technology is developed to fundamentally change the style of production. However, even in that case, it is reasonable to believe that the firms in an industry do not unanimously adopt the new technology immediately in the innovation revolution.

Secondly, interest rate has a positive impact on the research quotient. In other words, higher cost of capital promotes the research quotient. The difficulty of incorporating new capital financed from the financial market causes the firm to generate more revenue from every dollar input of R&D activities. This can be interpreted as follows: firms have long lists of R&D initiatives and innovative projects requested by the internal employee or driven by external rivalry pressure. Some of the projects carry positive net present value for the firm with low uncertainty; while some of the projects do not have a clear and reliable measure of the net present value. Further, some of the projects likely generate negative net present value, but might still be considered, or even implemented, due to the favor of the decision maker for multiple reasons, including enhancing the performance and leadership of the firm. Faced with a less friendly financing environment, the firm needs to prioritize the projects. This might mean that the projects without promising future positive net present values are given less consideration and investment. This increases the revenue per unit input on the R&D.

Alternatively, the positive impact of the interest rate on the research quotient implies that at a low interest rate environment, firms incline to finance more and support the less promising R&D projects. This might be due to the initiative of betting against odds to generate revenue, or adding highlights for the management team. The BVAR suggests that there is a crowding out effect of capital on R&D productivity: the easier access to capital, the lower revenue the R&D expense can generate. Specifically, if you hold everything else constant, per 1% increase of financing cost increase, the research quotient increases by 0.001041. This implies that if the financing cost decreases by 100 basis points, then, on average, the revenue of a United States firm decreases by $1.041 per $1,000 increase of the R&D inputs invested in the firm.

Thirdly, unemployment rate does not play an active role in affecting the research quotient. In other words, how R&D affects the firm revenue is not significantly determined by the labor productivity. At the bottom of business cycle, when the unemployment rate is high and firms have easier access to high quality labor forces with lower cost, firms do not necessarily generate better revenue from increasing R&D expenses. This intuitively makes sense, because the use and development of technology is more impactful on innovative projects of the firm, rather than the use and recruiting of skillful workers. This conclusion is evidenced by observing Table 1, the research quotients of the firms by industry. The industries with more intensive use of man hour and labor, but less use of machine and technology generally have lower research quotient values. This conclusion is also evidenced by the robustness check in Table 5, where we find no significant connection among the change of research quotient and the CPI and GDP growth rate. In summary, business cycle indicated by the unemployment rate and cross-checked by CPI and GDP growth rate does not affect the effectiveness of R&D inputs.

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Table 4: BVAR Results of the Capital and Labor Productivity Crowding Out Effect on Research Quotient

Note: Standard errors in ( ) & t-statistics in [ ]. Regression coefficients at 5% level of significance are marked with *.

	RD	INTR	M3	UNEMP
RD(-1)	0.329930*	26.29031*	-0.383503	7.325641
	(0.07801)	(10.7353)	(18.3481)	(8.15848)
	[4.22912]	[2.44895]	[-0.02090]	[0.89792]
RD(-2)	0.051821	6.427111	6.377748	1.643485
	(0.04502)	(6.18267)	(10.5692)	(4.69960)
	[1.15095]	[1.03954]	[0.60343]	[0.34971]
INTR(-1)	0.001041*	0.571473*	0.140276	0.048010
	(0.00045)	(0.06268)	(0.10656)	(0.04738)
	[2.31300]	[9.11684]	[1.31641]	[1.01330]
INTR(-2)	0.000208	0.110213*	0.018236	0.007896
	(0.00032)	(0.04526)	(0.07667)	(0.03409)
	[0.64124]	[2.43531]	[0.23785]	[0.23161]
M3(-1)	9.92E-05	0.038632	0.253391*	0.019849
	(0.00033)	(0.04508)	(0.07755)	(0.03427)
	[0.30460]	[0.85692]	[3.26727]	[0.57921]
M3(-2)	6.98E-05	0.014636	0.044389	0.003647
	(0.00020)	(0.02707)	(0.04668)	(0.02057)
	[0.35699]	[0.54077]	[0.95083]	[0.17727]
UNEMP(-1)	7.22E-05	-0.007970	0.005724	0.421620*
	(0.00066)	(0.09174)	(0.15683)	(0.07013)
	[0.10893]	[-0.08687]	[0.03650]	[6.01215]
UNEMP(-2)	0.000311	0.000346	0.034345	0.012722
	(0.00043)	(0.05919)	(0.10118)	(0.04538)
	[0.72860]	[0.00584]	[0.33943]	[0.28031]
C	0.060617*	-2.295072	2.503961	2.049602*
	(0.00933)	(1.28714)	(2.20025)	(0.97877)
	[6.49925]	[-1.78308]	[1.13804]	[2.09407]

