# Cross-border M&A as a Driver of Global Innovation

A Quantitative Study on Knowledge Transfer through International M&A

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**ABSTRACT**

This thesis aims to further elaborate on the topic of cross-border M&A as a driver of international exchange of knowledge by investigating the difference in innovation post M&A, compared to other transactions, for industry-related transactions, transactions between two innovative countries and transactions where the acquiring country is non-innovative while the target is innovative. Unlike previous research that mainly classifies countries as either emerging or advanced based on financial conditions, the classification of non-innovative and innovative countries is based on the Global Innovation Index, which has not before been used as an explanation factor in this research area. Using an OLS fixed-effects regression model on panel data relating to 761 cross-border acquisitions between 2000 and 2015, with data from mainly SDC Platinum and WRDS, while using three different measures of innovation (R&D intensity, Total Factor Productivity and Labour productivity), it is concluded that: i) comparability issues in the research area arise from different innovation unit definitions, ii) the results do not support previous research in terms of implementation issues from non-related transactions nor in terms of economies of scale and scope being the main drivers of innovation in an M&A context, iii) using innovative conditions of countries, rather than financial conditions, further contribute to the research area of cross-border M&A as a driver of global innovation.

Keywords: Innovation, Cross-border M&A, Globalisation, Emerging Markets, Total Factor Productivity

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# 1 Introduction

With an M&A market more active and global than ever, the research area attracts strong interest from researchers. Acquisitions in general, but especially cross-border acquisitions, have for many years been used as an instrument to achieve innovation and maintain a competitive advantage (Cassiman et al., 2005), still research shows ambiguous results where both positive, negative and conflicting results have been presented. This paper digs further into this, analysing subsamples based on identifiable transaction characteristics.

Innovation is attracting much interest as it is believed to be essential for a sustainable development in terms of social welfare and environmental consideration worldwide. As a result of the ongoing globalisation and increased consumption, these factors are not only more important than before, there are also increasing possibilities for less innovative areas to benefit from contributions in other countries. Englander, Evenson & Hanazaki (1988) raised already in 1988 that the contributors of innovation not necessarily are the largest users of the same and while the economic conditions, measured by e.g. GDP per capita, largely reflect the innovative conditions in one country, it is not necessarily so. As a vast majority of the world today is a part of the international M&A market, this thesis aims to contribute to a research area examining how global innovation is, and will be, achieved.

While previous research concludes that acquirers in developing markets gain innovative power by engaging in M&A in advanced markets, little has been concluded on the effect of innovative conditions of host countries. This paper contributes to existing research by investigating how international exchange of innovative knowledge can be transferred through M&A not only in economically exposed countries but also in developed markets with less innovative ability by introducing the Global Innovation Index to the research area. It is believed that the research is interesting from an emerging market perspective but also in terms of policy making and innovation research in general. Further, the discussion of this thesis effectively combines current topics such as globalisation, cross-border M&A and innovation.

The above is achieved using an OLS fixed-effects regression model on panel data consisting of financial data of 761 acquirers three years before to three years after the acquisition. All the included transactions are cross-border acquisitions between the years 2000 and 2015 reported by SDC Platinum. The related financial data was downloaded primarily from CRSP/Compustat Merged - Fundamentals Annual by Wharton Research Data Services and complemented with other data sources such as annual reports.

The results of this thesis support the ongoing discussion of comparability issues in the research area of innovation. Because innovation lacks defined units, the dataset is split into three commonly applied measures (R&D intensity, TFP and Labour productivity), as well as different subsamples, to further examine the drivers of innovation related to M&A.

As a result of the analysis, the thesis presents three main conclusions:

i) Diverse results are found between input and output measures, as well as between TFP and Labour productivity both measuring innovation output, emphasising the comparability issues in the research area

ii) The results cannot support previous research in terms of implementation problems from non-related transactions, because the related industry analysis shows that TFP is higher for non-related transactions, while there are no differences shown in terms of R&D intensity and Labour productivity. Also, previous research is challenged in terms of economies of scale and economies of scope being the main drivers of innovation. This because I then would have expected TFP and Labour productivity to be more aligned

iii) Introducing the concept of innovative and non-innovative countries adds to the discussion of emerging and advanced markets as I find differing results for advanced and innovative acquirers with regards to Labour productivity for advanced and innovative countries, and with regards to R&D intensity and TFP for emerging and non-innovative countries

It is shown how intangible assets of technology and innovation expertise are drivers of international knowledge transfer and that cross-border M&A is a tool for companies that are restricted in terms of national policies to gain access to developed technology. The empirical results, as well as the discussion of this thesis, are assumed to be useful tools to better understand international trade patterns relevant for future academic research as well as policy making.

# 2 Theory and Previous Literature

There is extensive research available regarding several of the critical elements in this paper, such as cross-border M&A, the effect of M&A on innovation and emerging market acquirers. The research area attracts interest from several different academic fields, which has resulted in organisational, managerial and financial theories (Desyllas, Hughes, 2010). This thesis is written within the finance department of Stockholm School and Economics and fill the void by focusing on the innovative conditions rather than the economic development of the host countries. Although the previous research regarding this connection is limited, research in related areas is central in terms of thesis structure as well as interpretation of the data results. This section presents the theoretical framework for this paper.

## 2.1 Why firms engage in cross-border M&A

The exact reasons for firms to engage in M&A in general and cross-border M&A in particular are individual from firm to firm. Previous research has though shown that it is possible to bundle arguments into four categories: i) increasing market share or market power, ii) increasing efficiency, iii) firm growth and iv) increase of R&D. It is important to understand the underlying aim of a transaction in order to evaluate its success. (Ikeda, Doi, 1983)

Going forward, this section will focus on why firms engage in cross-border M&A to increase either its innovation efforts or foster innovative results.

Cross-border M&A has played an important role in industrial globalisation. Holmstrom, Roberts, 1998 argue that knowledge transfer is a key driver in M&A activities, driven by the development of new technologies and operating as a channel for firms to expand and share their knowledge base in order to access new technologies, product markets and enhance R&D capabilities. Engaging in international M&A, firms can relocate activities in order to exploit efficiency gains through R&D since innovation is an important growth factor.

An alternative to cross-border M&A is Joint venture as it too provides an opportunity to learn international technology as long as the partnership is not dominated by the foreign partner. The risk of this is significant in cases where the foreign partner is superior in terms of brands and technology. While this is avoided by acquisition, another advantage is that competitors are kept distanced from the technology. (Holmstrom, Roberts, 1998)

Another alternative to engage in and learn from international expansion discussed by Helpman, Melitz & Yeaple (2004) is export. This article finds that exports are more common relative to cross-border acquisitions when the economies of scale are higher, or the trade barriers are lower.

## 2.2 Measuring innovation

Measuring innovation is problematic as it lacks well-defined units (Englander, Evenson & Hanazaki, 1988). Previous research divides innovation measures into input-measures and output-measures:

In terms of output, Total Factor Productivity (TFP) can be traced back to 1957 but there has been a renewed interest for the method more recently. (Van Beveren, 2012) Total Factor Productivity is an output measure described more in detail in Section 5.1.

Englander, Evenson & Hanazaki (1988) emphasise that there are many steps leading from R&D expenditure to actual innovation, e.g. TFP. They therefore retain a critical view on innovation studies using solely R&D expenditure as an indication of innovation. In the study, Englander, Evenson & Hanazaki (1988) also raise that firms investing heavily in R&D are not necessarily the users of the same innovative results, further emphasising that there is not necessarily a clear relationship between R&D and TFP.

Labour productivity is a simpler measure of productivity also described in Section 5.1. Tang (2017) compare TFP and Labour productivity in terms of multinational enterprises' foreign integration strategies and conclude that Labour productivity and TFP should be considered as different proxies for firm heterogeneity. The study found that Taiwanese companies with high Labour productivity to a larger extent looked for cheaper labour in low-cost countries. On the contrary, companies with high TFP engaged in cross-border M&A to a lower extent, and mostly in advanced countries, because of their technology being harder to transfer longer distances.

## 2.3 M&A as a driver of innovation

The active debate evolving around global M&A being the driver or break block of international innovation includes quantitative and qualitative input from several researchers.

R&D-based measures are the most common to measure innovation input and can, by those arguing that M&A has a negative impact on innovation, be said to be affected in terms of i) economies of scale (Lowering the average cost per product by producing larger volumes) and ii) economies of scope (Cost reduction from producing two products jointly compared to separately). These factors reduce R&D spending while leaving the innovative effect rather flat. (Cassiman et al., 2005, Henderson, Cockburn, 1994)

The discussion above suggests that the reduced R&D spending is a result of innovative efficiency but among those finding a negative correlation between M&A and innovative input, there are also those linking this to reduced innovative output. Contrasting the argument of economies of scale and scope, Hitt et al. (1996) suggest that investments in acquisitions leave managers unwilling to further invest and that the R&D budget therefore is reduced. Further, Hitt et al. (1996) mean that M&A is a substitute for in-house R&D and that this is the reason for active acquirers to have a lower R&D budget than firms not engaging in these transactions.

Szücs (2014) and Ornaghi (2009) also find a negative correlation between R&D and M&A. Szücs (2014) uses a data sample of 265 acquiring firms in the period 1990 to 2009 to show that mergers have a negative effect on innovation. Szücs (2014) does not compare subsamples in the analysis and include both cross-border and domestic acquisitions. Ornaghi (2009) is similar to Szücs (2014) in approach and conclusion focusing solely on the pharmaceutical industry.

Niching the discussion to cross-border M&A, previous research show how M&A increases the R&D spending, and thus innovation, in both the host country of the acquirer (Stiebale, 2013), and the target (Bertrand, 2009).

Stiebale (2013) suggests that the domestic R&D spending is higher for firms engaging in cross-border M&A compared to those that do not. Stiebale (2013) concludes that the domestic technology base increases from international M&A and that policies incentivising foreign acquisitions thus are beneficial for the innovative development of nations.

Bertrand (2009) instead examines the effect of cross-border M&A on target R&D. The article concludes that target R&D spending increases after the firm being acquired by a foreign company and that this is financed by internal resources as well as financial support from the acquirer. Internal and external R&D expenditures are compared, and both are found to be increasing. External R&D is often contracted to local research providers such as local public laboratories and universities. Important in the discussion is that innovative targets often also benefit from large, financially strong acquirers in terms of a strong brand name and larger scales, which in many cases are crucial to transform ideas to profit (Szücs, 2014).

Table 1 below provides an overview of M&A impact on innovation found in previous literature. The table is segmented into effect on input and effect on output. R&D expense and R&D intensity are examples of input measures. TFP, Labour productivity, patent count and patent quality are examples of output measures.

Table 1: Literature results

| | | Effect on input | | | Effect on output | | |
|---|---|---|---|---|---|---|---|
| *Author(s)* | *Year* | *Negative* | *Neutral* | *Positive* | *Negative* | *Neutral* | *Positive* |
| Bertrand, O. | 2009 | | | x | | | |
| Cefis et al | 2007 | | | x | | | x |
| Cassiman et al | 2005 | | x | | | | |
| Desyllas & Hughes | 2010 | | | x | | | |
| Ornaghi | 2009 | x | | | | | |
| Selvilir & Tian | 2012 | | | | | | x |
| Stiebale | 2013 | | | x | | | |
| Stiebale & Haucap | 2013 | x | | | x | | |
| Szücs | 2014 | x | | | | | |

## 2.4 Innovation and M&A in emerging markets

Although the main focus of this thesis is not to investigate the impact of M&A on innovation in emerging markets, previous research in the area brings relevant input to the discussion. That is because emerging countries often also are non-innovative.

Previous research (Kumar, 2009; Deng, Yang, 2015; Child, Rodrigues, 2005) investigate cross-border M&A in which the developing acquirer aims to gain access to strategic assets and expertise of innovation though the more developed target.

