Merger-specific Efficiency Gains

Dissertation

zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften an der wirtschaftswissenschaftlichen Fakultät der Julius-Maximilians-Universität Würzburg

Vorgelegt von:
Claudia Demmer
Würzburg, im Juni 2019

Erster Gutachter:
Professor Toker Doganoglu, Ph.D.
Zweiter Gutachter:
Professor Dr. Martin Kukuk

Meinen Eltern

Danksagung

Mein Dank gilt Herrn Prof. Toker Doganoglu, Ph.D., für die Bereitschaft, die Betreuung dieser Dissertation zu übernehmen. Seine Hilfsbereitschaft und kritische Würdigung haben die Herangehensweise und Resultate meiner Arbeit maßgeblich geprägt.
Herrn Prof. Dr. Martin Kukuk danke ich für die Zweitbegutachtung meiner Arbeit. Seine Korrekturen waren bei der Überarbeitung sehr hilfreich.
Mein besonderer Dank gilt der Firma Mubea und vor allem Herrn Dr. Thomas Muhr. Seine zielgerichtete und entschlossene Art hat diese Arbeit ins Leben gerufen, unterstützt und zum Ergebnis geführt. Für das Vertrauen und die Aufgeschlossenheit, die meiner Arbeit und mir entgegen gebracht wurden, bin ich sehr dankbar.
Ich danke allen, die durch aufmerksames Zuhören, angeregte Diskussionen, zahlreiche Korrekturen und das Einbringen von Wissen einen wertvollen Beitrag geleistet haben. Hervorzuheben sei insbesondere Manuel Steiner für die umfangreiche Hilfestellung bei der Beantwortung methodischer Fragen.
Von ganzem Herzen danke ich meiner Familie; insbesondere meinen lieben Eltern, meinem verstorbenen Vater, Dr. Franz Demmer, und meiner Mutter, Margaret Demmer. Ihr Vertrauen, ihre Unterstützung und ihr stetiges Fordern ernsthaften Bemühens bilden das Fundament meiner Arbeit.
Dr. Thomas Muhr und Margaret Demmer danke ich herzlich für die unermütliche Rückendeckung.

Zusammenfassung

Die vorliegende Dissertation beschäftigt sich mit der Frage, ob und inwieweit Fusionen zu Effizienzsteigerungen der beteiligten Parteien beitragen. Die Analyse konzentriert sich dabei auf europäische Firmen im verarbeitenden Gewerbe, die im Zeitraum von 2005 bis einschließlich 2014 entweder als Käufer oder als Kaufobjekt an einer horizontalen Fusion beteiligt waren.

Ergebnis dieser Dissertation ist, dass Fusionen einzigartige Prozesse sind. Allgemeingültige Aussagen hinsichtlich Zeitpunkt, Zeitraum und Umfang fusionsbedingter Effizienzgewinne sind daher nur bedingt möglich.

Die Ergebnisse dieser Dissertation deuten darauf hin, dass Effienzgewinne als direkte Konsequenz einer Fusion möglich sind. Effizienzveränderungen können mithilfe einer Total Factor Productivity (TFP)-Methode gemessen werden. Signifikante fusionsbedingte Effizienzgewinne sind für gekaufte Unternehmen wahrscheinlicher als für Käufer. Desweiteren treten sie frühestens ab dem zweiten Jahr nach einer Fusion auf. Die Verschmelzung von zwei Unternehmen, die beide im gleichen Hauptsegment tätig sind, führt allerdings eher zu Effizienzverlusten als Effizienzgewinnen. Effizienzgewinne werden vor allem kurz- bis mittelfristig durch Veränderungen in den Material- und Personalkosten herbeigeführt. Insgesamt sind fusionsbedingte Effizienzgewinne eher von der Art der Firmen als von der Art der Fusion abhängig. Die Analyse der Gründe für fusionsbedingte Effizienzgewinne zeigt, dass Firmen, die die Information über die Fusion selber veröffentlichen, kurz- bis mittelfristig Effizienzgewinne generieren. Des Weiteren sind mittelgroße Käufer eher in der Lage Effizienzgewinne zu generieren als kleine oder große Käufer. Zudem zeigt die Untersuchung, dass kapitalintensivere Unternehmen häufig Effizienzgewinne nach einer Fusion generieren.

Die vorliegende Arbeit ist wie folgt strukturiert.

In der Einleitung werden die Gründe für eine Beschäftigung mit der Frage nach fusionsbedingten Effizienzgewinnen dargelegt. Die Herausarbeitung von Faktoren, anhand derer sich der Zeitpunkt, der Umfang und der Zeitraum fusionsbedingter Effizienzgewinne bestimmen ließe, kann in der Praxis die Entscheidung für oder gegen eine Fusion erleichtern.

Das zweite Kapitel beinhaltet einen Literaturüberblick über ausgewählte empirische Studien, die sich mit der Frage nach fusionsbedingten Effizienzgewinnen bereits befasst haben. Eine Studie, die horizontale Fusionen von europäischen Firmen im verarbeitenden Gewerbe zwischen 2005 und 2014 untersucht, liegt bisher nicht vor. Die vorliegende Arbeit leistet mit der Analyse von Effizienzgewinnen eben solcher Fusionen einen Beitrag zur vorhandenen Literatur.
Das dritte Kapitel beschäftigt sich mit der Identifizierung von Fusionen. Die Fusionsdefinition entstammt der Europäischen Zusammenschlusskontrolle sowie den Richtlinien zur Bewertung horizontaler Fusionen. Anhand von Begriffsbestimmungen und festgelegten Kriterien schafft der europäische Gesetzgeber einen Rahmen zur Identifizierung von Fusionen.
Im Fokus des vierten Kapitels steht die Effizienzschätzmethode. In empirischen Studien wird vorwiegend die TFP-Methode zur Schätzung der Effizienz eingesetzt. Die TFP-Methode bedient sich der ökonometrischen Methode der linearen Regression in Kombination mit einem Kontrollfunktionsansatz. Die Schätzung der Parameter erfolgt mit Hilfe der verallgemeinerten Momentenmethode.
Die Ergebnisse der Effizienzschätzung gehen im fünften Kapitel in die Analyse fusionsbedinger Effizienzgewinne ein. Die Analyse erfolgt unter Zuhilfenahme der Difference-In-Difference (DID)-Methode und wird für Käufer und Gekaufte separat durchgeführt.
Das sechste Kapitel beschäftigt sich mit einer alternativen Methode zur Effizienzschätzung, der Stochastic Frontier Analysis (SFA)-Methode. Vergleichbar zur TFP-Methode handelt es sich um eine stochastische Methode. Im Gegensatz zur TFP-Methode wird die Produktionsfunktion als Grenzfunktion und nicht als durchschnittliche Funktion geschätzt. So ist es möglich, Effizienz in Prozent auszudrücken.
Es folgt im siebten Kapitel eine Analyse des Einflusses verschiedener fusions- und firmenspezifischer Faktoren auf die Effizienzveränderung bei Käufern und Gekauften. Die Analyse erfolgt mittels einer multiplen Regression und wird separat für kurz-, mittel- und langfristige Veränderung der Effizienz von Käufern und Gekauften durchgeführt.
Im achten Kapitel folgt die Schlussbetrachtung.

Summary

The present thesis analyzes whether and - if so - under which conditions mergers result in merger-specific efficiency gains. The analysis concentrates on manufacturing firms in Europe that participate in horizontal mergers as either buyer or target in the years 2005 to 2014.

The result of the present study is that mergers are idiosyncratic processes. Thus, the possibilities to define general conditions that predict merger-specific efficiency gains are limited.

However, the results of the present study indicate that efficiency gains are possible as a direct consequence of a merger. Efficiency changes can be measured by a Total Factor Productivity (TFP) approach. Significant merger-specific efficiency gains are more likely for targets than for buyers. Moreover, mergers of firms that mainly operate in the same segment are likely to generate efficiency losses. Efficiency gains most likely result from reductions in material and labor costs, especially on a short- and mid-term perspective. The analysis of conditions that predict efficiency gains indicates that firm that announce the merger themselves are capable to generate efficiency gains in a short- and mid-term perspective. Furthermore, buyers that are mid-sized firms are more likely to generate efficiency gains than small or large buyers. Results also indicate that capital intense firms are likely to generate efficiency gains after a merger.

The present study is structured as follows.

Chapter 1 motivates the analysis of merger-specific efficiency gains. The definition of conditions that reasonably likely predict when and to which extent mergers will result in merger-specific efficiency gains, would improve the merger approval or denial process.

Chapter 2 gives a literature review of some relevant empirical studies that analyzed merger-specific efficiency gains. None of the empirical studies have analyzed horizontal mergers of European firms in the manufacturing sector in the years 2005 to 2014. Thus, the present study contributes to the existing literature by analyzing efficiency gains from those mergers.

Chapter 3 focuses on the identification of mergers. The merger term is defined ac-

cording to the EC Merger Regulation and the Horizontal Merger Guidelines. The definition and the requirements of mergers according to legislation provides the framework of merger identification.

Chapter 4 concentrates on the efficiency measurement methodology. Most empirical studies apply a Total Factor Productivity (TFP) approach to estimate efficiency. The TFP approach uses linear regression in combination with a control function approach. The estimation of coefficients is done by a General Method of Moments approach.

The resulting efficiency estimates are used in the analysis of merger-specific efficiency gains in chapter 5. This analysis is done separately for buyers and targets by applying a Difference-In-Difference (DID) approach.

Chapter 6 concentrates on an alternative approach to estimate efficiency, that is a Stochastic Frontier Analysis (SFA) approach. Comparable to the TFP approach, the SFA approach is a stochastic efficiency estimation methodology. In contrast to TFP, SFA estimates the production function as a frontier function instead of an average function. The frontier function allows to estimate efficiency in percent.

Chapter 7 analyses the impact of different merger- and firm-specific characteristics on efficiency changes of buyers and targets. The analysis is based on a multiple regression, which is applied for short-, mid- and long-term efficiency changes of buyers and targets.

Chapter 8 concludes.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The Relevance of Merger-specific Efficiency Gains for Competition Policy

In Europe, the number of mergers that are notified to the European Commission has grown to approximately 300 mergers per year. In 2016, 362 mergers have been notified. Figure 1.1 shows the development of numbers over the last 20 to 30 years. Most countries regulate mergers. The purpose of regulating mergers is to control

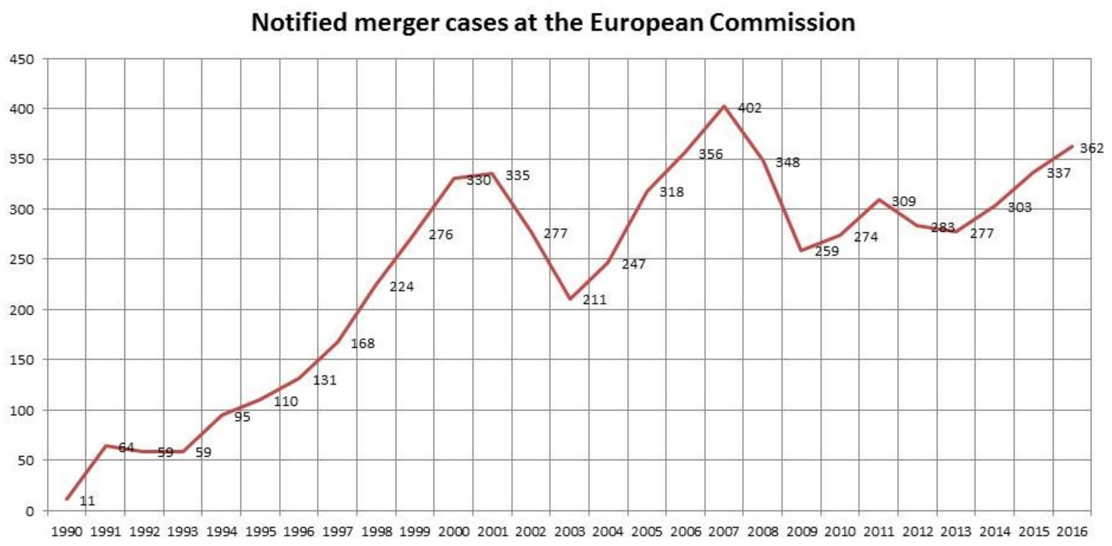


Figure 1.1: Notified Merger Cases at the European Commission (Commission, 2017b)

anti-competitive effects as those often cause negative welfare effects. The following introduction into the purpose of regulating mergers mainly follows Motta (2004).
In general, three merger types are differentiated. These merger types are horizontal, vertical and conglomerate mergers. Conglomerate mergers are mergers of two firms that make different products. They give little rise to competition concerns.

Vertical mergers occur when firms merge that produce the same product but at a different stage in the value chain. Vertical mergers are likely to eliminate double marginalization and thereby generate cost savings that lead to price decreases. Thus, regulation bodies expect anti-competitive in a minority of cases. Horizontal mergers occur when firms merge, which produce the same product at the same stage within the value chain. Horizontal mergers are likely to increase market power and thereby cause price increases. Thus, horizontal mergers are likely to have a negative welfare effect.[1] To avoid this, regulation bodies aim at identifying circumstances that do not allow mergers.

There are two main reasons for negative welfare effects. First, mergers may cause unilateral effects. Unilateral effects may occur if firms are capable to exercise market power in a unilateral way and to raise prices. If firms compete in prices, the merged firm exercises market power by charging a higher price, whereas the competitors would response with a price increase to the same extent. If firms compete in quantities, the merged firm could exercise market power by decreasing its output, which leads to a price increase. The competitors would response with an increase in output. In both scenarios, the price increase harms consumers as it increases prices and thereby reduces consumer surplus. Also, in both scenarios, the competitors will benefit of the merger because of the price and/or quantity increase.

Second, mergers may cause coordinated effects. Pro-collusive effects will occur if the merger generates a new market condition, which makes a collusion more likely. The market condition would allow firms to tacitly or explicitly agree on quantity or prices, which increases prices and therefore reduces consumer surplus as well as total welfare.

Both, unilateral as well as coordinated effects will only be explicitly negative if the merger does not gain any efficiency gains. Efficiency gains caused by a merger, further named merger-specific efficiency gains, may countervail negative effects and even increase welfare. This happens because the merged firm may have lower unit costs than the individual firms when operating independently, which leads to a decrease of prices. However, for the merged firm there is a trade-off between exercising market power by increasing prices and, on the contrary, attracting more consumers by decreasing prices. Exercising market power by increasing prices can be outweighed by decreasing prices to attract new customers if merger-specific efficiency gains are large enough in order to allow a significant price decrease.[2]

Thus, merger regulation takes merger-specific efficiency gains into account. The consideration of efficiency gains is implemented into the European law as "efficiency

[1]See Motta (2004) for an overview of the welfare effects of horizontal mergers.

[2]For a more details and a formal explanation see Williamson (1968) and Farrell and Shapiro (1990).

defense". The efficiency defense is part of the second phase of the merger control procedure. The second phase will be opened when the first phase results in the Commission's concerns that the merger has the potential to result in anti-competitive effects. The efficiency defense allows firms to debilitate the concerns of the Commission. Therefore, firms need to successfully argue that merger-specific efficiency gains will countervail anti-competitive effects. So far, the European Commission has never cleared a merger because of a successful efficiency defense in the second phase of the merger control procedure. Most of the mergers do not reach the second phase. For those that do, the firms' argumentation suffers from the capability to sufficiently satisfy the conditions of the efficiency defense.

Akhavein et al. (1997) note that the definition of specific conditions, which reasonably accurately predict when mergers are likely to result in efficiency gains, might improve the merger approval or denial process. Concluding, a motivation to (empirically) study merger-specific efficiency gains is to answer the question whether - and if so, under which conditions - mergers are likely to result in efficiency gains.

The Relevance of Merger-specific Efficiency Gains for Firms

In addition to the relevance for competition policy, merger-specific efficiency gains are relevant for firms. Firms often define their expectations and especially the price, which they are willing to pay for a merger, based on expected merger-specific efficiency gains.

In comparison to any other investment, firms expect mergers to pay off, which means that future profits generated by the merger should surpass the merger price. The price of a merger is determined by the value of assets, know-how, the amount of current profits etc. as well as by the value of merger-specific efficiency gains. Some factors, like assets and profits, can reasonably be evaluated based on annual financial statements. The evaluation of other factors like know-how and merger-specific efficiency gains is often vague.

Merger-specific efficiency gains have a specific position in the merger evaluation process as they are expected to be a unique value of a certain merger. The value cannot be achieved in a similar extent if firms operate independently or merge to another party. Thus, merger-specific efficiency gains are often claimed to be the only or most important tangible justification for a merger.

Expected merger-specific efficiency gains, also named synergies of mergers, ranged in average between 1 and 2.5% of combined sales in the years 2000 to 2010. Figure 1.2 shows a statistic of expected merger-specific efficiency gains of the Boston Consulting Group. Expected merger-specific efficiency gains are synergy potential that has been announced by merging parties before the merger. The statistic is based on announcements concerning mergers with a value of larger than USD 300 million. The data has been provided by Thomson Reuters.

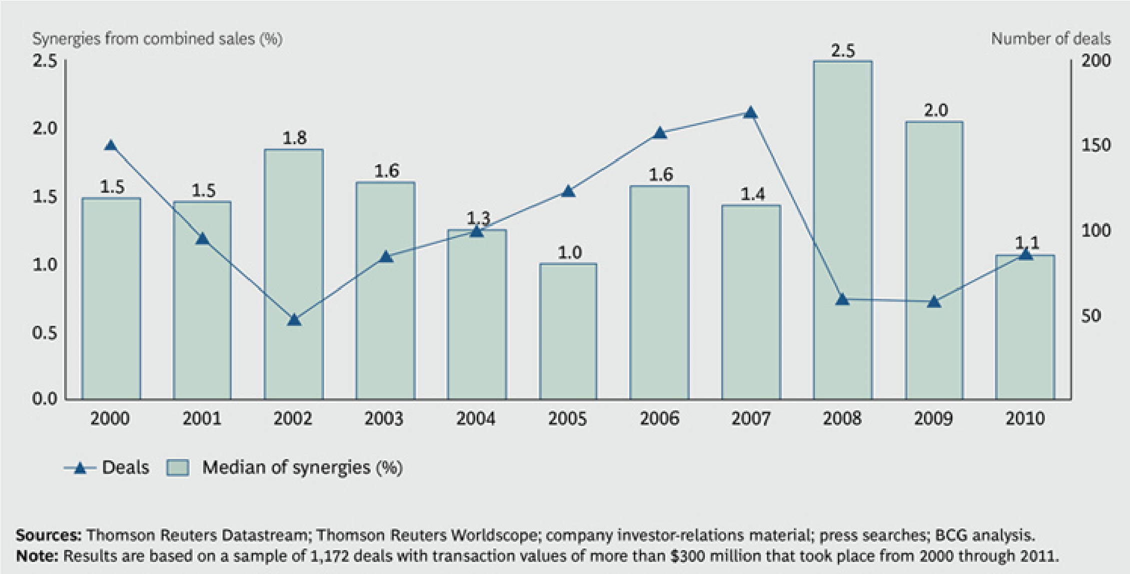


Figure 1.2: Expected Merger-Specific Efficiency Gains (BCG, 2017)

Point of Departure of the Present Study

Considerations and investigations of the present study are guided by the framework of the "efficiency defense". The EC Merger Regulation considers merger-specific efficiency gains in the form of an efficiency defense. The efficiency defense allows firms to defend the notified merger by justifying merger-specific efficiency gains that are likely to countervail possible anti-competitive effects of the merger.[3]

The European Commission will take efficiency claims into account if the claimed efficiency gains fulfill three conditions. These conditions are cumulative.

The first condition requires that *consumers benefit* from efficiency gains. This primary condition is divided into four sub-conditions.

First, efficiency gains should be *substantial*. I assume that substantial merger-specific efficiency gains are statistically significant.

Second, they should be *timely*. The meaning of timely can be discussed. In the following, I differentiate between short-term, mid-term and long-term efficiency gains. Short-term efficiency gains appear in the first post-merger year, mid-term efficiency gains appear in the third and long-term efficiency gains in the fifth post-merger period.

Third, efficiency gains should *benefit consumers in relevant markets* where it is otherwise likely that competition concerns would occur. I distinguish different kinds

[3]For more details of the assessment of horizontal mergers see Appendix 9.2 and the Horizontal Merger Guidelines (2004), C 31/13 at 78 to 88.

of horizontal mergers. This differentiation helps to identify mergers that are likely to result in those efficiency gains that benefit consumers in the relevant market. However, one of the most difficult aspects within the efficiency defense is to prove that efficiency gains will benefit consumers. Same counts for this study. A close analysis whether efficiency gains benefit consumers by e.g. price decreases is left open to further research.

Fourth, efficiency gains will be most likely to benefit the consumer, if they lead to *reductions in variable or marginal costs*. Labor and material are often defined as variable costs. In contrast, capital is often defined as fixed costs. It is also possible to define capital as variable costs assuming that capital changes by costly investments over a period of time. The differentiation about whether a cost component is completely variable or fix has an impact on the method of efficiency estimation.

The second condition requires that efficiency gains shall be a *direct consequence of the notified merger* and cannot be achieved to a similar extent by less anti-competitive alternatives. The applied Difference-In-Difference (DID) approach allows to analyze differences in efficiency changes of firms that are comparable. The resulting difference between efficiency changes of merging firms and similar non-merging firms are defined as merger-specific. Thus, the DID approach helps to identify efficiency gains that are merger-specific and cannot be achieved to a similar extent by less anti-competitive alternatives.

The third condition requires that efficiency gains are *verifiable* in a way that the Commission can be reasonably certain that the efficiency gains are likely to materialize. For this purpose, efficiency gains should be quantified. Verifiable efficiency gains have evidence such as internal documents, historical examples, and external experts' studies.

The verification of efficiency gains represent the center of this study. For this purpose, two different approaches to estimate efficiency, namely a Total Factor Productivity (TFP) and a Stochastic Frontier Analysis (SFA) approach, are applied and results are compared. However, an explicit analysis of whether internal documents, etc. give evidence for the measured efficiency gains is left open to further researches. The present study focuses on the identification of general circumstances that may indicate merger-specific efficiency gains and thereby replace the necessity of the kind of evidence mentioned above.

So far, none of the notified cases was cleared because of a successful argumentation concerning the restoration of effective competition in a second phase of the merger control process - neither because of efficiency gains (Cardwell, 2017) nor because of any other countervailing factors.[4] There might be several explanations for the little relevance of efficiency gains in legal practice. Three of them are shortly introduced.

[4]For details see merger statistics of the European Commission. (Commission, 2017b)

First, efficiency claims are relatively new in legal practice.[5] Secondly, in practice the three conditions are difficult to fulfill. (Cardwell, 2017). And third, even though merger-specific efficiency gains exist in theory, their existence is still discussed in empirical studies.

Purpose, Major Findings and Structure of the Present Study

The present study aims to contribute to the clarification about the circumstances that lead to merger-specific efficiency gains. Thus, the specific purpose of this study is to answer whether - and if so, under which conditions - mergers are likely to result in efficiency gains. For this purpose, I analyze efficiency changes of buyers and targets of horizontal mergers in the European manufacturing sector between 2005 and 2014.

Reviewing the literature concerning the subject of analysis shows that most empirical studies analyzing efficiency changes from mergers in the manufacturing sector apply a Total Factor Productivity (TFP) approach to estimate efficiency. Moreover, the Difference-in-Difference (DID) approach is often applied to identify merger-specific efficiency changes.

The merger identification process is given little attention in literature. A further examination shows that mergers are processes, whose identification is ambiguous. The merger identification requires the assumption that each merger or acquisition, which is legally constituted, will be followed by a change of control that influences a firm's operations.

The comparison of estimated efficiencies shows that, without controlling for any fixed effects e.g. yearly, industry- or country-specific effects, buyers as well as targets are likely to be on average, meaning through all years, more productive than an average firm. Moreover, buyers are on average more productive than targets.

