Industry Canada Industrie Canada

ECONOMIC RESEARCH AND POLICY ANALYSIS BRANCH

Working Paper Series

R&D Spending and M&E Investment in Canadian Manufacturing Industries

Malick Souare, Industry Canada

Weimin Wang, Industry Canada

Working Paper 2009-02

Canada

This publication is also available online in HTML: http://ic.gc.ca/eic/site/eas-aes.nsf/eng/h_ra02246.html

To obtain a copy of this publication or an alternate format (Braille, large print, etc.), please contact:

Economic Research and Policy Analysis Branch
Industry Canada
C.D. Howe Building
235 Queen Street
Ottawa, ON Canada
K1A 0H5

Telephone: 343-291-2627
Facsimile: 613-991-1261 and
E-mail: erpa-reap@ic.gc.ca

Cat. No. Iu172-1/2009-2E-PDF
ISBN 978-1-100-24928-5

Aussi offert en français sous le titre *Dépenses en R-D et investissements dans les M-M au sein des industries canadiennes de la fabrication*.

Government of Canada Gouvernement du Canada

Canada

Industry Canada

Economic Analysis and Statistics

R&D Spending and M&E Investment in Canadian Manufacturing Industries

Malick Souare, Industry Canada

Weimin Wang*, Industry Canada

Abstract

This paper elaborates a Vector Error Correction Model (VECM) in order to explore the causal relationship between research and development (R&D) expenditure and machinery and equipment (M&E) investment, and between these two variables and the skills. Within the same framework, we also investigate for other determinants of R&D and M&E. Thus, using data on Canadian manufacturing industries, the main empirical findings sum up as follows. First, we find evidence that R&D expenditure and M&E investment positively induce (Granger-cause) each other in the long run; but in the short run the causality occurs negatively in both ways, possibly due to resource constraints. Second, we find that skills is a key determinant of both R&D and M&E in the long run, and in the short run it also positively causes R&D. Further, there exists a positive long-run feed back from M&E to skills. Finally, we also find evidence that gross domestic product (GDP), competition, real exchange rates, and M&E capital depreciation seem to be other important determinants of R&D and M&E over time.

*Now with Statistics Canada

Table of Contents

1. Introduction

An important insight of the new growth theory or endogenous growth theory is that innovation (as measured, e.g., by research and development (R&D) spending) and the adoption and diffusion of new technologies (as measured, e.g., by investment in machinery and equipment (M&E)) are the major drivers of productivity improvements, especially over the long term[1]. For example, according to productivity experts, under-investments in both R&D activity and physical capital, particularly M&E, have contributed significantly to Canada's productivity gap with respect to the United States (U.S.), particularly in the manufacturing sector.

Although the role of innovation and diffusion of leading technologies as an engine of productivity improvements is both theoretically and empirically well established, an important related and unresolved issue is concerned with identifying the underlying factors that bring about these innovative activities. Related to this is the debate that surrounds the causal relationship between innovation (i.e. R&D spending) and investment in physical capital – in other words, what is the direction of causality between these two variables? These are important issues that need to be addressed, but unfortunately have received less attention in the existing literature. Moreover, a handful of empirical studies that have attempted to address these issues focused not only on the United States and United Kingdom data, but also resulted in conflicting results. The lack of agreement on these important issues sends an ambiguous message regarding policy choices to promote or manage innovation activities and hence to foster productivity. Therefore, country-specific studies become relevant.

For a country such as Canada, identifying the determinant factors of both R&D activity and investment in M&E is critical to understanding and analyzing the country's productivity problems and developing appropriate policies and strategies. Using Canadian manufacturing industry panel data, this paper investigates the factors that determine the R&D expenditure and M&E investment, with particular emphasis on the two-way relationship between these two variables.

The rest of the paper is organized as follows. In the next section we provide a brief review of the very few studies (both theoretical and empirical) that investigate the causal relationship between innovation and investment in physical capital (including M&E). Section 3 presents our empirical analysis on M&E investment and R&D expenditure in Canadian manufacturing industries. In this section, we outline the specifications of the models, describe the variables and data sources, and present the empirical results – which cover, among other things, the specific role of skills (measured as the share of hours worked by employees with a university degree and above) and some sensitivity tests across M&E-producing and -using industries. Finally, section 4 summarizes and concludes the paper.

[1] The neo-classical growth models focus on the accumulation of physical capital (including M&E) and emphasize the feature of diminishing returns, which implies that capital deepening would not be able to drive long-run productivity improvements.

2. A Brief Review of Literature

Previous studies that have investigated the determinants of both innovative activity and physical investment paid great attention to the causal relationship between these two variables. However, these studies have not reached a consensus on this relationship. For instance, Schmookler (1966) emphasized the relationship between innovation and investment in the business cycle context. He argued that innovation activity is endogenous, driven predominantly by demand conditions. This hypothesis was empirically supported by the positive correlation found between cycles of innovative effort (as proxied by patents) and cycles of output across industries producing capital goods. The shape of the long-term trend of these two indicators showed that cycles of output were leading cycles of relevant patenting activity in the capital goods industries. In other words, Schmookler claimed that investment in new capital goods (on the part of other firms or industries, for example) is the driving force behind (successful) innovations.

However, many endogenous growth models (see e.g., Romer (1990) and Grossman and Helpman (1991)) create a vertical link between innovative activity and physical investment. In fact, they assume that knowledge or designs generated by the action of profit maximizing firms in the R&D sector is used to produce new capital goods that serve as input in the production of final output. Therefore, it is implicitly assumed that the causality runs from R&D to physical investment.

Furthermore, some empirical studies have attempted to ascertain the causal relationship between innovation and investment. We begin with studies that focused on the United States case. Lach and Schankerman (1989), employing reduced-form vector autoregressive (VAR) models, investigate the dynamic relationship between (the logs of expenditures of) R&D and investment for a panel of 191 firms in science-based industries during the period 1973–81[2].

They find that R&D induces (Granger-causes) physical investment, but physical investment does not induce R&D. In other words, physical investment depends on the success of previous R&D efforts, in addition to the factors that determine investment.

Since the above evidence is derived from firm-level data, Lach and Rob (1996) attempt to ascertain whether the same feature of the relationship between the two variables exist at the industry-level as well. Towards this goal, they use data on 20 U.S. manufacturing industries (at the two and three digit level of the SIC for the period 1958–1983) and employ the same methodology as in Lach and Schankerman (1989). Their findings confirm that past R&D expenditures matter for current investments in machinery and equipment, but past investments do not affect current R&D. Or, R&D (Granger) causes capital investment and *not* the other way around.

However, Mairesse and Siu (1984), investigating the determinants of both R&D and physical investment, report different results on the causality between these two variables. Based on a sample of 93 firms with data from 1962 to 1977 and using VAR formulation, they do not detect any significant feedback interaction between the rates of growth of R&D and physical investment. Nonetheless, they find that both expected demand (as proxied by the growth of sales) and profitability (as proxied by the stock market one-period holding rate of return) appear to be important determinants for R&D expenditures and physical investment. Besides, Beggs (1984) argues that a fundamental shortcoming of the Mairesse and Siu (1984) framework is the complete lack of recognition of the competitive environment in which a firm exists.