Emerging giants engage in M&A to obtain competencies, technology and knowledge essential to the strategy rather than economies of scale or access to new geographic areas to a larger extent than Western companies. Further, the acquisitions are often driven by long-term strategies and the acquirer is willing to wait for the take-over to pay off. Kumar (2009) lists six areas in which emerging giants are different in their approach to M&A compared to the traditional view:

> **Rationale:** The key rationale for traditional M&A is cost efficiency, although acquirers in advanced countries often also are interested in new technologies, niche competences or access to new markets. Emerging giants are to a larger extent looking for technologies, brands and consumers in foreign countries.
>
> **Synergy levels:** Acquirers in advanced countries are often looking for companies with a similar business model, while acquirers in emerging markets often are low-cost commodity players looking for value-add acquisitions in terms of technology and brand.
>
> **Integration speed:** The traditional view on M&A is that integration efforts should start immediately after a transaction. The emerging view takes a slower approach where the target is pulled closer to the acquirer after some time.
>
> **Organisational fall-out:** Similar to the integration speed, it seems like the organisational fall-out is slower in emerging M&A. In traditional acquisitions it is common that the turnover of important personnel is high soon after the acquisition. This is not the case in emerging M&A.

**Goals:** While traditional acquirers have clear short-term goals of the acquisition and fuzzier long-term, the opposite is true for emerging acquirers.

An interesting way to put the difference between internationalisation according to the traditional theory compared to the observations of emerging firms, is that firms traditionally have exploit international opportunities to approach their competitive advantages. Contrasting this, Chinese firms today make such investments to address competitive disadvantages. They are characterised by a long-term strategic view with the aim to acquire advanced technology and R&D capabilities in order to develop a differentiation advantage, which could also be related to brand. (Child, Rodrigues, 2005)

Deng, Yang (2015) discuss how strategic motivations incentivises acquirers to engage in cross-border M&A, especially in advanced countries. They emphasise that many emerging market acquirers have gained access to brand names, product technology and extensive networks of distributors by involving in M&A in advanced countries.  The reason for this is often that high quality research and development institutions and workforce are not available domestically.

Regarding the characteristics of emerging market cross-border acquisitions in advanced countries, the typical transaction size tends to be small although 24 acquisitions were worth more than a billion dollars each from 2000 to 2008. It is also shown that the bootstrapping hypothesis stating that acquirers choose to adapt to the target's higher corporate governance standards hold. It can therefore be concluded that cross-border investment influence higher corporate governance standards in developing markets. (Bhagat, Malhotra & Zhu, 2011)

Another approach on how firms in emerging markets can benefit from knowledge transmit from advanced countries has been examined by Giannetti, Liao & Yu (2015). The research shows that directors with foreign experience provide knowledge of practises and corporate governance to firms in emerging markets in a way that increases the firm's Total Factor Productivity (TFP).

## 2.5 The impact of related and non-related transactions in M&A

Stiebale, Haucap (2013) examine the effect of horisontal mergers (mergers where the acquirer and target is actors in the same industry) and find that this reduces innovation in innovation intensive industries. Further, it is found that non-merging rivals in the same industry experience a negative impact on R&D as well as patents when the target of the transaction is categorised as inefficient.

Another study investigating the impact of technology overlap is Desyllas, Hughes (2010), focusing on high-innovative, US acquisitions. In the article, the knowledge base of the acquirer is measured and used to create subsamples of high and low. It is concluded that in related acquisitions, a strong knowledge base creates high absorptive capacity and is therefore an advantage in terms of innovation; R&D productivity increases. The opposite result extracts from unrelated mergers as a strong knowledge base indicates a lower degree of knowledge base diversity, which is critical in order to successfully import unrelated, internal knowledge.

The research in the area is though ambiguous. Contrasting the results of Desyllas, Hughes (2010), Cassiman et al. (2005) find the opposite relation between technological relatedness and innovation. Innovation is here measured as inputs, outputs, performance and organisational structure in the R&D process, and the data used is more in-depth focusing on a dataset of solely 31 transactions. They find that rival firms reap little technology gains from mergers.

# 3 Delimitation and Hypotheses

Building on previous literature, this thesis aims to fill in the gaps by formulating well-informed and relevant hypotheses building on economic intuition.

Although the term "innovative acquirer" is referred to, the impact of cross-border M&A on acquirer innovation is not investigated, neither does this thesis measure a causal relationship between acquirer innovation characteristics and post M&A innovation performance. Using a higher level of an innovation index based on acquirer country and not industry or firm, the study will mainly investigate the difference in innovation performance between different groups of cross-border acquirers after an M&A transaction. This in order to draw suggestive conclusions on heterogeneity in both innovation input and output. Further, the study is delimited to only include cross-border M&A and do not compare it to domestic M&A, as common by literature. The reason for this is that many domestic M&As involve internationally present acquirers, which is assumed to create a measurement bias.

As previous literature tends to find ambiguous results regarding the effect of M&A on innovation, it is interesting and important to further investigate how these differences can be explained by observable characteristics of the acquirer and the target. As previous research has shown that input and output are affected differently, each hypothesis is split into two parts. Part a relates to innovation input, while part b relates to innovation output.

Hypotheses 1 focus on the difference between industry-related and non-related transactions. I expect that there will be no difference between the two samples in respect to R&D intensity:

> Hypothesis 1a: *Cross-border acquirers, acquiring a target within the same industry, experience no difference in the effect of ex-post innovation input compared to the innovation levels of cross-border acquirers not acquiring a target within the same industry*

Further, companies in industries where economies of scale are high (affecting innovation output) tend to export instead of acquiring (Helpman, Melitz & Yeaple, 2004). Therefore, it should be a lower representation of companies with high TFP capabilities in the related acquisition sample as that is assumed to be driven by economies of scale to a larger extent than non-related transactions:

> Hypothesis 1b: *Cross-border acquirers, acquiring a target within the same industry, experience a negative effect on ex-post innovation output compared to the innovation levels of cross-border acquirers not acquiring a target within the same industry*

Going forward, in the discussion of subsamples in cross-border M&A and innovation, much emphasis has in previous research been put in emerging and advanced countries and how knowledge and resources are transferred across nations with different characteristics. I wanted to take this discussion further and introduce the concept of innovative and non-innovative countries to the research area. Each year, extensive research and effort is put into preparing an innovation index described in Section 4.3, though it has been noticeably absent in academic literature. The following hypotheses are based on this index in order to explain whether the innovativeness of the domestic country of the acquirer and the target can explain differences in effect on innovation from the transaction.

As Helpman, Melitz & Yeaple (2004) state that high trade barriers is one reason to go abroad rather than to export, it was seen as essential to limit the target group to either innovative (assumed low trading barriers) or non-innovative (assumed high trading barriers). As the flow of international knowledge is of interest, it was determined that innovative targets would be more relevant in this case. To secure the reasoning, tests were also run for non-innovative targets, though, this did not result in any significant results and was therefore excluded from the analysis.

Hypothesis 2a below states that when the target and acquirer are both innovative, R&D intensity is significantly higher after an acquisition compared to other transactions. The hypothesis is based on how M&A often is a substitute to innovation but how I expect innovative acquirers to have higher in-house capabilities than acquirers in non-innovative countries. It is therefore believed that innovative acquirers to a larger extent than others continue to develop the technology of the target also after an acquisition rather can copying it.

The fact that all innovative countries in the dataset also are advanced provides further support to the hypothesis, since technology transfer between emerging and advanced countries have been discussed in previous research. As the innovative acquirer does not only operate in a business climate that supports innovation, financial resources (equity and debt) are also expected to be more easily accessible. This further emphasis the above; innovative acquirers in general should have good abilities to further build on the technology of the innovative target:

> Hypothesis 2a: *Cross-border acquirers with a high innovation index, acquiring a target with a high innovation index, experience higher ex-post innovation input over and above any levels of innovation in comparison to other cross-border acquirers*

While I expect the input to be higher for these companies than for others, the difference is not expected to perceive into output. This is because acquisitions between innovative firms are expected that to a larger extent than others be driven of long-term, technology development. This means that I expect to see no immediate effect of the increased R&D on innovation output and that Hypothesis 2b therefore is formulated as:

> Hypothesis 2b: *Cross-border acquirers with a high innovation index, acquiring a target with a high innovation index, experience no difference ex-post innovation output over and above any levels of innovation in comparison to other cross-border acquirers*

For Hypotheses 3, I instead focus on how an acquirer from a non-innovative country acquiring a target in an innovative country is different from other transactions. Hypothesis 3a focuses on the innovative input (R&D) and Hypothesis 3b focuses on the innovative output (TFP and Labour productivity).

For Hypothesis 3a, I expect R&D to decrease, which opposite the expectation in Hypothesis 2a. The reason is that while an innovative acquirer is expected to be able to continue to build on technology, non-innovative acquirers are expected to instead copy and implement rather than to further develop the technology:

Hypothesis 3a: *Cross-border acquirers with a low innovation index, acquiring a target with a high innovation index, experience lower ex-post innovation input over and above any levels of innovation in comparison to other cross-border acquirers*

Second, while I expect no effect on innovation output in Hypothesis 2b, Hypothesis 3b instead states that the innovation output is expected to be higher when the acquirer is non-innovative, and the target is innovative compared to other transactions. The reason for this is that I expect non-innovative acquirers to a larger extent than innovative acquirers to use knowledge, resources and brand to more effectively transform R&D into sales. This is because these factors are not available domestically according to previous research.

Hypothesis 3b: *Cross-border acquirers with a low innovation index, acquiring a target with a high innovation index, experience higher ex-post innovation output over and above any levels of innovation in comparison to other cross-border acquirers*

# 4 Data

## 4.1 Transaction data

The dataset used in this thesis consists of acquisitions between the years 2000 and 2015. The acquisition year refers to the year in which the transaction was completed and was chosen in line with previous research (Rossi, Volpin (2004) include transaction data over nine years, Szücs (2014) include transaction data over 19 years). As the dataset was later to be complemented with consolidated financials of the acquirer over a period of three years before and after the acquisition, this is the most recent data possible to use. Also, because of the consolidated financials, only acquisitions of which the acquirer take control over the target is of interest, the screening was therefore limited to transactions in which the acquirer after the transaction owned 50% or more of the target shares. The screening was also reduced to completed transactions.

The sample consists of mergers and acquisitions during above mentioned years reported by SDC Platinum by Thomson Financials and was downloaded on 14 February 2019. Variables included in the SDC Platinum screening are year of transaction, target CUSIP and acquirer CUSIP (for definition), four-digit SIC codes for acquirer and target respectively (two-digit SIC codes used to determine related transactions) and acquirer nation and target nation (used together to determine cross-border).

Regarding SDC Platinum data, previous research raises concerns that the availability and quality of data is better in some countries (e.g. the US and UK) than in others (Rossi, Volpin, 2004). In the raw data downloaded from SDC Platinum, the number of acquirer countries represented was 211 over 396,217 transactions, the ratio of US acquirers was 30.8%.

Moreover, Rossi, Volpin (2004) draw to attention that the coverage of smaller companies increased over the years 1990-1999, which is the time period they examine. They though conclude that this does not affect their results. Given this conclusion and the fact that I am using a more recent dataset, I do not expect further examination of this limitation to bring value to my analysis.

Another important judgement regarding transaction data is how to handle multiple transactions by the same company over the observed period. Szücs (2014) removes duplicates within four years of each other while I kept only the first. As a result, the number of observations was reduced from 396,217 to 187,023.

## 4.2 Financial data

The consolidated financial data for acquiring firms covering three years before the first transaction to three years after the last transaction year (1997-2018) was downloaded from CRSP/Compustat Merged - Fundamentals Annual by Wharton Research Data Services. All absolute values are measured in USD and both active and inactive firms are included.

Aiming to use the most recent data available, I include 2018 year data in the analysis (financials three year after transactions completed in 2015). The data available for 2018 is limited which results in an underrepresentation of transactions completed in 2015. In the raw dataset downloaded from SDC Platinum, the ratio of observations from 2015 was 7.5%, in the final dataset, it was 1.0%.

It is central for the quality of the data analysis to provide a dataset with extensive data of Employees, Debt, Assets and R&D. Since merging SDC Platinum with WRDS resulted in extensive missing data, the dataset was complemented with these parameters from Eikon, Capital IQ and annual reports.

Thereafter, all transactions for which no acquirer financial data was available for one or more years between three years before the acquisition and three years forward were removed. The final dataset covers 761 transactions.

## 4.3 The Global Innovation Index

In this thesis, I compare acquisitions by/of innovative and non-innovative countries. This distinction is made based on the Global Innovation Index 2018: Energizing The World with Innovation (Dutta et al., 2018). This report is a result of a collaboration between Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO) as co-publishers, and their knowledge partners (e.g. Strategy& - Part of PWC network).