Comparing efficiency changes of merging and non-merging firms shows that targets are capable to increase efficiency in a short-term perspective after a merger. Those merger-specific efficiency gains of targets are timely and substantial. Furthermore, buyers seem to be capable to increase efficiency in a long-term perspective after the merger.

Applying an alternative method to estimate efficiency, Stochastic Frontier Analysis (SFA), shows a comparable distribution of efficiency estimates. Thus, efficiency estimates are robust. However, due to the requirements of data properties, the SFA approach can only be applied to certain industries. The analysis of merger-specific efficiency gains in two industries results in insignificant effects. Thus, applying a

[5] At the end of 2002 a draft of the horizontal merger guidelines including the treatment of efficiency existed. (Zampa, 2003) The Horizontal Merger Guidelines were released in 2004.

DID approach to analyze merger-specific efficiency gains requires a large data set. The analysis of the conditions that result in merger-specific efficiency gains shows that efficiency changes rather depend on firm characteristics than on merger characteristics. But, mergers of firms that mainly operate in the same industry are likely to result in merger-specific efficiency losses. Results also indicate that firms that announce their mergers are capable to generate merger-specific efficiency gains, at least in a short- to mid-term perspective. Furthermore, capital intense firms are more likely to generate merger-specific efficiency gains.

After the introduction in chapter 1 a literature review follows in chapter 2. The literature review introduces and discusses empirical studies with a related focus of the analysis. Thereby, the chapter reveals the problems of analyzing merger-specific efficiency gains.

Chapter 3 defines the merger term and discusses the merger identification in the available data set. Thereby, the chapter builds a framework of the analysis of merger-specific efficiency gains. In contrast to most empirical studies, I go into details of merger identification.

The main part of the analysis of merger-specific efficiency gains is the efficiency estimation. The efficiency estimation is the first step in the analysis and provides a basis for the further analysis. As TFP estimation is the most common approach for efficiency estimation in merger analysis, chapter 4 concentrates on TFP estimation. The applied approach considers a solution for one major econometric problem, namely endogeneity, that has recently received a lot of attention in the research field of productivity.

Chapter 5 uses efficiency estimates and analyzes whether efficiency changes are merger-specific or not. The methodology applied is a DID approach in combination with a Propensity Score Matching (PSM) approach. Those approaches allow to compare efficiency changes of merging firms with efficiency changes of similar non-merging firms. In consequence, the differences in efficiency development of both groups provide information about merger-specific efficiency changes.

As an alternative approach to estimate efficiency a SFA approach can be applied. The advantage of a SFA approach is that efficiency estimates can be interpreted as achieved percentage of a maximal possible efficiency. Thus, chapter 6 concentrates on a SFA approach. The approach is applied on two industries. For those industries, the application of a SFA approach is meaningful. As the application of a SFA approach requires certain data properties, an application is only meaningful for some industries.

Chapter 7 discusses the application of a simple multiple regressions to predict conditions that may cause merger-specific efficiency gains. The chapter analyzes the impact of merger categories, merger characteristics as well as firm characteristics on short-, mid- and long-term efficiency changes of merging firms. This thesis ends with the conclusion in chapter 8.

Chapter 2

Literature Review

Relationship between mergers and efficiency gains

The relationship between mergers and efficiency gains has widely been investigated. Many authors, such as Motta (2004) and Röller et al. (2006), have summarized the literature that deals with the relationship between mergers and efficiency gains. The papers of Williamson (1968) and Farrell and Shapiro (1990) represent two of the most cited contributions concerning the importance of this relationship. Williamson (1968) shows that horizontal mergers result in a trade-off between increasing and decreasing prices. On the one hand, merged firms may increase prices and thereby profits due to a greater degree of monopoly power. On the other hand, merged firms may decrease prices and thereby increase quantity and profits due to efficiency gains. Farrell and Shapiro (1990) discuss horizontal mergers in a Cournot model. They conclude that mergers must realize a substantial reduction in marginal costs to be capable to decrease prices.

Fisher and Lande (1983) demonstrate the complexity of an empirical support of the relationship of mergers and efficiency gains. One of the greatest challenges of empirical studies is to prove the existence of the relationship. Despite that the relationship between mergers and efficiency gains has widely been investigated, it remains undefined from an empirical point of view. Early empirical investigations, e.g. Ravenscraft and Scherer (1987) or Caves (1989), analyze specific cases to prove the existence of the relationship. More recent literature such as Maksimovic and Phillips (2001) and Blonigen and Pierce (2016) apply regression-based approaches. The more recent discussion of the relationship between mergers and efficiency gains concentrates on the extent of merger-specific efficiency gains and the conditions that may lead to merger-specific efficiency gains.

Empirical Studies of Mergers in the Manufacturing Sector

The relationship between mergers and efficiency gains has widely been investigated with focus on the manufacturing sector. Most of the empirical studies analyze the U.S. market. However, the minority of empirical studies explicitly focuses on horizontal mergers. In the following, some empirical studies that analyze the relationship of mergers and efficiency gains in the manufacturing sector will be reviewed. The review of empirical studies on this topic does not claim to be complete. Instead, it intends to give an impression of the diversity of existing empirical studies.

Lichtenberg and Siegel (1987) analyze efficiency of more than 18,000 plants of the U.S. manufacturing sector in the years 1972 to 1986. Approximately 21% of the analyzed plants changed their ownership during this period of time. The authors find that targets are on average less efficient than other firms before a merger. After the merger, they are capable to generate efficiency gains. However, it takes several years until significant efficiency gains appear after a merger.

Ravenscraft and Scherer (1987) analyze 634 mergers in 1968, 1971 and 1974 of manufacturing firms in the U.S.. They find that targets are on average more profitable before a merger than other firms. Ravenscraft and Scherer (1989) analyze the profitability of more than 2,000 U.S. manufacturing firm that were acquired between 1957 to 1977. They find that mergers decrease the profitability of targets.

McGuckin and Nguyen (1995) analyze more than 28,00 U.S. manufacturing plants operating in the food manufacturing industry (SIC 20) between 1977 and 1987. They find that merging parties are on average more efficient than non-merging parties. Furthermore, they find that targets are capable to generate efficiency gains after a merger.

Maksimovic and Phillips (2001) analyze more than 50,000 U.S. manufacturing plants between 1974 and 1992. They find that buyers are on average more efficient than other firms. Furthermore, they show that buyers generate efficiency gains after a merger. Later on Maksimovic et al. (2013) analyze more than 40,000 U.S. manufacturing plants between 1977 and 2004. Similarly to their previous study, the authors find that buyers are on average more efficient than other firms. Furthermore, they find that targets are on average less efficient than other firms.

Gugler et al. (2003) analyze 45,000 worldwide mergers of firms operating in either the manufacturing or in the service sector between 1981 and 1998. Approximately 42% of all mergers were horizontal mergers. They identify some mergers that are capable to increase efficiency. However, according to their results the majority of mergers appear to reduce welfare.

Bertrand and Zitouna (2008) analyze 371 horizontal mergers of French manufacturing firms that took place between 1993 and 2000. They find that mergers increase efficiency of targets.

Recently, Blonigen and Pierce (2016) analyzed mergers of U.S. manufacturing firms that took place between 1997 and 2007. They find that mergers are unlikely to result in efficiency gains.

The TFP Approach in Merger Analysis

Most empirical studies that analyze the relationship of mergers and efficiency apply a Total Factor Productivity approach to estimate efficiency, respectively productivity. As productivity is an omitted variable, which cannot be observed by the econometrican, the estimation of productivity is often done with the help of a fixed effect (FE) or control function (CF) approach.[1] The following four empirical studies are examples for the application of a TFP approach in the context of the merger analysis. The applied approaches will further be shortly described.

McGuckin and Nguyen (1995) apply a multiple regression to estimate the production function. The residual is defined as estimate for TFP. This is the basic model to estimate TFP. They apply a gross output approach and use value of shipments as proxy for value of output. They define a Cobb Douglas production function with capital, labor and material as input factors and use plant-level data of manufacturing plants in the U.S. aggregated on a four-digit SIC code level provided by the Bureau of the Census.

Maksimovic and Phillips (2001) use a FE model to estimate TFP. They also apply a gross output approach and use the total value of shipments as proxy for value of output. They define a translog production function with capital and labor as input factors and use plant-level data of manufacturing plants in the US aggregated on a three-digit SIC code level provided from the Bureau of the Census.

Bertrand and Zitouna (2008) use a FE related model to estimate TFP. They also apply a gross output approach and use turnover as proxy for value of output. They define a Cobb Douglas production function with capital, labor, intermediate goods and subcontracting as input factors and use firm-level data of manufacturing firms in France provided from the French census of manufacturing.

Recently, Blonigen and Pierce (2016) use a CF model based on Olley and Pakes (1996) including the extensions of Levinsohn and Petrin (2003) and Ackerberg et al. (2015) to estimate TFP. They apply a gross output approach and use revenue as proxy for value of output. They define a translog production function with capital and labor as input factors and use material as proxy for productivity. They use plant-level data of manufacturing plants in the U.S. aggregated on a three-digit NAICS code level provided from the Bureau of the Census.

[1] Chapter 4 will introduce the TFP approach.

The SFA Approach in Merger Analysis

Reviewing literature that empirically analyzes efficiency changes from mergers by applying a SFA approach results in the following finding. The SFA approach is applied in several empirical studies analyzing efficiency changes in the context of mergers. Most of those studies analyze mergers in the banking sector. DeYoung et al. (2009) summarize empirical studies that analyze mergers in the banking sector. However, the authors primarily summarize results rather than applied approaches. Exemplary studies of the empirical studies in merger analysis in the banking sector that apply a SFA approach, are introduced in the following. These empirical studies apply a frontier cost function approach instead of a frontier production function approach. Without going into details, a cost frontier has certain advantages with regard to efficiency estimation.[2]

Lang and Welzel (1999) analyze 283 mergers of Bavarian banks that took place in the years 1989 to 1997. The authors use a frontier cost function approach to estimate efficiency. Their results show no evidence for merger-specific efficiency gains.

Gjirja (2003) analyzes banking mergers in Sweden between 1984 and 2002. She also uses a frontier cost function approach to estimate efficiency. Her results also show no evidence for merger-specific efficiency gains.

Ashton et al. (2007) analyze 61 UK bank mergers between 1988 and 2004. They also apply a frontier cost function approach to estimate efficiency. Their results show that mergers result in efficiency gains.

This brief literature review shows that empirical studies applying a SFA approach in the context of merger analysis mostly concentrate on one industry and one country. To the best of my knowledge, empirical studies applying SFA to analyze efficiency changes from mergers in the manufacturing sector are lacking.

Conclusion

The most recent analysis of merger-specific efficiency gains in the manufacturing sector is the analysis of Blonigen and Pierce (2016). They find that mergers are more likely to result in markups than in efficiency gains. Even though empirical studies have been investigating the relationship between mergers and efficiency gains since the 1980s, the empirical support of the existence of merger-specific efficiency gains is still a debate. Most empirical studies apply a TFP approach to estimate efficiency in the manufacturing sector. The SFA approach is primarily applied by empirical studies that analyze mergers in the banking sector.

The present study intend to contribute to the existing literature with regard to

[2]For details of the advantages of cost frontier approaches towards production frontier approaches see e.g. Greene (2007), Coelli et al. (2005) and Kumbhakar and Lovell (2003).

three issues. First, the present study intend to contribute the analysis of merger-specific efficiency gains in the European manufacturing sector. Secondly, it focuses on merger-specific efficiency gains of horizontal mergers in the European manufacturing sector. And thirdly, it discusses the possibilities of an application of a SFA approach to the merger analysis in the manufacturing sector.

Chapter 3

Merger Identification

3.1 Introduction

Efficiency gains are one possible approach to maximize profits. In contrast to other approaches such as price increases, efficiency gains are beneficial not only to firms, but also to society. This is, because they allow firms to reduce their costs and therefore their prices.
Various circumstances may lead to efficiency gains. One of these circumstances are mergers. Mergers allow previously independent firms to operate dependently. This dependency may cause efficiency gains due to better allocation of resources, exchange of know-how or managerial experience.[1] Efficiency gains from mergers are further called merger-specific efficiency gains.
The present study analyses horizontal mergers of manufacturing firms in Europe between 2005 and 2014. This chapter aims to introduce and explain the data set used for the analysis. The beginning of the analysis focuses on the identification of mergers. As mergers are legal processes in Europe, mergers can be identified with the help of the European Merger Regulation's definitions. In contrast to other empirical studies, the present study explicitly discusses how the data set can meet the criteria of a merger definition. The purpose of this discussion is to highlight the assumptions needed for merger identification. This chapter shows that the assumptions needed for merger identification have a strong impact on the interpretation of results from the analysis of merger-specific efficiency gains.

3.2 Definitions

The European Merger Regulation provides two definitions that help to identify mergers. Firstly, any identified merger should meet the general merger definition accord-

[1] For more details about the interpretation of merger-specific efficiency gains see Appendix 9.3.

ing to article 3 EC Merger Regulation (RL [EC] No 139/2004). Secondly, identified mergers can be divided into horizontal merger and other kind of mergers with according to the definition of horizontal mergers.

Mergers

The EC Merger Regulation defines a merger of previously independent firms (or parts of firms) as a process that leads to a concentration. This process is initiated by a change of control based on legal rights, treaties, and/or contracts.[2]

According to the merger definition, on the one hand in order to identify mergers, one needs information about rights, contracts or any other means that constitute a merger. The constitution of a merger is a necessary condition as without constitution the merger cannot take place. On the other hand, to identify mergers needs information about whether a change of control took place on a lasting basis or not. The change of control on a lasting basis is a sufficient condition as it distinguishes those mergers that are only constituted from mergers that lead to a concentration. The disadvantage of identifying mergers according to this definition is that a change of control on a lasting basis is an abstract requirement whose fulfillment can not be easily identified in a data set. There are several possibilities for an identification. One possibility is to define criteria that indicate a change of control on a lasting basis. Another possibility is to concentrate the analysis on mergers, which have been notified to the European Commission. Those mergers fulfill the sufficient condition as mergers are only notified to the EC if they do so. The problem with this identification criterion is that mergers will only be notified to the European Commission if they have a certain dimension.[3] As only a minority of mergers have this dimension, applying the suggested approach leads to a small data set and a case study of merger-specific efficiency gains would be more useful than a statistical analysis. Therefore, the identification of the majority of mergers requires additional information.

Any merger that took place in the European Union satisfies one of the following two requirements. Firstly, the merger is too small to come to the attention of EC merger regulation and therefore does not need to be notified. Or secondly, the merger has been declared and then approved. In both cases, one can assume that the anti-competitive effects of the merger are not dominant – at least in the European market. Otherwise, the EC would have intervened.

Yet, mergers might still result in markups. A markup increase causes an output increase, if output is defined as sales, for example. This output increase has a positive effect on the ratio of output and input. As efficiency is measured as the ratio of

[2]For a detailed definition of a merger according to the EC Merger Regulation see Appendix 9.1.

[3]For details about the dimension of regulated mergers see Appendix 9.1.

output and input, the estimate considers both, markup as well as cost changes. The estimation of pure cost changes requires a separation of cost changes from markup changes. [4] Further analysis of merger-specific efficiency gains defines efficiency without separating cost reductions from markup increases. The analysis could be improved by a separation of markup and cost effects on efficiency.

Horizontal Mergers

Horizontal mergers are mergers of competitors, meaning firms that operate in the same product and geographical market. The market definition has a strong impact not only on the definition of a horizontal market, but also on the merger regulation process itself. It is the primary step in each merger regulation process and determines whether the merger is further analyzed or not. The EC uses tools like the SSNIP test to define a market. The market definition itself is a focus of research. Therefore, some literature in the field of merger-specific efficiency gains focuses on the analysis of the market definition.

Instead of concentrating on the market definition, in the present study I conform with the common approach in literature and define a market according to the US SIC Code level. Thus, I follow the example of authors like Yan (2011). Nevertheless, it should be mentioned that the purpose of US SIC Codes as well as NACE Rev. 2 Codes is to classify firms with similar production technology as one industry. Therefore, it is appropriate to use these codes to estimate a common production technology. However, it is debatable whether it is appropriate to use them to identify a market. In conclusion, horizontal mergers are defined as mergers of firms with similar production technology. Firms with similar production technology are assumed to operate in the same market and are therefore assumed to be competitors. This means that analyzing efficiency gains resulting from horizontal mergers based on this assumption means analyzing efficiency gains resulting from mergers of firms with similar production technology.

Given the logic behind merger-specific efficiency gains, it is likely that firms with similar production technology are capable of increasing their efficiency through a merger, as it is simpler for them to share resources or know-how. If one rejects the assumption that those firms are competitors, one should be careful when interpreting efficiency gains, which result from a merger of competitors.

[4] See for example Blonigen and Pierce (2016).

3.3 Data Description

This section concentrates on identifying mergers in the available data set provided by ZEPHYR of Bureau van Dijk. The raw data set includes 323,100 deals worldwide between 2005 and 2014 with deal status "completed" or "assumed completed". At least one of the involved firms[5] acts in a manufacturing industry according to the US SIC Code classification. Out of these 323,100 deals, 51,128 mergers are identifiable. This section describes the selection process and the resulting data set.

Data Requirements, Availability and Selection

A merger is identified according to its deal type. A deal can be classified as a "merger" or "acquisition", for example. The information on whether a merger leads to a minority or majority stake can be used to identify the fulfillment of the sufficient condition, meaning whether a change of control on a lasting basis took place. Legal rights, contracts or any other means that constitute a majority stake[6] indicate the fulfillment of the sufficient condition as the change of control on a lasting basis is likely. (Commission (2014) at 44.) Although, a minority stake[7] may also indicate the fulfillment of the sufficient condition, the fulfillment is more likely with a majority stake. (European Commission, 2014) Deals that lead to a majority stake are named "acquisition" by ZEPHYR.
Mergers according to the definition of subsection 3.2 are deals of types "mergers" and "acquisitions" according to the definition of ZEPHYR.

Furthermore, as defined in subsection 3.2, horizontal mergers need to be identified. In the data set, firms are identified as competitors if they operate in the same industry. (Yan, 2011) Most firms operate in several industries. The core ore main and the subordinate activity of a firm can be distinguished. A firm's main activity is the industry in which the firm generates most sales, while subordinate activities are those industries in which a firm generates minor sales. In conclusion, a horizontal merger can be categorized by whether the merged firms are competitors as one or both act mainly or subordinately in the same industry.
Table 3.1 shows categories of horizontal mergers.[8]

[5] Involved firms according to ZEPHYR are buyer ("Acquirer"), target and seller ("Vendor").

[6] A majority stake means a stake of more than 50% according to the definition of ZEPHYR.

[7] A minority stake means a stake of less than 50% according to the definition of "ZEHPYR"

[8] Classifying mergers by main and subordinate activity of buyer and target follows Maksimovic and Phillips (2001). They use the matching system for the analysis of buyer and seller, as their study focuses the market of asset deals and the motivation of transacting assets. As this study focuses on the effects of a merger on the efficiency of the merged parties, the classification system is transferred to the matching of buyer and target. As firms may act in several industries, a merger can be classified as horizontal depending on more than one matching of activities.

Table 3.1: Horizontal Merger Categories

		Buyer main activity	sub activity
Target	**main activity**	main2main	main2sub
	sub activity	sub2main	sub2sub

Depending on the matching of main or subordinate activities of the buyer and target, horizontal mergers can be categorized into four categories. If the main activity of two merging firms is the same, the merger will be named main-to-main merger (main2main). If the target's main activity matches the buyer's subordinate activity the merger will be named main-to-sub (main2sub); the other way around, it will be named sub-to-main (sub2main). And finally, if the subordinate activity of two merging firms is the same the merger will be named sub-to-sub (sub2sub).
Table 3.2 shows available variables that are further considered to indicate a merger.

Table 3.2: Merger indication: Available Variables

Available Variable	**Indication**
Notification to the European Commission (EC)	Notification to the EC is a deal to be a merger according to the definition.
Deal type	Mergers and acquisitions are types of deals which indicate a change of control.
Deal status	Completed or assumed completed deal status indicates the actual completion of a merger.
Regulatory body name	Notification to a regulatory body indicates a merger of a certain dimension.
Regulatory body country	Notification in a EU Member State indicates the relevance of the merger to the European market.
Category of source	Primary sources indicate the truthfulness of information about a merger.

Data Description

After removing duplicates and mergers with an unknown merger year and/or missing information about a buyer or target, the data set includes information on 198,971 deals. A deal may consist of several buyers and/or targets. Table 3.3 shows a summary of the statistics on the number of buyers, targets and merging parties per deal.

Table 3.3: Merger Parties per Deal

Variable	**obs.**	**Min**	**Max**	**Median**	**Mean**	**Std. Dev.**
buyers / deal	198,971	1	39	1	1.04	0.34
targets / deal		1	18	1	1.24	0.83
merging parties / deal		2	40	2	2.29	0.89

The number of merging parties can reach a maximum of 40 including all buyers and targets per deal. A deal including 40 parties is unlikely to be useful for identifying merger-specific efficiency gains as many other factors besides the merger itself can be expected to have an impact on efficiency and thus the measurement of merger-specific factors. The average number of merging parties is close to two. It can be expected that most of the deals meeting the criteria consist of two merging parties. Limiting the data to horizontal mergers results in 51,128 mergers. Figure 3.1 shows the number of mergers per year.

The number of mergers between 2005 and 2009, as shown in figure 3.1, developed

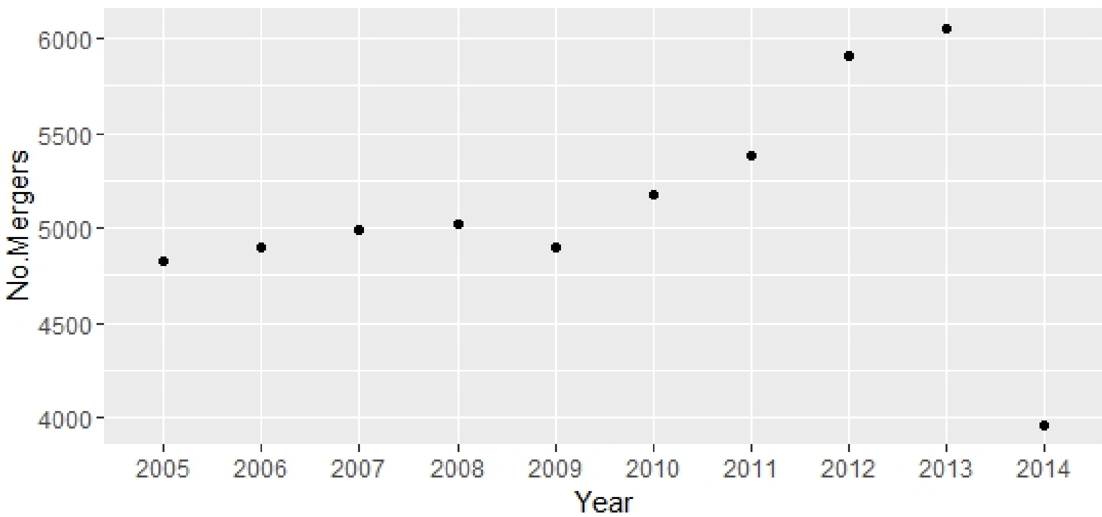


Figure 3.1: Mergers per year

similarly to worldwide M & A-activities. However, in contrast to the data set, the worldwide number of M & A-activities has decreased since 2010. (IMAA-Institute, 2017a) Differences might be caused by improved possibilities for the Bureau van Dijk to collect data. The data set shows a relatively small number of mergers in 2014. A reason for this might be that with the start of data collection, at the beginning of

2015, not all information had yet been added to the database.
Table 3.4 shows the summary statistics for indicators after implementing restrictions.