Table 5: Robustness Check of the Impact of Unemployment Rate on Research Quotient

	RQ	CPI	GDP
RQ(-1)	0.925713	25.63379	-78.6331
	(0.19290)	(23.8163)	(47.8741)
	[4.79881]	[1.07631]	[-1.64250]
RQ(-2)	-0.32074	-25.654	19.21136
	(0.15089)	(18.6292)	(37.4474)
	[-2.12562]	[-1.37708]	[0.51302]
CPI(-1)	0.000973	1.224754	-0.39733
	(0.00151)	(0.18608)	(0.37405)
	[0.64544]	[6.58188]	[-1.06224]
CPI(-2)	-0.00119	-0.23891	0.354310
	(0.00150)	(0.18526)	(0.37240)
	[-0.79469]	[-1.28956]	[0.95142]
GDP(-1)	-1.04E-05	-0.06724	0.284367
	(0.00068)	(0.08422)	(0.16929)
	[-0.01524]	[-0.79840]	[1.67972]
GDP(-2)	-0.00065	-0.02158	-0.09184
	(0.00065)	(0.07982)	(0.16045)
	[-1.01142]	[-0.27036]	[-0.57240]
C	0.061473	2.869708	13.08525
	(0.02190)	(2.70436)	(5.43613)
	[2.80642]	[1.06114]	[2.40709]

An impulse-response analysis of interest rate, money supply, and unemployment rate on the research quotient, presented in Figure 2, shows that money supply does not have significant and direct impact on the research quotient. This shows an important conceptual difference: in general, the availability of capital for the financial market does not represent the availability of capital for firms' financing. We choose the impulse-response structure, rather than the normal VAR structure presented in Table 4, because money supply is regarded as an exogenous variable. Therefore, this study employs the impulse-response structure to identify the impact of money supply on research quotient, as monetary policy and a firm's R&D effectiveness do not have ex ante interaction.

The result illustrated in Figure 2 shows that money supply does not drive the change of R&D effectiveness of a firm. While the relationship between money supply and interest rate is based on the classical price and quantity curve, the impact of interest rate on research quotient cannot be transmitted to the impact of money supply on research quotient. In other words, interest rate reflects the cost of financing by a firm, yet money supply does not reflect the availability of capital of a firm.