To avoid comparability issues, as the measurements and definitions in the index have developed over the years, the Global Innovation Index from 2018 is used and apply to all years of transactions. An example of such change is “ease to pay taxes”, which was previously a criterion but excluded in the 2018 index. 2018 is the eleventh edition of the index as the projects was first introduced by Professor Dutta at INSEAD in 2007. Professor Dutta aimed to find new metrics and approaches to capture innovation beyond the traditional level of research and development expenditure.

The framework of the index is the simple average of the Input and Output sub-indices. The Innovation Input Sub-index consists of factors related to Institutions (political environment, regulatory environment, business environment), Human capital and research (education, tertiary education, research & development), Infrastructure (ICTs, general infrastructure, ecological sustainability), Market sophistication (credit, investment, trade, competition, market scale) and Business sophistication (knowledge workers, innovation linkages, knowledge absorption). The Innovation Output Sub-index consists of Knowledge and technology outputs (knowledge creation, knowledge impact, knowledge diffusion) and Creative outputs (intangible assets, creative goods and services, online creativity).

The report then presents a table with Switzerland being the most innovative country with a score of 68.40. The least innovative country is Yemen with a score of 15.04. Different approaches to differentiating between non-innovative and innovative markets was discussed. Splitting the list in two was unsuccessful as it resulted in a strong weight towards advanced acquirers and targets. It was also determined that the same differentiation should be used for both target and acquirer as it could otherwise be that a transaction between very similar markets would be classified as a trans-innovation transaction. As the dataset consists of a large amount of US acquirers, the median score of acquirers is unreasonably high. Instead, the split is made determined by the median of the target sample, 54.36.

Table 2 shows the four subsamples based on innovation of target and acquirer and the median innovation score for acquirer and target within each group. 81 % of the transactions involved an innovative acquirer while 54% involved an innovative target.

Table 2: Innovation index

| Host country innovation | | | | Median innovation score | |
|---|---|---|---|---|---|
| *Acquirer* | *Target* | *Observations* | *Ratio* | *Acquirer* | *Target* |
| Innovative | Innovative | 310 | 41% | 59.81 | 59.81 |
| Innovative | Less innovative | 303 | 40% | 59.81 | 51.32 |
| Less innovative | Innovative | 96 | 13% | 52.98 | 59.81 |
| Less innovative | Less innovative | 52 | 7% | 48.68 | 33.44 |
| Total | Total | 761 | 100% | 59.81 | 54.36 |

Table 3 provides an overview of the innovatively advanced countries included in the sample. It is clear that the US is overrepresented as acquirer with 82% of the advanced acquirers being US firms. The target group is more well-diverse but as well with US as largest player representing 31% of all acquisitions. There are 12 innovative host countries represented in the dataset.

Table 3: Innovatively advanced countries

| | | *Frequency* | | | |
|---|---|---|---|---|---|
| *Country* | *Innovation score* | *as Acquirer* | *as Acquirer (ratio)* | *as Target* | *as Target (ratio)* |
| Switzerland | 68.40 | 8 | 1% | 15 | 4% |
| Netherlands | 63.32 | 12 | 2% | 25 | 6% |
| Sweden | 63.08 | 2 | 0% | 12 | 3% |
| United Kingdom | 60.13 | 27 | 4% | 107 | 26% |
| United States | 59.81 | 503 | 82% | 128 | 32% |
| Finland | 59.63 | 3 | 0% | 5 | 1% |
| Germany | 58.03 | 6 | 1% | 47 | 12% |
| Israel | 56.79 | 31 | 5% | 10 | 2% |
| Japan | 54.95 | 7 | 1% | 17 | 4% |
| Hong Kong | 54.62 | 5 | 1% | 10 | 2% |
| Luxembourg | 54.53 | 1 | 0% | 0 | 0% |
| France | 54.36 | 8 | 1% | 30 | 7% |
| Total | | 613 | 100% | 406 | 100% |

Table 4 is more extensive with 38 countries represented. Though, the total frequency is lower for acquirers as well as targets. Although this could be because of higher quality of data in these countries, it is a strong indication that technologically advanced countries are engaged in more acquisitions.

Comparing Table 3 and 4, questions rise regarding the differences between e.g. the US (innovative) and Canada (non-innovative) or Sweden (innovative) and Norway (non-innovative) as they might seem similar in many aspects. This discussion is important as distinguishing between innovative and non-innovative is an essential but difficult part of the thesis. Ideally, the dataset would be extensive enough to create subsets that are more distinguished. Though, the results will later show that there are differences between these subsamples, thus the dataset provides the right conditions for analysis.

Table 4: Less innovatively advanced countries

| | | Frequency | | | |
|---|---|---|---|---|---|
| *Country* | *Innovation score* | *as Acquirer* | *as Aqquirer (ratio)* | *as Target* | *as Target (ratio)* |
| China | 53.06 | 14 | 9% | 20 | 6% |
| Canada | 52.98 | 68 | 46% | 109 | 31% |
| Norway | 52.63 | 2 | 1% | 9 | 3% |
| Austria | 51.98 | 0 | 0% | 3 | 1% |
| Australia | 51.32 | 1 | 1% | 35 | 10% |
| New Zealand | 51.29 | 0 | 0% | 4 | 1% |
| Iceland | 51.24 | 1 | 1% | 0 | 0% |
| Bermuda | 50.50 | 12 | 8% | 3 | 1% |
| Spain | 48.68 | 5 | 3% | 14 | 4% |
| Italy | 46.32 | 4 | 3% | 20 | 6% |
| Portugal | 45.71 | 0 | 0% | 2 | 1% |
| Hungary | 44.94 | 0 | 0% | 1 | 0% |
| Bulgaria | 42.65 | 0 | 0% | 1 | 0% |
| Poland | 41.67 | 0 | 0% | 6 | 2% |
| Greece | 38.93 | 2 | 1% | 1 | 0% |
| Thailand | 38.00 | 0 | 0% | 4 | 1% |
| Russia | 37.90 | 0 | 0% | 3 | 1% |
| Cayman Islands | 37.79 | 0 | 0% | 2 | 1% |
| Tunisia | 37.42 | 0 | 0% | 1 | 0% |
| Mexico | 35.34 | 7 | 5% | 18 | 5% |
| India | 35.18 | 4 | 3% | 9 | 3% |
| Kuwait | 34.43 | 1 | 1% | 0 | 0% |
| South Africa | 34.27 | 5 | 3% | 4 | 1% |
| Colombia | 33.78 | 0 | 0% | 4 | 1% |
| Brazil | 33.44 | 1 | 1% | 15 | 4% |
| Ireland-Rep | 33.44 | 10 | 7% | 12 | 3% |
| Peru | 31.80 | 0 | 0% | 3 | 1% |
| Argentina | 30.65 | 2 | 1% | 15 | 4% |
| Indonesia | 29.80 | 1 | 1% | 6 | 2% |
| Dominican Rep | 29.33 | 1 | 1% | 0 | 0% |
| Chile | 28.66 | 3 | 2% | 6 | 2% |
| Panama | 28.66 | 0 | 0% | 1 | 0% |
| Ecuador | 26.80 | 0 | 0% | 1 | 0% |
| Singapore | 26.53 | 2 | 1% | 12 | 3% |
| El Salvador | 25.11 | 0 | 0% | 2 | 1% |
| Ghana | 24.52 | 0 | 0% | 1 | 0% |
| Belgium | 22.88 | 2 | 1% | 7 | 2% |
| Nigeria | 22.37 | 0 | 0% | 1 | 0% |
| Total | | 148 | 100% | 355 | 100% |

## 4.4 IMF classification of emerging and advanced countries

Beside the innovative/non-innovative classification applied in this thesis, I classify acquirers as emerging and advanced. Doing this, I use the International Monetary Fund (IMF) classification where the main criteria are per capita income level (average over a number of years), export diversification and degree of integration into the global financial system. The underlying sources are the WEO database, the UN COMTRADE database and the IMF's Balance of Payments Statistics Database.

Table 5 below presents the countries represented in the dataset as either target or acquirer in alphabetical order followed by its classification from the Global Innovation Index compared to the IMF classification. All innovative companies are also advanced but so are also many of the non-innovative companies.

Table 5: Innovation index and IMF classification overview

| *Countries* | *Innovation index* | *IMF classification* | *Countries cont.* | *Innovation index* | *IMF classification* |
|---|---|---|---|---|---|
| Argentina | Non-innovative | Emerging | Ireland-Rep | Non-innovative | Advanced |
| Australia | Non-innovative | Advanced | Israel | Innovative | Advanced |
| Austria | Non-innovative | Advanced | Italy | Non-innovative | Advanced |
| Belgium | Non-innovative | Advanced | Japan | Innovative | Advanced |
| Bermuda | Non-innovative | Advanced | Kuwait | Non-innovative | Emerging |
| Brazil | Non-innovative | Emerging | Luxembourg | Innovative | Advanced |
| Bulgaria | Non-innovative | Emerging | Mexico | Non-innovative | Emerging |
| Canada | Non-innovative | Advanced | Netherlands | Innovative | Advanced |
| Cayman Islands | Non-innovative | Advanced | New Zealand | Non-innovative | Advanced |
| Chile | Non-innovative | Emerging | Nigeria | Non-innovative | Emerging |
| China | Non-innovative | Emerging | Norway | Non-innovative | Advanced |
| Colombia | Non-innovative | Emerging | Panama | Non-innovative | Emerging |
| Dominican Rep | Non-innovative | Emerging | Peru | Non-innovative | Emerging |
| Ecuador | Non-innovative | Emerging | Poland | Non-innovative | Emerging |
| El Salvador | Non-innovative | Emerging | Portugal | Non-innovative | Advanced |
| Finland | Innovative | Advanced | Russia | Non-innovative | Emerging |
| France | Innovative | Advanced | Singapore | Non-innovative | Advanced |
| Germany | Innovative | Advanced | South Africa | Non-innovative | Emerging |
| Ghana | Non-innovative | Emerging | Spain | Non-innovative | Advanced |
| Greece | Non-innovative | Advanced | Sweden | Innovative | Advanced |
| Hong Kong | Innovative | Advanced | Switzerland | Innovative | Advanced |
| Hungary | Non-innovative | Emerging | Thailand | Non-innovative | Emerging |
| Iceland | Non-innovative | Advanced | Tunisia | Non-innovative | Emerging |
| India | Non-innovative | Emerging | United Kingdom | Innovative | Advanced |
| Indonesia | Non-innovative | Emerging | United States | Innovative | Advanced |

# 5 Methodology

In this section, I establish the methodology of my study which will be investigating the ex-post difference in acquirer innovation input and output between different characteristics of both acquirer and target in cross-border M&A transactions. To test my hypotheses, I define a panel data model and the results are presented in the following way: In *Section 5.1 I* specify my innovation output measures. In *Section 5.2* I define my baseline specification. In *Section 5.3* I present the control variables used in my model. Lastly, in *Section 5.4* the regressions that are applied as robustness checks are presented in order to control for the robustness of the Global Innovation Index used as well as analysing the change in acquirer innovation activity both before and after the M&A transaction.

## 5.1 Measuring Innovation

Since the literature section of this study has covered the motivation for obtaining knowledge as being one motive to engage in cross-border acquisitions, different proxies to test the difference in the levels of innovation after an acquisition are used. Three indirect measures of innovation widely used in literature are applied; R&D intensity (input), TFP (output) and Labour productivity (output).