Table 3.4: Mergers per Indicator

Label	**obs.**	**target**	**buyer main**	**buyer sub**
	51,128	**main**	34,502	12,566
		sub	5,351	11,716
deal type "Merger"	774	**main**	739	108
		sub	91	247
deal type "Acquisition"	50,354	**main**	33,763	12,458
		sub	5,260	11,469
deal status "Completed"	36,541	**main**	24,243	9,204
		sub	3,916	8,639
deal status "Assumed completed"	14,587	**main**	10,259	3,362
		sub	1,435	3,077
notified to a regulatory body	3,182	**main**	2,205	780
		sub	368	870
notified to the European Commission	280	**main**	190	83
		sub	36	71
notified in the EU	735	**main**	518	187
		sub	74	123
primary source	20,617	**main**	13,455	5,541
		sub	2,339	5,187

After implementing restrictions, the overall data set consists of 51,128 mergers, which amounts to 15.82% of the raw data set. In the described data set 51,128 out of 107,320 mergers are horizontal, which amounts to 47.6%. This share is comparable to the share of horizontal mergers in the data set used by Maksimovic and Phillips (2001), as this data set consists of 51.4% horizontal mergers[9]. The majority of horizontal deals are main2main mergers. The minority of deals are sub2main mergers. It seems that buyers primarily decide to extent their main activities by merging other firms. Targets are favored if their main activity contributes to this extension of activities.
ZEPHYR declares deals of deal type "merger" as rare; in this data set only 1.5% of all deals are "mergers". 98.5% of all deals are classified as "acquisitions". 28.5%

[9] Assuming matching of activities based on a three-digit US SIC industry classification code.

of all mergers, or 14,587, have the deal status "assumed completed". The majority of mergers have the deal status "completed". Only 6.2% of all mergers have been notified to a regulatory body and only 280 have been notified to the European Commission. 40.32% of all mergers are mergers according to a primary source. A merger according to a primary source means that the information about the merger origins from a filing or press release by one of the involved companies. In contrast, a secondary source means that the deals have only been identified in a "news" source. For the purpose of merger identification, it is not distinguished whether the information about the deal is from a primary or secondary source.

3.4 Discussion and Conclusion

Mergers are deals, which have either the deal status "completed" or "assumed completed" and are defined as a "merger" or "acquisition" that leads to a majority stake. Horizontal mergers are mergers of buyers and targets that operate in the same 3-digit US SIC Code industry.

The merger identification is based on the following three assumptions. First, each deal in the ZEPHYR data set, which is listed as completed or assumed completed, is assumed to be constituted by legal rights, treaties, and/or contracts and has implicitly or explicitly been approved by a regulatory body. Secondly, deals that are called mergers or acquisitions (if they lead to a majority stake) are assumed to lead to a concentration. And thirdly, 3-digit US SIC coded industries are assumed to be markets, such that firms operating in the same industry operate in the same market and are consequentially competitors.

These assumptions have the following impact on the analysis of merger-specific efficiency gains. Assuming that any listed deal is constituted allows the date that is listed in the data set to be interpreted as the merger date. A change of control is possible afterwards. Therefore, a merger-specific efficiency gain can be expected from this date onward. This assumption divides the observed data into pre- and post-merger observations. In reality, this divide might be less precisely than assumed. This is, because firms do not necessarily change control directly after signing a contract, which constitutes a merger. Moreover, the signing is often followed by an analysis of possibilities to reallocate resources, exchange know-how or managerial experience, for example. This analysis can take a lot of time and human resources. A change of control so that merging firms reallocate resources and rearrange the organization of a firm takes time and therefore often cannot be expected directly after the constitution of a merger. Taking this into consideration, it makes sense to analyze merger-specific efficiency gains in different time periods after the merger. If the analysis of possibilities in the first phase after the merger consumes resources, one can expect an efficiency loss in the short-term after the merger. If this analysis is followed by an efficient change of control, one can expect efficiency gains in the mid- or long-term after the merger.

The assumption that each listed deal is approved either implicitly or explicitly by responsible regulatory bodies allows assuming that for those mergers the anti-competitive effect can be neglected as the merger would have been denied otherwise. This argumentation only holds if regulatory bodies always decide correctly: Any merger that may result in anti-competitive effects is notified and analyzed and the merger approval process is capable of anticipating any anti-competitive effect. Even though, anti-competitive effects such as markup increases might have been countervailed by cost reductions, the present study does not separate the analysis of merger-specific cost reductions from merger-specific markups. Thus, the estimated efficiency changes consist of both markup as well as cost changes. Blonigen and Pierce (2016) have recently shown that mergers in the US market are likely to result in merger-specific markups. The present study could be improved by the analysis of merger-specific markups.

Furthermore, a concentration is indicated by one factor: the constitution of a majority stake. A majority stake can either be constituted by a "merger" or an "acquisition". This indicator is based on the assumption that the constitution of a majority stake is followed by a change of control. Therefore, this indicator separates deals that are only constituted from those that result in a concentration. In reality, a firm acquiring the majority stake of another firm often (but not necessarily always) intervenes in operations. Consequently, the control of a firm is not always actively changed. Nevertheless, a majority stake offers at least the opportunity to intervene in operations and thereby change the control. This opportunity is sufficient to cause a firm's reaction so that the anticipation of the intervention changes the behavior of firms. Often firms tend to become more efficient before the merger. (Blonigen and Pierce, 2016) This trend can partly be explained by the fact that firms make additional efforts to be efficient after receiving information about an acquisition. This effort is supposed to prevent interventions in the firm's operations. It can be discussed whether this pre-merger efficiency gain is also merger-specific. In the present study, those pre-merger efficiency gains are defined as non-merger specific.

Finally, horizontal mergers are assumed to be mergers of firms in the same 3-digit US SIC Code industry. The approach applied identifies mergers of firms with similar production technologies. It is likely that firms with similar production technologies have a lot of potential to share know-how, resources and experiences. Therefore, for such firms, merger-specific efficiency gains are likely. However, on the one hand, firms with similar technologies do not necessarily sell the same product. On the other hand, firms that are selling the same product have a similar production technology. Moreover, firms with similar production technologies have the possibility to produce the same products. Consequently, firms that operate in the same 3-digit US SIC Code industry are either competitors or potential competitors. Therefore, analyzing mergers of firms that operate in the same 3-digit US SIC Code industries, results in the analysis of mergers of actual or potential competitors. Thus, the approach is sufficient to identify horizontal mergers.

Chapter 4

Productivity Estimation

4.1 Introduction

The estimation of efficiency has major impact on the analysis of merger-specific efficiency gains as it is the first step and thereby the input of the analysis. A common approach of empirical studies analyzing merger-specific efficiency gains is the application of a Total Factor Productivity (TFP) approach (e.g. Maksimovic and Phillips (2001) and Blonigen and Pierce (2016)). TFP is a measure of technical efficiency in production, named productivity.
Origins of the TFP concept have been constructed in the late 1950s. Although, the concept has been existing for a long time, it receives a lot of attention in recent empirical studies. According to Van Beveren (2012) there are two reasons for this attention. Firstly, the availability of firm data, especially financial firm data, increases the possibilities of empirical studies to apply econometric methods to analyse topics in the field of industrial organization, for example. Secondly, a lot of methodological improvements have been developed since the origins of TFP that allows to control several econometric issues, e.g. endogeneity and selection bias. The TFP approach is used in different contexts. Among others, De Loecker and Warzynski (2012) and De Loecker et al. (2016) implement the TFP approach into markup estimation. Their approach allows to analyse markets with regard to productivity as well as with regard to markups. Recently, Blonigen and Pierce (2016) applied this approach in the context of merger analysis.[1]

4.2 Methology

The basic TFP model is a regression of a production function with a standardized normal distributed error term. The residual is the productivity estimate. (Syverson,

[1]For more details about markup estimation and the approach of De Loecker and Warzynski (2012) see Appendix subsection 9.5.

2011)[2] The basic TFP model assuming a Cobb Douglas production function for a panel data set model would be:

$$y_{it} = \alpha_k k_{it} + \alpha_l l_{it} + \omega_{it} + \nu_{it} \tag{4.1}$$

with

$$\epsilon_{it} = \omega_{it} + \nu_{it} \tag{4.2}$$

where y_{it} is either log gross output or log value added. k_{it} and l_{it} are log input factors, capital and labor. ϵ_{it} is a composite error term including ω_{it}, the productivity term and ν_{it}, a random error term. Productivity is only observable for the firm, but not for the econometrician. The random error term is unobservable for both, the firm and the econometrician.

The basic model, as introduced in equation (4.1), has been improved by several authors.[3] The methodological improvements tend to control for the problem of measurement errors, misspecification of the functional form of the production technology and the problem of a selection bias.[4] However, one of the major and most discussed issues of the basic TFP model is endogeneity.

Without any further assumptions it is econometrically impossible to identify both components, ω_{it}, the productivity term and, ν_{it}, the random error term, of the error term, ϵ_{it}. Furthermore, the basic model will only result in unbiased estimates if the error term is exogenous, meaning $E[\epsilon_{it}|\mathbf{x}_{it}] = 0$. This is only the case if the firm's input choice is independent of random noise as well as independent of its productivity. In reality, it is difficult to argue that the input choice of a firm is independent of its productivity. If the input choice depends on productivity, the model has an endogenity problem. Endogeneity results from the fact that we do not observe the productivity term, ω_{it}. Therefore, productivity is an omitted variable and causes, due to simultaneity, endogeneity. More precisely: A firm knows its productivity when it chooses input factors. Therefore, assuming input factors to be independently chosen from productivity might be incorrect. As productivity is a component of the error term, ϵ_{it}, this causes endogeneity, $E[\epsilon_{it}|\mathbf{x}_{it}] \neq 0$. Thus, endogeneity is one of the most relevant problems in TFP models.

Several solutions to endogeneity can be found in literature.[5] Most recent empiri-

[2]The TFP approach is categorized as an average production function approach. In contrast to frontier approaches, which are introduced in chapter 6 the productivity estimate itself is meaningless. Nevertheless, the differences between productivity allows to differentiate whether productivity is above or below average and whether productivity growth is positive or negative.

[3]For a summary of methodological improvements of the TFP approach see e.g. Van Beveren (2012), Aguirregabiria (2009) and Syverson (2011).

[4]See Appendix 9.4 for an overview of problems and possible solutions.

[5]Four main solutions to endogeity are:

1. Instrumental Variables (IV),

cal studies apply the control function approach to solve the endogeneity problem.[6] Although, there are several comprehensive overviews that summarize among others the methodological improvements to control for endogeneity, I will introduce two main possible approaches. The introduction follows Aguirregabiria (2009).

The Fixed Effect Approach

An appropriate way to control for endogeneity is the fixed effect approach. The basic idea of FE is to implement a time invariant and firm-specific effect, $\omega_{it} = \omega_i$, that captures all endogenous variation of $\mathbf{x}_{it}$. ω_i is the fixed effect.
The fixed effect approach requires three main assumptions. First of all, the added firm-specific fixed effect, ω_i, must be time invariant, which means that this fixed effect represents the mean efficiency of firm i over time. Secondly, after adding the firm-specific fixed effect, the input choice is independent of the random error term, ν_{it}. ξ_{it} is interpreted as an idiosyncratic productivity shock, later also defined as innovation. This exogeneity can be written as $E[\nu_{it}|\mathbf{x}_{it}] = 0$. And third, the added firm-level fixed effect is independent of the error term, which can be written as $E[\nu_{it}|\omega_i] = 0$.
Although the fixed effect model has several advantages from a theoretical side, it is rarely applied in practice. One reason is that the number of observed periods are normally small and therefore T consistency of ω_i is not possible. Another reason is that even if T consistency of ω_i is possible, the assumption of partly time invariant productivity will be a strong one. In the context of analyzing merger-specific efficiency gains this means that pre- and post-merger fixed effect are needed.[7]

The Control Function Approach

In the context of the analysis of merger-specific efficiency gains, the Control Function (CF) approach is helpful to control for endogeneity. The approach allows to control for endogeneity without implementing fixed effects for firms. Blonigen and Pierce (2016) recently applied the approach to analyze merger-specific efficiency gains.
The following introduction mainly summarizes the approaches of Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015) and Wooldridge (2009). Olley and Pakes (1996) introduced a CF approach that used investment as variable

2. Fixed Effects (FE),
3. Generalized Method of Moments (GMM), and
4. Control Functions (CF).

[6]For a detailed explanation of possible solutions see Appendix section 9.4.
[7]For more details about the fixed effect approach see Appendix section 9.4.

to build a control function that is capable to approximate the omitted variable "productivity". The approach was extended by Levinsohn and Petrin (2003), who used material instead of investment as proxy.[8]

The model: The basic model based on a Cobb Douglas[9] production function can be written as:

$$y_{it} = \alpha_l l_{it} + \alpha_k k_{it} + \omega_{it} + \nu_{it} \tag{4.3}$$

Each period a firm chooses the input factor labor. The decision of labor can be described as a function depending on the state variables $(l_{i,t-1}, k_{it}, \omega_{it}, r_{it})$, where r_{it} describes input prices[10].[11]

$$l_{it} = f_L(l_{i,t-1}, k_{it}, \omega_{it}, r_{it}) \tag{4.4}$$

Furthermore, the decision of capital investment can be similarly described.

$$i_{it} = f_K(l_{i,t-1}, k_{it}, \omega_{it}, r_{it}) \tag{4.5}$$

Assumptions: The CF approach requires the following four assumptions.
(CF1) $f_K(l_{i,t-1}, k_{it}, \omega_{it}, r_{it})$ is invertible in ω_{it}.
(CF2) There is no cross-sectional variation in input prices, which means that input prices are uniform for all firms: $r_{it} = r_t$.
(CF3) ω_{it} follows a first-order Markov process.
(CF4) Capital, k_{it}, is built over time. It is determined by the capital investment decision, i_{it}: $k_{i,t+1} = (1-\delta)k_{it} + i_{it}$ where δ is a depreciation rate. The capital investment chosen at period t and will not become productive before period t+1.

Estimation: The estimation process follows a two-step approach. In a first step, the estimation of α_l is done using the CF approach. For this, assumptions (CF1) and (CF2) are needed. In a second step, the estimation of α_k is done based on the assumptions (CF3) and (CF4).

[8] Levinsohn and Petrin (2003) argue that investment fails to approximate productivity in the case of zero investment. Therefore, they use material instead of investment. The model remains the same.

[9] Alternatively, the production function could be e.g. nonparametrically defined. I do not apply this approach as I will concentrate on the approximation of productivity rather than the production function itself. Nevertheless, results could possibly be approved by a nonparametrically defined production function. For short introduction to the nonparametrical specification of the production function see Appendix section 9.4.

[10] Alternatively, r_{it} could be defined as a vector of control variables, $\mathbf{z}_{it}$

[11] Olley and Pakes (1996) assume l_{it} to be perfectly flexible and to have no adjustment costs. Thereby, l_{it} is not a state variable.

Step 1: Assumptions (CF1) and (CF2) allow to invert equation (4.5), which results in $\omega_{it} = f_K^{-1}(l_{i,t-1}, k_{it}, i_{it}, r_{it})$. Plugging this into the production function described in equation (4.3) results in:

$$\begin{aligned} y_{it} &= \alpha_l l_{it} + \alpha_k k_{it} + f_K^{-1}(l_{i,t-1}, k_{it}, i_{it}, r_{it}) + \nu_{it} \\ &= \alpha_l l_{it} + \phi_t(l_{i,t-1}, k_{it}, i_{it}) + \nu_{it} \end{aligned} \tag{4.6}$$

where $\phi_t(l_{i,t-1}, k_{it}, i_{it}) \equiv \alpha_k k_{it} + f_K^{-1}(l_{i,t-1}, k_{it}, i_{it}, r_{it})$.

Without any parametric assumption on f_K the model is a semiparametric partially linear model. It is semiparametric, as f_K would be non-parametric and the production function itself is parametric. While f_k would be non-linear, the production function is a linear function. The estimation is possible with semiparametric methods, e.g. a kernel estimation[12]. Alternatively, e.g. Olley and Pakes (1996) approximate the nonparametric expression $\phi(l_{i,t-1}, k_{it}, i_{it})$ by polynomial series.

This first step of estimation captures the endogenous part of the error term with the help of additional regressors. Thus, instead of using instruments to capture the endogenous part in the existing regressors, the endogenous part of the error term is captured. The unobservable variable, ω_{it}, is approximated by the control function which is flexible in the variables, $l_{i,t-1}, k_{it}, i_{it}$. The identification of α_l is possible if there is enough variation left.

Step 2: Given the assumptions (CF3) and (CF4) and given α_l it is possible to estimate α_k. The assumptions allow to describe productivity as:

$$\omega_{it} = E[\omega_{it}|\omega_{i,t-1}] + \xi_{it} = h(\omega_{i,t-1}) + \xi_{it} \tag{4.7}$$

where $h(\cdot)$ is an unknown function and ξ_{it} is an innovation, which is mean independent of the information at period t-1 or before. We can write $\phi_{it} = \phi_t(l_{i,t-1}, k_{it}, i_{it})$. From step 1, we known that $\phi_t(l_{i,t-1}, k_{it}, i_{it}) = \alpha_k k_{it} + \omega_{it}$. Then again, it is possible to plug equation (4.7) in, which results in:

$$\begin{aligned} \phi_{it} &= \alpha_k k_{it} + h(\omega_{i,t-1}) + \xi_{it} \\ &= \alpha_k k_{it} + h(\phi_{i,t-1} - \alpha_k k_{i,t-1}) + \xi_{it} \end{aligned} \tag{4.8}$$

$h(\cdot)$ is nonparametrically defined. From step 1 consistent estimates result for $\hat{\phi}_{it}$. It is possible to write $\hat{\phi}_{it} = y_{it} - \hat{\alpha}_l l_{it}$. The model described in equation (4.8) is a partial linear model, but with an unknown parameter, α_k. A possible approach to estimate

[12] In Appendix section 9.4 the kernel estimation, i.e. the Nadaraya-Watson estimator, is explained in the context of an unspecified production function. In the context of the CF approach, the production function is partly parametrically specified. Nevertheless, the application of the kernel estimation is comparable.

α_k and $h(\cdot)$, which is applied by Olley and Pakes (1996), is an iterative procedure.[13] $h(\cdot)$ can be defined as e.g. quadratic function, which results in $h(\omega) = \pi_1\omega + \pi_2\omega^2$. Solving $\hat{\omega}_{it}^{\alpha_k} = \hat{\phi}_{it} - \alpha_k k_{it}$ results in an initial value for α_k that can be plugged into $\hat{\phi}_{it} = \alpha_k k_{it} + \pi_1\hat{\omega}_{it}^{\alpha_k} + \pi_2(\hat{\omega}_{it}^{\alpha_k})^2 + \xi_{it}$. Running an OLS regression results in a new coefficient for α_k. This coefficient is used to calculate a new value for $\hat{\omega}_{it}^{\alpha_k}$. The iteration process is run until it converts.

Extensions: The CF approach has been improved by several authors.[14] Two main improvement are of further relevance. Those are the improvements of Ackerberg et al. (2015) as well as Wooldridge (2009).

Ackerberg et al. (2015) argue that a collinearity between labor and the state variables makes it impossible to estimate the labor coefficient in the first step. Thus, they recommend to estimate all coefficients in a second step.

Inserting the inverse of the capital investment function, f_K^{-1}, into the labor decision, f_L, results in:

$$\begin{aligned} l_{it} &= f_L(l_{i,t-1}, f_K^{-1}(l_{i,t-1}, k_{it}, i_{it}, r_{it}), \omega_{it}, r_{it}) \\ &= G_t(l_{i,t-1}, k_{it}, i_{it}) \end{aligned} \tag{4.9}$$

Labor, as defined in equation (4.9), is determined by the state variables $(l_{i,t-1}, k_{it}, i_{it})$. There should be no cross-sectional variation left, which means that α_l cannot be estimated in the first step.[15] Instead, α_l should also be estimated in the second step. The estimation of all coefficients in the second step requires exogenous variation in labor. This variation needs to be independent of productivity and should not influence the capital decision. The authors solve this problem by assuming different input prices for labor and capital, which results in:

$$l_{it} = f_L(l_{i,t-1}, k_{it}, \omega_{it}, r_{it}^L) \tag{4.10}$$

Furthermore, the decision of capital investment can be similarly described.

$$i_{it} = f_K(l_{i,t-1}, k_{it}, \omega_{it}, r_{it}^K) \tag{4.11}$$

[13] Alternatively, a Minimum Distance approach can be applied. For more details see Aguirregabiria (2009).

[14] See e.g. Van Beveren (2012) and Aguirregabiria (2009) for an overview of improvements. Mollisi and Rovigatti (2017) argue that only some of those improvements have been implemented in Stata or R packages, so far. In the present study the "prodest" package in Stata is used to estimate the coefficients of the production function. The "prodest" package is still in progress, which means that not all theoretical improvements of the TFP model such as the approach of Ackerberg et al. (2015) have yet been completely implemented.

[15] Of cause, in most data sets labor has still some cross-sectional variation. But this variation is assumed to result from cross-sectional variation of input prices. However, this variation of input prices is endogenous.

The labor input price, r_{it}^L, is assumed to have cross-sectional variation and is assumed to be independent of r_{it}^K.[16]

Wooldridge (2009) further improves the CF approach by introducing a GMM approach. The GMM approach allows to implement the moment conditions of the semiparametric estimation in the first step into a GMM approach for the second step. Thereby, the estimation of coefficients is possible in one step. The two-step approach has two main disadvantages that can be solved by the GMM approach. Firstly, to obtain the standard errors of the input coefficients requires a bootstrapping procedure. In contrast, GMM approach results in robust standard errors for input coefficients. And secondly, the error terms of the first and second step are assumed to be uncorrelated. Contrary, the GMM approach efficiently estimates coefficients without this assumption.
Wooldridge (2009) suggests to rewrite $\omega_{i,t-1}$ as $\omega_{i,t-1} = g(l_{i,t-2}, k_{i,t-1}, i_{i,t-1})$ where $g(\cdot)$ is an unknown function with lagged state variables $(l_{i,t-2}, k_{i,t-1}, i_{i,t-1})$ as dependent variables. Moreover, the first-order Markov process in equation (4.7) can be rewritten into $\omega_{it} = h(\omega_{i,t-1}) + \xi_{it} = h(g(l_{i,t-2}, k_{i,t-1}, i_{i,t-1})) + \xi_{it}$. Taking this expression into account the production function in equation (4.3) can be rewritten into

$$y_{it} = \alpha_l l_{it} + \alpha_k k_{it} + h(g(l_{i,t-2}, k_{i,t-1}, i_{i,t-1})) + \epsilon_{it} \tag{4.12}$$

where $\epsilon_{it} = \xi_{it} + \nu_{it}$. The resulting moment conditions are

$$E(\epsilon_{it} | k_{it}, l_{i,t-1}, k_{i,t-1}, i_{i,t-1}, ..., l_{i1}, k_{i1}, i_{i1}) = 0 \tag{4.13}$$

These moment conditions are sufficient to identify the coefficients α_l and α_k in equation (4.12). The moment conditions allow to estimate α_l without assuming that the choice of labor, l_{it}, independent of the innovation term, ξ_{it}. Thereby, the GMM approach considers the extension of Ackerberg et al. (2015). Furthermore, $h(\cdot)$ and $g(\cdot)$ can be estimated by a kernel estimation procedure. The only assumptions needed for this approach is that the state variables $(l_{i,t-1}, k_{it}, i_{it})$ and their lags are mean independent of the innovation term, ξ_{it}, and the random error term, ν_{it}.

4.3 Application

So far, the TFP methodology has been introduced assuming a Cobb Douglas production function. I further assume a translog production function because the later is more flexible than the Cobb Douglas. The interaction term between labor, l_{it},

[16] Ackerberg et al. (2015) introduce different possible interpretations to those assumptions. For a summary of those interpretations see Aguirregabiria (2009).

and capital, k_{it}, is mean dependent of the random error term, ν_{it}, as capital, k_{it}, is mean dependent of the random error term, ν_{it}. To estimate the coefficients, the GMM approach of Wooldridge (2009) can be applied.[17] The translog production function can be described as

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \nu_{it} \tag{4.14}$$

The production function is estimated for each of the three-digit US SIC coded industries in the manufacturing sector.