Later, Chiao (2001) challenges the one-way inducement (from R&D to physical investment) raised by Lach and Schankerman (1989) and Lach and Rob (1996) – hereafter LSLR. Using a more complete panel data of firms in science-based industries, Chiao (2001) re-estimates the VAR suggested by LSLR and find that their results do not hold, after extending the sample that matches their criteria by including more time periods and/or more firms. More specifically, it is demonstrated that the (Granger) causality between R&D and investment occurs both ways – i.e. current R&D spending responds to past physical investments and vice versa. Further, using a dynamic simultaneous approach, Chiao (2001) reports evidences of the two-way contemporary and intertemporary relationships between the two variables, i.e., current and previous R&D (Granger) causes current physical investment and current and previous physical investment (Granger) causes current R&D[3].

A final U.S. study we consider is Baussola (2000). This paper provides new insights for the understanding of the relationship between R&D and investment, using aggregate data for the United States economy on industrial R&D expenditures and investments in M&E over the period 1953–1993. Baussola (2000) rightfully argues that the bulk of existing studies that address the empirical relationship between R&D and physical investment involve an unappealing feature in that they all use the *differentiated* VAR formulation. However, the causality test conducted with such a specification only indicates short run causal relationship between these two crucial economic variables, as the long-run components of the series may have been removed – through the required or suitable stationary transformation. Therefore, to take into account a possible long-run relationship, Baussola (2000) considers the existence of cointegration between the two variables and uses causality tests that incorporate long run effects. Using first the standard (Granger) causality approach, his results indicate a clear direction of causality from R&D to investment, and a feed-back relationship is rejected. That is, in the short run it is only R&D that induces investment. However, when he performs the causality tests in a cointegrating framework – which includes an error correction term, accounting for any long-run link – the results again show short run causality running from R&D to investment only. But more importantly, there is also evidence of two-way long-run feedback between the two variables. Although, Baussola (2000) made an improvement over the existing literature, his approach may be improved by accounting for other determinants of both R&D and M&E investment.

Now consider the following two UK studies. Nickell and Nicolitsas (1996) use a panel of British industrial firms to show that R&D expenditure positively affects investment in most UK industries and that the reverse relationship does not hold. However, this empirical finding for the UK economy seems time and firm specific. Using a different panel of UK firms (namely 185 firms over 1984–1992) to replicate the LSLR dynamic analysis conducted with U.S. data, Toivanen and Stoneman (1998) find that investment induces (Granger causes) R&D and not the reverse.

In the next sections, we contribute to the aforementioned literature by investigating the dynamic relationship between R&D and M&E using data on the Canadian economy. Moreover, we improve over the bulk of the existing studies in this area by exploring other factors that determine the R&D spending and M&E investment within the same empirical framework.

2 Their scientific sector sample comprises firms in the chemical, drug, communications, computer, scientific instruments, and electric components industries.

3 It is worth mentioning that by construction, a reduced-form VAR framework – which allows testing Granger causality or temporal precedence – overlooks the contemporaneous relations between variables.

3. Empirical Analysis

As emphasised previously, the causal link between M&E investment and R&D expenditure is one of the important implications of endogenous growth theory and should be taken into account in empirical studies that aim to explore behaviours of M&E investment and R&D expenditure. In this section we present our empirical analysis on M&E investment and R&D expenditure in Canadian manufacturing industries.

3.1. The Model

Vector autoregressive (VAR) models are often used in the literature to incorporate causal links between M&E investment and R&D expenditure. For our purpose, a VAR system is written as:

$$(1)\quad \begin{cases} \ln\left(RD_{it}\right)\alpha_{1i} + \sum\limits_{m=1}^{M}\left(\beta_{1m}\ln\left(RD_{it-m}\right) + \gamma_{1m}\ln\left(ME_{it-m}\right)\right)\sum\limits_{p=1}^{P}\left(a_{1p}\ln\left(x_{pit}\right) + b_{1p}\ln\left(x_{pit-1}\right)\right) + \mu_{it} \\ \ln\left(ME_{it}\right)\alpha_{2i} + \sum\limits_{m=1}^{M}\left(\beta_{2m}\ln\left(RD_{it-m}\right) + \gamma_{2m}\ln\left(ME_{it-m}\right)\right)\sum\limits_{p=1}^{P}\left(a_{2p}\ln\left(x_{pit}\right) + b_{2p}\ln\left(x_{pit-1}\right)\right) + \upsilon_{it} \end{cases}$$

where t and i represent time and industry respectively, RD is business expenditures on R&D, ME is investments in M&E, x is a set of exogenous variables including GDP, skills (measured as the share of hours worked by employees with a university degree and above), competition, real exchange rates and real interest rates, α_{1i} and α_{2i} are industry-specific intercepts, and and μ_{it} are υ_{it} the disturbances with zero means. The system (1) can be estimated using either single-equation methods such as OLS, WLS, 2SLS, W2SLS and LIML or full-system methods such as 3SLS and FIML.[4] Single-equation methods estimate one equation at a time; while full- system methods estimate all equations simultaneously and hence potentially yield more efficient estimates when there are cross-equation restrictions.

Note that both temporal and one-year-lagged values of each exogenous variable are included in the system that allows us to explore both short- and long-term impacts of each exogenous variable on R&D expenditure and M&E investment. Testing the null hypothesis $a_{1p} + b_{1p} = 0\ \left(\text{or } a_{2p}\ b_{2p} = 0\right)$ can tell whether the variablex_p has significant impact on R&D expenditure (or on M&E investment) in the long run.

The standard Granger causality test can be performed using the VAR system (1). By definition, R&D expenditure does not Granger cause M&E investment if all β_2 are zero, and M&E investment does not Granger cause R&D expenditure if all γ_2 are zero. The Granger causality test will be affected by the choice of number of lags for the dependent variables. To choose the optimal lag length based on the VAR system (1), various criteria or test statistics are calculated and are shown in Table 1. All criteria and the LR test statistics suggest that the optimal lag length for the VAR system (1) is two, i.e., M=2.

Generally the two dependent variables are not stationary. Unit root test results suggest that the first difference of the two dependent variables are stationary, hence the system (1) needs to be differentiated. After the transformation, the coefficients of exogenous variables can still be interpreted as elasticity. The coefficient of $\Delta\ln\left(x_{pt}\right)$ is the temporal elasticity of R&D or M&E with respect to x_p. The long-run elasticity is proportional to the sum of the coefficients of $\Delta\ln\left(x_{pt}\right)$ and $\Delta\ln\left(x_{pt-1}\right)$; testing whether the sum is null indicates whether the exogenous variable x_p has long-run impact on R&D or M&E.