### 5.1.1 Innovation Measures - Input

In this study, I use research and development expenses (R&D) to measure innovation efforts as it is stated by Keller (2010) to be the most important variable for measuring innovation input. In line with previous literature, R&D intensity is defined as:

$$R\&D\ Intensity_{i,t} = \frac{R\&D\ Expenditures_{\ i,t}}{Sales_{i,t}} \tag{1}$$

The traditional metric of R&D expenditure has been frequently used by literature but is also criticised as not being as accurate in measuring changes in innovation compared to other measures. This is because R&D is captured at one point in time, thus does not reflect the actual innovation level of the firm; innovation is a stochastic process. Additionally, availability of R&D data is limited due to limitations in firm level R&D reporting in many countries. (Keller, 2010)

### 5.1.2 Productivity Measures - Output

Many theories exist on measurements of productivity, which in this thesis is referred to as innovation output. A common classification of measures is single factor measures and multifactor measures. The single factor measurement used in this study is Labour productivity, which uses the single factor employment as an input to measure the effect on productivity. Multifactor measurements use additional factors, such as intermediate goods and capital. Labour productivity is a simple measurement which does not account for other factors that could affect productivity as the denominator does not truly capture changes in intermediate goods. To capture this effect, total factor productivity (TFP) is a more comprehensive measure, though, because it is more complex, the risk of measurement errors increases. Using both of these established productivity measures is assumed to provide the thesis with a more balanced view on productivity output.

### 5.1.3 Measuring Labour Productivity

Labour Productivity is defined as:

$$Labour\ Productivity_{i,t} = \frac{Sales_{\ i,t}}{Total\ Employment_{i,t}} \qquad (2)$$

Where $i$ denotes the specific acquirer and $t$ the year.

### 5.1.4 Measuring Total Factor Productivity

A common object of interest for economists is the estimation of the production function (Levinsohn, Petrin, 2003). In this study, total factor productivity (TFP) is derived as a measure of technology (innovation output). The level of TFP determines how efficient a firm is in utilising inputs in production (Comin, 2017). To estimate TFP, data on unit input and output are used in order to calculate the residual in the correlation between output and input. In this study, I use financial statement data to proxy for input and output quantities. The production function is usually written as a Cobb-Douglas function as illustrated below:

$$Y_{i,t,j} = A_{i,t,j} K_{i,t,j}^{\beta_k} L_{i,t,j}^{\beta_l} M_{i,t,j}^{\beta_m} \qquad (3)$$

where $\beta_k, \beta_l$ $and$ $\beta_m = 1$ indicate constant returns to scale, Y represents output of firm *i* in industry *j* in period *t*, K L and M represent usage of capital, labour and materials used. A captures the efficiency of firms transforming input to output = the TFP, and can be thought of as a firm-specific level of productivity. Taking the natural logarithms for the variables in the estimation of the production function of equation 3, the transformed equation is illustrated below:

$$y_{i,t} = \beta_0 + \beta_k k_{i,j,t} + \beta_k l_{i,j,t} + \beta_k m_{i,j,t} + \omega_{i,j,t} + \eta_{i,j,t} \quad (4)$$

Where y is the natural logarithm of output which is value added, using sales as a proxy, l is the natural logarithm of labour input measured by total employment, m is the natural logarithm of intermediate input measured as cost of goods sold, which is an equivalent measure to intermediate inputs that can proxy for the unobserved productivity shocks in the estimation (Levinsohn, Petrin, 2003). This proxy variable in the production function is supposed to capture all costs related to production, like materials and energy but because of data limitations I am unable to separate the information and thus rely on cost of goods sold as the measure of inputs. k is the natural logarithm of physical capital proxied by total assets.

The error term has two components: $\omega_{i,j,t}$ and $\eta_{i,j,t}$. $\omega_{i,j,t}$ is correlated with input choice and is unobservable. $\eta_{i,j,t}$ is observable with input choice. As argued by Levinsohn, Petrin (2003), $\omega_{i,j,t}$ is determined by intermediate input and capital: $\omega_{i,j,t} = \omega_{i,j,t}(k_t, m_t)$. From that reasoning, the equation can be rewritten as:

$$y_{i,t} = \beta_k l_{i,j,t} + \phi_{i,j,t}(k_{i,j,t}, m_{i,j,t}) + \eta_{i,j,t} \quad (5)$$

$$\phi_{i,j,t}\left(k_{i,j,t}, m_{i,j,t}\right) = \beta_0 + \beta_k k_{i,j,t} + \beta_k m_{i,j,t} + \omega_{i,j,t}(k_t, m_t) \qquad (6)$$

One concern in the estimation of the productivity function is the possible correlation between unobservable productivity shocks and level of input, as these shocks are not observable by econometricians in the data, but possibly observable by the individual firm *i*. Firms are then likely to respond to a productivity shock by increasing its level of inputs. This unobservable shock is most likely to produce a biased estimate of a production function, if not accounted for. Several approaches to resolve this "*simultaneity*" problem has been introduced by literature; the fixed effects estimator, the investment proxy (Olley, Pakes, 1992), intermediate inputs (Levinsohn, Petrin, 2003), and the GMM estimation (Blundell, Bond, 2000). The semi-parametric technique suggested by Olley, Pakes (1992) and Levinsohn, Petrin (2003) are similar methods and manage to correct for the endogeneity bias using different proxies for firm specific private knowledge of productivity.

In this study the semi-parametric model developed by Levinsohn, Petrin (2003) is applied using positive materials to proxy for unobserved TFP shocks, as data availability enables us to use this approach. A similar approach was introduced by Olley, Pakes (1992), which is a semi-parametric estimation model also mitigating the survivorship bias and simultaneity problem. The model uses the firm's investment decision, and thus require positive investments to observe productivity shocks. Due to the fact that the model requires positive investment, there is a risk that many observations are dropped and disturb the production function. The technique is hard to implement since it requires positive investment in each period and is difficult to implement in a dataset.

Due to the broad range of industries in the sample, some firms are less capital intensive, and the dataset therefore lacks comparability. By using intermediate inputs as a proxy, where data on materials is used to account for firm knowledge of productivity, the study is easier to implement due to more availability of firm-level data on materials. Intermediate inputs can also smoothly track productivity shocks by responding to the whole productivity term which captures the entire shock using only investments and not solving the endogeneity problem fully. Therefore, this study employs the method of Levinsohn, Petrin (2003) using cost of goods sold as proxy for intermediate input. Further, the method can be applied with either the value-added method or the gross revenue method. In this study applies the gross revenue method is applied.

In order to estimate firm-level TFP with the Levinsohn and Petrin method, each acquirer is grouped by their respective *Standard Industry Classification* code (henceforth SIC code). The industry groups are derived on the basis of a one-digit SIC code, since classifying firms with a two-digit SIC code generates groups with an insufficient number of firms in each industry, in order to run each industry production function with the semi-parametric approach.

### 5.1.5 Measurement Issues with TFP

There are several measurement issues that appear when both using TFP and Labour productivity to measure productivity. TFP is a proxy based on production of outputs, inputs and intermediate goods (Levinsohn, Petrin, 2003). However, relying on firm-level productivity analysis with the values of production, material input and capital rather than on data on physical volumes, TFP fails to differentiate between price mark-up and productivity level (Katayama, Lu & Tybout, 2003). Another problem is due to the survivorship bias, meaning that the dataset contains missing values because of firms that have dropped out from the sample.

## 5.2 Baseline Specification

The baseline specification used in this thesis investigates the difference in the levels of innovation activity after the M&A transaction for different subgroups, as specified by the hypotheses. The empirical design is based on an OLS fixed-effects regression model on the panel dataset. The equation for the baseline specification is presented below:

$$Innovation_{i,t} = a + \beta_1 Post + \beta_2 X + \beta_3 (Post * X) + \delta Z_{i,t} + Year_t + Firm_i + \mu_{i,t} \quad (7)$$

where *i* is the firm index and *t* is the time index.

*Innovation* is the dependent variable analysed with three different variables, the natural logarithm of R&D intensity, the natural logarithm of Labour productivity and TFP for firm *i* in year *t*.

*Post* represents a binary variable taking the value of one for the three consecutive years after an M&A transaction, between *t+1* and *t+3* and zero for all other years for firm *i* in year *t*. The approach to focus on the three-year ex-post window is similar to other studies on acquisitions and innovation (Danzon et al., 2007; Hall, 1990a, 1999; Healy et al., 1992; Hitt et al., 1991). Desyllas, Hughes (2010) argue that this period of time is enough for acquisition effects to materialise while it is short enough to avoid noise and reduction of sample observations.

*X* represents a binary variable taking the form of three different subgroups in order to answer each of the hypotheses. *X* also represents the *lower order effect* of *X* on the dependent variable

*Innovation*. For answering Hypothesis 1a and 1b the variable takes the value of one if acquirer and target are present in the same industry, compared by their respective two-digit SIC codes. If acquirer and target two-digit SIC code is the same, this is defined as overlapping industries *(overlap)*. Answering Hypotheses 2a and 2b, the binary variable *X* takes the value of one if both acquirer and target in the transaction are classified as innovative, based on the Global Innovation Index *(HighInnovation)*. The last Hypotheses 3a and 3b again focus on the previously mentioned index and acquirer-target pair innovation levels, giving the binary variable *X* the value of one if the acquirer country is classified as non-innovative and the target country is classified as innovative *(LowInnovation)*.

*Post * X* is the interaction term in the regression model, taking the value of one if both the *Post* dummy and the *X* dummy have the value of one. The coefficient $\beta_3$ is defined as the effect of the product of *Post * X* on the dependent variable *Innovation* over and above the additive lower order effects of $\beta_1$ and $\beta_2$ and any firm-specific effects. This would mean that a positive and statistically significant interaction term tells us that the subgroup has a stronger and positive innovation input/output ex-post an M&A transaction as compared to other transaction groups. An interaction effect focuses on how two variables interact when accounting for the variance in the dependent variable over and above the contributions of the individual additive effects (Afshartous, Preston, 2011). This interaction term will in the model represent the *moderating effect* of variable *X* on the relationship between *Post* and *Innovation* and, if statistically significant, show the marginal difference in the baseline model between the lower order effect *X* and when *X* takes the value of zero. In figurative terms, the *moderating effect* is the variation in the slope of the regression line of the dependent variable and the time dummy, as a function of *X* (Hartmann, Moers, 1999). For instance, a positive significant coefficient of $\beta_3$ indicates that the slope of the regression line for when $X = 1$ is significantly more positive than the slope for when $X = 0$.

There are several challenges with including interaction terms in a regression model, as pointed out by Hartmann and Frank GH (1999), specifically that the lower order effects $\beta_1$ and $\beta_2$ are likely to be correlated with t heir product $\beta_3$.[1] This meaning that *Post*X* is likely to be highly correlated with both *Post* and *X;* this was also observed in the regressions as *X* was omitted in the regression. Despite this, the coefficient of an interaction term is still always interpretable (Hartmann, Moers, 1999). The reason why *X* is omitted from the model is because of the collinearity with the firm fixed effects, since the acquirers in the sample do not change industry or innovation index from year to year, meaning that there will not be any variation left in the *X* dummy after controlling for the acquirer dummies. However, this still enables us to interpret the interaction term, omitting one of the lower order effects, because of inclusion of firm fixed effects. Still, firm fixed effects are crucial in terms of interpreting the interaction coefficient in order for it to represent effects *over and above* all firm and industry specific effects, since industry specific effects are to be captured in the firm dummies.

The interpretation of the baseline regression with an interaction term is different from a model without interactions. In a model without an interaction term, $\beta_1$ would represent the effect on the dummy *Post* on *Innovation* for all firms, both when $X = 0$ and $X = 1$. The inclusion of an interaction term changes the interpretation of $\beta_1$ to represent the effect of *Post* on *Innovation* when subgroup $X = 0$. Interpreting the interaction term for instance when coefficient $\beta_3 > 0$, it would be interpreted as the difference between the effect of *Post* on *Innovation* being greater conditional on $X = 1$ compared to the effect conditional on $X = 0$. An interference interaction effect would happen when $\beta_3 < 0$, then difference in the effect of *Post* on *Innovation* is smaller when $X = 1$. Analysing only the interaction coefficient, due to the omitted lower order effect, $\beta_2$ does not enable us to assess the combined marginal effect $\beta_2 + \beta_3$ , but only the difference in the marginal effect $\beta_3$; the difference in the slope between the two subgroups. Even though the interaction variable is the focal point in order to answer the hypotheses, it is important to regard the above-mentioned critique on using interaction variables.

$\delta Z$ represents the control variables used in the model, which are attributes that according to literature have a potential effect of the level of innovation output and input of a firm. These are further presented in section 5.3 and A.2. *Firm* represents firm fixed effects controlling for unobserved time-

[1] Singularity of the matrix causes the statistical program STATA to be unable to calculate certain regression coefficients, in this example caused by multicollinearity. Common by literature, variable centering is used in order to reduce multicollinearity, but collinearity does not cause lower power of the test, why I choose to keep the model specification (Dunlap, Kemery, 1988, Cronbach, 1987).

invariant unobservable omitted variables across firms, and *Year* captures time fixed effects. As recommended by Petersen (2009), standard errors are clustered at the firm level.