The labor choice, l_{it}, is assumed to be non dynamic. In contrast to equation (4.4), the non dynamic labor choice has no adjustment costs. Furthermore, lagged labor, $l_{i,t-1}$, is not a state variable. The assumption of a non dynamic labor choice follows Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Similarly to the introduction to the CF approach, input prices are assumed to be uniform for all firms. But, instead of including year-dummies for input prices, r_t, or any other control variables into the the capital investment decision, all input choices are assumed to be mean independent of any yearly effects.[18]

Instead of investment, I use material, m_{it}, as proxy for productivity. Thereby, this study follows Levinsohn and Petrin (2003).[19] Consequently, the investment decision is a material demand decision. The choice of material is assumed to depend on the state variable "capital", k_{it}, as well as productivity, ω_{it}:

$$m_{it} = f_K(k_{it}, \omega_{it}) \tag{4.15}$$

Similarly to equation (4.12) the production function can be further described as

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{lk} l_{it} k_{it} + h(g(k_{i,t-1}, m_{i,t-1})) + \epsilon_{it} \tag{4.16}$$

where $\epsilon_{it} = \xi_{it} + \nu_{it}$. Even though, $h(\cdot)$ can be unspecified, it is further approximated by a second order polynomial, which results in $h(\omega) = \pi_1 \omega + \pi_2 \omega^2$. This approxima-

[17] Material as well as capital enters the production function linearly. Alternatively, both could enter the production function quadratically. Moreover, an interaction term with other variables for the proxy could be appropriate. Those quadratic and interaction terms are further droppped due to the possibilities of the prodest package in Stata. The prodest package is, as far as the present study is concerned, the only one that can be used for the estimation of a translog function in combination with the CF approach and the extension of Wooldridge (2009).

[18] The yearly effects will be considered in the DID approach applied in chapter 5.

[19] The choice of material instead of investment as proxy for productivity is mainly data driven. On the one hand, the investment variable is not directly observable and therefore needs to be generated out of the capital variable. Consequently, the investment variable is highly correlated with the capital variable. On the other hand, the creation of the investment variable reduces the available data set significantly. This reduction is caused by the elimination of one year of observations as for the calculation of the investment value a lag is needed. See Appendix section 9.10 for a detailed description on the resulting data set after creating the investment variable.

tion is implemented in the stata package "prodest" and is therefore chosen. Furthermore, it would allow to estimate the innovation term $\xi_{it} = h(g(l_{i,t-2}, k_{i,t-1}, i_{i,t-1}))$. Using capital as well as one lag of input variables as instruments results in the following moment conditions:

$$E(\epsilon_{it}|k_{it}, l_{i,t-1}, l^2_{i,t-1}, k_{i,t-1}, m_{i,t-1}, l_{i,t-1}k_{it}, m_{i,t-2}) = 0 \tag{4.17}$$

$l_{i,t-1}k_{it}$ acts as the instrument for $l_{it}k_{it}$. This instrument is based on the assumption that the interaction of lagged labor and capital is mean independent of innovation and random error. $k_{it}, k_{i,t-1}, m_{i,t-1}$ act as their own instruments. These are the state variables, which are also per assumption mean independent of innovation and random error. For the flexible variables, l_{it} and m_{it}, the lagged values are used as instruments because for those the assumption of mean independence of innovation and random noise also holds. As lagged material is already used as an instrument for $m_{i,t-1}$, the e.g. second lag, $m_{i,t-2}$, is a useful instrument for m_{it}. However, any lags of flexible and state variables are possible instruments as they are assumed to be independent of innovation and random noise. Furthermore, any state variable is assumed to be independent of innovation and random noise and can therefore act as an instrument.
Assuming a zero mean idiosyncratic error term, u_{it}, productivity can be written as

$$\omega_{it} = E[y_{it} - \hat{y}_{it}] \tag{4.18}$$

4.4 Data

The data set used to estimate productivity is provided by AMADEUS of Bureau van Dijk. The raw data set includes financial information of 623,473 firms in Western Europe in the years 2005 to 2014. The final data set consists of 131,232 firms.

Requirements, Availability and Selection

The application of the TFP approach requires input and output variables to estimate the production function. Traditionally, input variables cover at least capital and labor. (Van Beveren, 2012) Most empirical studies (e.g. Maksimovic and Phillips (2001) and Blonigen and Pierce (2016)) that analyze manufacturing industries add at least material as input variable. As the available data set consists of information published in balance sheets and profit and loss accounts, like sales, costs of employment, and book value of total assets, financial values are further used to approximate the input and output variables.[20]

The variable capital, k_{it}, represents the capital stock that is available to be used in production. (Maksimovic and Phillips, 2001) Furthermore, capital is chosen in advance of its realization and depreciates over time. (Konings et al., 2001) Thus, the capital value as listed in the balance sheet needs to be adjusted by depreciation. In the context of this study, capital is defined as "Tangible fixed assets" (TFAS) adjusted by the "depreciation" (DEPR). The resulting capital value can be interpreted as the capital stock at the beginning of a period, which is available to be used in production. (Konings et al., 2001)

Labor, l_{it}, represents the amount of labor that a firm chooses to maximize its profit. A firm can engage any amount of labor at wage on the labor market. (Konings et al., 2001) Wages are assumed to be uniform across firms. The 'Cost of employees' (STAF) equals the sum of employees multiplied wages. In contrast to the number of employees, the cost of employees considers also the qualification of employed persons.

Material, m_{it}, is approximated by cost of material (MATE). Cost of material is the only available value that can be chosen to approximate the input variable material. Most empirical studies, which estimate a production function, define output, y_{it}, as either gross output or value added. (Van Beveren, 2012) A value added approach is often applied by empirical studies that analyze on an aggregated level, like the analysis of a whole economy or sector. In the context of aggregated data sets, a value added approach is preferred as the output of one firm or industry is often the input of another industry or firm. Thus, the problem of double-counting inputs or outputs will occur if a gross output approach is applied. In a value added approach, intermediate inputs are netted out and the problem of double-counting inputs disappears. However, for the analysis of industries on finer levels the gross output approach is more appropriate. (McGuckin and Nguyen, 1995) The advantage of a gross output approach is that sales, turnover or revenue is likely to approximate theoretical output of a production much better than e.g. profit, earning before interest and taxes (EBIT) or earnings before interest, taxes, depreciation and appreciation (EBITDA), which are measures for value added. Thus, the productivity estimate resulting from a gross output approach better represents a true value of total factor productivity than the productivity estimate resulting from a value added approach. (Mcguckin and Nguyen, 1993) The gross output approach is appropriate for an analysis on an industry-level. (McGuckin and Nguyen, 1995) Therefore, this empirical study applies a gross output approach. Similarly to other empirical studies (e.g. Van Beveren (2012)), sales approximates the output variable.

[20]See Appendix 9.6 for a detailed overview of available information in "AMADEUS" and a discussion about the matching of available information to the requirements of efficiency estimation.

Description

The AMADEUS data set includes information of 623,473 firms in Western and Eastern Europe from 2005 to 2014. Firms are legal entities. They are classified as manufacturing according to the US SIC Code. Table 4.1 summarizes raw data for input and output variables. The negative values in table 4.1 may primarily result from typing or measurement errors. Still, negative sales will be possible if more products are returned than sold. In this case, the products returned generate negative sales. However, in general it is unlikely that firms produce a negative output, have capital value, labor or material costs.

Table 4.1: Raw Data for Input and Output Variables

	N	Min	Max	Mean	St. Dev.
output[21]	2,421,285	-121,742	202,458,000	25,009	616,329.6
labor	2,232,114	-373,100	364,994,951	4,465	265,878.9
employees	3,251,537	0	566,300	134.8	1,721.201
capital	2,297,070	-20,882,308	109,400,661	6,047	230,610.2
material	1,884,687	-2,215,893	298,700,068	13,714	344,964.5

The following five restrictions are set to data.[22] First, firms are classified as manufacturing according to US SIC Code as well as NACE Rev. 2. Both classification systems are common in literature. While the US SIC code is a US classification system that has been replaced by the NAICS code, the NACE Rev. 2 code is a European classification system. On the one hand, the US SIC code considers industries like printing and publishing as manufacturing, while NACE does not. On the other hand, the NACE code considers industries like repair, installation and maintenance as manufacturing, while US SIC does not. Combining both classification systems allows to concentrate on a common understanding of manufacturing industries. Therefore, results are comparable to US as well as to European merger literature. As most relevant literature is US literature, this study classifies industries according to the US SIC code.

Second, firms need to be located in a Member State of the European Union or a country with legal and economic systems that are strongly related to the standards of the European Union. These countries are partners of the Stabilisation and Association Agreement (SAA), the European Free Trade Association (EFTA) or the European Economic Area (EEA).[23] The purpose of this restriction is to focus the

[22]See Appendix section 9.7 for a further discussion of efficiency restrictions.

[23]Therefore, the analyzed data set includes mergers in the European Union as well as in Switzer-

analysis on one geographical market. Considering e.g. the EU as one geographical market, would eliminate a country like Switzerland from the analysis. This elimination seems unreasonable as the country is located in the center of Europe and most imported/exported goods origin/are sold from/to the EU. The applied restriction combines countries that are neighbors and that can be aggregated to one geographical market.

Third, output values of firms need to be deflated. In the context of this study, sales need to be deflated by a three digit producer price index (PPI) available from Eurostat. The approach follows Konings et al. (2001). The PPI measures price changes from the producers' point of view. Deflating output by a PPI eliminates the impact of price changes on output. Therefore, deflated output is a proxy for produced quantity. In the context of productivity estimation, deflating output provides productivity estimates that measure the relation of produced goods and costs.[24]

Fourth, the logarithm of values requires positive output, labor, capital and material values. For input values, negative values would mean that costs are valuable, which does not fit the definitions of costs. Negative output values mean negative revenue values. According to the definition revenue needs to be positive. Thus, negative output values are ignored as they are likely to be caused by measurement or typing errors.

Fifth, in the context of this study an industry is analyzed if it includes at least 60 observations per year and industry. It would also be possible to choose a different number of observations. Finally, enough variation is needed to estimate the coefficients and to further analyze efficiency changes. However, each observation represents a firm. An industry with 60 or more operating firms is likely to be competitive. The assumption of exogenous and uniform prices is more reasonable in competitive industries.

Table 4.2 shows summary statistics after implying restrictions. After implementing all restrictions the data set consists of 131,232 firms in 93 industries with 857,526 observations. On average each firm appears 6.5 times in the data set.

Table 4.4 shows the summary statistics for the number of observations per industry. While the data set consists of 131,232 firms, approximately 2.1 million manufacturing firms are overall located in the EU according to Eurostat (Eurostat, 2017a).

The data set size for productivity analysis is mainly restricted by two requirements. First, the requirement is that firms are manufacturing according to US SIC Code as well as NACE Rev. 2 and second, the the necessity of the variable 'material' reduces the data set significantly.[25] After implementing restrictions the data set is reduced

land (EFTA), Norway, Liechtenstein, Iceland (EEA), Albania, Macedonia, Montenegro, Serbia, Bosnia Herzegovina and Kosovo (SAA).

[24]See Appendix section 9.6 for further information about output deflation.

[25]See Appendix section 9.7 for a detailed discussion on efficiency restrictions.

Table 4.2: Input and Output Variables

	N	Min	Max	Mean	St. Dev.
output	857,526	1	71,911,323	26,179	392,798.7
labor		1	14,455,269	3,721	39,162.98
employees	687,161	0	86,607	117.3	736.45
capital		1	12,353,301	4,731	63,809.35
material		1	53,308,581	16,181	309,693.4

Table 4.3: Observations per Industry

	N	Min	Max	Mean	St. Dev.
n / ind.	93	396	63,110	9,221	10,831.72

to approximately 21% of the original data set. Nevertheless, with 131,232 firms and 857,526 observations the data set is large compared to the data set of Maksimovic and Phillips (2001), who use 50,000 plants per year.

The average output of firms included in the data set is approximately 26 M€. According to Eurostat the average turnover of firms located in the EU is approximately 3 M€[26]. (Eurostat, 2017a) The data set seems to consist mainly of firms that are not Small and Medium-sized Enterprises (SME). The same applies with regard to the average number of employees. While a firm in the data set employs approximately 118 persons on average, the average number of employees per firm in the EU is 13[27]. (Eurostat, 2017a) Average labor costs are 3.7 M€, which is higher than the average of 0.5 M€[28] in the EU. (Eurostat, 2017a). But, the average labor costs per employee of 32 k€ in the data set differs only little from the overall average labor costs per employer of 39 k€[29] in the EU in 2014. (Eurostat, 2017a)

The choice of input variables for productivity estimation differs depending on data availability, purpose of the analysis and object of study. Often, only an aggregated input variable like Costs of Goods Sold (e.g. DeLoecker and Eeckhout (2017)) is available in the data set. Depending on the purpose of the analysis authors (e.g. De Loecker and Warzynski (2012)) add input variables like export status. Most lit-

[26] Average turnover is calculated as turnover divided by number of enterprises.

[27] Average number of employees per firm is calculated as employees divided by number of enterprises.

[28] Average labor cost is calculated as personal costs divided by number of enterprises.

[29] Labor costs per employer is calculated as average of labour cost per FTE weighted by number of employees per country.

erature, analyzing manufacturing industries use at least the input variable capital, labor, and material (e.g. Blonigen and Pierce (2016) and Maksimovic and Phillips (2001).).

Merger Data Set

Matching the ZEPHYR data to the AMADEUS data, meaning implementing the requirement that the Identification Numbers of ZEPHYR are available in the AMADEUS data set, reduces the merger data set to 8,517 mergers with an identified buyer (17% of the original data set) and 4,610 mergers with an identified target (9% of the original data set). Implementing the restriction that for all variables positive values are needed, results in data sets with 2,866 mergers with an identified buyer (46% further reduction) and 1,632 mergers with an identified target (41% further reduction).[30] Table 4.4[31] shows summary statistics for buyers and targets with only positive input and output values. The table shows that buyers are on average larger than targets as mean output as well as mean number of employees are larger for buyers than for targets.

Table 4.4: Positive Input and Output Values of Merger Parties

	Deals	**Firms**	**Obs.**	**Max**	**Mean**	**Std. Dev.**
Buyer						
output	3,620	2,234	33,186	197,600,000	2,378,922	11,059,031
labor	4,489	2,769	39,575	33,840,000	476,192	2,253,701
employees	4,929	3,132	42,326	566,300	8,722	37,030.67
capital	4,615	2,875	39,538	62,000,000	574,282	2,778,261
material	3,004	1,925	25,437	51,170,000	414,945	1,702,235
Target						
output	1,943	1,790	16,892	32,520,000	134,273	804,445.1
labor	2,287	2,149	19,203	7,757,000	14,824	138,507.4
employees	2,649	2,490	20,562	186,000	437.6	3,411.013
capital	2,357	2,215	19,325	10,190,000	28,762	249,168.8
material	1,679	1,552	14,160	5,746,000	62,667	261,091.2

[30]For more details about the matching process see Appendix section 9.9.

[31]Due to the restrictions the minimum values are always 1 respectively 0 for the number of employees. For the purpose of reducing redundant information, the minimum values are not included in the table 4.4.

4.5 Results

Production Function

Table 4.5 summarizes the coefficients of the production function, described in equation (4.14), after estimating the production function for all industries. The mean output elasticity for labor for all 93 industries is 0.39[32]. Thus, increasing the input factor labor by 1% causes on average an output increase of 0.39%. By this, the input factor has the second largest impact on output after material. The mean output elasticity for material is 0.60. The high impact of material is typical for the manufacturing sector. Therefore, material is an important factor that needs to be considered in a production function of a manufacturing industry. The mean output elasticity for capital for all 93 industries is 0.01, which means that a capital increase of 1% causes on average an output increase of only 0.01%[33]. By this, the capital coefficient has the smallest impact on output. The squared labor coefficient shows that on average the manufacturing sector is characterized by increasing returns to scale in the input factor labor. Thus, an additional unit in labor has a higher impact on output if labor is already large. This fact may give an incentive for mergers as firms benefit if they increase in size. Furthermore, labor and capital are substitutes. In manufacturing industries, this substitutional effect is often caused by the fact that the more machinery equipment, i.e. capital, the less labor force is needed. The standard deviation is largest for the coefficient of labor. Thus, manufacturing industries seem to differ regarding their labor intensity. Also for capital, the coefficient varies a lot across industries and the standard deviation is high.

Table 4.5: Summary Statistics: Coefficients of the Production Function

Statistic	N	Mean	St. Dev.	Min	Max
labor	93	0.338	0.189	−0.377	0.957
capital	93	0.095	0.155	−0.525	0.438
material	93	0.590	0.116	0.031	0.824
labor*labor	93	0.009	0.020	−0.074	0.072
labor*capital	93	−0.013	0.024	−0.063	0.083

Table 4.6 summarizes the results of the production function estimation for two industries, industry 208 "Beverages" and 371 "Motor Vehicles and Motor Equipment". Industry 208 is the industry with most mergers and therefore of special interest and

[32] According to De Loecker and Warzynski (2012) the output elasticity of labor can be calculated as follows: $\hat{\theta}^l_{it} = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it}$.

[33] The output elasticity of capital can be calculated as follows: $\hat{\theta}^k_{it} = \hat{\beta}_k + \hat{\beta}_{lk} l_{it}$.

industry 371 is the most important industry in Europe.[34]
Industry 208, the industry for "Beverages", is characterized by a mean output elasticity for material of 0.44. The mean output elasticity for labor is 0.33. The mean output elasticity for capital has a value of 0.05, whereby the coefficient for capital is insignificant. Furthermore, the industry shows significant increasing returns to scale for the labor input factor. The complementary effect between labor and capital is insignificant. The Hansen's J test tests whether the chosen instruments are exogenous. In case of a significant value the hypothesis that instruments are exogenous is rejected and it is likely that the instruments are endogenous. In case of industry 208, the Hansen's J value is highly significant, which tells that the hypothesis that the instruments are exogenous is rejected. Thus, the validity of the estimates in this industry can be strongly doubted. Overall, the Hansen's J test indicates for the majority of industries that the instruments are exongenous. Thus, all industries are further analyzed including those that suffer from endogeneity as they represent with 30% a minority.[35]
Industry 371, the industry for "Motor Vehicles and Motor Equipment" is characterized by a mean output elasticity for material of 0.66. The mean output elasticity for labor is 0.32. The mean output elasticity for capital is 0.01, whereby the coefficient for capital is weakly significant. The industry is characterized by decreasing return to scale in the input factor labor. The Hansen's J test indicates that the instruments are exogenous and the estimates are credible. Table 4.6 shows that industries may differ strongly. The impact of material but also labor on output is much higher in industry 371 than in industry 208. For industry 208 there might be some omitted variables that cause the endogeneity of instruments. Even though, the mean coefficient for labor square as shown in table 4.5 indicates that the manufacturing sector is characterized by increasing economies of scales for some industries. In the case of the present study the most relevant industry in Europe, industry 371, shows decreasing returns to scale in the input factor labor. Thus, for this industry growing in size due to mergers might not be the best strategy. Furthermore, the mean productivity of industry 208 is with a value of 2.711 much higher than the mean productivity of industry 371, which is 0.0778. Figure 4.1 shows the distribution of productivity estimates for both industries. The figure shows that the standard deviation of efficiency of industry 208 is much higher than the standard deviation of efficiency of industry 371.

[34] For a detailed description and analysis of both industries see chapter 6.
[35] See Appendix subsection 9.8 for an overview of all Hansen's J tests.

Table 4.6: TFP Production Function - Industry 208 and 371

	Dependent variable:	
	Industry 208: output	Industry 371: output
number of obs	21766	22846
number of firms	3302	3327
avg obs per firm	6.6	6.9
labor	0.1424 ***	0.5695 ***
capital	0.0468 *	-0.007
material	0.4363 ***	0.6579 ***
labor*labor	0.0148 ***	-0.0169 ***
labor*capital	0.0012	0.0014
Hansen's J	30.58***	4.72
Mean productivity	2.711	0.0778
Note:	*p<0.1; **p<0.05; ***p<0.01	

Productivity

Table 4.7 shows summary statistics of productivity estimates, which are calculated according to equation (4.18). The mean productivity of all firms equals 0.9049.[36] The mean productivity of buyers, 1.3966, and of targets, 1.3197, is higher than the overall mean productivity. All differences in means are significant according to the t-test.

Table 4.7: Summary Statistics: Productivity

	N	Min	Max	Mean	St. Dev.
All	857,526	-7.1148	11.4352	0.9049	0.9122
Buyers	23,230	-1.6662	11.4352	1.3966	1.2135
Targets	12,988	-2.5828	9.4661	1.3197	1.2755

Figure 4.2 shows the distribution of productivity. Most firms have a productivity between 0 and 1. The distribution of productivity shows a peek in this range, which is smaller for buyers and targets. The distributions of productivity of both, buyers

[36]The mean productivity of non-merging firms is similar to the mean productivity of all firms. Thus, the mean productivity of non-merging firms is not separately reported.