However, the differentiated VAR system neglects the long-run feedbacks or causality between the two dependent variables. The long-run causality between R&D activity and M&E investment is an important aspect of the interaction between the two variables. Endogenous growth models (see, e.g., Romer (1990) and Grossman and Helpman (1991)), predict that R&D promotes investment in new capital goods. Nevertheless, it takes time to generate knowledge that can be used for producing new capital through R&D activities. On the other hand, successful (profitable) investment in new capital induces more R&D activities due to higher returns. And, it also takes time for an investment in new capital to be successful. Therefore, the interaction between R&D expenditure and M&E investment may mainly show up in the long run and may possibly not show up in the short-run. Thus, to explore the long-run causality between R&D expenditure and M&E investment, we add the cointegration equation between the two variables into the differentiated version of the VAR system (1), i.e.

$$(2)\quad \begin{cases} \Delta \ln\left(RD_{it}\right) = \alpha'_{1i} + \delta_1\left[\ln\left(RD_{\mathrm{it}-1}\right) - \lambda \ln\left(ME_{it}-1\right)\right] \\ \quad + \sum_{m=1}^{M}\left(\beta'_{1m}\Delta \ln\left(RD_{\mathrm{it}-m}\right)\gamma'_{1m}\Delta \ln\left(ME_{\mathrm{it}-m}\right)\right) \\ \quad + \sum_{p=1}^{P}\left(a'_{1p}\Delta \ln\left(x_{pit}\right) + b'_{1p}\Delta \ln\left(x_{\mathrm{pit}-1}\right)\right) + \xi_{it} \\ \Delta \ln\left(ME_{it}\right) = \alpha'_{2i} + \delta_2\left[\ln\left(RD_{it-1}\right) - \gamma \ln\left(ME_{\mathrm{it}-1}\right)\right] \\ \quad + \sum_{m=1}^{M}\left(\beta'_{2m}\Delta \ln\left(\mathrm{RD}_{\mathrm{it}-m}\right) + \gamma'_{2m}\Delta \ln\left(ME_{\mathrm{it}-m}\right)\right) \\ \quad + \sum_{p=1}^{P}\left(a'_{2p}\Delta \ln\left(x_{pit}\right) + b'_{2p}\Delta \ln\left(x_{pit-1}\right)\right)\varsigma_{it} \end{cases}$$

The system (2) is called the vector error correction model (VECM). The cointegration equation, $\ln\left(RD_{it}\right) - \lambda \ln\left(ME_{it}\right)$, represents the long-run equilibrium path of the two variables and can be estimated using the Johansen procedure. The cointegration coefficient, λ, is expected to be positive, meaning that R&D expenditure and M&E investment are complement to each other in the long-run. The cointegration equation can also be interpreted as an error correction term. If one of the two variables deviates from the long-run equilibrium, the other variable would change correspondently to push their relationship back to the long-run equilibrium path. So the coefficient of the cointegration equation in the R&D equation $\left(\delta_1\right)$ is expected to be negative, and that in the M&E equation $\left(\delta_2\right)$ is expected to be positive – Thus, these coefficients ‘measure' the speed of adjustment towards the equilibrium path.

3.2. Variables and Data Sources

A panel data set is created for the purpose of this paper. The data set covers the period of 1963 to 2003 and 18 manufacturing industries that are 3-digit NAICS based with some combination according to data availability. Except the regulation/competition index, the source of all other data is Statistics Canada.

The two dependent variables in our models are *R&D expenditure* and *M&E investment*. Total intramural business expenditure on R&D is used for the variable *R&D expenditure* and the non-residential investment in machinery and equipment is used for the variable *M&E investment*.

The R&D data we have is NAICS based for the period 1994 to 2003 and SIC based for the period of 1963-1993. The NAICS-based data is extended back to 1963 using the growth rates of SIC-based data. The nominal values of R&D are deflated using industrial GDP deflators.

There are six variables that are use as exogenous determinants of R&D expenditure and M&E investment, i.e., *GDP*, *skill*, *competition*, *the real exchange rate*, *the real interest rate*, and *M&E depreciation*. The inclusion of GDP is to control the scale effect because larger industries (in terms of GDP) tend to spend more on R&D and invest more in M&E [5]. Skilled labour is important to both R&D activity and M&E investment. R&D activity is to generate new knowledge, technology and products and people who conduct R&D have to be highly skilled by the nature of R&D. The importance of skilled labour to M&E investment comes from the capital- skill complementarity that has been well discussed and documented in the literature since Grilliches (1969). Following the convention, we measure the skill variable using the hours worked share of workers with at least a university degree in total [6].

The degree of competition may force firms to improve their competitiveness by doing more R&D and using more new technologies embodied in new M&E capital, so we include the *competition* variable in our model to control the effect of competition. The *competition* variable is calculated as the inverse of the regulation impact indicators from OECD that measure the extent of anti (or pro)-competitive product market regulations [7]. The OECD data is ISIC Rev3 based and covers the period of 1975 to 2003.

Both M&E investment and R&D spending in Canadian manufacturing industries involve purchases from the U.S. and hence may be affected by the movement of the Canada-U.S. bilateral exchange rate. So the real bilateral exchange rate is included in our model to capture such impact. The *real exchange rate* is obtained by deflating the nominal exchange rate using industrial product price index (IPPI) for total manufacturing of the two countries. The nominal exchange rate is defined as the amount of Canadian dollar required in exchange for one U.S. dollar. As a result, an increase in the *real* *exchange rate* indicates a depreciation of the Canadian dollar relative to the U.S. dollar in real term.

The real interest rate is generally considered as the cost of borrowing. A higher real interest rate will reduce the present values of gains from more M&E investment and R&D spending and hence discourage M&E investment and R&D spending. On the other side, a high real interest rate may be necessary for households to save more to meet an increase in demand for M&E investment and R&D spending. As a result, we may observe the co-movement between the real interest rate and M&E investment and R&D spending. In this paper we focus on the long-run impact of the real interest rate and use the 10-year average yield to Government of Canada marketable bonds, deflated using IPPI for total manufacturing, as our measure of the *real interest rate*.

The inclusion of the M&E capital depreciation is to control for the replacement demand for M&E investment because this part of M&E investment is simply to keep production constant.

3.3. Empirical Results

The OLS and FIML estimation results of the VAR system (1) are shown in Table 2. Note that the coefficients on all variables are the same and the p-values are slightly different in the two sets of estimations. Both sets of estimation results show that: (1) GDP has positive and significant impact on both R&D expenditure and M&E investment in the short-run as well as in the long-run; (2) the skills variable has positive and significant impact in both the short-run and the long-run on R&D expenditure, but not on M&E investment[8]; (3) the competition variable has positive and significant impact on M&E investment, but not on R&D expenditure; (4) the impact of the real exchange rate on both R&D expenditure and M&E investment is negative and significant in the short-run, but not significant in the long-run[9]; (5) the real interest rate has positive and significant impact in both the short-run and the long-run on R&D expenditure[10], but not on M&E investment; and (6) the M&E capital depreciation has positive and significant impact in both the short-run and the long-run on M&E investment, but not on R&D expenditure. The Granger causality test results (the null hypotheses: $\gamma_{11} = 0$ and $\gamma_{12} = 0$ in R&D equation and $\beta_{21} = 0$ and $\beta_{22} = 0$ in M&E equation) show that R&D expenditure Granger causes M&E investment while M&E investment does not Granger cause R&D expenditure.

The estimation results of the VECM system (2) are presented in Table 3. There are two differences between the VECM and the VAR estimation results regarding the impact of the exogenous variables. First, the impact of competition variable on M&E investment is not significant at the 10% level in the VECM estimation. Second, the M&E capital depreciation has negative and significant impact on R&D expenditure in the VECM estimation. Such negative impact of the M&E capital depreciation on R&D expenditure seems not straightforward. To understand this, we can assume that the total M&E investment can be decomposed into two parts: new-capital-related M&E investment and replacing-forgone-capital-related M&E investment. The first part of M&E investment and R&D expenditure should be complement to each other, as explained in the new growth theory, while the second part of M&E investment does not require extra R&D but compete with R&D activities for resources. The increase in M&E depreciation would cause more second part of M&E investment and hence less resources available for R&D (with other things being equal). In reality we do not have the decomposed data of M&E investment, so the two opposite effects may offset each other and therefore not show up in empirical works. That is probably the situation in the VAR estimation. The negative effect of the M&E depreciation on R&D expenditure becomes significant in VECM estimation, might because the long-run complementarity relationship between M&E investment and R&D expenditure is controlled for.