With time fixed effects, variations over time that can influence innovation are controlled for. By including firm fixed effects in the model, the aim is to deal with the endogeneity issue by capturing unobservable and time-invariant heterogeneity within firms. Problems may arise when unobservable factors affecting innovation are not captured by the control variables, thus causing the model to face the problem of omission of key variables leading to biased coefficients in the main variables. Firm fixed effects alleviates this problem. Since there might be other omitted factors that affect innovation ex-post M&A for a firm, avoiding the issue of endogeneity and including firm fixed effects allows us to interpret $\beta_3$ as the additional effect of the time after an M&A transaction over and above any firm specific effects, including those coming from the type of subgroup the firm belongs to.

## 5.3 Control Variables

In the model, included control variables are presented by previous literature as affecting both innovation inputs and outputs based on firm-level characteristics:

**Firms size** - Firm size is used as a control variable as previous literature show that larger firms enjoy better access to external finance and economies of scale, since developing new products involves high fixed costs. Larger firms are also better at absorbing new technologies. (Cohen, Levinthal, 1990)

**Capital Intensity** – Following Bertrand, Betschinger & Petrina (2014), capital intensity is calculated as the ratio of firms' tangible assets divided by total employment. Higher values of capital intensity is shown to have a positive relation to firm innovation. Capital intensity reflects the general technology function of firms (Bertrand, 2009).

**Export** – In terms of innovation input, exporters are more likely to engage in R&D since entering new markets help firms to gain more knowledge of production processes and absorbing new technologies (Baldwin, Gu, 2004;Crespi, Zuniga, 2012). Salomon, Shaver, 2005 argue that exporting is associated with increased innovation since firms learn from foreign markets by exporting, thereby enhancing their efficiency. With regards to innovation output, Lileeva, Trefler (2010) argue that exporters that increased productivity had invested in innovation and exporting firms contemporaneously choose to invest in technologies that leads to productivity enhancement (Aw, Roberts & Xu, 2011;Bustos, 2011).

**Debt Ratio** – Debt ratio is included as a control variable since Sevilir, Tian (2012) show that firms with lower leverage are more innovative. However, Cassiman, Colombo (2006) argue for the opposite, that firms conducting M&A can have increased financial leverage, which leads to implications for R&D investments by decreasing innovation efforts. In this case, debt ratio can be a financial constraint proxy for acquirers in the sample.

Related literature in the field of M&A, innovation and productivity argues for further suggested control variables to affect innovation (variables not included the set of controls in this thesis): *Firm Age* is commonly used by previous research and as proposed by He, Tian (2013) younger firms tend to have higher innovation. *Ownership Structure* tends to have an important role in risky projects involving investment in R&D. Lastly, many studies use *Herfindahl Index* which is supposed to show how competitive firms are in their respective markets and capture innovation.

Due to limitations in the dataset, these control variables are not included, which can lead to the issue of biased estimation of the results. However, it is assumed that using firm fixed effects will ease this issue. Further specification on control variables used in the model is found in Table 11 in the Appendix. All control variables are winsorised at the 1st and 99th percentiles.

## 5.4 Robustness

In this section, two robustness tests on the baseline specification are described. The results from these tests are discussed in *Section* 6.2 and results are shown in Table 14 to Table 18 in the Appendix.

In the first robustness test, the Global Innovation Index classification is replaced with the definition of emerging or advanced markets presented by the International Monetary Fund (IMF). I aim to use this index as a comparison to the main results in order to examine whether it yields the same direction of the coefficients in the hypotheses. Related literature of emerging firms is also better linked to the IMF index of emerging country classification. The alternative classification of acquirers based on the IMF index is presented in comparison to the main model index in Table 5.

The second robustness test considers the time aspect of the regression model. Since the main study variable is a binary variable covering all the three consecutive years after an M&A transaction, I will evaluate its comprehensiveness by separating the effect on innovation on a year-on-year basis both pre and post an M&A transaction. This means that I include one dummy for every three years before and dummies for all three years after the event. This test will yield results that assess the robustness of the design of the main model and will additionally enable indications on the difference in the levels of each separate year on innovation inputs and outputs. I am aware of the drawbacks of using several year dummies, as it is expected to decrease the explanatory power of the model, and therefore present it mainly for illustrative reasons. The results of the implementation of the second robustness tests are presented in Section A.6 in the appendix.

Additionally, I illustrate the development of the median TFP, R&D intensity and Labour productivity for the full dataset graphically to provide additional depth into how firms' innovation levels develop three years before the M&A transaction to three year after the event. This graph is presented in A.3 in the appendix.

# 6 Empirical Results

In this section the obtained results for the specifications described in Section 5 are presented. First, the results of the baseline regression on hypotheses 1a and 1b (see section 6.1.1) hypotheses 2a and 2b (see section 6.1.2) and hypotheses 3a and 3b (see section 6.1.3) are presented. Additionally, in Section 6.2, the outcome of the robustness tests is presented.

## 6.1 Main results: Baseline Regression

### 6.1.1 Baseline regression on technology overlap

The first regression, addressing Hypothesis 1a is performed on R&D Intensity. Column (1) in Table 6 presents the results for an OLS firm and year fixed effects regression with the study variable Post*Overlap, where the interaction variable overlap represents whether acquirer and target are present in the same 2-digit SIC industry. Within this model, the interaction coefficient is negative (-0.102) and insignificant, meaning that it cannot be concluded whether there is a difference in the effect of R&D Intensity between transactions that have overlapping technologies and firms that do not.

Hypothesis 1b is performed on both Labour productivity and TFP in order to provide a more detailed picture of the difference in the level of innovation between firms with overlapping technologies (related) and no overlapping technologies (non-related). Column (2) presents a regression on Labour productivity showing that the interaction term Post*Overlap is positive (0.0087) but insignificant. Column (3) refers to TFP and determine a negative (-0.295) and significant interaction term on the 1% level, meaning that the hypothesis that acquirers in related transactions experience a smaller effect on innovation output over and above any effects of other acquirers can be accepted.

**Table 6:** Baseline regression - Hypothesis 1

| Hypotheses | Hypothesis 1a | Hypothesis 1b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post*Overlap | **-0.102** | **0.0087** | **-0.295**** |
| | (0.076) | (0.039) | (0.146) |
| Post | **-0.292***** | **0.015** | **-0.080** |
| | (0.086) | (0.044) | (0.165) |
| Overlap | - | - | - |
| | - | - | - |
| *Control variables* | | | |
| *DEBT RATIO* | 0.027 | 0.0046 | -0.070* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.141** | 0.522*** | -0.456*** |
| | (0.071) | (0.036) | (0.136) |
| *EXPORT* | -8.85e-06 | 1.14e-05 | 0.00033*** |
| | (5.69e-05) | (2.92e-05) | (0.00011) |
| *SIZE* | -0.109* | -0.197*** | 1.019*** |
| | (0.066) | (0.034) | (0.126) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.059 | 0.269 | 0.124 |

This table shows the regression results for hypothesis 1 where a fixed effects model is used to examine the potential difference in innovation input and output ex-post an M&A transaction between acquirer subgroups. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post*Overlap*, the study variable is an interaction variable between the dummy variable *Post* and the dummy variable *Overlap*. The variable *Post* is a binary indicator taking the value of one for the three years between *t+1* and *t+3* after an M&A deal. The variable *Overlap* is a binary indicator taking the value of one if both acquirer and target share the same 2-digit SIC code. In all our regressions, we control for *DEBT RATIO* as measured by the natural logarithm of total debt divided by total assets; *CAPITAL INTENSITY* as measured by the natural logarithm of tangible assets to total employment; *EXPORT* as measured by foreign income before tax expenses and *SIZE* as measured by the natural logarithm of total employment. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *Overlap* is omitted because of collinearity with firm fixed effects.

### 6.1.2 Baseline regression on innovative acquirer and innovative target

Next, regarding Hypothesis 2a on R&D intensity, Column (1) in Table 7 presents the results for an OLS firm and year fixed effects regression with the study variable Post*HighInnovation, where the interaction variable overlap represents when both the acquiring and the target country are classified as innovative. Within this model, the interaction coefficient is positive (0.284) and significant on the 1% level, meaning there is a higher level of innovation input for highly innovative acquirers acquiring innovative targets as compared to other acquirers.

Hypothesis 2b is performed on both Labour Productivity and TFP starting with column (2) presenting a regression on Labour productivity showing that the interaction term Post*HighInnovation is positive (0.000836) but insignificant. In Column (3) the dependent variable is TFP and determine a negative (-0.568) and significant interaction term on the 5% level, meaning there is a lower level of innovation output for acquisitions between two innovative countries as compared to other transactions.

**Table 7:** Baseline regression - Hypothesis 2

| Hypotheses | Hypothesis 2a | Hypothesis 2b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post*HighInnovation | **0.284*** ** | **0.00836** | **-0.568** ** |
| | (0.079) | (0.0388) | (0.145) |
| Post | **-0.474*** ** | **0.0169** | **-0.014** |
| | (0.079) | (0.0411) | (0.153) |
| HighInnovation | - | - | - |
| | - | - | - |
| *Control variables* | | | |
| *DEBT RATIO* | 0.024 | 0.0048 | -0.075** |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.124** | 0.523*** | -0.495*** |
| | (0.071) | (0.036) | (0.136) |
| *EXPORT* | -6.80e-06 | 1.15e-05 | 0.00033*** |
| | (5.67e-05) | (2.92e-05) | (0.00011) |
| *SIZE* | -0.089 | -0.196*** | 0.973*** |
| | (0.066) | (0.034) | (0.126) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.065 | 0.269 | 0.128 |

This table shows the regression results for hypothesis 2 where a fixed effects model is used to examine the potential difference in innovation input and output ex-post an M&A transaction between acquirer subgroups. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post*HighInnovation*, the study variable is an interaction variable between the dummy variable *Post* and the dummy variable *HighInnovation*. The variable *Post* is a binary indicator taking the value of one for the three years between *t+1* and *t+3* after an M&A deal. The variable *HighInnovation* is a binary indicator taking the value of one if both acquirer and target are classified with a high innovation index, defined by the Global Innovation Index (2018). In all our regressions, we control for *DEBT RATIO* as measured by the natural logarithm of total debt divided by total assets; *CAPITAL INTENSITY* as measured by the natural logarithm of tangible assets to total employment; *EXPORT* as measured by foreign income before tax expenses and *SIZE* as measured by the natural logarithm of total employment. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *HighInnovation* is omitted because of collinearity with firm fixed effects.

### 6.1.3 Baseline regression on non-innovative acquire and innovative target

Addressing Hypothesis 3a on R&D intensity, Column (1) in Table 8 presents the results for an OLS firm and year fixed effects regression with the study variable Post*LowInnovation, where the interaction variable overlap represents that the acquirer is from a country classified as non-innovative and the target country is classified as innovative. Within this model, the interaction coefficient is negative (-0.102) and significant on the 1% level meaning that there is a lower level of innovation output for acquirers in non-innovative countries acquiring targets in innovative countries as compared to other transactions.

Hypothesis 3b is performed on both Labour Productivity and TFP starting with column (2) presenting a regression on Labour productivity showing that the interaction term Post*HighInnovation is positive (0.0087) but insignificant. In Column (3,) the regression is conducted on the dependent variable TFP and determine a negative (-0.265) and significant interaction term on the 1% level, meaning there is a higher level of innovation output for acquirers in non-innovative countries acquiring innovative targets as compared to other acquirers.