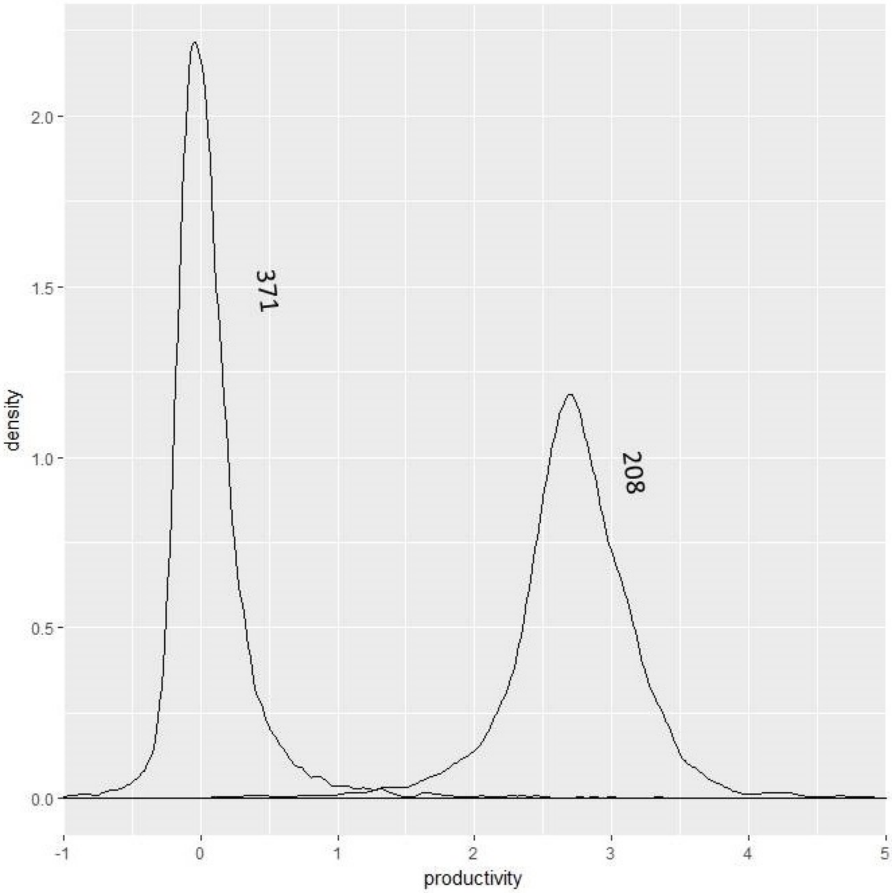


Figure 4.1: Distribution of Productivity - Industry 208 and 371

and targets, show a right hand tail in the range between 2.5 and 4. This right-hand tail is larger for buyers. Targets' productivity shows an additional small peek in the area of 5. These peeks and right-hand tails are partly caused by the observations of the year 2014. The data set for this year is incomplete. Similarly to what is shown in figure 3.1, the overall data set consists of less observations for 2014 than for the other years. Furthermore, industries like industry 208 that have a high mean productivity partly explain the right-hand tail. The Hansen's J test indicates that for those industries the specified control function might be insufficient to control for endogeneity. Another reason for the right-hand tails and peeks might be caused by firms that are much more productive than the average firms. Those firms are buyers and targets. Even though, productivity is a measure that cannot be interpreted itself, it is possible to interpret differences. Therefore, mean productivity indicates that buyers and targets are more efficient than other firms. Furthermore, it indicates that buyers are more efficient than targets.
Figure 4.3 shows the development of mean productivity over time. The mean productivity of all firms decreases from approximately 1 in 2005 to 0.82 in 2014. It stagnates in 2010. The data set is incomplete for the year 2014. This year cannot

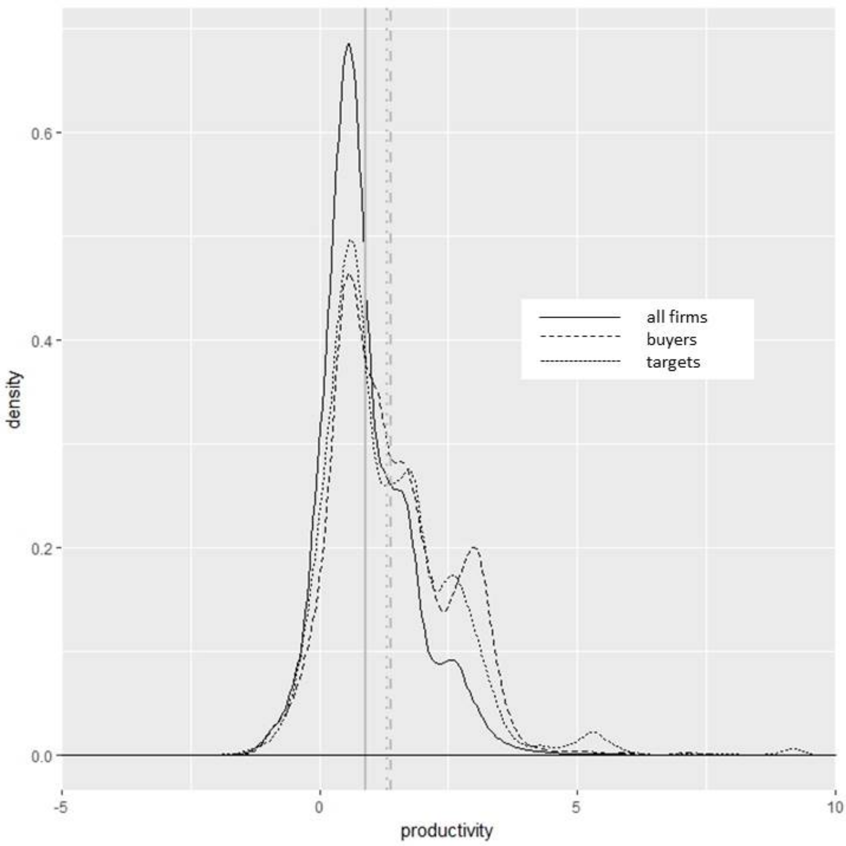


Figure 4.2: Distribution of Productivity

be interpreted. Mean productivity of buyers declines from approximately 1.5 in 2005 to 1.1 in 2012. It slightly increases in 2013. Mean productivity of targets develops differently as it stagnates in the range of 1.3 to 1.35 in the years 2005 through 2013. It slightly increases in 2007, 2010 and 2013. The higher mean efficiency of buyers and targets might be caused by many facts. However, four possible impacts are shortly discussed. First, yearly effects may cause higher mean efficiency. Figure 3.1 shows that an increasing number of mergers took place in the years 2010 to 2013. A possible impact could have been that in those years firms are overall more efficient. However, the overall mean efficiency is not increasing. Thus, it is unlikely that yearly effects determine the higher mean productivity of buyers and targets. Quite the contrary, as mean productivity is decreasing from 2010 to 2013 it could be expected that the true mean productivity of buyers and targets, meaning a mean productivity that is adjusted by yearly effects, is even higher than shown in table 4.7 and figures 4.2 and 4.3. Secondly, the higher mean productivity of buyers and targets might be influenced by firm-size. It is possible that e.g. larger firms are more productive than smaller firms. Table 4.4 in comparison to table 4.2 shows that buyers are on average ten times larger regarding their output than an average firm. Furthermore, targets are approximately five times larger than an average firm.

Thus, it is possible that larger firms are more productive than smaller firms and the higher mean productivity of buyers and targets is partly explained by firm-size effects. Thirdly, it is possible that firms in certain countries are more productive than firms in other countries. If firms in more productive countries tend to merge more often it is likely that the higher mean productivity of buyers and targets is partly explained by a country-specific effect. Most buyer and targets are located in Great Britain, Germany, Spain and France.[37] If the higher mean productivity is caused by country-specific effects, it could be expected that firms in those four countries are highly productive. Fourth, profitability might have an impact on productivity. One may argue that profitability is just another measure for productivity. However, this study defines productivity as the ratio of output to the input factors labor, material, and capital, while profitability is defined as the difference between output, i.e. sales, and costs, i.e. labor, material and other costs. Nevertheless, productivity and profitability are likely correlated (Foster et al., 2008). A highly profitable firm has more possibilities to invest in e.g. a merger than unprofitable firms. Thus, it is likely that a highly productive and therefore profitable firm is a buyer. Furthermore, as any investment needs to benefit, the price paid for a target is often a multiple of its profitability. Thus, a highly productive and therefore profitable firm has a high market price and is more likely to be a target than an unprofitable firm. Due to this argumentation productivity and the fact that firms merge might be correlated.

Table 4.8 shows the results of regressing year, country and industry dummies on productivity. The constant term represents mean productivity of all firms in industry 201 in Austria (AT) in the year 2005. The results show that for all years, most countries and industries the coefficient is highly significant. Through the years 2005 to 2014 productivity shows a significant downward trend. Figure 4.3 illustrates this downwards trend. Furthermore, the mean productivity per industry and country differ significantly. Firms in Montenegro (ME) have the lowest mean productivity, while firms in Bulgaria (BG) have the highest mean productivity. There might be several explanations for differences in mean productivity per country. Among others, accounting principles are country-specific, which causes that measures of revenue and costs may differ between countries. Furthermore, firms that operate in industry "Tires and Inner Tubes" (Industry 301) have the lowest mean productivity, while firms that operate in industry "Miscellaneous Products of Petroleum and Coal" (Industry 299) have the highest productivity. Again, there might be several explanations for differences. Overall, the dummy variables explain 79.3% of the variation of productivity. The results indicate that it is important to control for yearly, country- and industry-specific effects when analyzing the impact of a merger on productivity.

[37] For an overview of buyers and targets per country see Appendix table Table 9.8.

Table 4.8: Regression of Year, Country and Industry Dummies on Productivity

	Dependent variable:						
	productivity						
2006	−0.010***	SK	−0.054***	282	1.589***	344	0.186***
2007	−0.015***	202	1.613***	283	2.476***	345	−1.070***
2008	−0.057***	203	2.036***	284	1.324***	346	−0.224***
2009	−0.076***	204	−0.106***	285	−0.402***	348	2.203***
2010	−0.083***	205	−0.040***	286	3.028***	349	0.417***
2011	−0.115***	206	0.296***	287	1.106***	350	3.424***
2012	−0.129***	207	2.654***	289	1.189***	351	0.651***
2013	−0.130***	208	2.337***	299	5.847***	352	0.513***
2014	−0.117***	209	1.433***	301	−1.372***	353	0.465***
BA	−0.149***	211	5.341***	302	0.115***	354	0.929***
BE	−0.003	221	0.683***	306	−0.657***	355	1.035***
BG	0.171***	225	−0.389***	308	0.280***	356	0.554***
CH	−0.134***	227	0.277***	311	1.574***	357	3.120***
CZ	−0.127***	228	2.354***	316	0.005	361	0.200***
DE	−0.023***	229	−0.700***	321	−0.384***	363	0.065***
EE	−0.150***	232	−0.629***	322	−0.582***	364	0.929***
ES	−0.129***	238	0.259***	323	2.488***	366	2.079***
FI	−0.038***	239	0.516***	324	0.522***	367	1.494***
FR	0.032***	242	0.002	325	−0.358***	369	0.020***
HU	−0.014**	243	0.314***	326	−0.378***	371	−0.288***
LI	−0.194	244	1.128***	327	0.229***	373	1.353***
LU	−0.027*	249	0.294***	328	0.257***	374	0.306***
LV	−0.033	251	−0.377***	329	−0.574***	375	0.970***
ME	−0.249***	252	−0.444***	331	0.717***	381	1.476***
NL	0.058***	262	0.520***	332	1.194***	382	1.571***
NO	−0.116***	265	0.650***	333	1.066***	384	1.417***
PL	0.025***	267	0.166***	334	−0.231***	391	−0.265***
PT	−0.004	271	0.603***	336	1.215***	394	0.874***
RO	0.055***	275	0.543***	339	1.154***	399	1.154***
RS	−0.135***	278	1.920***	341	0.819***	Constant	0.481***
SE	−0.124***	279	2.402***	342	1.472***		
SI	−0.076***	281	1.923***	343	0.328***		
Observations			857,526				
R^2			0.793				
Note:			*p<0.1; **p<0.05; ***p<0.01				

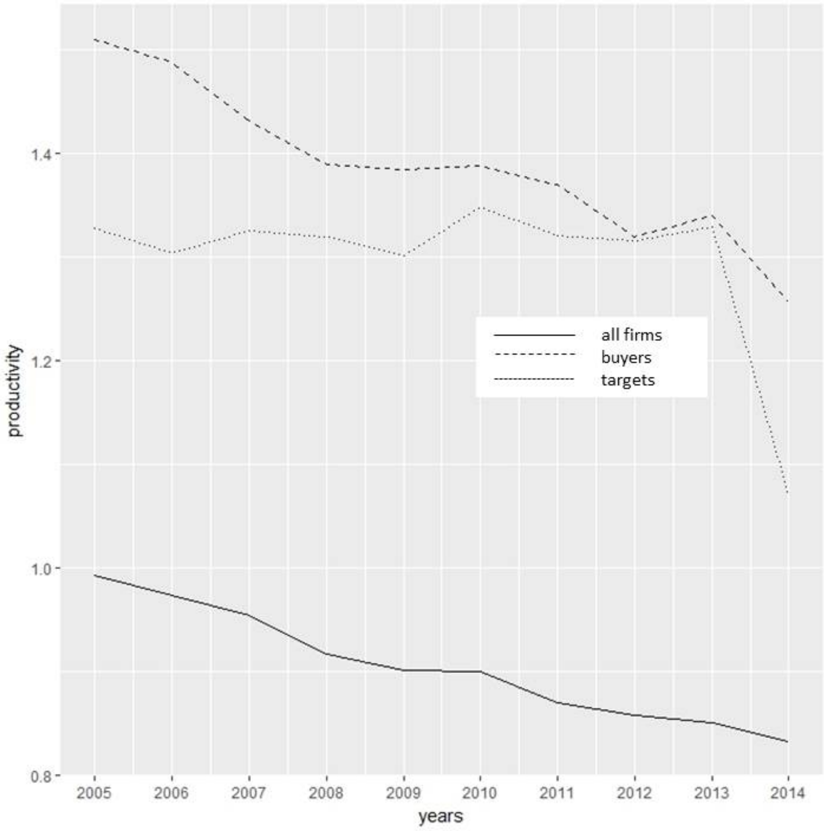


Figure 4.3: Productivity by Year

Figure 4.4 shows the development of standardized mean productivity over pre- and post-merger periods. Productivity is standardized by demeaning yearly effects per industry. Changes of mean productivity per year and industry equal a technical change, which is year- and industry-specific. Demeaning by technical change is necessary as mergers take place in different years. Post-merger period 9 and pre-merger period -9 of buyers as well as post-merger periods 6 to 9 of targets cannot be interpreted as the number of observations is too small, meaning smaller than 60. The merger period 0 is eliminated from the data set. An interpretation in the merger period is difficult as mergers may have a different impact, depending on whether they take place at the beginning or at the end of a period. Therefore, the merger period cannot be defined as either pre- or post-merger period. The mean productivity of buyers declines from approximately 0.13 in the pre-merger period -8 to 0.1 in pre-merger period -7 and stagnates until pre-merger period -4. It then starts to increase to 0.15 until the merger takes place. After the merger it increases from 0.15 in post-merger period 1 to 0.18 in post-merger period 2. It stagnates one period and increases afterwards to 0.21 until post-merger period 8. Mean productivity of targets starts at approximately 0.4 in pre-merger period -8 and decreases to 0 until pre-merger period -2. It then starts to increase to 0.1 until post-merger period 4. It drops in post-merger period 5 to below 0.05.

The development of mean productivity over periods indicates that productivity of buyer as well as targets decrease or stagnates until the second pre-merger period.

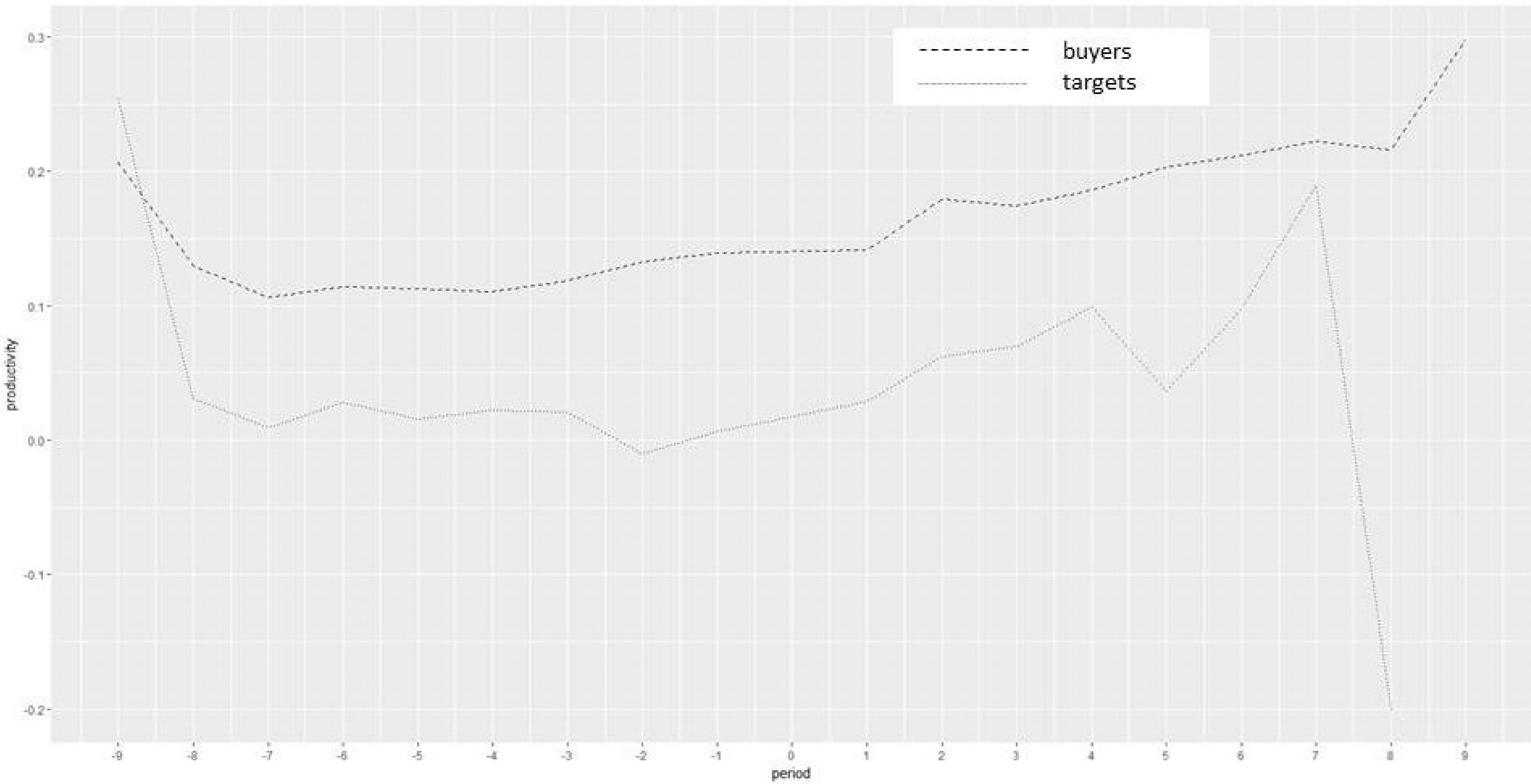


Figure 4.4: Productivity by Period

4.6 Conclusion

This chapter focuses on a TFP approach to estimate productivity, a measure of technical efficiency. The applied approach controls for endogeneity. The approach is easily applied due to a new stata package named“prodest”. It allows to estimate a gross output model assuming a translog production function. The estimation is based on a GMM approach. Originally, the package has been implement for the estimation of a value added model assuming a Cobb Douglas production function using either the two step approach of Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg et al. (2015) or the GMM approach of Wooldridge (2009). The package was extended, which made it possible to estimate the gross output model assuming a translog production function. However, as the "prodest" package is still in progress, corrections and extensions of the application are possible. In general, there are several improvements of the TFP approach, but not all of them have been implemented so far in programs like R or Stata. Thus, the estimation of a gross output model assuming a translog production function can be further improved by e.g. interaction terms between all input variables or by using overidentifying restrictions. The improvement of the implementation is left open to further studies. Nevertheless, estimates are valid for the majority of industries and can be analyzed. Results show that production technologies differ across industries, which leads to different coefficients for the input factors. Nevertheless, labor and material are the most important input factors. Differences between industries are shown in the detailed analysis of two industries, industry 208 "Beverages" and 371 "Motor Vehicles and Motor Equipment". They differ not only by the impact of input factors on output, but also by the significance of coefficients. Furthermore, the TFP approach including the control function fits the data set of industry 371 better than the data set of industry 208.

Results show that buyers and targets are both more productive than an average firm. Furthermore, results indicate that buyers are likely to be more productive than targets. All firms, except buyers tend to decrease productivity during the years from 2005 through 2013. The comparison of standardized productivity estimates shows that, without time- and industry-specific effects, both, buyers and targets, seem to increase productivity after a merger.

Chapter 5

The DID Approach

5.1 Introduction

This chapter analyzes merger-specific efficiency gains based on productivity estimates resulting from the application of a TFP approach. The analysis is done separately for buyers and targets.

The approach applied to identify merger-specific efficiency gains is the Difference-In-Difference (DID) approach. Empirical studies use different approaches to identify merger-specific efficiency gains. The applied approaches range from a simple comparison of treated firms with non-treated firms (e.g. Maksimovic and Phillips (2001)), over the often applied DID approach (e.g. Blonigen and Pierce (2016)) to a demanding approach of decomposing the Malmquist Index (e.g. Zschille (2014)). The identification of merger-specific efficiency gains based on a DID approach is possible with the assumption that merging firms will be comparable to non-merging firms if they are identical in certain characteristics. This assumption allows to identify differences in efficiency changes between merging and non-merging firms as merger-specific. The identification of identical firms is possible with a Propensity Score Matching (PSM) approach. This approach allows to estimate the likelihood of a firm to participate in a merger depending on firm characteristics. The likelihood of a firm to participate, namely the Propensity Score, is used to match merging firms to non-merging firms. The matched non-merging firms create a control group. The mean efficiency change of the control group is used as approximation for efficiency changes that are not merger-specific. Any deviation of the merging firms' efficiency change is assumed to be merger-specific.

5.2 All Firms as Control Group

This introduction follows Angrist and Pischke (2014). It does not intend to be a complete overview. It rather introduces the basics of a DID model.
The DID approach is useful to evaluate the impact of a treatment, $Treat_i = \{0, 1\}$, e.g. a merger, on an outcome, y_{it}, e.g. efficiency. Therefore, units, e.g. firms, are separated into two groups. Those firms that are treated, $Treat_i = 1$, are aggregated into the treatment group. Those firms that are not treated, $Treat_i = 0$, are aggregated into the control group. Furthermore, firms are observed before and after the treatment, $Post_t = \{0, 1\}$. In the case of this study, the pre-treatment time periods, $Post_t = 0$, are named pre-merger periods and the post-treatment time periods, $Post_t = 1$ are named post-merger periods. Typically, firms should be observable in pre- and post-merger periods.
The basic DID model can be then described as

$$y_{it} = \alpha + \beta Treat_i + \gamma Post_t + \delta_{DID}(Treat_i * Post_t) + \epsilon_{it} \tag{5.1}$$

where α is a constant term that captures the mean efficiency of non-merging firms in a pre-merger period. β is an estimate for the fixed differences in mean efficiency between treatment and control group. γ is an estimate for the difference in mean efficiency between pre- and post-merger period. δ_{DID} is an estimate for the difference in mean post-merger efficiency between treatment and control group. It estimates the effect a merger has on efficiency. Thus, it is an estimate for merger-specific efficiency changes. ϵ_{it} is random error term.
The basic model as introduced in equation (5.1) can be extended by fixed effects, θ_j, for e.g. countries or industries. These country- or industry-specific fixed effects allow to control for exogenous effects that are non-merger-specific. Furthermore, it is possible to add fixed effects, $\sum_j \theta_j * \tau_t$, which control for country- or industry-specific time trends. The basic model including fixed effects to control for e.g. country- or industry-specific time trends can be described as

$$y_{it} = \alpha + \beta Treat_i + \gamma Post_t + \delta_{DID}(Treat_i * Post_t) + \sum_j \theta_j * \tau_t + \epsilon_{it} \tag{5.2}$$

In the following, all non-merging firms build a control group. Defining all non-merging firms as a control groups creates the problem that only for merging firms pre- and post-merger periods can be defined. As mergers take place in different years it is impossible to define certain years as pre- or post-merger periods for non-merging firms.[1] As a consequence, mean pre- or post-merger efficiency of non-merging firms

[1] Blonigen and Pierce (2016) define the first year of the panel data set as pre-merger year of the control group and the last year as post-merger year. The present study drops this approach for

cannot be estimated as a reference. However, it is possible to estimate the difference between overall mean efficiency of non-merging firms and pre- respectively post-merger mean efficiency of merging firms.
Applying equation (5.2) under the mentioned circumstances results in

$$y_{it} = \alpha + \beta Treat_i + (\mathbf{Post}_{it} * Treat_i)'\delta_{\mathbf{t},\mathbf{DID}} + \sum_j \theta_j * \tau_t + \epsilon_{it} \tag{5.3}$$

where y_{it} is the efficiency of firm i in period t. If pre- and post-merger efficiency of non-merging firms is observable, α would be an estimate for mean pre-merger efficiency of non-merging firms. However, under the mentioned circumstances α is the overall mean efficiency of non-merging firms. Furthermore, the term $\gamma Post_t$ drops out of equation (5.2). δ would have been an estimate for the difference of mean pre- and post-merger efficiency of merging firms. Another differences to the basic DID model defined in equation (5.2) is that the treatment effect, $\delta_{\mathbf{t},\mathbf{DID}}$, is assumed to be a vector. Instead of estimating the difference between mean post-merger efficiency of merging firms and mean efficiency of non-merging firms, this vector allows to estimate differences for each post-merger period. $\mathbf{Post}_{it}$ is a vector of dummy variables, which equals one, if the observed year t is a post-merger period of firm i, e.g. $Post_{i1} = \{1$, if firm i merged in year t-1, 0 otherwise$\}$. As the panel data set consists of ten years, a maximum of nine post-merger periods can be observed. As a consequence, the vector of post-merger period dummies is a 1×9 vector. As firms merge in different years, it is important to control for yearly effects that are independent of a merger. Therefore, the model described in equation (5.3) includes fixed effects that control for industry-, country- and firm-size-specific time trends. As the included fixed effects are for each characteristic, the model extracts means per characteristic. But, as e.g. the fixed effect for an industry extracts the mean efficiency of this industry, the additional fixed effect for e.g. small-sized firms extracts the mean efficiency for small-sized firms in that certain industry. The industry-specific time trend is controlled by yearly fixed effects per three-digit US SIC coded industry. The country-specific time trend is controlled for by yearly fixed effects per country. The firm-size-specific time trend is controlled by a yearly fixed effect per firm size. Firms are classified as either micro, small, medium-sized or large.[2]. These fixed effects net out effects of omitted variables.
Table 5.1 shows the results of the regression according to equation (5.3) using all non-

three reasons. First, the last year of the panel data set, 2014, seems to be biased. Second, as $\mathbf{Post}_t$ is a vector it would be only possible to define the last year of the data set as one element of the vector, which only helps to control one period but not the others. Third, it seems inappropriate to compare pre- or post-merger efficiency of the treatment group with only one year of the control group. Results are difficult to interpret.