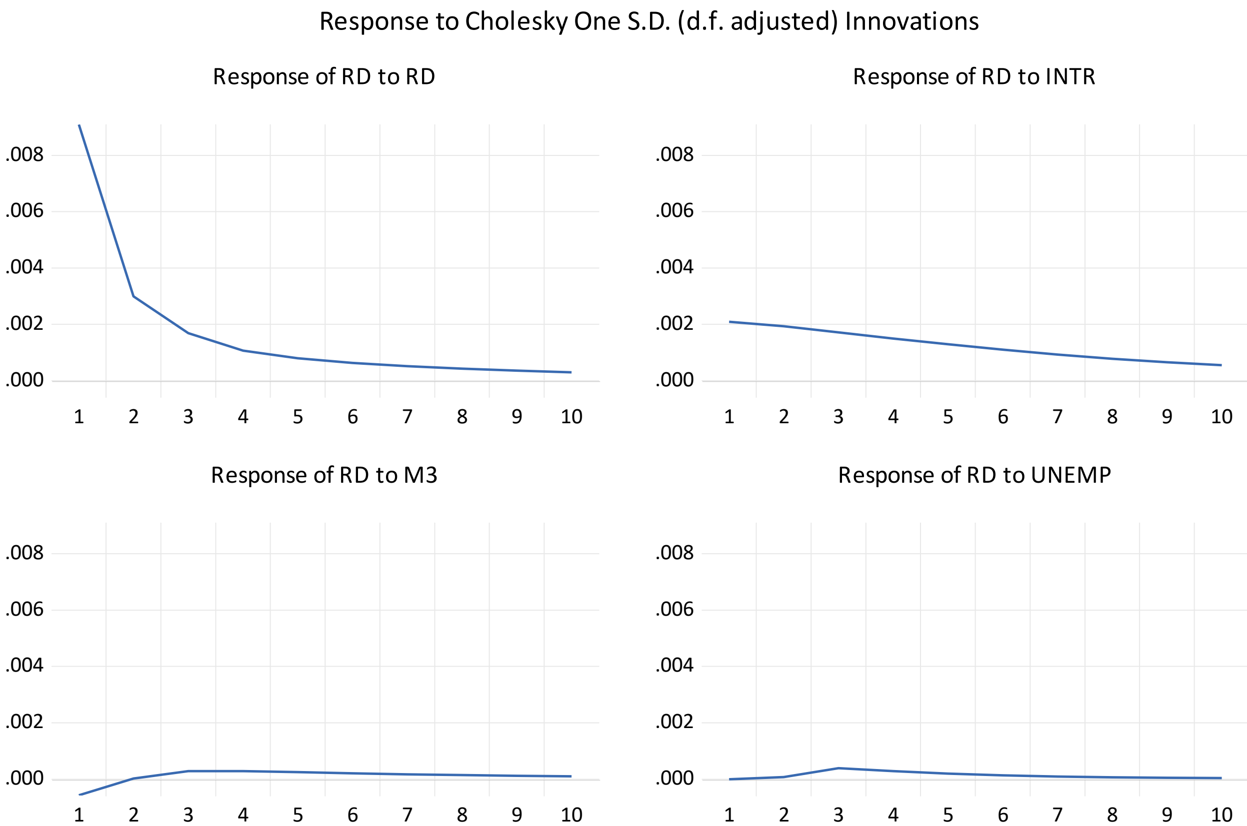

Figure 2: Impulse Response of Interest Rate, Money Supply, and Unemployment Rate on the Research Quotient

5. Concluding Remarks

This study uses the research quotient data of firms in the United States from 1975 to 2015 to measure the change of the R&D effectiveness and explore the reasons for such change. We find that in 1975, per 1% increase in R&D spending will increase the firm average revenue by 0.1875%; however, such research elasticity of revenue decreases to 0.085% in 2015.

We further find that when the cost of capital is low, the R&D effectiveness of a firm is compromised. The BVAR suggests that there is a crowding out effect of capital on R&D productivity: the easier access to capital, the lower revenue the R&D expense can generate. However, labor productivity does not have such crowding out effect on research effectiveness.

The results seem to show that the less capital is provided to the R&D department of a firm, the more productive the R&D activities would be; and the higher the labor productivities do not increase the R&D effectiveness. Both conclusions are inconsistent with normal understandings on the value and the expected outcomes of R&D activities a firm would conduct. In fact, we suggest the following reasoning on the controversial results:

Firstly, the efficiency of a firm utilizing capital for R&D activities depends on its capability of transforming capital inputs into revenue outputs, not the amount of capital that is provided. In fact, overly supplied capital on R&D tends to cause waste and low efficiency, rather than a better use of per unit R&D budget. The same reasoning holds that how well a child develops physically depends on how the body absorbs the nutrition, rather than the number of bottles of vitamin gels.

Secondly, we suggest the R&D core personnel stability theory. We argue that a firm tends to keep its core R&D force and key personnel for innovative activities. Even with fluctuations of the business cycle, employers are reluctant to fire the core R&D force. When the economic environment is unfavorable, firms might shrink the budgets for other departments, but will retain the core R&D positions. Therefore, in a period of high unemployment rate, while the firm can obtain a more skillful work force at a lower cost, these positions are largely irrelevant to the key R&D positions of the company.

the fluctuations of business cycle do not make the employers easily fire the core R&D force. In bad times of the economic environment, firms might shrink the budget for other positions, but will still keep the core R&D positions.

The next step of this study is to find evidence to support the two arguments proposed above. Specifically, further studies can focus on the empirical evidence that firms prioritize their R&D projects when faced with higher financing costs and constraints of R&D project funding. Also, further studies can focus on finding evidence for the R&D core personnel stability theory. However, it is a human resources topic, and requires massive amounts of time series data to show firms' firing decisions at a dynamic setting.

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