Now we focus on the causality between R&D expenditure and M&E investment in the VECM estimation. As shown in Table 3, the coefficients on the cointegration equations (or the error-correction terms) are statistically significant with the right signs in both equations, implying that the two variables do react positively to each other to keep their long-run equilibrium relationship. The short-run causality tests show that M&E investment does not Granger cause R&D expenditure, while R&D expenditure Granger causes M&E investment negatively. However, we find that the negative causality runs from M&E investment to R&D expenditure in the short-run when the M&E depreciation is excluded in the R&D equation. The negative causality between R&D expenditure and M&E investment possibly indicates that the two types of activities compete for resources in the short-run. This argument finds support in Chiao (2001), who argues that investment projects (including R&D and M&E investments) are subject to the sufficiency of many resources, including financial, physical, and human resources, the extent to which may alter the contemporary and over-time relationship between R&D and physical investment. As a result, e.g., the crowding-out effect or substitutability between current or short-run R&D and physical investment (including M&E) may arise, partly due to the consideration in the optimal allocation of current and future resources. In summary, R&D expenditure and M&E investment are complement to each other in the long run but compete for resources in the short-run.

3.4. The Role of Skills

Both Table 2 and Table 3 indicate that the skills variable has significant impact on R&D expenditure, but not on M&E investment. This is not consistent with the so-called capital-skill complementarity hypothesis [11]. A possible reason for the inconsistency may be because that the skills are assumed to be exogenous to M&E investment in our model and such an assumption neglects possible feedbacks between skills and M&E investment. To investigate this issue we assume the skills variable is also endogenous, and rewrite the VECM system (2) as:

$$
(3) \quad \begin{cases}
\Delta \ln(RD_{it}) = \widetilde{\alpha}_{1i} + \delta_1 [\ln(RD_{it-1}) - \lambda_1 \ln(\text{Skills}_{it-1})] + \delta_2 [\ln(ME_{it-1}) - \lambda_2 \ln(\text{Skills}_{\text{it}-1})] \\
\quad + \sum_{m=1}^{M} \left(\tilde{\beta}_{1m} \Delta \ln(RD_{it-m}) + \tilde{\gamma}_{1m} \Delta \ln(ME_{it-m}) + \tilde{\theta}_{1m} \Delta \ln(\text{Skills}_{it-m}) \right) \\
\quad + \sum_{p=1}^{P} \left(\tilde{a}_{1p} \Delta \ln(x_{pit}) + \tilde{b}_{1p} \Delta \ln(x_{pit-1}) \right) + \xi_{it} \\
\Delta \ln(ME_{it}) = \widetilde{\alpha}_{2i} + \delta_3 [\ln(RD_{it-1}) - \lambda_1 \ln(\text{Skills}_{it-1})] + \delta_4 [\ln(ME_{it-1}) - \lambda_2 \ln(\text{Skills}_{it-1})] \\
\quad + \sum_{m=1}^{M} \left(\tilde{\beta}_{2m} \Delta \ln(RD_{it-m}) + \tilde{\gamma}_{2m} \Delta \ln(ME_{it-m}) + \tilde{\theta}_{2m} \Delta \ln(\text{Skills}_{\text{it}-m}) \right) \\
\quad + \sum_{p=1}^{P} \left(\tilde{a}_{2p} \Delta \ln(x_{pit}) + \tilde{b}_{2p} \Delta \ln(x_{pit-1}) \zeta_{it} \right) \\
\Delta \ln(\text{Skills}_{it}) = \widetilde{\alpha}_{3i} + \delta_5 [\ln(RD_{\text{it}-1}) - \lambda_1 \ln(\text{Skills}_{it-1})] \delta_6 [\ln(ME_{it-1}) - \lambda_2 \ln(\text{Skills}_{it-1})] \\
\quad + \sum_{m=1}^{M} \left(\tilde{\beta}_{3m} \Delta \ln(RD_{it-m}) + \tilde{\gamma}_{3m} \Delta \ln(ME_{it-m}) + \tilde{\theta}_{3m} \Delta \ln(\text{Skills}_{\text{it}-m}) \right) \\
\quad \sum_{p=1}^{P} \left(\tilde{a}_{3p} \Delta \ln(x_{pit}) + \tilde{b}_{3p} \Delta \ln(x_{pit-1}) \right) + \varsigma_{it}
\end{cases}
$$

Note that there are two error-correction terms in the system, one is the long-run cointegration between R&D and skills, and the other is the long-run cointegration between M&E and skills [12]. The cointegration coefficients, λ_1 and λ_2, are expected to be positive, implying that both R&D and M&E are complement to skills. The values of δ_1 and δ_4 are expected to be negative, indicating that the long-run causality runs positively from the skills to R&D and M&E, respectively. The values of δ_5 and δ_6 are expected to be positive, implying that the long-run causality runs positively from R&D and M&E, respectively, to skills.

To derive the long-run causality from M&E to R&D, we can rearrange the two cointegration equations in the R&D equation as

$$
\delta_1 \left[\ln(RD_{it-1}) - \tfrac{\lambda_1}{\lambda_2} \ln(ME_{\text{it}-1}) \right] + \left(\delta_2 + \delta_1 \tfrac{\lambda_1}{\lambda_2} \right) [\ln(ME_{\text{it}-1}) - \lambda_2 \ln(\text{Skills}_{\text{it}-1})]
$$

which implies that the value of δ_1 would also indicate the long-run causality from M&E to R&D if ${}^{\lambda_1}/_{\lambda_2}$ is significant. Similarly, the value of δ_4 would indicate the long-run causality from R&D to M&E if ${}^{\lambda_2}/_{\lambda_1}$ is significant.

The OLS estimation results of the VECM system (3) are presented in Table 4. Note that the impacts of all exogenous variables on R&D expenditure and M&E investment remain almost unchanged. Also, the long- and the short-run causalities between M&E and R&D are the same as the previous estimation, i.e., in the long-run the two variables positively cause each other, while in the short-run there is no causality running from M&E to R&D and there is a negative causality running from R&D to M&E. As for the impact of and on the skills, the test results show that in the short-run the skills positively Granger cause R&D, but no causality runs from both R&D and M&E to the skills and from the skills to M&E. In the long-run the skills and M&E Granger cause each other positively, the skills cause R&D positively but R&D does not cause the skills. The finding of the positive long-run causality between the skills and M&E reconciles this paper with the capital-skill complementarity hypothesis and the empirical works along the line in the literature.

Finally, in the next sub-section, we examine the robustness of the two-way relationship between R&D expenditure and M&E investment across different categories of industries.

3.5. M&E Producing Industries vs. M&E Using Industries

In this subsection we try to break down all manufacturing industries into two groups (M&E capital-producing industries and -using industries) and explore possible differences in R&D spending and M&E investment and inter-group impact. There are four industries that are considered to be capital-producing industries, i.e., machinery manufacturing, computer and electronic product manufacturing, electrical equipment, appliance and component manufacturing and transportation equipment manufacturing. All other manufacturing industries are considered to be capital-using industries.