[2]Firms are characterized according to the definition of the European Commission (Commission, 2017a) as either micro, small, medium-sized or large firms based on their revenue.

merging firms as control group. For targets, results show no significant difference between mean pre-merger efficiency and the overall mean efficiency of non-merging firms. But, the differences between post-merger efficiency of periods 2 to 4 and 7 and mean efficiency of targets is significant. The differences are positive. Thus, differences indicate merger-specific efficiency gains. The difference is increasing from approximately 0.05 in period 2 over 0.06 in period 3 to 0.1 in period 4. The difference reaches 0.17 in period 7. Results show a significant and continuous increase of efficiency of targets after the merger beginning in post-merger period 2. Thus, assuming that firms are randomly merging the observable targets benefit from sustainable merger-specific efficiency gains.

For buyers, results show significant difference between pre-merger mean efficiency and the overall efficiency of non-merging firms. Buyers are in average 0.06 more efficient than non-merging firms. But, results also show that buyers are incapable to increase their efficiency significantly until post-merger period 5. In post-merger period 5 to 7 buyers are capable to increase efficiency significantly by 0.3 compared to pre-merger efficiency. Thus, assuming that firms merge randomly there are two findings. First, buyers already have a higher efficiency than other firms before the merger. Secondly, buyers benefit from merger-specific efficiency gains in a mid- to long-term perspective. The adjusted R^2 value of both regressions, the one for targets as well as the one for buyers, is high with a value of 0.93 and 0.80. The high value is partly caused by the added fixed effects for the time trends per industry, country and firm-size.[3] However, the high value also indicates that the chosen variables including the dummy variables for pre- and post-merger periods explain 80 to 90% of the variance of productivity.

Nevertheless, results can be discussed with regard to several points. First, the available data set underlies a selection bias, as only merging firms are observable that did not exit the market. Thus, it is likely that firms that continue in the market are those that are capable to increase efficiency. In contrast, any party of mergers, that have caused merger-specific efficiency losses, might not be observable due to a market exit. Secondly, an efficiency gain in a mid- or long-term after a merger might be caused by additional effects. Thus, an efficiency gain will be difficult to be linked to a merger if it appears five to seven years after the merger. Third, as already mentioned, it is likely that firms do not merge randomly. Thus, the application of a PSM approach is useful to create a control group of non-merging firms that is

[3] The applied R package "felm" allows to extract coefficients of fixed effects, but not their p-values. Thus, fixed effects are not reported in the table. Furthermore, the number of fixed effects is 93 industries times 10 years, 32 countries times 10 years and four different firm-sizes times 10 years, which equals 1,290 fixed effect. For the purpose of clarity, I will not report the fixed effects. However, results of the regression of yearly, country- and industry-specific dummy variables on productivity as shown in table 4.8 illustrate the high impact of the chosen fixed effects on productivity.

comparable to the treatment group of merging firms.

5.3 Control Group based on PSM

Theoretically the treatment effect, δ_{DID}, measures the average treatment effect for all treated firms with an individual treatment effect of:

$$\delta_i = y_i^1 - y_i^0 \tag{5.4}$$

where y_i^1 is the efficiency of firm i with treatment and y_i^0 is the efficiency of firm i without treatment. The problem is, that only one efficiency is observable per firm. Thus, an individual treatment effect cannot be calculated. A possible solution to this problem is the calculation of an Average Treatment Effect (ATE), which can be described as

$$\delta_{ATE} = E[\delta_i] = E[y_i^1 - y_i^0] = \delta_{DID} \tag{5.5}$$

So far, all non-merging firms build a control group. The expected difference between the mean efficiency of merging and non-merging firms is assumed to approximate the treatment effect. However, this approximation is based on the assumption that firms are treated randomly, meaning that firms merge randomly. Especially in non experimental environments, researches often face the problem of identifying the impact of a treatment. The problem of identification rises from the fact that units are not treated randomly. Thus, the comparison of results of a treatment to a control group may be biased because of a selection bias. (Dehejia and Wahba, 2002) E.g. in the case of a merger, firms do not merge randomly. Depending on firm characteristics and other circumstances firms decide to participate in a merger. However, assuming firms only differ by the fact that some of them merge and others do not. In this case, it can be expected that - until the merger - the efficiency of merging firms develop in a similar way to the efficiency of firms that do not merge. A divergence in the efficiency development of the merger is likely to be caused by the merger.
As a solution to the non random assignment of firms to a treatment it is possible to calculate the Average Treatment Effect on the Treated (ATT), which is defined as:

$$\begin{aligned}\delta_{ATT} &= E[\delta_i|Treat_i = 1] \\ &= E[y_i^1|Treat_i = 1] - E[y_i^0|Treat_i = 1]\end{aligned} \tag{5.6}$$

Table 5.1: DID Regression using All Firms as Control Group

	Dependent variable:	
	efficiency	
	target	buyer
pre.merger	-0.002	0.060***
	(0.011)	(0.004)
post.period1	0.015	-0.010
	(0.028)	(0.010)
post.period2	0.052 *	0.013
	(0.031)	(0.011)
post.period3	0.063 *	0.001
	(0.033)	(0.011)
post.period4	0.096 ***	0.011
	(0.036)	(0.012)
post.period5	0.037	0.025 *
	(0.043)	(0.014)
post.period6	0.082	0.034 **
	(0.056)	(0.016)
post.period7	0.165**	0.039**
	(0.078)	(0.019)
post.period8	-0.288	0.028
	(0.290)	(0.027)
post.period9	-	-
Observations	857,662	865,416
Adjusted R^2	0.93	0.80
Note:	*p<0.1; **p<0.05; ***p<0.01	

The problem in solving equation (5.6) is that $E[y_i^0|Treat_i = 1]$ is not observable. The unobservable can be substituted:

$$\begin{aligned} E[y_i^0|Treat_i = 1] &= E[y_i^0|Treat_i = 0] \\ \Leftrightarrow E[y_i^0|Treat_i = 1] - E[y_i^0|Treat_i = 0] &= 0 \end{aligned} \tag{5.7}$$

This substitution is only possible if the following assumptions hold:
(PSM 1) $y_i^1, y_i^0 \perp\!\!\!\perp Treat_i|X_i$, which requires that the post-merger efficiency of treated and non treated firms are independent of the treatment assignment given a set of observable covariates X_i, which are not affected by the treatment.
(PSM 2) $0 < P(Treat_i = 1|X_i) < 1$, which requires that the probability of the assignment of treatment is positive.
The purpose of Propensity Score Matching (PSM) is to estimate the probability of a firm to be treated, meaning to participate in a merger, based on its firm characteristics. It is then possible to estimate the probability to participate in a merger for each firm, even if it does not. These probabilities are used for a matching. For each firm that merges it is possible to define at least one firm that has not merged but has a similar probability to participate in a merger, based on its firm characteristics. These firms build a control group. The PSM method allows to control for a selection bias.
Caliendo and Kopeinig (2008) describe the five implementation steps of the PSM approach. First, propensity scores need to be estimated. Secondly, the matching algorithm is chosen. Thirdly, the overlap or common support is checked. Fourth step includes the effect estimation and fifth step the sensitivity analysis. The further introduction to PSM follows closely Caliendo and Kopeinig (2008) but is limited to the aspects that are relevant for this study:
Step 1: The estimation of the propensity score depends on the variable choice of covariates X. Those covariates X must credibly satisfy the condition that the outcome is independent of the treatment conditional to the propensity score. This also includes that the variables should not be influenced by the anticipation of a treatment.
Step 2: A matching approach that is straight forward is the Nearest Neighbor Matching. This approach matches the non merging firm as matching partner to the merging firm that is closest in terms of its propensity score.
Step 3: The overlap of both groups, control and treatment, can be guaranteed by applying a Minima and Maxima Comparison approach. This approach deletes any firm with a propensity score that is smaller than the minimum and/or larger than the maximum of the other group.
Step 4: The matching quality can be tested by applying a t-test. This test can

be used to check differences in covariates between the control and the treatment group. Differences are expected to be significant before the matching, as treated and non-treated firm differ regarding the values of covariates. After the matching, differences should not be significant as the matching aims to create two groups of firms that are identical regarding the values of covariates.
Step 5: A growing number of researches apply a sensitivity analysis that tests whether the assumptions hold.

In the context of the analysis of merger-specific efficiency gains it is likely that firms are not randomly treated. According to Blonigen and Pierce (2016) buyers find targets that are tending towards higher future productivity. Thus, an efficiency gain after the merger could be spuriously assigned to a merger effect, when none exists. Thus, in the second analysis the DID approach is applied in combination with a PSM approach to control for the selection bias.
Step 1: The propensity score, meaning the probability of a merger, is estimated using a logit regression. The chosen covariates are firm characteristics.[4] Similarly to Blonigen and Pierce (2016) an industry dummy, meaning a "3-digit US SIC" dummy, productivity in the merger period and capital intensity are chosen as covariates. Additionally, a country dummy is used. The chosen covariates are assumed to fulfill the condition that the post-merger efficiency is independent of the merger, after controlling for the assignment to the treatment (PSM 1).
Step 2: The Nearest Neighbor approach is applied to match non merging firms as matching partners to the merging firms.
Step 3: Neither the Minima and Maxima Comparison approach nor any other approach is applied to guarantee the overlap of both groups. Applying any of those approaches would cause a selection bias.
Step 4: The matching quality is tested by applying a t-test to check differences in the covariates "productivity in the merger period" and "capital intensity".
Step 5: An explicit sensitivity analysis will not be applied. However, the common trend in productivity before the merger of treatment and control group will be discussed. A common trend of both groups before the treatment indicates that the treatment is likely to explain differences after the treatment.
After building a control group using a PSM appraoch, the DID model applied is related to Blonigen and Pierce (2016) and defined as follows:

$$y_{it} = \Sigma_k \alpha_k x_{ik} + \beta Treat_i + (\mathbf{Post}_t * Treat_i)' \delta_{\mathbf{t,DID}} + \mathbf{Post}_t' \gamma + \sum_j \theta_j * \tau_t + \epsilon_{it} \quad (5.8)$$

[4] In contrast to Blonigen and Pierce (2016) the present study concentrates on firm characteristics of merging firms and does not additionally include firm characteristics of parent firms.

where x_{ik} are the k covariates used in the logit regression in step 1.[5]

The results of the PSM approach are further reported step by step.
Step 1: Table 5.2 shows the significant coefficients of the logit regression for targets. Table 5.3 shows the significant coefficients of the logit regression for buyers. The number of independent variables is large. Thus, for the purpose of clarity only the significant coefficients are reported. It can be discussed whether the number of covariates is too large. According to Caliendo and Kopeinig (2008) it is a possible approach to run the logit regression with only one covariate in the first step, and then add an additional covariate in the second step. This iteration is stopped when the last added covariate is insignificant. In the context of the present study this approach is not applied. All added covariates are needed because each of them is suppose to be relevant for a matching in the second step of the PSM approach.
Results in table 5.2 show that the probability to be a target in 2006 is significantly, positively influenced by the fact that a firm operates in industry 324 and significantly, negatively influenced by the fact that a firm operates in industry 349. In 2007, firms that operate in industry 208 or 229 are significantly more often targets. Furthermore, firms that operate in Bulgaria, Czech, Germany, Spain, France, Portugal, Romania or Sweden are significantly less often targets. In 2008, the efficiency in the merger year has a positive impact on a firm's probability to be a target. Furthermore, firms that operate in industry 262 are significantly more often targets. In 2009, the capital intensity has a significant positive impact on the likelihood to be a target. In 2010, firms that operate in industry 208, 324, 336 or 357 are significantly more often targets. In 2011, firms that operate in industry 311, 391 and 394 have a significantly higher probability to be a target. Furthermore, the capital intensity has a significant positive impact on a firm's probability to be a target. In 2012 and 2013, none of the chosen covariates have a significant impact on the likelihood of a firm to be a target.
Results in table 5.2 show that the majority of chosen covariates has a significant impact on a firm's probability to be a buyer. Especially, the covariates "merger year efficiency" as well as "capital intensity" are significant for all years. Both have a significant positive impact. Some industries also have a positive impact on a firm's probability to be a buyer. For many of those industry, the impact is only significant in certain years. In 2009, industry 20 "Food Products" had a significant impact. In 2011, the impact of the textile industry (22) was positive. In 2013, the impact is positive for e.g. industry 30 "Rubber and Plastics" and 37 "Transportation". Other industries, e.g. the industry for Stone, Clay and Glass (32) including the industry

[5]As I add interaction terms to control for the country-, industry- and firm-size-specific time trend, country and industry dummies will not be added as covariates.

for Cement (324), have a positive impact in most of the years. An analysis of the reason for this positive impact might be interesting. As this is not focus of the present study, a deeper analysis will be left open for further research. Interestingly, firms that are located in wealthy countries, like Switzerland (CH) and Scandinavian countries (Finland (FI), Norway (NO), Sweden (SE)), have a higher probability to be a buyer.

Table 5.2: PSM: Logit Regression for Targets

	Dependent variable: target							
	2006	2007	2008	2009	2010	2011	2012	2013
Merger year efficiency	0.288	−0.378	0.408*	−0.267	−0.407	0.141	0.01	0.202
ind208	−0.568	2.494*	−0.735	18.472	2.471**	1.108	−0.695	17.888
ind229	−18.291	2.375*	0.927	−0.050	−18.161	−16.924	0.908	0.201
ind262	−19.266	−17.735	1.640**	0.309	−17.992	1.767	−18.269	−0.326
ind286	−19.821	−16.723	−0.225	0.847	2.662*	−17.759	1.273	18.975
ind311	−19.444	−16.661	−18.334	0.545	−17.349	2.870*	−18.257	−0.358
ind324	2.425**	−17.627	−18.164	−0.253	2.551**	−17.400	−18.262	−0.040
ind336	−18.736	−17.182	−17.664	0.608	2.865**	−17.399	−18.289	0.019
ind349	−2.103*	0.861	−1.257	17.176	−1.265	0.454	−0.792	17.081
ind357	−19.358	−16.276	0.063	1.015	3.093*	−17.319	−18.493	−0.608
ind391	−18.866	−17.249	−17.421	0.359	−18.026	3.046**	−18.436	0.043
ind394	−19.127	−17.185	−17.800	0.734	−17.357	2.458*	1.253	−0.056
countryBG	0.624	−1.931*	−0.244	−0.534	17.793	−0.448	16.864	0.368
countryCZ	0.636	−3.196***	16.568	16.168	16.622	0.057	17.639	17.002
countryDE	17.838	−1.839**	15.819	−0.080	17.356	17.246	16.441	17.406
countryES	19.01	−3.806***	17.667	17.352	17.079	16.476	17.302	17.941
countryFR	17.779	−2.814***	16.518	16.917	17.477	17.079	17.58	17.517
countryPT	0.913	−3.510***	0.284	16.793	18.037	16.905	16.485	17.625
countryRO	0.748	−2.616**	16.859	15.838	−0.051	16.732	0.009	0.376
countrySE	18.14	−2.078**	17.407	0.045	18.341	17.63	17.449	18.732
capital.intensity	−0.143	0.148	0.124	0.315**	0.194	0.312**	−0.045	0.043
Constant	−24.678	−5.124***	−23.918	−42.491	−24.755	−25.242	−24.546	−43.301
Observations	72,025	89,609	96,093	99,316	106,454	108,394	108,604	101,873
Note:	*p<0.1; **p<0.05; ***p<0.01							

Table 5.3: PSM: Logit Regression for Buyers

	Dependent variable: buyer							
	2006	2007	2008	2009	2010	2011	2012	2013
Merger year efficiency	0.687***	0.554***	0.565***	0.450***	0.437***	0.864***	0.583***	0.641***
ind202	−0.687	−2.440**	0.101	−0.215	−0.083	−0.501	−0.602	−0.023
ind203	−2.218***	−1.115*	−2.043***	−0.168	−1.170*	−1.217*	−0.597	−0.447
ind204	−2.166**	−0.217	−0.365	1.189***	−0.262	0.407	−0.426	−0.865
ind206	−1.313	0.78	0.145	1.011*	−0.660	1.795***	0.531	1.523***
ind207	−2.467**	−1.882*	−1.082	−1.042	−0.756	−18.411	−17.873	−0.623
ind208	−1.232***	−0.249	−0.989**	−0.093	0.064	−0.607	−0.750*	−0.388
ind209	−1.776***	−0.471	−0.443	−0.476	−0.516	−1.693**	−0.357	−0.580
ind211	−21.011	−20.106	−2.209*	−19.099	−19.140	−20.564	−18.561	−0.834
ind225	−0.189	−15.504	0.821	−15.815	−16.019	1.643**	−0.109	0.549
ind228	−1.872*	−17.748	−17.331	−17.529	−17.587	0.194	−1.725	−16.462
ind229	−0.098	−0.160	0.73	−16.139	−16.275	1.616*	−0.216	0.017
ind242	−0.921	−0.997	−0.771	−1.961*	0.172	0.08	−1.903*	0.262
ind243	−1.309**	−1.287*	−1.471**	−2.331**	−17.102	−0.143	−0.773	−1.522**
ind262	0.856**	0.726	0.065	1.339***	−0.941	1.537***	−0.554	−0.030

ind265	−1.292**	−1.990*	−0.291	0.15	−0.219	0.38	−0.599	0.071
ind267	0.001	−1.476	0.421	−0.593	0.126	0.725	0.969**	0.776*
ind271	−0.452	1.303**	−16.741	0.657	−0.022	0.3	0.673	1.398**
ind281	−1.548**	−1.966*	−17.379	0.511	−17.801	−0.917	−1.607	−0.601
ind283	−1.268**	0.599	−0.135	−0.039	−0.135	−0.430	−0.253	−0.007
ind285	1.073**	1.027	0.558	1.576***	1.214**	1.596**	0.143	0.738
ind286	−2.920***	−2.231**	−18.151	−18.183	−1.007	−19.056	−1.411*	−1.098
ind299	−22.405	−21.006	−3.724***	−1.677	−19.790	−4.814***	−2.700**	−2.738***
ind301	−16.386	−16.234	−15.215	−16.030	−16.177	−14.830	−14.852	1.934*
ind306	−16.662	−16.251	−15.481	−16.126	−0.428	−15.270	0.658	1.168**
ind308	−0.837**	−0.506	−1.621***	−0.181	−0.715	−0.141	−0.022	−0.262
ind322	0.203	−16.243	−15.547	1.306*	−16.373	2.713***	1.415**	0.518
ind324	1.793***	2.448***	2.238***	−16.919	2.057***	2.273***	1.922***	2.801***
ind325	0.858*	2.166***	−0.568	0.842	−0.181	−15.632	1.175**	1.080**
ind326	−17.063	−16.482	0.175	1.088	−16.492	−15.507	1.279**	1.15
ind327	−1.886**	−0.407	−1.378**	−0.549	−0.578	−0.171	0.776**	0.555
ind339	−1.948**	−17.470	−2.401**	−17.025	−2.166**	−17.033	−0.524	−1.461*
ind342	−2.478**	−1.954*	−16.633	−1.711	−1.467*	−1.811*	−1.091*	−0.367
ind344	−1.819***	−1.779***	−3.167***	−16.592	−1.625***	−1.439**	−0.579	−1.801***
ind345	−16.280	1.829**	−15.246	1.680**	−16.090	−14.768	−15.129	1.702**

ind349	−1.675***	−1.068**	−1.727***	−1.341**	−2.791***	−0.536	−1.170***	−0.719*
ind353	−0.375	−0.223	0.489	0.224	0.42	1.298***	0.521	0.884**
ind354	−17.926	−17.330	−1.939*	−0.252	−1.640	−16.881	−2.008*	−1.134
ind355	−1.333**	−0.722	−1.078**	−1.421*	−0.827	−1.483*	−0.831	0.255
ind356	−1.344**	−0.775	−1.242**	−0.123	−1.412**	−0.356	−0.542	−0.730
ind357	−18.543	−17.903	−1.854*	−0.967	−0.639	−1.430	−1.580	−0.938
ind363	−16.986	−17.202	1.180*	0.442	−16.513	1.572*	1.278**	0.401
ind364	−1.364	−16.937	−16.321	1.125**	−0.984	0.99	−1.121	−0.232
ind369	−0.234	0.425	−0.753	−16.336	0.441	1.123*	0.105	1.200***
ind371	−0.811	−0.379	−2.084**	−0.296	−0.557	−0.094	−0.235	0.768*
ind373					−0.689	−0.105	0.244	1.049**
ind374	−17.340	−16.812	1.047	1.053	−16.663	−15.982	0.665	1.518*
ind375	0.25	1.285	−16.117	0.763	−17.006	−16.435	1.464**	1.659**
ind381	−1.254*	−1.095	−0.037	−0.170	−1.266	−1.162	−0.185	−0.765
ind382	−0.066	0.426	−17.269	−17.196	−17.591	−17.468	0.131	1.447**
ind384	−0.690	−1.759*	−1.026	−0.781	−0.229	−0.659	−0.376	0.6
ind391	−17.044	−16.104	−15.591	−16.159	0.401	2.000**	−15.441	−14.383
ind399	−17.957	−17.240	−1.807*	−1.105	−1.341	−1.287	−1.736*	−0.409
countryBG	−17.828	−1.003	−2.651***	−2.150***	−1.952***	−2.714***	−16.680	−1.668***
countryCH	−17.507	5.144***	3.036***	−18.255	−18.229	2.249*	4.329***	3.099***

countryCZ	−1.684**	0.308	−1.968***	−2.271***	−1.696***	−1.884***	−1.273**	−2.182***
countryDE	0.06	1.749*	−0.202	−0.676	−0.414	−0.865**	−0.422	−0.786**
countryES	0.104	0.518	−0.984**	−1.144**	−1.884***	−1.316***	0.218	−0.184
countryFI	1.536***	3.138***	0.852*	0.826*	0.840*	1.358***	0.899**	0.578*
countryFR	−0.656	0.421	−1.325***	−1.704***	−1.361***	−1.686***	−1.143***	−2.005***
countryHU	−0.902	−1.057	−2.080**	−1.383**	−2.894***	−0.903*	−1.727**	−3.508***
countryLV	−17.340	−15.744	−16.725	−17.345	−17.338	3.191***	1.544	0.636
countryNL	2.492***	4.996***	2.348***	−18.341	1.885**	26.006		23.567
countryNO	0.535	2.510**	0.325	0.639	−0.099	0.11	−0.020	−0.373
countryPL	−2.797***	−0.401	−2.052***	−2.961***	−2.538***	−2.481***	−2.950***	−3.036***
countryPT	−1.475**	−0.498	−2.860***	−1.601***	−1.466***	−17.347	−2.233***	−2.874***
countryRO	−3.409***	−1.104	−2.567***	−2.646***	−2.866***	−3.410***	−4.035***	−3.825***
countryRS	−17.395	−15.941	−2.396***	−1.449**	−1.874***	−1.043*	−2.244***	−3.493***
countrySE	−2.116**	1.318	−0.870*	−0.475	−0.383	−1.103**	−0.083	−0.807**
countrySK	−1.226	−15.774	−1.956**	−2.885***	−17.432	−2.942***	−16.489	−3.406***
capital.intensity	0.211***	0.271***	0.153***	0.187***	0.100**	0.126***	0.089**	0.067**
Constant	−4.921***	−6.809***	−4.709***	−4.967***	−4.751***	−5.613***	−5.262***	−4.981***
Observations	71,318	88,827	95,292	98,471	105,535	107,518	107,839	101,237

Note: *p<0.1; **p<0.05; ***p<0.01

Step 2: Figure 5.1 shows histograms of propensity scores for treatment and control group. Most firms have a propensity score close to zero. For targets as well as buyers the mean propensity score is higher than for firms that are non targets or non buyers. Propensity scores close to zero for treated observations tell that the chosen covariates explain little about the probability, why firms participate in a merger. Other variables may better identify a treatment. Due to the limitations of the available data set a different choice of covariates to identify a treatment is left open for further studies.