**Table 8:** Baseline regression - Hypothesis 3

| Hypotheses | Hypothesis 3a | Hypothesis 3b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post*LowInnovation | **-0.102** | **0.0087** | **0.265**** |
| | (0.076) | (0.039) | (0.221) |
| Post | **-0.292***** | **0.015** | **-0.291** |
| | (0.086) | (0.044) | (0.165) |
| LowInnovation | - | - | - |
| | - | - | - |
| *Control variables* | | | |
| *DEBT RATIO* | 0.027 | 0.0046 | -0.070* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.141** | 0.522*** | -0.456*** |
| | (0.071) | (0.036) | (0.136) |
| *EXPORT* | -8.85e-06 | 1.14e-05 | 0.00033*** |
| | (5.69e-05) | (2.92e-05) | (0.00011) |
| *SIZE* | -0.109* | -0.197*** | 1.019*** |
| | (0.066) | (0.034) | (0.126) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.065 | 0.269 | 0.122 |

This table shows the regression results for hypothesis 3 where a fixed effects model is used to examine the potential difference in innovation input and output ex-post an M&A transaction between acquirer subgroups. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post*LowInnovation*, the study variable is an interaction variable between the dummy variable *Post* and the dummy variable *LowInnovation*. The variable *Post* is a binary indicator taking the value of one for the three years between *t+1* and *t+3* after an M&A deal. The variable *LowInnovation* is a binary indicator taking the value of one if acquirer is classified with a low innovation index and target classified with a high innovation index, defined by the Global Innovation Index (2018). In all our regressions, we control for *DEBT RATIO* as measured by the natural logarithm of total debt divided by total assets; *CAPITAL INTENSITY* as measured by the natural logarithm of tangible assets to total employment; *EXPORT* as measured by foreign income before tax expenses and *SIZE* as measured by the natural logarithm of total employment. Robust standard errors (clustered at the firm-level) are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Note*: The binary variable *LowInnovation* is omitted because of collinearity with firm fixed effects.

## 6.2 Robustness

Two robustness tests of the baseline hypotheses are conducted following the description in Section 5.4. The results can be found in Section A.5 and A.3 included in the Appendix.

First, Table 14 presents the results from the robustness test relating to Hypothesis 2 but using the IMF classification to separate transactions with acquirer and target both based in advanced countries. First, relating to R&D intensity, the interaction term is positive (0.636) and significant on the 5% level and in line with the initial baseline regression using the Global Innovation index classification. In the regression in Column (2), Labour Productivity is presented, and the coefficient is positive (0.121) and significant on the 1% level contrasting the results in the baseline regression where no significant result was found for this measurement. However, in the regression on Column (3) the sign flips and yields a negative and statistically coefficient (-0.703) on the 5% level, which is in line with the baseline results for TFP.

Table 15 then reports the same as above but relating to Hypothesis 3 where transactions where the acquirer is emerging, and the target is advanced have been separated from the general dataset. The interaction term in Column (1) shows a negative coefficient (-1.11) on a 1% significance level showing that innovation input levels are smaller after an acquisition for the subgroup compared to other acquirers. This is in line with the main results. The robustness test in Hypothesis 3b does not yield any significant results for neither TFP nor Labour productivity. The main regressions showed positive and significant results with regards to TFP.

Further, in the second robustness test, increasing the study variable to three separate dummies, I aim to study the difference in the levels of the separate yearly effects in innovation input and output. Relating to Hypothesis 1, Table 16 in the Appendix, Column (3) on TFP show that there is a significant difference only in year two, i.e. Post Dummy (t+2)*Overlap is statistically significant and negative. This is interpreted as that in the second year after an acquisition related transactions experience negative post innovation levels compared to non-related transaction. Although not significant, also the other years show negative results.

With regards to Hypotheses 2a and 2b, Table 17 in the Appendix Column (1) reports a positive and significant pattern on the level of innovation input measured by R&D intensity with the yearly interaction dummies being positive in the first year (0.206) on a 5% significance level and in the second year (0.181) on a 5% significance level. Testing the results of Hypothesis 2b, I find significant results indicating a negative and decreasing TFP level pattern as shown by Column (3); in the first year results show a smaller effect of innovation of (-0.407) with a significance level of 5%, in the second year the difference in the effect is decreasing further to (-0.559) with a significance level of 5% and in the third year there is a further decrease of the coefficient to (-0.815) with a significance level of 1%.

# 7 Discussion

## 7.1 Discussion of hypotheses 1

Hypothesis 1a: *Cross-border acquirers, acquiring a target within the same industry, experience no difference in the effect of ex-post innovation input compared to the innovation levels of cross-border acquirers not acquiring a target within the same industry*

Hypothesis 1b: *Cross-border acquirers, acquiring a target within the same industry, experience a smaller effect on ex-post innovation output compared to the innovation levels of cross-border acquirers not acquiring a target within the same industry*

Regarding hypothesis 1a and 1b the regressions show the following key findings: i) Whether the acquirer and target are in the same industry or not does not matter for innovative efforts (no difference in R&D), ii) There is a significant, negative difference in TFP comparing transactions within the same industry to those in different industries. Moreover, I find that there is no difference in Labour productivity. The results are expected and in line with the hypotheses except for Labour productivity, where the results were expected to be in line with TFP.

Merging two firms, the absolute level of R&D increases which in the literature review is said to affect R&D in terms of i) economies of scale, ii) economies of scope. It has previously been discussed how TFP is less driven by economies of scale, and more about technology advancement, compared to Labour productivity. As the results show that there is no difference in Labour productivity depending on industrial overlap in transactions, the results indicate that there are further factors than economies of scale and scope affecting R&D efforts from acquiring a target within the same industry.

Though, it is also found that TFP is significantly higher for different industry acquisitions, indicating that there are gains from acquiring complementing technologies rather than substituting, or at least relating, technologies. Despite this, it has in previous research been discussed how there might be implementation problems for non-related mergers; something that is not evident from this analysis.

The difference between effect on input and output is interesting from the discussion relating to correlation between the two presented in previous research. Previous research shows that firms investing heavily in R&D not necessarily are the users of the results. The fact that the acquiring company in a cross-border, non-related acquisition seems to better transform R&D efforts to long-term, efficient use of resources compared to in related acquisition is important knowledge for the research area of world innovation. This further emphasise the conclusion that non-related acquisitions not necessarily are problematic because of implementation problems.

## 7.2 Discussion of hypotheses 2

Hypothesis 2a: *Cross-border acquirers with a high innovation index, acquiring a target with a high innovation index, experience higher ex-post innovation input over and above any levels of innovation in comparison to other cross-border acquirers*

Hypothesis 2b: *Cross-border acquirers with a high innovation index, acquiring a target with a high innovation index, experience no difference ex-post innovation output over and above any levels of innovation in comparison to other cross-border acquirers*

Regarding hypothesis 2a and 2b, the following key findings are presented: i) The R&D intensity after a cross-border acquisition is significantly higher when the acquirer as well as the target are based in innovative countries compared to other acquisitions, ii) There is a significant, negative difference in TFP comparing transactions where the acquirer as well as target are based in innovative countries compared to other transactions. More, I find that there is no effect in Labour productivity. The results are expected and in line with the hypotheses except for TFP, where I expected to see results in line with Labour productivity.

As robustness, I also perform the same regressions but using the IMF classification of emerging and advanced countries. I find that there is a positive difference in R&D, a positive difference in Labour productivity and a negative difference in TFP. All results are significant. Comparing innovative companies with advanced and non-innovative companies with emerging, I find the same results for TFP and R&D while Labour productivity is positive and significant using the IMF classification and not significant using the Global Innovation Index classification.

The results differ from what was expected regarding TFP, where I find that innovative acquirers acquiring innovative targets, though higher R&D, have lower TFP. This is also significant for advanced countries classified according to IMF. The result indicates that innovative companies in general become less effective into transforming innovative efforts to actual outputs after an acquisition compared to other transactions. A reason for this could be that the acquirers choose to engage in cross-border M&A although the conditions for import as well as export are beneficial, are interested in long-term innovative activities that not necessarily result in immediate output to a larger extent compared to other companies.

The higher R&D value was expected as the innovative countries also are advanced and should have access to financial resources to a larger extent than emerging countries. This is further emphasised by the result being the same for IMF and Global Innovation Index classification in this regard. M&A has by previous research been stated as a substitute to innovation and although rejecting or accepting this is outside the scope of this thesis, the results indicate that the effect is at least less distinct in acquisitions between two advanced or two innovative countries.

Interesting in the discussion is also the different effects on Labour productivity and TFP. It has in previous literature been discussed how these productivity measures are different in terms of TFP measuring level of technology advancement, while Labour productivity is a measure describing how effectively labour is transferred into sales. The results indicate that innovative companies (higher TFP after acquisition) in innovative countries (high innovation index) do not engage in cross-border M&A even in other innovative countries. Alternative approaches such as exports, give these companies control of their technology and also benefit avoidance of implementation issues from transferring knowledge. It though indicates that the most innovative companies in the world to a lower extent than others engage in cross-border M&A activities.

## 7.3 Discussion of hypotheses 3

Hypothesis 3a: *Cross-border acquirers with a low innovation index, acquiring a target with a high innovation index, experience lower ex-post innovation input over and above any levels of innovation in comparison to other cross-border acquirers*

Hypothesis 3b: *Cross-border acquirers with a low innovation index, acquiring a target with a high innovation index, experience higher ex-post innovation output over and above any levels of innovation in comparison to other cross-border acquirers*

Regarding hypothesis 3a and hypothesis 3b, the following key findings are presented: i) R&D intensity is lower for acquirers in non-innovative countries acquiring targets in innovative countries compared to other transactions, ii) TFP is higher for acquirers in non-innovative countries acquiring targets in innovative countries compared to other transactions. I do not find any significant results in terms of Labour productivity. The results were expected except for Labour productivity, where I expected results in line with TFP.

In line with hypotheses 2, I also performed the same tests using the IMF classification of advanced and emerging markets. I found negative, significant results for R&D in line with the innovation index results. No significant results were found for Labour productivity and TFP.

First, regarding R&D, it is interesting to see how the opposite is found when the acquirer is emerging/non-innovative compared to when the acquirer is advanced/innovative. This is in line with what was expected and emphasises that emerging acquirers use M&A as a tool to gain access to innovation and to implement it in the operations rather than to further develop it. That they are successful in doing so is emphasised by the TFP being higher for the subsample compared to the overall dataset, indicating high factor productivity after M&A.

That there is no significant result with regards to the IMF index classification is also interesting to interpret. This indicates that acquirers in non-innovative, advanced countries are the ones that best benefit from cross-border M&A for innovation purposes. One plausible reason for this is that these firms benefit from their financial conditions in the implementation of the new technology.

Another approach to the result above is that non-innovative, advanced countries engage in cross-border M&A to a larger extent when they have the right conditions to increase TFP. Another reason could be that the trading policies of the acquiring country makes it difficult to import, for which reason a subsidiary abroad might be beneficial. Sales presence could be a third but less likely explanation when the target is innovative as that, according to previous research, incentivises export above M&A.

# 8 Research limitations

This paper has been written with the intention to present a fair view on the international M&A market between the years 2000-2015. Although care has been taken in conducting as well as presenting qualitative and quantitative analysis, there are limitations that the reader should be aware about.

First, matching datasets from different sources in order to combine transaction data with financial data resulted in a significant decrease of number of observations, thus number of transactions included in the final dataset is far from the actual number of transactions between the years of interest. The limitation was though expected as comparable articles present the same data limitation. Still, it cannot be concluded that the data drop is random as it has previously been raised in this thesis that the data sources used are biased in terms of data quality. As the datasets used mainly are American, the overview of nations presented under Data & Method clearly shows an overrepresentation of American companies while emerging markets are underrepresented.

To reduce the impact of this, extensive work has been put into complementing the datasets both manually and using datasets from other providers. This was especially important for R&D expenses, which is not always reported by the company but even more commonly not presented in databases, while it holds a central position in this paper. While the data collection created a more extensive dataset, the risk of non-comparable definitions of factors increased with this approach. These problems also arise from the use of global data where different accounting standards have been applied to present the numbers.

Where data was still missing, the judgement to drop the observation was made as it would otherwise be misleading in further analysis. Proceeding with the statistical analysis, I am aware of the limitations of the method used and that interpretation has to be done with caution given the discussion in Section 5.2.

As the statistical approach only enables observation of the difference in innovation between groups and time through an interaction term, I cannot conclude whether there are any disparities in the overall difference in the groups tested. This since my main effects was left out because of multicollinearity with the firm effects. I therefore believe that it would be interesting to see the effect of propensity score matching, though data limitations restrained this approach

# 9 Further research

As a result of the judgements and limitations I have experienced working on this thesis, I wish to see further research in the area to further precise the drivers of global innovation:

First, as globalisation is something that has been ongoing for a long period of time historically but now moving faster than ever before, each year of extra observations will be extremely valuable. I wish to see longer time series, comparisons over time and analysis of actual effects on innovative advancement in the world and in exposed areas that can be traced back to cross-border M&A.