We estimate the VECM system (3) for the two groups separately. The total GDP of the four capital-producing industries is added into the system as an exogenous variable for the capital-using industries. This variable indicates total M&E produced in Canada and is expected to positively correlate with M&E investment in the capital-using industries. The OLS estimation of the VECM system (3) for the capital-using industries is presented in Table 5. The results show that the impact of the total GDP of the capital-producing industries (GDPP) is positive and statistically significant on M&E investment of the capital-using industries. Its impact on R&D expenditure of the capital-using industries is negative but not significant. The negative sign is consistent with the story that M&E investment and R&D expenditure compete with each other for resources in the short-run. The inferences derived from the Table 5 on the impact of all other exogenous variables and the short- & long-run causalities between R&D and M&E are the same as those for all industries.

The total M&E investment of capital-using industries is added as an exogenous variable when estimating the VECM system (3) for the capital-producing industries. This variable indicates the total demand for M&E from the capital-using manufacturing industries. The OLS estimation results are presented in Table 6. As shown in the table, the total M&E investment of the capital-using industries has positive and significant impact on the M&E investment in the capital-producing industries. We may interpret this as a demand-driven effect. Capital-producing industries may invest more in M&E to meet an increased demand for their output. The behaviour of M&E investment in capital-producing industries is different from those in all other industries in several aspects. First, there is no causality from R&D to M&E in both the short-run and the long-run in the capital-producing industries. Second, the impact of GDP is not significant, and third, the impact of the skills becomes significant. On the other hand, the behaviour of R&D expenditure in the capital-producing industries is the same as all other industries. It is worth mentioning that in the capital-producing industries, R&D expenditure responds negatively to a change in M&E investment, indicated by the negative coefficients of M&E investment, M&E depreciation and total M&E investment in the capital-using industries. In summary, M&E investment in the capital-producing industries is driven by demand (M&E investment in the capital-using industries) other than supply (own R&D expenditure), while R&D expenditure just follows.

4 OLS denotes Ordinary Least Squares, WLS is Weighted Least Squares, 2SLS is Two-Stage Least Squares, LIML is Limited-Information Maximum Likelihood, and FIML denotes Full-Information Maximum Likelihood.

5 We include GDP directly in the models instead of using R&D to GDP ratio and M&E investment to GDP ratio. The latter is equivalent to restrict the coefficients of GDP to be one in both equations and may overestimate the scale effect.

6 It is quite common to use educational attainment to differentiate between skilled and unskilled workers, for example, see Duffy et al. (2004).

7 For further details on the construction of regulation impact indicators, see Conway *et al*. (2006). However, it is worth mentioning that the scale of regulation impact indicator is 0-1 from least to most restrictive, which indicates that a high value of this indicator reflects a less competitive environment. Therefore, for ease of interpretation, competition intensity is defined in our empirical analysis as the reciprocal of the regulation impact indicator, so that a high value indicates greater competition.

8 See more discussions on the impact of skills on R&D and M&E later in the paper.

9 The real exchange rate is defined as Canadian $ / U.S. $, so it increases as the Canadian dollar depreciates. The negative impact of the real exchange rates implies that R&D expenditure and M&E investment will drop when the Canadian dollar depreciates relative to the U.S. dollar.

10 Alexandrakis (2003) has the same findings on the relationship between the long-run real interest rate and R&D using U.S. data.

11 The hypothesis, which has been well discussed since Grilliches (1969), suggests that capital and skilled labour are more complementary than are capital and unskilled labour. There are empirical evidences that support the hypothesis, for example, see Flug and Hercowitz (2000), Duffy et al. (2004), Papageorgiou and Chmelarova (2005), and Krusell et al. (2000).

12 Another possible specification is to add just one error-correction term involving all three endogenous variables. However, such specification is not helpful for understanding the pair-wise causalities among them.

4. Summaries and Conclusions

In this paper we explore the factors that determine the R&D expenditure and M&E investment, with particular emphasis on the two-way relationship between these two variables, using data on the Canadian manufacturing industries. The interest in this issue arises, on the one hand, from the fact that innovation (as measured, e.g., by R&D spending) and the adoption and diffusion of new technologies (as measured, e.g., by M&E investment) have been identified as key drivers of productivity improvements. On the other hand, there seems to have a consensus that under-investments in both R&D activity and M&E, have significantly contributed to Canada's productivity gap with respect to the U.S., particularly in the manufacturing sector.

Therefore, for a country such as Canada, identifying the determinant factors of both R&D activity and investment in M&E is critical to understanding and analyzing the country's productivity problems and developing appropriate policies and strategies.

Towards this aim, we develop a Vector Error Correction Model (VECM) to explore the causal relationship between R&D expenditure and M&E investment and between these two variables and the skills (which is measured as the share of hours worked by employees with a university degree and above). Within the same framework, we also investigate for other determinants of R&D and M&E. Our main empirical results are as follows. First, we find evidence that R&D expenditure and M&E investment positively induce (Granger-cause) each other in the long run; but in the short run the causality occurs negatively in both ways, possibly due to resource constraints. Second, we find that the skills is a key determinant of both R&D and M&E in the long run, and in the short run it also positively causes R&D. Further, there exists a positive long-run feed back from M&E to skills. Finally, we also find evidence that GDP, competition, real exchange rates, and M&E capital depreciation seem to be other important determinants of R&D and M&E over time.

References

Alexandrakis, C. (2003) "R&D and Real Interest Rate in the U.S.: Theory and Empirics", Working Paper 03-15, Emory University.

Beggs, J. (1984) Comment on – Mairesse, J. and A. Siu (1984) "An Extended Accelerator Model of R&D and Physical Investment", *R&D, Patents, Productivity* (Ed.) Z. Griliches, The University of Chicago Press, Chicago, pp. 271–97.

Baussola, M. (2000) "The Causality Between R&D and Investment", *Economics of Innovation and New Technology*, 9 (4), pp. 385–399.

Bernstein, J. and M. Nadiri (1984) "Rate of Return, Research and Development and Structure of Production", in *Temporary Equilibrium and Costs of Adjustment* (Eds) Bernstein, J. and M. Nadiri, MIT Press, Boston.

Chiao, C. (2001) "The Relationship between R&D and Physical Investment of Firms in Science- Based Industries", *Applied Economics*, 33 (1), pp. 23–35.

Conway, P., De Rosa, D., Nicoletti, G. and F. Steiner (2006) "Regulation, Competition and Productivity Convergence", OECD Economics Department Working Paper No. 509.

Duffy, J., Papageorgiou, C., and F. Perez-Sebastian (2004) "Capital-Skill Complementarity? Evidence from a Panel of Countries", *Review of Economics and Statistics*, v. 86 (1), pp. 327–44.

Griliches, Z. (1969) "Capital-Skill Complementarity", *Review of Economics and Statistics*, v. 51 (4), pp. 465–68.

Grossman, G. and E. Helpman (1991) *Innovation and Growth in the Global Economy*, Cambridge, Mass. and London: MIT Press.

Flug, K., and Z. Hercowitz (2000) "Equipment Investment and the Relative Demand for Skilled Labour: International Evidence", *Review of Economics Dynamics*, v. 3 (3), pp. 461–485.

Krusell, P., Ohanian, L., Rios-Rull, J. and G. Violante (2000) "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis", *Econometrica*, v. 68 (5), pp. 1029–53.