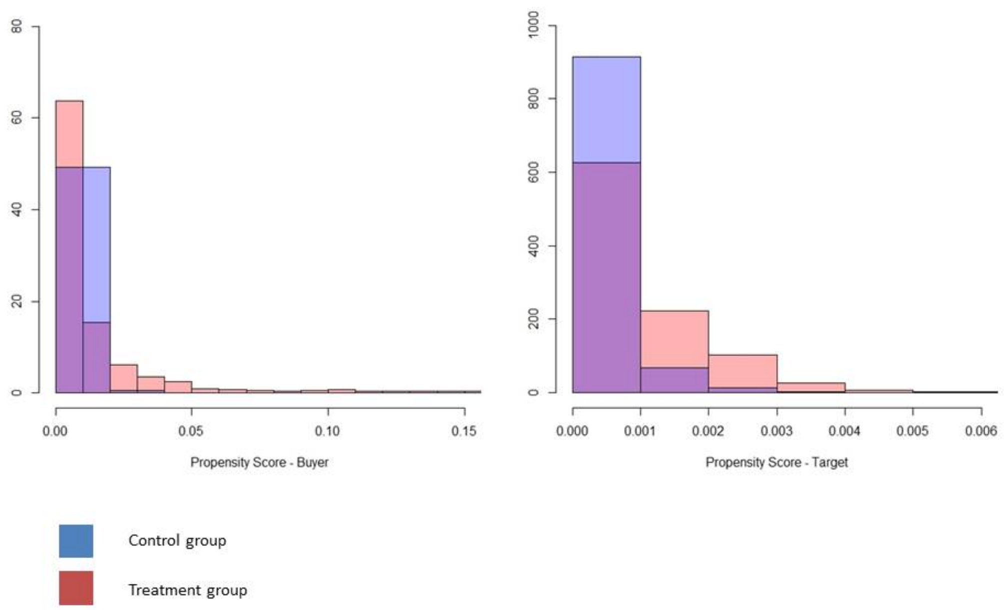


Figure 5.1: Propensity Score

Step 3: It is possible to apply an approach to guarantee the overlap of both groups. If e.g. a Minima and Maxima Comparison approach is applied, this would cause that most targets with a propensity score larger 0.02 are eliminated from the analysis because no firm with a similar propensity score can be matched. For buyers the approach would cause that the majority of buyers with a propensity score larger 0.001 are eliminated from an analysis. The advantage of a perfect fit of both groups, treatment and control group, comes with high costs as it reduces the number of observations significantly. Additionally, it results in a selected group of mergers. The analysis of merger-specific efficiency gains aims to be representative. Therefore, I refrain from the application of an approach that guarantees an overlap, as it would result in an analysis of a selected group of mergers, whose efficiency changes are unlikely to be representative. However, the matching of treatment and control firms and thereby the results of a PSM approach can be improved by e.g. a different choice of covariates that better identify, when firms are going to merge.

Step 4: Table 5.4 summarizes mean values of covariates that are used in the logit regression. It shows means before and after the PSM. Differences in means of covariates are highly significant before the matching. The mean productivity of targets as well as the mean productivity of buyers is significantly higher than that of firms that are neither targets nor buyers. Productivity of buyers is higher than productivity of targets. Log capital intensity of targets as well as of buyers is smaller than of non targets or non buyers. Log capital intensity of targets is smaller than of buyers. As expected, all differences in means are insignificant after the PSM according to the Welch Two Sample t-test. The results indicate that the matching of treatment and control firms is sufficient to identify difference in post-merger efficiency as merger-specific.

Table 5.4: Mean Values of Covariates Before and After Matching

	before		after	
	Merger year efficiency	capital intensity	Merger year efficiency	capital intensity
non-target	0.897	-0.535	1.261	0.120
target	1.206	-0.038	1.206	-0.038
t-test	***	***	p=0.586	p=0.275
non-buyer	0.893	-0.538	1.297	-0.213
buyer	1.332	-0.200	1.332	-0.200
t-test	***	***	p=0.398	p=0.803

Welch Two Sample t-test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Step 5: The common trend before a treatment indicates that a treatment is likely to explain differences after a treatment. Thus, figure 5.2 shows the efficiency development of targets and buyers. Figure 5.2 illustrates the development of efficiency before controlling for any time-, country-, industry- or firm-size-specific effects. However, a similar development before the merger may indicate a common trend. On the left side, figure 5.2 shows efficiency per period of treatment and control group of targets. Pre-merger mean efficiency of the treatment group is in most periods higher than efficiency of the control group. This difference gets larger in post-merger periods. From period -3 onward mean efficiency of targets develops into a different direction than mean efficiency of firms of the control group. This development goes in line with the consideration of Blonigen and Pierce (2016) that targets are likely to increase efficiency already before the merger.[6] On the right side, figure 5.2 shows efficiency per period of treatment and control group of buyers. Mean efficiency of the treatment group is higher than of the control group from the pre-merger period 5 onward. Treatment and control group show a common trend till post-merger period 1. Afterwards, mean efficiency of the treatment group increases, mean efficiency of the control group decreases. In the further analysis, all pre-merger periods are aggregated into a mean pre-merger efficiency. Alternatively, it is possible to add dummy variables per pre-merger period. This allows to see a common trend in pre-merger period after applying a DID approach.[7] However, aggregating all pre-merger periods results in DID coefficients, which are comparable to coefficients resulting from adding a dummy variable for each pre-merger period. In contrast, matching in pre-merger period -1 results in different DID coefficients than matching in the merger period. Thus, it can be discussed whether a merger has already an impact on efficiency at the time when firms anticipate it. However, it is further assumed that the merger starts with the merger year.

[6] Anticipating the pre-merger increase or decrease of efficiency results in a matching of treatment and control firms in period -1. See Appendix section 9.12 for results of a matching in period -1.

[7] See Appendix section 9.11 for a regression including all pre-merger periods separately.

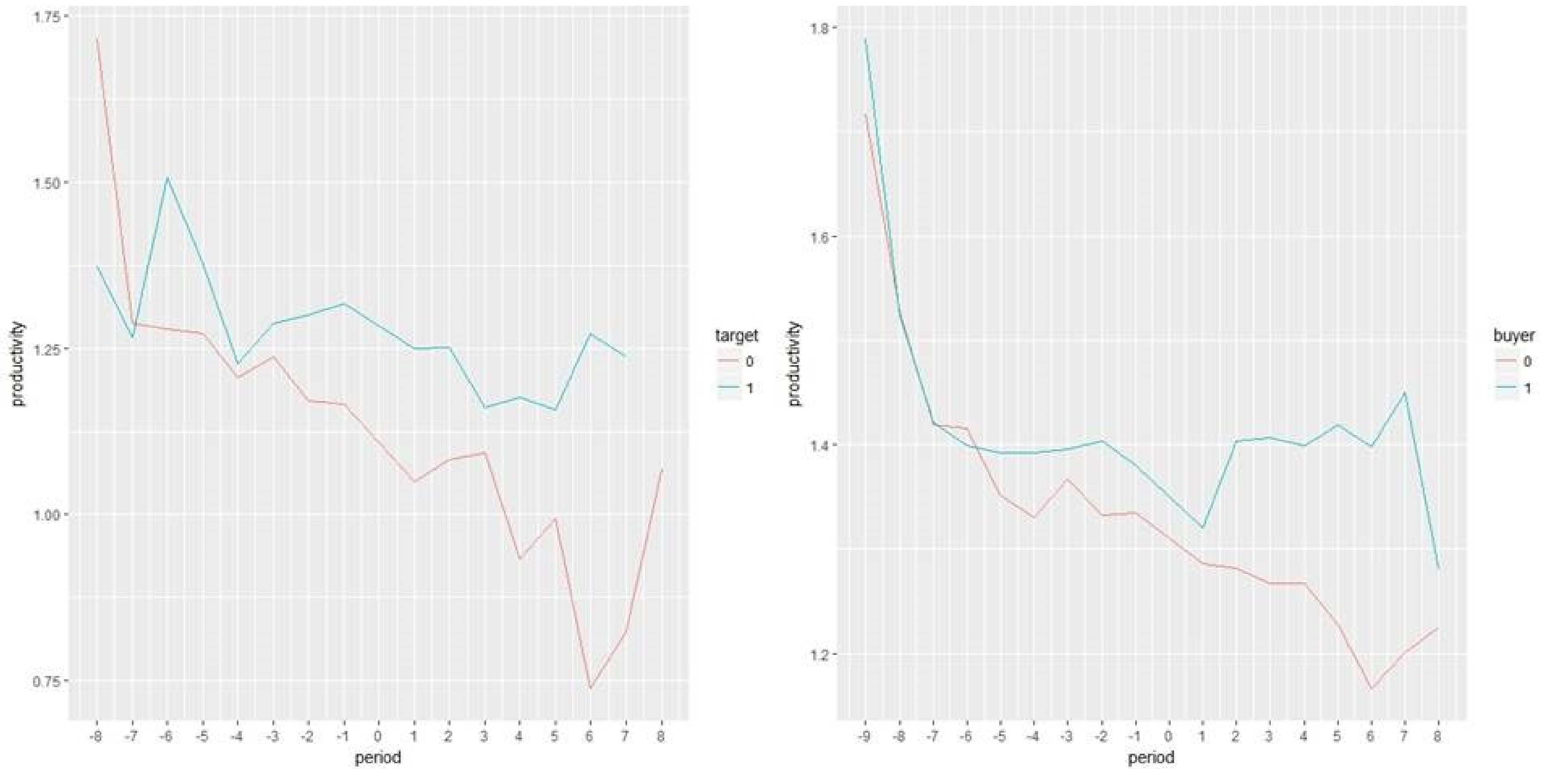


Figure 5.2: PSM: Mean Efficiency of Treatment and Control Group

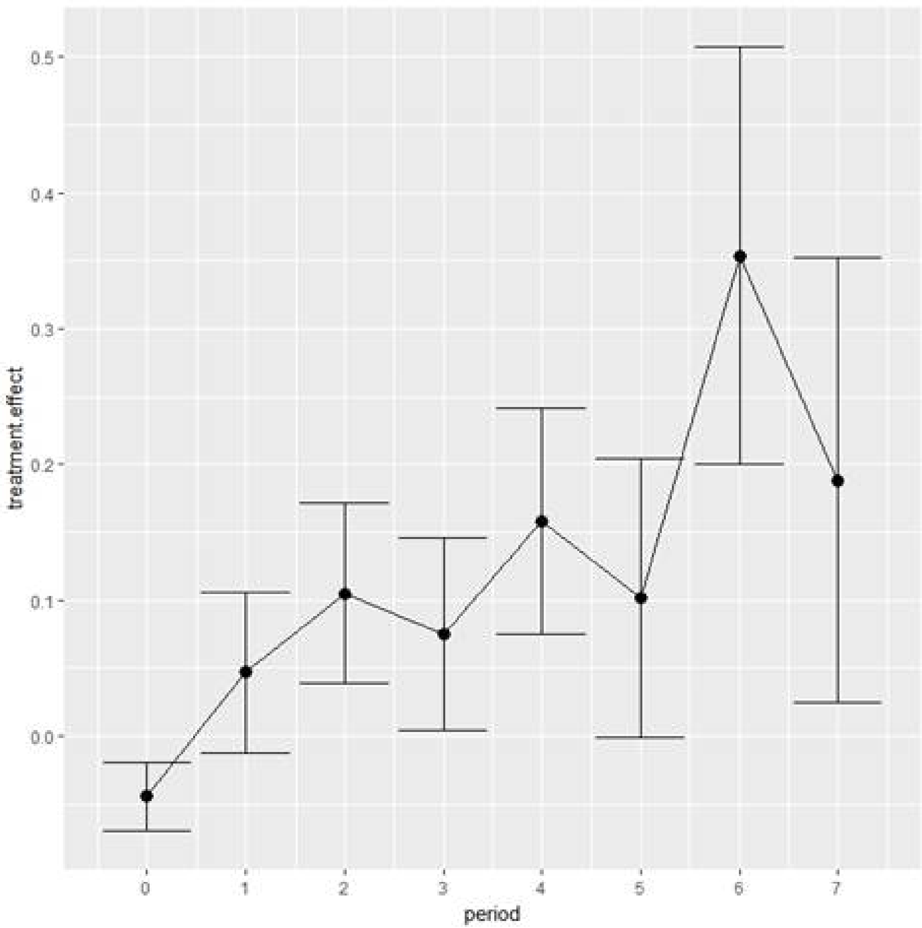
Table 5.5 summarizes results of the DID model introduced in equation (5.8) using matched firms as control group.

Targets are highly significant less efficient than their control firms in pre-merger periods, meaning by factor -0.05. Targets can fetch up efficiency after the merger. The difference is already fetched up in the second post-merger period, in which targets are 0.11 more efficient than before the merger. The efficiency of targets is then increasing period-by-period with a small slump in post-merger period 5. Post-merger periods 6 and 7 cannot be interpreted due to the number of observations. Period 8 and 9 are eliminated from the data set as there are no observations for targets. The data set for targets consists of 4,543 observations. The adjusted R^2 is 88% for efficiency.
Buyers are highly significantly more efficient than their control group in pre-merger periods, meaning by factor 0.02. They lose this advantage in the first post-merger period, as their efficiency decreases by 0.02 compared to their pre-merger efficiency. In post-merger period 3, the efficiency increases by 0.1 compared to their pre-merger efficiency. For all other periods, estimates are not significant. The data set for buyers consists of 41,198 observations. The adjusted R^2 is 95% for efficiency.

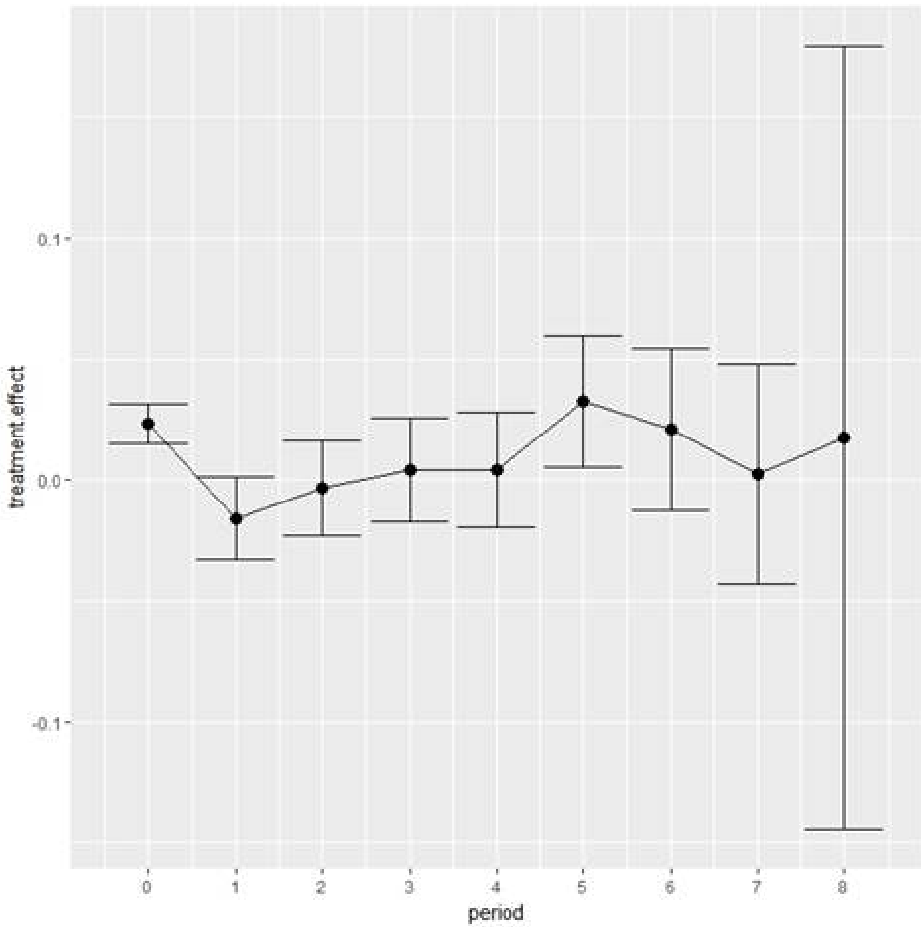
Figure 5.3 shows the estimates and confidence intervals of the treatment effect for targets and buyers.

Table 5.5: DID Regression using Matched Firms as Control Group

	Dependent variable:	
	efficiency	
	target	buyer
pre.merger	-0.045***	0.023***
	(0.034)	(0.004)
post.period1	0.047	-0.016 *
	(0.003)	(0.009)
post.period2	0.105 ***	-0.003
	(0.031)	(0.010)
post.period3	0.075 **	0.004
	(0.036)	(0.011)
post.period4	0.158 ***	0.004
	(0.036)	(0.012)
post.period5	0.102 *	0.033 **
	(0.052)	(0.014)
post.period6	0.354***	0.021
	(0.078)	(0.017)
post.period7	0.188**	0.003
	(0.083)	(0.023)
post.period8	-	0.017
		(0.083)
post.period9	-	-
Observations	4,543	41,198
Adjusted R^2	0.88	0.95
Note:	*p<0.1; **p<0.05; ***p<0.01	



targets



buyers

5.4 Conclusion

The analysis of merger-specific efficiency gains based on the DID and PSM approach results in three major findings.
First, mean efficiency of buyers as well as of targets is higher than that of other firms. And, buyers are more efficient than targets. A possible explanation for this finding is that firms merge if they are efficient and therefore have enough liquidity to invest in a merger. This might explain the high average efficiency of buyers. Furthermore, it is likely that buyers invest in firms if they are efficient and thereby capable to pay off the investment. This might explain the high average efficiency of targets. The higher average efficiency of buyers in comparison to that of targets might indicate that merging means "the most efficient one eats the more efficient one" rather than only "the big one eats the little one".
Secondly, targets and buyers generate merger-specific efficiency gains. Targets are especially in a short- and mid-term perspective after the merger significantly more efficient, meaning in post-merger periods 2, 3, and 4. In contrast, buyers reach a significantly higher efficiency in a long-term perspective after the merger, meaning in periods 5, 6, and 7. Furthermore, merger-specific efficiency gains are larger for targets than for buyers. Overall, this finding indicates that efficiency gains from mergers are reasonably likely, at least when firms stay in the market and are therefore observable. Targets seem to be capable to generate merger-specific efficiency gains faster than buyers. This might be due to size. As shown in table 4.4 in chapter 4 buyers are on average larger than targets. Buyers generate on average a turnover of 2.4 M€, which means they are small firms, while targets generate on average a turnover of 0.1 M€, which means they are micro firms. If one assumes that merger-specific efficiency gains are a consequence of a change of control, it is likely that a change of control can be faster and more effectively be implemented in smaller than in larger firms. Furthermore, buyers are the investors and often take the lead for a post-merger integration. An integration often primarily consists of an adaptation of the targets' processes, which means that targets' operations change. Buyers might adapt themselves to the new environment created by the merger on a long-term perspective. Furthermore, as buyers are larger than targets, it is likely that it takes some time until merger-specific efficiency gains are significant for buyers.
Third, the application of the PSM approach shows that it is difficult to predict the probability of a firm to participate in a merger based on its firm characteristics. This finding goes together with the discussion about merger identification in chapter 3. It shows that from both perspective, the theoretical as well as the empirical perspective, the merger analysis would benefit from an identification process that allows to identify the change of control on a lasting basis. So far, the merger analysis

suffers by the fact that is impossible to predict if a deal, which is legally constituted, results in a change of control on a lasting basis. The change of control on a lasting basis is a sufficient requirement for merger-specific efficiency gains. Nevertheless, a DID approach using a control group based on a PSM approach results in similar findings than a DID approach using all firms as control group. But, the later results in more significant findings. Thus, even though the matching could be improved, the PSM approach highlights differences between merging firms and non-merging firms.

Chapter 6

The SFA Approach

6.1 Introduction

So far, the analysis of merger-specific efficiency gains in chapter 5 is based on the productivity estimates resulting from the TFP approach introduced in chapter 4. Alternatively, a Stochastic Frontier Analysis (SFA) approach can be applied to estimate productivity. In the context of SFA, productivity is usually named efficiency. The difference between the applied TFP approach and the SFA approach is the location of the estimated production function and thereby the estimate of efficiency. Or, in more formal terms, the two approaches differ in their assumptions about the error term, ϵ_{it}. While the TFP approach defines the production function as an average production function, the SFA approach defines the production function as a frontier production function. In a TFP approach, the residual of multiple regression is estimate of productivity. In contrast to TFP, SFA decomposes the residual into a random noise and an inefficiency term. This inefficiency is a measure of the distance to the frontier. It can be interpreted as the percentage by which a firm fails to achieve the maximal efficiency. Therefore, in contrast to TFP, the efficiency measure of the SFA approach itself is meaningful as it can be interpreted as the percentage of a maximum possible efficiency. To conclude, using efficiency estimates resulting from an SFA approach allows one to make a statement about the extent of merger-specific efficiency gains.

The advantage of meaningful efficiency estimates comes with costs. The SFA approach requires the data set to have a certain property. This property can be tested by the skewness of the OLS residuals. They indicate the existence of inefficiency if they are left-skewed. The available data set only partly satisfies this requirement. Therefore, this chapter concentrates on efficiency estimation and the analysis of merger-specific efficiency gains in two industries. Those industries are industry 208 "Beverages" and industry 371 "Motor Vehicles and Motor Equipment". Industry 208 is the industry with the most identifiable buyers and targets. 113 buyers and 85 targets can be identified in industry 208. In the overall data set, 2,866 buyers and 1,632 targets can be identified in 95 industries. Therefore industry 208 covers 4% of identified buyers and 5% of identified targets. Thus, the results of the analysis of merger-specific efficiency gains in industry 208 represent a minority of mergers. Industry 371, which is named "Manufacture of motor vehicles, trailers and semi-trailers" in the NACE Code system, is the industry with the largest turnover in the manufacturing sector in the European Union. It achieved 1,041,195 M€ in 2016. (Eurostat, 2017b) Thus, it determined 14% of the overall turnover of the European manufacturing sector. As this industry is the largest industry in the European manufacturing sector, it has been chosen to be analyzed in detail.

Definition of Efficiency

Literature distinguishes several definitions of efficiency. In the context of merger-specific efficiency gains, efficiency is defined as entrepreneurial efficiency (Klumpp, 2006). Entrepreneurial efficiency is a measure of a producer's performance.
It is possible to differentiate between technical - also named productive - and allocative efficiency. In both cases, markets are assumed to be imperfect. In imperfect markets inefficiency exists. Technical efficiency measures the degree of success that a producer achieves in maximizing the output at a given input, or minimizing the (use of) input at a given output. (Greene, 2007) Allocative efficiency measures the degree of success of a producer achieves in allocating inputs to their correct disposal. While the measurement of allocative efficiency requires price information, the measurement of technical efficiency is possible with the assumption that input and output prices are uniform for all firms. (Greene (2007), Kumbhakar and Lovell (2003)) I further assume competitive input and output markets, which leads to uniform prices for all firms. Therefore, the following analysis will concentrate on the analysis of technical efficiency. Furthermore, the measurement of technical efficiency requires the assumption that firms differ in the way they use available production technology. The usage leads to differences in technical efficiency.