Second, it would be interesting to dig deeper into the differences between innovative countries and developed countries and non-innovative countries and developing countries. In this thesis I conclude that there are many similarities and that non-innovative, developed countries can adapt to an emerging view on M&A in order to benefit from innovative acquisitions. Further emphasis on this phenomenon is a research area that hopefully will attract research interest going forward. I would also encourage further studies to look at acquirer characteristics, since this study only uses country level classifications and does not group acquirers based on firm level data.

Third, the perspective of the target is interesting and something that has been strongly focused on in previous literature. While previous research shows the effect of cross-border M&A in many cases are different for target compared to acquirer, the hypotheses of this thesis has not previously been examined. Technological relatedness between target and acquirer may lead to higher innovation in the merged entity due to the complementary nature of the firms' R&D efforts, enabling relocation of R&D activities in order to strengthen innovation and firms' competitive position. In another context, acquirers searching for efficiency in technological knowledge might redeploy the gains in R&D efficiency from the merged entity to the acquirer, taking advantage of the target. It would be interesting to see whether the results I conclude in this thesis, from the perspective of the acquirer, also holds for target. This is very important in order to conclude on whether cross-border M&A is a driver of global innovation or not.

Building on above, this thesis aims to contribute to, but does not fully answer, whether the global M&A market is positive or not in terms of social and sustainable development. It is assumed that innovation contributes to these factors, but innovation can look very differently. It would be interesting to see future research examining which kind of research that increases; e.g. is there a development towards more sustainable solutions or rather consumption and fast fashion? What is the effect on social welfare in emerging markets from cross-border M&A?

Last, I believe that access to a more extensive dataset would create opportunities for further research to examine differences in specific industries or between specific countries. Also, results could be more precise by examining unobserved effects of heterogeneity.

# 10 Conclusion

This thesis has aimed to further examine why previous research presents ambiguous results regarding the effect of M&A on innovation by comparing different subsamples using different measures. The dataset was first divided into related and non-related transactions depending on the industry of target and acquirer. Previous research in the area is extensive, though there has been limited focus on the actual difference between the two. Further, I contribute to existing research by introducing the concept of innovative and non-innovative countries as an alternative to the traditional classification based on national financial conditions.

First, I conclude that the ongoing discussion regarding comparability of measurements of innovation is essential for the research area; I find diverse results in innovation input and output but also between TFP and Labour productivity, both measuring innovation output.

Second, the related industry analysis shows no difference in R&D intensity or Labour productivity but that acquirers in related transactions have lower TFP than those engaging in non-related transactions. Previous literature has suggested that implementation problems may arise from non-related acquisitions while my results show that this not necessarily is the case. Further, the analysis concludes that the total effect on innovation is more complex than a discussion of economies of scale and scope can explain, as I then would have expected a similar difference in Labour productivity as in TFP.

Third, classifying countries as either innovative or non-innovative based on the Global Innovation Index and comparing the results to a traditional classification of emerging and advanced markets, I show differing results for advanced and innovative acquirers with regards to Labour productivity for advanced and innovative countries, and with regards to R&D intensity and TFP for emerging and non-innovative countries

The results above are interesting as they indicate that there is a difference between advanced and innovative countries. In the discussion, it was presented how non-innovative, advanced acquirers engaging in cross-border M&A most often are aiming to acquire i) developed technology rather than technology expertise, ii) import efficiency. Export is another plausible reason but less likely as innovative targets most often have low trading barriers and that export therefore would be incentivised in this case.

Regarding R&D intensity, a clear variation between innovative acquirers and non-innovative acquirers was presented. The results were also consistent with the results of the traditional IMF classification, indicating that advanced acquirers and innovative acquirers both are more R&D intensive than the general transaction in the full dataset. The result shows how innovation spend is done in innovative and advanced countries emphasising how emerging or non-innovative acquirers copy and implements the innovation output. On the contrary, an advanced or innovative acquirer aims to find targets where they can further build on the technology. A plausible reason for this is that the technology is more easily accessible in innovative or advanced countries. It also stresses how M&A is less often used as a substitute to innovation in a transaction between two advanced companies compared to the overall transactions included in the dataset.

Although the R&D intensity is significantly higher for advanced and innovative acquirers, I find that the TFP is significantly lower. Although the result was unexpected, a possible explanation presented is that firms that choose to engage in M&A even though they have the right conditions to instead import and export directly, do this for long-term innovative reasons that does not immediately transform into output.

To conclude, this thesis emphasises the importance of knowledge transfer internationally and stresses that technology is an intangible and tradeable asset where some companies have a competitive advantage because of its jurisdiction. Cross-border M&A is a tool for companies that are restricted in terms of national policies to gain access to developed technology.

To better understand the international M&A market, I therefore encourage researchers and policy makers to be more aware of the complexity around measurement units of innovation as well as its effect on different subsamples. In this thesis, empirical evidence of measurement and subsample differences have been presented, which is believed to be useful information to better understand international trade patterns.

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# Appendix

## A.1 Descriptive statistics

### A.1.1 Overview of data split by year

Table 9: Observations per year

| *Year* | *Observations* | *Ratio* |
|---|---|---|
| 2000 | 251 | 33% |
| 2001 | 98 | 13% |
| 2002 | 61 | 8% |
| 2003 | 43 | 6% |
| 2004 | 38 | 5% |
| 2005 | 24 | 3% |
| 2006 | 29 | 4% |
| 2007 | 30 | 4% |
| 2008 | 31 | 4% |
| 2009 | 19 | 2% |
| 2010 | 27 | 4% |
| 2011 | 24 | 3% |
| 2012 | 16 | 2% |
| 2013 | 21 | 3% |
| 2014 | 41 | 5% |
| 2015 | 8 | 1% |
| Total | 761 | 100% |

### A.1.2 Overview of data split by sector

Table 10: Industries

| *Industry* | *Observations* | *Ratio* |
|---|---|---|
| Mining & Construction | 48 | 6% |
| Manufacturing | 402 | 53% |
| Transportation & Public Utilities | 68 | 9% |
| Wholesale Trade | 14 | 2% |
| Retail Trade | 23 | 3% |
| Finance, insurance & real estate | 60 | 8% |
| Services | 146 | 19% |
| Total | 761 | 100% |

## A.2 Variable definitions

**Table 11:** Variable definitions

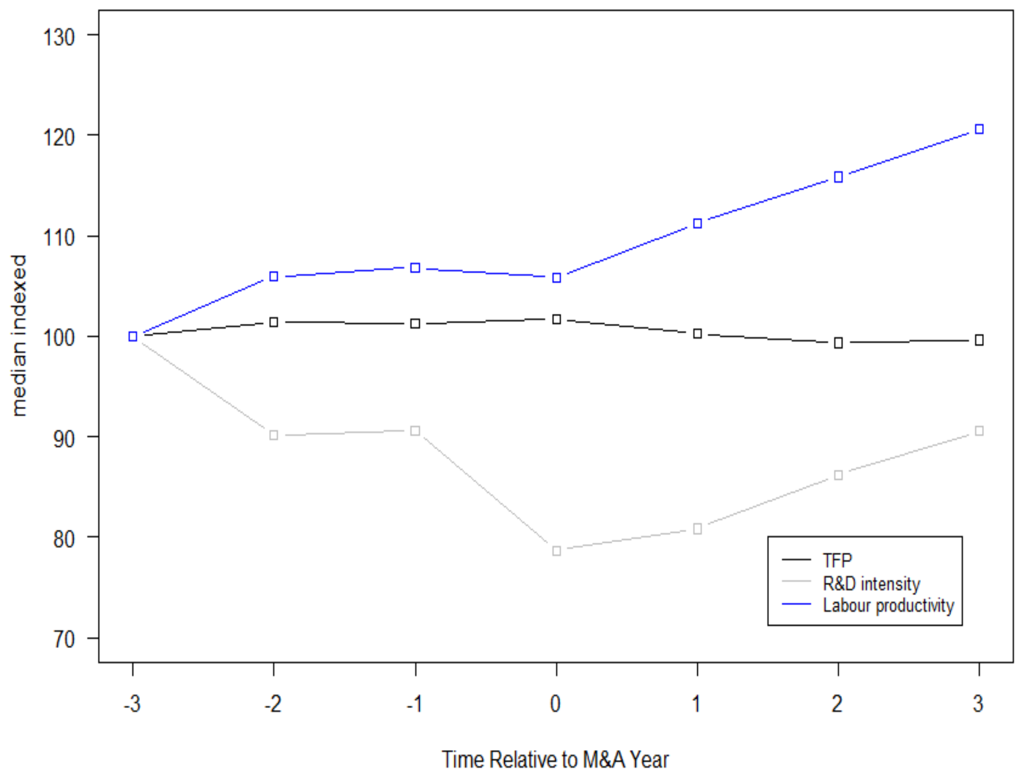
| Variable | Definition |
|---|---|
| Dependent Variables | |
| R&D Intensity $_{i,t}$ | Research and development (R&D) expenditures divided by sales for firm *i* measured at the end of fiscal year *t* |
| Labor Productivity $_{i,t}$ | Sales divided by total employment for firm *i* measured at the end of fiscal year *t* |
| Total Factor Productivity $_{i,t}$ | Production function employing the Levinsohn and Petrin (2003) estimation technique |
| Explanatory Variables | |
| Post $_{i,t}$ | Binary indicator taking the value of one in the three years between *t+1* and *t+3* after an M&A deal for firm *i* |
| Post Dummy $_{t}$ | Binary indicator taking the value of one for each separate year; *t+1, t+2 and t+3* after an M&A deal for firm *i* |
| Control Variables | |
| Debt Ratio $_{i,t}$ | Natural logarithm of book value of debt divided by book value of total assets for firm *i* measured at the end of fiscal year *t* |
| Capital Intensity $_{i,t}$ | Natural logarithm of tangible assets divided by total employment for firm *i* measured at the end of fiscal year *t* |
| Export $_{i,t}$ | [Total earnings before tax – domestic earnings before tax] for firm *i* during fiscal year *t* |
| Size $_{i,t}$ | Total employees for firm *i* during fiscal year *t* |

This table include definitions of the main variables used in our baseline regressions.

## A.3 Graphical overview

Table 12 below shows how the medians of TFP, R&D intensity and Labour productivity develop from three years before the acquisition to three years after indexed to year minus three. While TFP appears to remain rather flat, R&D intensity decreases before acquisition to instead increase after the event. Labour productivity instead increases after the event.

Table 12: Graphical overview of median development at time of acquisition



## A.4 Pearson's Pairwise Correlation Analysis

**Table 13:** Pearson's pairwise correlation analysis

| | R&D Intensity | Labor Productivity | TFP | DEBT RATIO | CAPITAL INTENSITY | EXPORT | SIZE |
|---|---|---|---|---|---|---|---|
| R&D Intensity | 1 | | | | | | |
| Labor Productivity | -0.0761*** | 1 | | | | | |
| TFP | -0.1098*** | 0.0742*** | 1 | | | | |
| DEBT RATIO | -0.0232 | 0.0849*** | 0.0513*** | 1 | | | |
| CAPITAL INTENSITY | 0.2002*** | 0.5466*** | 0.1439*** | 0.1362*** | 1 | | |
| EXPORT | -0.0347** | 0.0496*** | 0.0324** | -0.0294 | 0.0425** | 1 | |
| SIZE | -0.1594*** | -0.3570*** | 0.0892*** | 0.1049*** | -0.3541*** | 0.2286*** | 1 |

This table depicts the Pearson's pairwise correlation coefficients between the main variables used in the regressions. *R&D Intensity* is the natural logarithm of R&D expenditures divided by sales. *Labor Productivity* is the natural logarithm of sales divided by total employment. *Total Factor Productivity (TFP)* is measured by the Levinsohn-Petrin estimation algorithm. *DEBT RATIO* is the natural logarithm of total debt divided by total assets. *CAPITAL INTENSITY* is the natural logarithm of tangible assets to total employment. *EXPORT* is foreign income before tax expenses. *SIZE* is the natural logarithm of total employment. *** p<0.001, ** p<0.01, * p<0.05.