Lach, S. and R. Rob (1996) "R&D Investment and Industry Dynamics", *Journal of Economics and Management Strategy*, vol. 5, pp. 217-249.

Lach, S. and M. Schankerman (1989) "Dynamics of R&D and Physical Investment in the Scientific Sector", *Journal of Political Economy*, 97, pp. 880–904.

Mairesse, J. and A. Siu (1984) "An Extended Accelerator Model of R&D and Physical Investment", *R&D, Patents, Productivity* (Ed.) Z. Griliches, The University of Chicago Press, Chicago, pp. 271–97.

Nickell, S. and D. Nicolitsas (1996) "Does Innovation Encourage Investment in Fixed Capital?", Working Paper, no. 309, CEPR.

Papageorgiou, C., and V. Chmelarova (2005) "Nonlinearities in Capital-Skill Complementarity", *Journal of Economic Growth*, v. 10(1), pp. 59–89.

Romer, P. (1990) "Endogenous Technical Change", *Journal of Political Economy*, 98 (5), pp. 71–102.

Schmookler, J. (1966) *Invention and Economic Growth*, Harvard University Press, Cambridge, MA.

Toivanen, O. and P. Stoneman (1998) "Dynamics of R&D and Investment: UK Evidence", *Economics Letters* 58, pp. 119–126.

Tables

Table 1: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SIC	HQIC
0	−661.9818	NA	0.027979	2.099362	2.470072	2.242816
1	−3.733303	1258.756	0.004131	0.186355	0.583544	0.340055
2	19.77013	44.80772 *	0.003902 *	0.129327 *	0.552996 *	0.293275 *
3	23.25816	6.629296	0.003908	0.130824	0.580972	0.305018

* Indicate the lag order selected by the criterion.

LR: sequential modified likelihood ratio test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SIC: Schwarz information criterion
HQIC: Hannan-Quinn information criterion

Table 2: Estimation Results of the *Differentiated* VAR (p-values in brackets)

	Lag	OLS				FIML			
		$\Delta\ln(\mathrm{RD})$	Wald Test *	$\Delta\ln(\mathrm{ME})$	Wald Test *	$\Delta\ln(\mathrm{RD})$	Wald Test *	$\Delta\ln(\mathrm{ME})$	Wald Test *
$\Delta\ln(\mathrm{RD})$	−1	−0.0893 (0.0062)		−0.0145 (0.1666)		−0.0893 (0.0000)		−0.0145 (0.2130)	
	−2	−0.1537 (0.0000)		0.0228 (0.0288)		−0.1537 (0.0000)		0.0228 (0.0478)	
$\Delta\ln(\mathrm{ME})$	−1	0.0679 (0.3231)		−0.6896 (0.0000)		0.0679 (0.4061)		−0.6896 (0.0000)	
	−2	0.0268 (0.6673)		0.0461 (0.0216)		0.0268 (0.7402)		0.0461 (0.0176)	
$\Delta\ln(\mathrm{GDP})$	0	0.4528 (0.0041)	6.4683 (0.0110)	0.1169 (0.0208)	10.4515 (0.0012)	0.4528 (0.0177)	3.9960 (0.0456)	0.1169 (0.0013)	13.0759 (0.0003)
	−1	0.1147 (0.4734)		0.1145 (0.0258)		0.1147 (0.5933)		0.1145 (0.0219)	
$\Delta\ln(\mathrm{Skills})$	0	0.4201 (0.0053)	15.8011 (0.0001)	−0.0138 (0.7749)	0.0492 (0.8245)	0.4201 (0.0271)	12.3111 (0.0005)	−0.0138 (0.7592)	0.0502 (0.8228)
	−1	0.5061 (0.0012)		−0.0028 (0.9558)		0.5061 (0.0249)		−0.0028 (0.9475)	
$\Delta\ln(\mathrm{COM})$	0	0.0056 (0.8673)	0.0621 (0.8032)	0.0046 (0.6690)	2.8130 (0.0935)	0.0056 (0.9208)	0.0284 (0.8663)	0.0046 (0.6172)	3.2971 (0.0694)
	−1	−0.0175 (0.5974)		0.0212 (0.0459)		−0.0175 (0.6788)		0.0212 (0.0371)	
$\Delta\ln(\mathrm{EXR})$	0	−0.0060 (0.0029)	0.4828 (0.4871)	−0.0012 (0.0569)	0.0983 (0.7539)	−0.0060 (0.0085)	0.3315 (0.5648)	−0.0012 (0.1135)	0.0607 (0.8054)
	−1	0.0074 (0.0013)		0.0014 (0.0515)		0.0074 (0.0050)		0.0014 (0.1022)	
$\Delta\ln(\mathrm{INT})$	0	0.0148 (0.0012)	16.3601 (0.0001)	0.0021 (0.1474)	0.0652 (0.7984)	0.0148 (0.0037)	13.8045 (0.0002)	0.0021 (0.2224)	0.0536 (0.8170)
	−1	0.0097 (0.0164)		−0.0016 (0.2099)		0.0097 (0.0440)		−0.0016 (0.2406)	
$\Delta\ln(\mathrm{MED})$	0	0.5524 (0.1996)	0.0184 (0.8922)	7.5717 (0.0000)	123.43 (0.0000)	0.5524 (0.2259)	0.0158 (0.8999)	7.5717 (0.0000)	139.44 (0.0000)
	−1	−0.5071 (0.1869)		−6.3813 (0.0000)		−0.5071 (0.2611)		−6.3813 (0.0000)	
Industry effect		Included		Included		Included		Included	
Causality Test $\chi^2(2)$		$\gamma_{11}=0$ and $\gamma_{12}=0$ 1.0774 (0.5835)		$\beta_{21}=0$ and $\beta_{22}=0$ 7.1780 (0.0276)		$\gamma_{11}=0$ and $\gamma_{12}=0$ 0.8443 (0.6556)		$\beta_{21}=0$ and $\beta_{22}=0$ 5.6837 (0.0583)	
Adjusted R^2		0.08		0.85		0.08		0.85	
Sample		684		684		684		684	

* Test $a_1 + b_1 = 0$ for each exogenous variable in R&D equation and $a_2 + b_2 = 0$ for each exogenous variable in M&E equation. The corresponding test statistics follows χ^2 distribution with the degree of freedom to be one.