## A.5 Robustness test using IMF classification

### A.5.1 Robustness test of Hypotheses 2a and 2b using IMF classification

**Table 14:** Robustness 1 - Hypothesis 2

| Hypotheses | Hypothesis 2a | Hypothesis 2b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post*Advanced | **0.636 **** | **0.121**** | **-0.703**** |
| | (0.094) | (0.049) | (0.182) |
| Post | **-0.868 ***** | **-0.077** | **0.313** |
| | (0.106) | (0.055) | (0.203) |
| Advanced | - | - | - |
| | - | - | - |
| *Control variables* | | | |
| *DEBT RATIO* | 0.016 | 0.0032 | -0.067* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.158** | 0.519*** | -0.442*** |
| | (0.070) | (0.036) | (0.135) |
| *EXPORT* | 1.40e-06 | 1.33e-05 | 0.00032*** |
| | (5.6e-05) | (2.91e-05) | (0.00011) |
| *SIZE* | -0.118** | -0.198*** | 1,023*** |
| | (0.065) | (0.034) | (0.126) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.079 | 0.272 | 0.128 |

This table shows the regression results for hypothesis 2 where a fixed effects model is used to examine the potential difference in innovation input and output ex-post an M&A transaction between acquirer subgroups. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post*Advanced*, the study variable is an interaction variable between the dummy variable *Post* and the dummy variable *Advanced*. The variable *Post* is a binary indicator taking the value of one for the three years between *t+1* and *t+3* after an M&A deal. The variable *Advanced* is a binary indicator taking the value of one if both acquirer and target countries are classified as advanced, defined by the International Monetary Fund. In all our regressions, we control for *DEBT RATIO* as measured by the natural logarithm of total debt divided by total assets; *CAPITAL INTENSITY* as measured by the natural logarithm of tangible assets to total employment; *EXPORT* as measured by foreign income before tax expenses and *SIZE* as measured by the natural logarithm of total employment. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *Advanced* is omitted because of collinearity with firm fixed effects.

## A.5.2 Robustness test of Hypotheses 3a and 3b using IMF classification

**Table 15:** Robustness 1 - Hypothesis 3

| Hypotheses | Hypothesis 3a | Hypothesis 3b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post*Emerging | **-1.11*** ** | **0.0832** | **-0.287** |
| | (0.223) | (0.115) | (0.429) |
| Post | **-0.314*** ** | **0.0175** | **-0.246** ** |
| | (0.073) | (0.0378) | (0.141) |
| Emerging | - | - | - |
| | - | - | - |
| *Control variables* | | | |
| *DEBT RATIO* | 0.026 | 0.0046 | -0.075* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.133** | 0.522*** | -0.457*** |
| | (0.071) | (0.036) | (0.137) |
| *EXPORT* | -1.21e-05 | 1.17e-05 | 0.00034*** |
| | (5.67e-05) | (2.92e-05) | (0.00011) |
| *SIZE* | -0.106* | -0.197*** | 1.016*** |
| | (0.066) | (0.034) | (0.127) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.070 | 0.270 | 0.122 |

This table shows the regression results for hypothesis 3 where a fixed effects model is used to examine the potential difference in innovation input and output ex-post an M&A transaction between acquirer subgroups. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post*Emerging*, the study variable is an interaction variable between the dummy variable *Post* and the dummy variable *Emerging*. The variable *Post* is a binary indicator taking the value of one for the three years between *t+1* and *t+3* after an M&A deal. The variable *Emerging* is a binary indicator taking the value of one if acquirer country is classified as emerging and target country classified as advanced, defined by International Monetary Fund. In all our regressions, we control for *DEBT RATIO* as measured by the natural logarithm of total debt divided by total assets; *CAPITAL INTENSITY* as measured by the natural logarithm of tangible assets to total employment; *EXPORT* as measured by foreign income before tax expenses and *SIZE* as measured by the natural logarithm of total employment. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *Emerging* is omitted because of collinearity with firm fixed effects.

## A.6 Robustness test using three time-dummies

### A.6.1 Robustness test of Hypotheses 1a and 1b using three time-dummies

**Table 16:** Robustness 2 - Hypothesis 1

| Hypotheses | Hypothesis 1a | Hypothesis 1b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post Dummy $_{t+1}$ *Overlap | **-0.0257** | **0.028** | **-0.243** |
| | (0.098) | (0.050) | (0.187) |
| Post Dummy $_{t+2}$ *Overlap | **-0.0552** | **0.027** | **-0.298*** |
| | (0.097) | (0.049) | (0.185) |
| Post Dummy $_{t+3}$ *Overlap | **-0.091** | **-0.110** | **-0.206** |
| | (0.098) | (0.050) | (0.188) |
| Post Dummy $_{t+1}$ | 0.052 | 0.048 | 0.262 |
| | (0.093) | (0.047) | (0.178) |
| Post Dummy $_{t+2}$ | 0.269** | 0.031 | 0.416*** |
| | (0.110) | (0.056) | (0.210) |
| Post Dummy $_{t+3}$ | 0.359*** | 0.031 | 0.518** |
| | (0.131) | (0.067) | (0.249) |
| *Control variables* | | | |
| *DEBT RATIO* | 0.018 | 0.0042 | -0.079* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.135** | 0.523*** | -0.449*** |
| | (0.071) | (0.036) | (0.136) |
| *EXPORT* | -1.1e-05 | 1.26e-05 | 0.00034*** |
| | (5.72e-05) | (2.92e-05) | (0.00011) |
| *SIZE* | -0.118** | -0.197*** | 1.017*** |
| | (0.066) | (0.034) | (0.127) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.055 | 0.272 | 0.123 |

This table reports regressions of innovation outcome measured by R&D Intensity, Labor Productivity and Total Factor Productivity in the three-year period ex-post an M&A deal between t+1 and t+3, measured separately by a yearly M&A dummy for each year after the deal. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post Dummy*Overlap*, the study variable is an interaction variable between the dummy variable *Post Dummy* and the dummy variable *Overlap*. The variable *Post Dummy* is a binary indicator taking the value of one for each separate year; *t+1, t+2 and t+3* after an M&A deal. The variable *Overlap* is a binary indicator taking the value of one if acquirer is classified with a low innovation index and target classified with a high innovation index, defined by the Global Innovation Index (2018). Definitions of control variables are in table x. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *Overlap* is omitted and not shown in the regression results, because of collinearity with firm fixed effects.

A.6.2 Robustness test of Hypotheses 2a and 2b using three time-dummies

**Table 17:** Robustness 2 - Hypothesis 2

| Hypotheses | Hypothesis 2a | Hypothesis 2b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post Dummy $_{t+1}$ *HighInnovation | **0.206**** | **-0.035** | **-0.407**** |
| | (0.098) | (0.051) | (0.187) |
| Post Dummy $_{t+2}$ *HighInnovation | **0.181**** | **-0.0177** | **-0.559**** |
| | (0.097) | (0.052) | (0.185) |
| Post Dummy $_{t+3}$ *HighInnovation | **0.136** | **0.011** | **-0.815***** |
| | (0.099) | (0.065) | (0.189) |
| Post Dummy $_{t+1}$ | -0.044 | 0.077* | 0.287 * |
| | (0.085) | (0.041) | (0.161) |
| Post Dummy $_{t+2}$ | 0.167* | 0.052 | 0.475** |
| | (0.103) | (0.058) | (0.197) |
| Post Dummy $_{t+3}$ | 0.258** | 0.018 | 0.732*** |
| | (0.125) | (0.049) | (0.238) |
| *Control variables* | | | |
| *DEBT RATIO* | 0.018 | 0.0043 | -0.082* |
| | (0.023) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.126* | 0.521*** | -0.477*** |
| | (0.071) | (0.091) | (0.136) |
| *EXPORT* | -706e-06 | 1.29e-05 | 0.00032*** |
| | (5.71e-05) | (1.33e-05) | (0.00011) |
| *SIZE* | -0.108* | -0.198** | 0.985*** |
| | (0.066) | (0.069) | (0.126) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.057 | 0.272 | 0.131 |

This table reports regressions of innovation outcome measured by R&D Intensity, Labor Productivity and Total Factor Productivity in the three-year period ex-post an M&A deal between t+1 and t+3, measured separately by a yearly M&A dummy for each year after the deal. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post Dummy*HighInnovation*, the study variable is an interaction variable between the dummy variable *Post Dummy* and the dummy variable *HighInnovation*. The variable *Post Dummy* is a binary indicator taking the value of one for each separate year; *t+1, t+2 and t+3* after an M&A deal. The variable *HighInnovation* is a binary indicator taking the value of one if acquirer is classified with a low innovation index and target classified with a high innovation index, defined by the Global Innovation Index (2018). Definitions of control variables are in table x. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *HighInnovation* is omitted and not shown in the regression results, because of collinearity with firm fixed effects.

## A.6.3 Robustness test of Hypotheses 3a and 3b using three time-dummies

**Table 18:** Robustness 3 - Hypothesis 3

| Hypotheses | Hypothesis 3a | Hypothesis 3b | |
|---|---|---|---|
| *Dependent variables* | R&D Intensity | Labor Productivity | TFP |
| Regression | (1) | (2) | (3) |
| *Explanatory variables* | | | |
| Post Dummy $_{t+1}$ *LowInnovation | **-0.410*** | **0.224***** | **0.095** |
| | (0.251) | (0.076) | (0.286) |
| Post Dummy $_{t+2}$ *LowInnovation | **-0.269** | **0.221***** | **0.366** |
| | (0.266) | (0.075) | (0.282) |
| Post Dummy $_{t+3}$ *LowInnovation | **-0.187** | **0.206***** | **0.365** |
| | (0.283) | (0.077) | (0.287) |
| Post Dummy $_{t+1}$ | 0.091 | 0.046 | 0.113 |
| | (0.068) | (0.039) | (0.148) |
| Post Dummy $_{t+2}$ | 0.271** | 0.017 | 0.206 |
| | (0.117) | (0.049) | (0.186) |
| Post Dummy $_{t+3}$ | 0.329** | -0.00167 | 0.369* |
| | (0.161) | (0.0613) | (0.229) |
| *Control variables* | | | |
| *DEBT RATIO* | 0.017 | 0.0054 | -0.080* |
| | (0.027) | (0.012) | (0.045) |
| *CAPITAL INTENSITY* | -0.131 | 0.521*** | -0.447*** |
| | (0.096) | (0.036) | (0.136) |
| *EXPORT* | -1.11e-05 | 1.13e-05 | 0.00034*** |
| | (3.25e-05) | (2.91e-05) | (0.00011) |
| *SIZE* | -0.117 | -0.197*** | 1.018*** |
| | (0.087) | (0.034) | (0.127) |
| *Regression details* | | | |
| Year FE | YES | YES | YES |
| Firm FE | YES | YES | YES |
| Firms | 555 | 555 | 555 |
| Observations | 3,885 | 3,885 | 3,885 |
| $R^2$ | 0.058 | 0.276 | 0.123 |

This table reports regressions of innovation outcome measured by R&D Intensity, Labor Productivity and Total Factor Productivity in the three-year period ex-post an M&A deal between t+1 and t+3, measured separately by a yearly M&A dummy for each year after the deal. The three dependent variables are: *R&D Intensity* defined as the natural logarithm of R&D expenditures divided by sales; *Labor Productivity* defined as the natural logarithm of sales divided by total employment and *Total Factor Productivity (TFP)* measured by the Levinsohn-Petrin estimation algorithm. *Post Dummy*LowInnovation*, the study variable is an interaction variable between the dummy variable *Post Dummy* and the dummy variable *LowInnovation*. The variable *Post Dummy* is a binary indicator taking the value of one for each separate year; *t+1, t+2 and t+3* after an M&A deal. The variable *LowInnovation* is a binary indicator taking the value of one if acquirer is classified with a low innovation index and target classified with a high innovation index, defined by the Global Innovation Index (2018). Definitions of control variables are in table x. Robust standard errors (clustered at the firm-level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Note*: The binary variable *LowInnovation* is omitted and not shown in the regression results, because of collinearity with firm fixed effects.