Table 3: Estimation Results of the VECM (p-values in brackets)

	Lag	OLS				FIML			
		Cointegration equation: $\ln(RD_{it-1}) - 1.1298 \times \ln(ME_{it-1})$ (0.0000)							
		$\Delta \ln(\mathrm{RD})$	Wald Test *	$\Delta \ln(\mathrm{ME})$	Wald Test *	$\Delta \ln(\mathrm{RD})$	Wald Test *	$\Delta \ln(\mathrm{ME})$	Wald Test *
Cointegration equation		−0.1728 (0.0000)		0.0138 (0.0384)		−0.1728 (0.0000)		0.0138 (0.0702)	
$\Delta \ln(RD)$	−1	0.0077 (0.8151)		−0.0222 (0.0453)		0.0077 (0.6993)		−0.0222 (0.0991)	
	−2	−0.0655 (0.0432)		0.0158 (0.1491)		−0.0655 (0.0015)		0.0158 (0.1776)	
$\Delta \ln(\mathrm{ME})$	−1	0.0082 (0.8999)		−0.6849 (0.0000)		0.0082 (0.9192)		−0.6849 (0.0000)	
	−2	0.0618 (0.2965)		0.0433 (0.0309)		0.0618 (0.3938)		0.0433 (0.0267)	
$\Delta \ln(\mathrm{GDP})$	0	0.4318 (0.0038)	6.8572 (0.0088)	0.1186 (0.0187)	10.6110 (0.0011)	0.4318 (0.0154)	4.7045 (0.0301)	0.1186 (0.0016)	13.3909 (0.0003)
	−1	0.1209 (0.4244)	6.8572 (0.0088)	0.1140 (0.0261)	10.6110 (0.0011)	0.1209 (0.5341)	4.7045 (0.0301)	0.1140 (0.0237)	13.3909 (0.0003)
$\Delta \ln(\mathrm{Skills})$	0	0.3665 (0.0102)	14.7696 (0.0001)	−0.0095 (0.8432)	0.0191 (0.8900)	0.3665 (0.0215)	12.1782 (0.0005)	−0.0095 (0.8329)	0.0189 (0.8907)
	−1	0.4813 (0.0011)	14.7696 (0.0001)	−0.0008 (0.9874)	0.0191 (0.8900)	0.4813 (0.0084)	12.1782 (0.0005)	−0.0008 (0.9855)	0.0189 (0.8907)
$\Delta \ln(\mathrm{COM})$	0	0.0313 (0.3215)	0.8361 (0.3605)	0.0025 (0.8145)	1.9307 (0.1647)	0.0313 (0.5360)	0.4004 (0.5269)	0.0025 (0.7853)	2.3200 (0.1277)
	−1	0.0105 (0.7379)	0.8361 (0.3605)	0.0190 (0.0747)	1.9307 (0.1647)	0.0105 (0.7987)	0.4004 (0.5269)	0.0190 (0.0584)	2.3200 (0.1277)
$\Delta \ln(\mathrm{EXR})$	0	−0.0057 (0.0028)	0.5009 (0.4791)	−0.0013 (0.0516)	0.1028 (0.7485)	−0.0057 (0.0079)	0.3497 (0.5543)	−0.0013 (0.1122)	0.0624 0.8027)
	−1	0.0071 (0.0012)	0.5009 (0.4791)	0.0015 (0.0465)	0.1028 (0.7485)	0.0071 (0.0071)	0.3497 (0.5543)	0.0015 (0.0993)	0.0624 (0.8027)
$\Delta \ln(\mathrm{INT})$	0	0.0134 (0.0020)	15.5541 (0.0001)	0.0022 (0.1261)	0.1111 (0.7389)	0.0134 (0.0047)	13.3822 (0.0003)	0.0022 (0.2011)	0.0894 (0.7649)
	−1	0.0092 (0.0156)	15.5541 (0.0001)	−0.0016 (0.2190)	0.1111 (0.7389)	0.0092 (0.0445)	13.3822 (0.0003)	−0.0016 (0.2562)	0.0894 (0.7649)
$\Delta \ln(\mathrm{MED})$	0	0.4300 (0.2915)	8.7888 (0.0030)	7.5815 (0.0000)	124.42 (0.0000)	0.4300 (0.3480)	8.4913 (0.0036)	7.5815 (0.0000)	132.99 (0.0000)
	−1	−1.4307 (0.0002)	8.7888 (0.0030)	−6.3076 (0.0000)	124.42 (0.0000)	−1.4307 (0.0007)	8.4913 (0.0036)	−6.3076 (0.0000)	132.99 (0.0000)
Industry effect		Included		Included		Included		Included	
Causality Test $\chi^2(2)$		$\gamma'_{11} = 0$ and $\gamma'_{12} = 0$ 1.0909 (0.5796)		$\beta'_{21} = 0$ and $\beta'_{22} = 0$ 7.2855 (0.0262)		$\gamma'_{11} = 0$ and $\gamma'_{12} = 0$ 0.7389 (0.6911)		$\beta'_{21} = 0$ and $\beta'_{22} = 0$ 5.2337 (0.0730)	
Adjusted R^2		0.18		0.85		0.18		0.85	
Sample		684		684		684		684	

* Test $a'_1 + b'_1 = 0$ for each exogenous variable in R&D equation and $a'_2 + b'_2 = 0$ for each exogenous variable in M&E equation. The corresponding test statistics follows χ^2 distribution with the degree of freedom to be one.

Table 4: OLS Estimation of the VECM with the Skills to be Endogenous (p-values in brackets)

		Cointegration equation 1: $\ln(RD_{it-1}) - 1.1655 \times \ln(\mathrm{Skills}_{\mathrm{it}-1})$ (0.0000)		Cointegration equation 2: $\ln(ME_{it-1}) - 0.7516 \times \ln(\mathrm{Skills}_{\mathrm{it}-1})$ (0.0032)			
	Lag	$\Delta\ln(\mathrm{RD})$	Causality Test $\chi^2(2)$	$\Delta\ln(\mathrm{ME})$	Causality Test $\chi^2(2)$	$\Delta\ln(\mathrm{Skills})$	Causality Test $\chi^2(2)$
Cointegration equation 1		−0.1923 (0.0000)	$\delta_1 = 0, \delta_2 = 0$ 87.4415 (0.0000)	0.0110 (0.1141)	$\delta_3 = 0, \delta_4 = 0$ 14.4771 (0.0007)	−0.0012 (0.8387)	
Cointegration equation 2		0.1035 (0.0170)		−0.0553 (0.0002)		0.0234 (0.0507)	
$\Delta\ln(\mathrm{RD})$	−1	0.0148 (0.6520)		−0.0210 (0.0570)	$\tilde{\beta}_{21} = 0, \tilde{\beta}_{22} = 0$ 6.5221 (0.0383)	0.0064 (0.4743)	$\tilde{\beta}_{31} = 0, \tilde{\beta}_{32} = 0$ 0.7466 (0.6885)
	−2	−0.0633 (0.0492)		0.0147 (0.1749)		0.0053 (0.5502)	
$\Delta\ln(\mathrm{ME})$	−1	0.0407 (0.5418)	$\tilde{\gamma}_{11} = 0, \tilde{\gamma}_{12} = 0$ 0.6820 (0.7110)	−0.6688 (0.0000)		0.0107 (0.5614)	$\tilde{\gamma}_{31} = 0, \tilde{\gamma}_{32} = 0$ 0.3721 (0.8302)
	−2	0.0362 (0.5452)		0.0342 (0.0904)		0.0039 (0.8152)	
$\Delta\ln(\mathrm{Skills})$	−1	0.3265 (0.0264)	$\tilde{\theta}_{11} = 0, \tilde{\theta}_{12} = 0$ 5.3314 (0.0696)	−0.0157 (0.7516)	$\tilde{\theta}_{21} = 0, \tilde{\theta}_{22} = 0$ 1.2604 (0.5325)	−0.1571 (0.0001)	
	−2	−0.0706 (0.6569)		−0.0588 (0.2718)		−0.0486 (0.2675)	
$\Delta\ln(\mathrm{GDP})$	0	0.4817 (0.0014)		0.1270 (0.0121)		0.0454 (0.2727)	
	−1	0.1864 (0.2164)		0.1319 (0.0095)		0.0278 (0.5039)	
$\Delta\ln(\mathrm{COM})$	0	0.0239 (0.4559)		0.0037 (0.7313)		−0.0029 Δln(COM) (0.7389)	
	−1	−0.0264 (0.4085)		0.0037 (0.7308)		0.0028 (0.7467)	
$\Delta\ln(\mathrm{EXR})$	0	−0.0060 (0.0022)		−0.0015 (0.0214)		0.0008 0.1439)	
	−1	0.0047 (0.0311)		0.0012 (0.1141)		−0.0029 (0.0000)	
$\Delta\ln(\mathrm{INT})$	0	0.0094 (0.0279)		0.0019 (0.1799)		−0.0053 (0.0000)	
	−1	0.0087 (0.0198)		−0.0012 (0.3369)		−0.0030 (0.0055)	
$\Delta\ln(\mathrm{MED})$	0	0.3464 (0.3983)		7.5152 (0.0000)		0.9767 (0.3584)	
	−1	−0.8543 (0.0498)		−6.0772 (0.0000)		−0.1445 (0.2284)	
Industry effect		Included		Included		Included	
Adjusted R^2		0.18		0.86		0.05	
Sample		684		684		684	

Table 5: Estimation Results of the VECM for Capital-Using Industries

	Cointegration equation: $\ln(RD_{\mathrm{it}-1}) - 1.0715 \times \ln(ME_{it-1})$ (0.0000)						
	Lag	$\Delta \ln(\mathrm{RD})$			$\Delta \ln(\mathrm{ME})$		
		Coefficient	P-value	Wald Test *	Coefficient	P-value	Wald Test *
Cointegration equation		−0.1852	0.0000		0.0136	0.0536	
$\Delta \ln(\mathrm{RD})$	−1	0.0040	0.9136		−0.0200	0.0821	
	−2	−0.0624	0.0860		0.0170	0.1312	
$\Delta \ln(\mathrm{ME})$	−1	0.0392	0.6286		−0.6874	0.0000	
	−2	0.0718	0.3158		0.0400	0.0717	
$\Delta \ln(\mathrm{GDP})$	0	0.6340	0.0049	3.8941 (0.0485)	0.2121	0.0024	11.4019 (0.0007)
	−1	0.0174	0.9396	3.8941 (0.0485)	0.1338	0.0610	
$\Delta \ln(\mathrm{Skills})$	0	0.3756	0.0254	11.8136 (0.0006)	−0.0094	0.8566	0.1497 (0.6988)
	−1	0.5379	0.0021	11.8136 (0.0006)	−0.0225	0.6776	
$\Delta \ln(\mathrm{COM})$	0	0.0602	0.1536	2.6581 (0.1030)	−0.0040	0.7597	0.0256 (0.8730)
	−1	0.0378	0.3619	2.6581 (0.1030)	0.0010	0.9368	
$\Delta \ln(\mathrm{EXR})$	0	−0.0078	0.0026	1.0841 (0.2978)	−0.0016	0.0494	1.8083 (0.1787)
	−1	0.0104	0.0004	1.0841 (0.2978)	0.0005	0.5604	
$\Delta \ln(\mathrm{INT})$	0	0.0162	0.0060	8.5294 (0.0035)	0.0035	0.0549	1.8159 (0.1778)
	−1	0.0071	0.1703	8.5294 (0.0035)	−0.0002	0.9107	
$\Delta \ln(\mathrm{MED})$	0	0.2856	0.5867	7.4590 (0.0063)	7.7951	0.0000	79.0222 (0.0000)
	−1	−1.4294	0.0028	7.4590 (0.0063)	−6.6398	0.0000	
$\Delta \ln(\mathrm{GDPP})$	0	−0.1653	0.4752	2.3218 (0.1276)	0.1163	0.1057	10.3722 (0.0013)
	−1	−0.3024	0.1813	2.3218 (0.1276)	0.1904	0.0067	
Industry effect		Included			Included		
Causality Test $\chi^2(2)$		$\gamma'_{11}=0$ and $\gamma'_{12}=0$ 1.1560 (0.5610)			$\beta'_{21}=0$ and $\beta'_{22}=0$ 6.4264 (0.0402)		
Adjusted R^2		0.18			0.86		
Sample		532			532		

* Test $a_1 + b_1 = 0$ for each exogenous variable in R&D equation and $a_2 + b_2 = 0$ for each exogenous variable in M&E equation. The corresponding test statistics follows χ^2 distribution with the degree of freedom to be one.

Table 6: Estimation Results of the VECM for Capital-Producing Industries

	Lag	Cointegration equation: $\ln(RD_{\mathrm{it}-1}) - 1.1576 \times \ln(ME_{\mathrm{it}-1})$ (0.0000)					
		$\Delta\ln(RD)$			$\Delta\ln(\mathrm{ME})$		
		Coefficient	P-value	Wald Test *	Coefficient	P-value	Wald Test *
Cointegration equation		−0.0751	0.0355		0.0098	0.5911	
$\Delta\ln(\mathrm{RD})$	−1	0.0008	0.9925		0.0607	0.1737	
	−2	0.0044	0.9596		0.0327	0.4688	
$\Delta\ln(\mathrm{ME})$	−1	−0.0249	0.7511		−0.7652	0.0000	
	−2	0.0061	0.9360		−0.0002	0.9969	
$\Delta\ln(\mathrm{GDP})$	0	0.2660	0.0386	19.9550 (0.0000)	−0.1246	0.0594	1.2657 (0.2606)
	−1	0.5098	0.0001		0.0241	0.7166	
$\Delta\ln(\mathrm{Skills})$	0	0.4583	0.0456	6.5102 (0.0107)	0.0881	0.4535	3.1628 (0.0753)
	−1	0.2882	0.1956		0.1795	0.1173	
$\Delta\ln(\mathrm{COM})$	0	−0.0372	0.2816	1.2145 (0.2705)	0.0059	0.7385	1.2842 (0.2571)
	−1	−0.0170	0.6087		0.0228	0.1833	
$\Delta\ln(\mathrm{EXR})$	0	−0.0005	0.8101	0.0175 (0.8947)	−0.0004	0.7097	0.4516 (0.5016)
	−1	0.0003	0.9094		0.0011	0.3300	
$\Delta\ln(\mathrm{INT})$	0	−0.0002	0.9728	1.2608 (0.2615)	−0.0021	0.3759	1.2612 (0.2614)
	−1	0.0072	0.0779		−0.0015	0.4703	
$\Delta\ln(\mathrm{MED})$	0	0.8265	0.0437	0.1456 (0.7028)	6.9144	0.0000	84.4213 (0.0000)
	−1	−0.9669	0.0201		-5.1550	0.0000	
$\Delta\ln(\mathrm{MEU})$	0	−0.1547	0.0910	1.3100 (0.2524)	0.1560	0.0010	2.7893 (0.0949)
	−1	0.0072	0.9451		−0.0454	0.3993	
Industry effect		Included			Included		
Causality Test $\chi^2(2)$		$\gamma'_{11} = 0$ and $\gamma'_{12} = 0$ 0.1274 (0.9383)			$\beta'_{21} = 0$ and $\beta'_{22} = 0$ 2.2123 (0.3308)		
Adjusted R^2		0.23			0.92		
Sample		152			152		

* Test $a'_1 + b'_1 = 0$ for each exogenous variable in R&D equation and $a'_2 + b'_2 = 0$ for each exogenous variable in M&E equation. The corresponding test statistics follows χ^2 distribution with the degree of freedom to be one.