Overview of Efficiency Measurement Methods

Figure 6.1 shows an overview of methods used to measure efficiency. Literature distinguishes two main categories of efficiency measurement methods. The first category contains methods to measure absolute efficiency. These methods are theoretical approaches, which define optima by maximizing a production function or minimizing a cost function under certain assumptions, for example. The second category contains methods to measure relative efficiency. Empirical studies apply

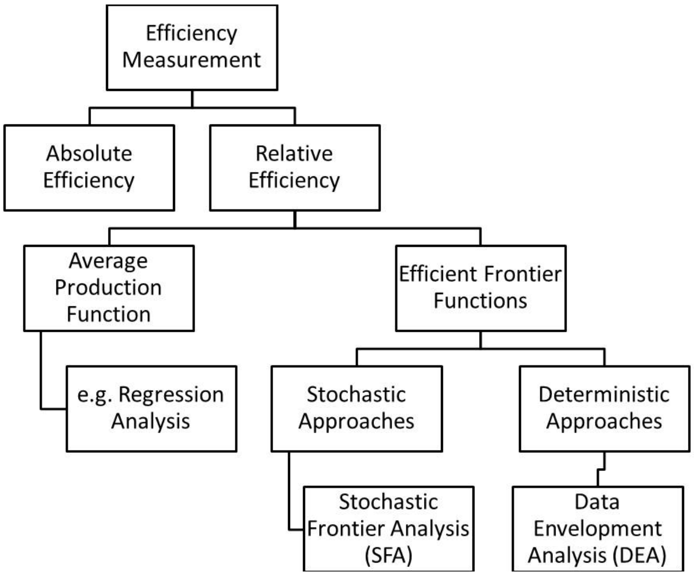


Figure 6.1: Overview of Efficiency Measurement Methods (Bielecki, 2011)

this category of methods as it allows the measurement of efficiency based on observations. The measurement of relative efficiency is mainly based on the assumption that producers' performances are comparable. Producers' performances can either be compared to an average or to best practices. The TFP approach applied in chapter 4 is an average production function approach. In contrast, the SFA is a frontier function approach. The frontier function captures all best practice observations. The distance to this frontier function is a measure of inefficiency. Frontier function approaches, in contrast to average production function approaches, allow the interpretation of the efficiency estimate as the achieved percentage of maximal efficiency. The most prominent frontier approaches are SFA and Data Envelopment Analysis (DEA).[1] SFA is a parametric approach. In contrast to nonparametric approaches like DEA, SFA needs additional assumptions i.e. the distributional assumption of inefficiency.

DEA defines the frontier function by connecting best practice observations with the help of linear programming. Consequently, all observations located on the frontier are interpreted as 100% efficient. Any deviation from the frontier function is negative and represents inefficiency. A separation whether the location of a data point results from coincidence or inefficiency is not possible. Thus, the DEA approach denies the existence of coincidence.

In contrast, the SFA approach considers coincidence by defining the deviation as a composite of random noise, representing coincidence, and inefficiency. This composition is captured by the residual resulting from a regression-like approach to estimate the frontier function. The estimation of the frontier function as well as

[1] Approaches like Deterministic Frontier Analysis (DFA) or Free Disposal Hull (FDH) are a combination of stochastic and deterministic approaches.

the decomposition of the residual requires distributional assumptions about the two components of the composite error term.

6.2 Methodology

There are many comprehensive summaries of Efficient Frontier Approaches and Stochastic Frontier Analysis.[2] Therefore, in this study the overall introduction will be omitted in favor of a concentration on an introduction to the model applied and the comparison to the applied TFP model in chapter 4. The applied model can be written as

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} \\ &+ \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 \\ &+ \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \epsilon_{it} \end{aligned} \tag{6.1}$$

with

$$\epsilon_i = v_i - u_i \tag{6.2}$$

where v_i $i.i.d.N(0, \sigma_v^2)$ is a random error term and u_i $i.i.d.N^+(\mu, \sigma_u^2)$ is a truncated normal distributed inefficiency term. u_i and v_i are assumed to be independently distributed of each other, and the regressors. Due to the non positive inefficency term, the expected value of ϵ_i is also not positive, $E(\epsilon_i) = -E(u_i) \leq 0$.[3]
Similar to the applied TFP model, the production technology is approximated by a translog function. In contrast to the applied TFP model, the interaction term between all variables, including material, is considered. This is because the applied SFA model described in equation (6.1) is a simple cross-sectional regression model without any dynamic variable or control function. In contrast to the applied TFP model, material is considered as an input variable and not as proxy for productivity or efficiency to build a control function. Furthermore, capital is a free variable that it is chosen each period independently from the input choice of the previous period. Contrarily, the applied TFP model assumes capital to be a dynamic variable. Thus, the applied SFA assumes an exogenous composite error term: Neither the random error term nor inefficiency is correlated with input choices. While the discussion in TFP literature focuses on the solution of endogeneity, this discussion is less dominant in the SFA literature. Instead, SFA literature discusses, among other topics, the distributional assumptions of the inefficiency term. Besides truncated normal, the inefficiency term is often assumed to be either half-normal or gamma

[2] For an introduction to efficiency measurement and frontier approaches see e.g. Kumbhakar and Lovell (2003), Coelli et al. (2005), or Greene (2007).

[3] For more details see Kumbhakar and Lovell (2003) and Appendix 9.13.

distributed. I assume a truncated normal distributed inefficiency term.[4] The distributional assumption on efficiency is the main difference between the applied SFA model and the applied TFP model. The TFP model imposes assumptions to generate enough moments to estimate the parameters by applying a GMM approach. The SFA model assumes a one-sided distributed inefficiency term, which generates an infinite number of moments. This allows one to apply a maximum likelihood approach to estimate the parameters of the production function. The one-sided distributed inefficiency term shifts the production function and thereby defines it as a frontier. Furthermore, the deviation from the frontier is a composition of random error and inefficiency. The distributional assumptions help to decompose the residual into both parts, inefficiency and random noise.[5]

6.3 Application

One way to estimate the SFA model is to apply the three step approach introduced by Coelli (1996). This approach is, among others applied in the R package "frontier".[6]

In a first step, the position of the production function is ignored and all parameters are estimated using Ordinary Least-Squares (OLS) so that $(X'X)^{-1}X'y$ gives unbiased estimates for the unknown β parameters except for the intercept, β_0. Due to the assumption that u_i and v_i are independently distributed of the regressors, it is possible to apply OLS to estimate all parameters except the intercept. The intercept will be biased as the frontier function is a shifted production function. The OLS ignores any shifting as it assumes a standard normal distributed error term. In a second step, the estimated production function is shifted by using Corrected Ordinary Least-Square (COLS) to adjust the intercept β_0 and the σ^2 parameters. This adjustment results from a two-phase grid search of $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$. γ has a value between 0.0 and 1. Setting all other parameters, in this case σ_v^2 and σ_u^2 to zero, a grid search of γ with increments of e.g. 0.1 results in estimates of β_0 and σ^2. In a third step, the values of the second step are starting values for an iterative procedure to estimate the parameters that maximize the likelihood function. The iterative procedure, e.g. David-Fletcher-Powell Quasi-Newton method, requires the vector of first partial derivatives. It updates the vector of parameters until either the convergence criterion, meaning that the proportional change in the likelihood function and each

[4] There is no reason to prefer a truncated normal distribution over a half-normal, exponential or gamma distribution. They all have advantages and disadvantages Coelli et al. (2005). Nevertheless, many empirical studies assume a truncated normal distributed inefficiency as the truncated normal distribution is flexible and implemented in the R package "frontier", for example.

[5] For more details see Kumbhakar and Lovell (2003) and Appendix 9.13.

[6] It is an intuitive approach and follows the development of SFA as introduced in basic literature, e.g. Kumbhakar and Lovell (2003) or Bogetoft and Otto (2011).

of the parameters is less than a certain value, e.g. 0.00001, or the maximum number of iterations, e.g. 100, is reached. The iteration procedure applied has the advantage that the first-order partial derivatives are sufficient to estimate the parameters. In contrast to other iterative procedures, it allows estimate parameters that maximize the likelihood function without using the matrix of second-order partial derivatives. According to Coelli (1996), the second-order partial derivatives of the log-likelihood function of the composite error term are preferably avoided. This avoidance results in an iteration process that works well with the starting points. Therefore the described three-step approach is a pragmatic approach to estimate the parameters of the maximum likelihood function.

Additionally, the three-step approach, even in the first step, provides results that allow one to test whether a shift of the production function in a second step and the application of a frontier approach make sense. They only make sense if the OLS residuals resulting from the OLS regression in the first step are left-skewed. Thereby, they indicate the existence of inefficiency. Otherwise, the existence of inefficiency is unlikely. This results in SFA residuals that are dominated by random noise. Thus, if OLS residuals are right-skewed, inefficiency estimates will indicate that most firms are highly efficient. In the case of right-skewed OLS residuals, the truncated normal distribution will collapse to a normal half-normal distribution, which means that the random noise is still normal distributed but the inefficiency term is half normal instead of truncated normal distributed. In this case, the inefficiency term has zero mean. As inefficiency is assumed to be a non-positive deviation from the frontier, a zero mean may indicate that the inefficiency term is only non-positive due to its restriction. Thus, a zero mean of inefficiency leads to the question if the assumption of a non-positive deviation from the frontier is plausible. If this assumption is not plausible, the frontier approach is maybe incorrectly specified or the data set is incompatible to a frontier approach.

I follow the three step approach of Coelli (1996). In a first step, the skewness of the residuals of an OLS is tested. Thus, the panel data set is treated as a cross-sectional data set. Running the OLS regression on the overall manufacturing sector indicates whether inefficiency can be expected in the manufacturing sector assuming that all manufacturing firms are comparable. Furthermore, running the OLS regression industry-wise indicates whether inefficiency can be expected in certain industries, assuming that producers' performances are comparable over time.

In a second step, I concentrate on two important industries that satisfy the requirement of left-skewed OLS residuals so that:

$$\begin{aligned} v(\hat{\epsilon_{OLS}}) &= E[(\frac{\epsilon_{OLS} - E(\epsilon_{OLS})}{\sigma_{\epsilon_{OLS}}})^3] \\ &= \frac{E(\epsilon_{OLS}^3) - 3Var(\epsilon_{OLS})E(\epsilon_{OLS}) - E(\epsilon_{OLS})^3}{Var(\epsilon_{OLS})^{\frac{3}{2}}} < 0 \end{aligned} \tag{6.3}$$

6.4 Data

The data set used for the SFA approach is identical to the data set described in section 4.4. For the purpose of clarity, I include the summary statistics for the overall data as shown in table 6.1 as well as summary statistics for industry 208 as shown in table 6.2 and industry 371 as shown in table 6.3.

After implementing all restrictions the data set consists of 131,232 firms in 93 industries with 857,526 observations. The data set for industry 208 consists of 21,766 observations. The data set for industry 371 consists of 22,846 observations. Both industries represent 5% of the observations of the overall data set. To conclude, the results of the analysis of both industries are not representative of the overall manufacturing sector.

While the mean output in the overall data set is approximately 26 M€, the mean output of industry 208 is larger, at approximately 28 M€. Firms in industry 371 have a mean output of approximately 140 M€. Output is often used as a measure of firm size. Thus, the mean size of firms in both industries, 208 and 371, is larger than the mean size of firms in the manufacturing sector. Furthermore, the mean size of firms in industry 371 is five times larger than the mean size of firms in the manufacturing sector. It can be expected that the production function of industry 371 is characterized by economies of scale. Economies of scale cause larger increases in output for an additional unit of input if the input usage is already large. Traditionally, the more output, such as sales, a firm generates, the more input a firm uses. In some industries, firms benefit from economies of scale when they grow in size. In this case, the more output a firm generates, the less input it uses per output unit.

Even though firms in the overall data set are on average larger, which means they generate more sales, than firms in industry 208, the mean value of input variable "labor" is larger in the overall data set with approximately 3.7 M€, than in the industry 208 with approximately 3.4 M€. However, the mean value of the input variable "capital" is larger in industry 208 with approximately 7.3 M€ than the mean value of the overall data set, which is approximately 6 M€. To conclude, the industry 208 is expected to be more automatized and therefore less labor intensive and more capital intensive than other industries in the manufacturing sector.

While the mean firm size in industry 371 is five times larger than the mean firm size in the overall manufacturing sector, the mean value of the input variable "labor" is only four times larger. However, the mean value of the input variable "capital" is, at approximately 6.9 M€, only marginally larger than the overall mean value. Thus, firms in industry 371 on average use almost the same amount of capital as firms in the overall manufacturing sector, but with four times more labor input they generate a five times larger output value. It can be expected that firms in the industry 371 are on average highly efficient.
The mean value of the input variable "material" is 16.2 M€ in the overall manufacturing sector. Therefore, the material cost ratio, meaning the ratio of material to output, is 62% in the overall manufacturing sector. Contrarily, the material ratio in industry 208 is 48% and 72% in industry 371 respectively. Therefore, the production process can be expected to be more value adding in industry 208 than in other industries in the manufacturing sector, especially industry 371. Production technologies that are characterized by a large material ratio are, for example, assembling processes. The production of motor vehicles is a typical assembling production. It can be expected that the estimates of the coefficients of the production technology for industry 208 and 371 differ, especially for the input variable "material".

Table 6.1: Input and Output Variables

Statistic	N	Mean	St. Dev.	Min	Max
output	857,918	26,197.000	392,724.100	0.924	71,911,323.000
labor	857,918	3,722.850	39,155.280	1	14,455,269
employees	687,486	117.334	736.301	0	86,607
capital	857,918	6.049	2.101	0.000	16.329
material	857,918	16,190.260	309,629.100	1.000	53,380,581.000

Table 6.2: Input and Output Variables - Industry 208

Statistic	N	Mean	St. Dev.	Min	Max
output	21,766	28,553.950	277,447.500	0.949	30,208,745.000
labor	21,766	3,419.174	38,588.070	1	3,625,358
employees	16,464	101.704	812.644	0	57,557
capital	21,766	7.330	1.783	0.000	15.350
material	21,766	13,744.350	114,350.400	1	8,162,000

Table 6.3: Input and Output Variables - Industry 371

Statistic	N	Mean	St. Dev.	Min	Max
output	22,846	139,842.700	1,688,828.000	0.992	68,319,688.000
labor	22,846	14,159.830	143,594.100	1	6,068,000
employees	18,705	409.714	2,614.984	0	86,607
capital	22,846	6.852	2.344	0.000	15.794
material	22,846	100,832.100	1,250,722.000	1.000	53,380,581.000

6.5 Results

Inefficiency in the European Manufacturing Sector

The likelihood of inefficiency in the European manufacturing sector is indicated by the skewness of the OLS residuals. Therefore, the model introduced in equation (6.1) will be run as a OLS regression ignoring the time index. Results are shown in table 6.4. The results show the estimates of a production function for the manufacturing sector. Even though the industries will be treated separately later, this production function aggregating all industries shows that all input variables have a highly significant impact on output. Furthermore, it shows that the impact of labor is the largest after material. The mean output elasticity of material is 0.66. The mean output elasticity of labor is 0.37. Furthermore, all input variables show positive scale effects as the squared values are positive for all of them. To conclude, the manufacturing sector is dominated by economies of scale, which means that an increase of already large input values has a higher impact on output than an increase of small input values. This may give firms an incentive to grow in size. Furthermore, the production function shows that all input factors are substitutes, which means that an increase in one of them substitutes the amount of another. The production function shown in table 6.4 is a typical industrial production function as output is significantly influenced by the three major inputs: material, capital and labor. Furthermore, firms have an incentive to grow in size and thereby also to merge as large firms benefit from economies of scale. Additionally, capital such as machinery traditionally substitutes labor as well as material, and labor substitutes material. Residuals have a skewness of -0.6213. They fulfill the requirement defined in equation (6.3). The skewness of the residuals indicates that inefficiency is likely in the European manufacturing sector. The assumption that producers' usage of an available production technology differs, which leads to different levels of efficiency, seems to be correct. Therefore, the application of a frontier approach may provide

Table 6.4: OLS regression using the Overall Data Set

	Dependent variable:
	output
capital	0.015***
	(0.001)
labor	0.439***
	(0.001)
material	0.402***
	(0.001)
capital.sqr	0.002***
	(0.0001)
labor.sqr	0.072***
	(0.0002)
material.sqr	0.069***
	(0.0001)
capital:labor	−0.004***
	(0.0002)
labor:material	−0.130***
	(0.0002)
capital:material	−0.0001
	(0.0002)
Constant	1.674***
	(0.005)
Observations	857,918
R^2	0.962
Adjusted R^2	0.962
Residual Std. Error	0.312 (df = 857908)
F Statistic	2,416,152.000*** (df = 9; 857908)
Note:	*p<0.1; **p<0.05; ***p<0.01

for most industries insights into producers' efficiency.

Inefficiency in certain Industries

Table 6.5 summarizes the skewness of OLS residuals per industry. OLS residuals of 43% of all industries are right-skewed. The majority of industries show OLS residuals that are left-skewed. The industry with the smallest skewness is industry 375 with -9.72, which is the industry for "Motorcycles, Bicycles, and Parts". According to the OLS residuals, it can be expected that firms in this industry are highly inefficient. The same can be expected for industry 332 "Iron and Steel Foundries" as the skewness is the second smallest at -5.32.[7] Instead of applying a SFA approach to all industries, I focus on two industries that have left-skewed OLS residuals. These industries are used to apply an SFA approach and analyze the resulting efficiency estimates with regard to merger-specific efficiency gains. The chosen industries are industry 208 "Beverages", as this is the industry with most identifiable buyers and targets, and industry 371 "Motor Vehicles and Motor Equipment".

Production Technologies

Efficiency estimation is done yearly and according to industry (see equation (6.1)). In a first step, instead of showing results from 10 regressions per industry, I will explain coefficients that result from an SFA approach including yearly fixed effects. These results are sufficient to show the components and differences of production functions. Table 6.6 reports the estimates of coefficients after running a regression including yearly fixed effects for industry 208 and 371 respectively.[8]

Industry 208: The intercept represents the shift of the production function in 2005. The estimates for the yearly fixed effects shows that 2006 does not differ significantly from 2005. All other years show significant negative impacts, meaning the production function has shifted downwards. This shift can be interpreted as a negative technical change in the industry. Therefore, technical change decreased in the years 2006 to 2014. As there is incomplete data for 2014, this shift might be biased. The negative trend in technical change might also be biased due to the fact that the output variable is the only deflated variable. All other variables are non-deflated. Deflated values are proxies for quantities. (Van Beveren, 2012) Thus, the output factor measures quantity, while input factors are measures of

[7]Several studies discuss the productivity changes in the steel industry. For example, Collard-Wexler and De Loecker (2015) analyze the technological change caused by the innovation of the minimill and how this innovation drove inefficient firms out of the US Steel industry. They analyze the years 1964 to 2002.

[8]Later, I will explain more about the estimates of the yearly coefficients when interpreting output elasticity in figure 6.2 to 6.4.

Table 6.5: Skewness per Industry

skewness	ind.	skewness	ind.	skewness	ind.	skewness	ind.
0.84	201	0.36	261	1.07	322	0.51	352
0.3	202	0.48	262	-0.3	323	0.06	353
-0.19	203	-0.34	265	-0.49	324	0.09	354
0.61	204	2.57	267	-0.91	325	-0.48	355
-2.97	205	0.25	271	-1.1	326	-0.17	356
-0.62	206	0.76	275	0.16	327	-0.88	357
-0.41	207	0.84	278	-0.58	328	-0.58	361
-1.38	**208**	-2.05	279	-2.37	329	6.22	363
-1.34	209	-2.19	281	-1.96	331	-3.07	364
0.95	211	0.21	282	-5.37	332	-1.78	366
-1.91	221	-1.12	283	-1.47	333	-1.85	367
1.16	225	-1.4	284	-0.62	334	0.12	369
0.86	227	1.38	285	1.22	336	**-2.09**	**371**
-2.71	228	-2.29	286	-0.11	339	-2.38	373
-1.68	229	-4.46	287	0.78	341	-0.28	374
0.93	232	-4.26	289	-2.08	342	-9.72	375
1.05	238	-3.48	299	-0.37	343	-0.88	379
0.25	239	-1.52	301	1.4	344	0.46	381
0.07	242	1.09	302	2.22	345	0.02	382
-0.99	243	-1.66	306	0.08	346	-1.62	384
-0.28	244	-0.44	308	1.2	348	0.02	391
-2.41	249	-0.79	311	0.63	349	3.35	394
-0.35	251	0.46	316	0.22	350	1.57	399
-0.44	252	-0.1	321	0.63	351		

costs. In a consequence, efficiency measures the degree of success that firms achieve in producing quantities at a certain level of costs. Costs and thus input variables may inflate, while output is deflated to an index basis of 2010.[9]For more details about output deflation see Appendix 9.6. This might cause a shrinking gap between output and inputs, which is partly represented by a negative trend in the intercept. Out of all input factors, the impact of capital is the smallest compared to the other input variables. If capital increases by one percent, this causes an insignificant increase in output. Furthermore, capital and labor are substitutes, meaning that an increase in capital causes a decrease in labor and vice versa. This is what can be expected, as it partly shows that more machinery and therefore automation needs

[9].

less labor force. Contrarily, capital and material are complementary: more capital means more material.
One percent of labor increases output significantly by 0.4%. Labor and material are substitutes. Furthermore, the marginal impact of material on output equals approximately 0.2%.
γ is defined as $\gamma = \frac{\sigma_u}{\sigma_u + \sigma_v}$. It converges to one if σ_u is large and to zero if σ_v is large. In the case of industry 208, γ is closer to one than to zero, which tells that σ_u is large meaning that the variance of the composite error term is dominated by σ_u and not by the variance of noise. This is a desired, but also expected result as the OLS skewness was tested before running the SFA regression. The left-skewed OLS residuals already indicated that the composite error term would be dominated by inefficiency and not by the variance of noise.
μ is the mean of the composite error term. It is negative, partly due to inefficiency. The mean efficiency is 80%.
σ^2 is defined as $\sigma^2 = \sigma_u^2 + \sigma_v^2 = \frac{\sigma_u^2}{\gamma} = \frac{\sigma_v^2}{(1-\gamma)}$. Therefore, σ^2 is close to σ_u^2 if γ is close to one and close to σ_v^2 of γ is close to zero. As γ is closer to one than to zero, σ converges rather to σ_u^2 than towards σ_v^2.
The coefficients of the SFA approach indicate a higher impact of labor, but a lower impact of material on output than the coefficients of the TFP approach (as shown in table 4.6). The impact of capital on output is comparably low.
Industry 371: The shift of the production function, representing technical change, is not significantly different when comparing 2005 to 2006 or 2007. For industry 371, for the year 2009, the shift is positive compared to the previous year. All other years show a similar negative trend of technical change in industry 208.
Again, the impact of capital is the smallest compared to the other input variables. If capital increases by one percent, this causes a significant increase of 0.08% in output.
One percent of labor increases output significantly by 0.4%. Labor and material are substitutes.
Furthermore, an increase of material by one percent causes an output increase of 0.3%.
Again, γ is closer to one than to zero. γ is even larger for industry 371 than for industry 208. μ is negative and even more negative for industry 208 than for industry 371. This might be due to inefficiency or due to random noise. The mean efficiency indicates that this might be partly due to mean inefficiency. The mean efficiency is 85%.
Similar to industry 208, σ converges rather to σ_u^2 than towards σ_v^2.
The coefficients of the SFA approach indicate a lower impact for both, labor as well as material, on output than the coefficients of the TFP approach (as shown in

table 4.6). The marginal impact of capital on output is comparably low. But, in contrast to the TFP approach the marginal impact of capital is significant in the SFA approach.

In general, industries differ regarding their production technology and inefficiency. The impact of capital on output differs for industry 371 compared to industry 208. Capital has a larger, more positive and more significant impact on output in the production of motor vehicles than in the production of beverages. Furthermore, the substitute effect between labor and material is larger for industry 208 than for industry 371. For both industries, a one percent increase in labor causes a significant output increase between 0.4 and 0.5%. Labor and material are substitutes in both industries, but the substitute effect is larger for industry 208 than for industry 371. To conclude, labor usage is similar in the production of motor vehicles and the production of beverages. A one percent output increase resulting from the production of motor vehicles requires a little less labor than in the the production of beverages. Furthermore, mean efficiency is 5% larger in industry 371 than in industry 208.

The results of the regressions with yearly fixed effects as summarized in table 6.6, show highly significant coefficients for the year dummies. These coefficients indicate that years differ somehow. In fact, there year-specific effects that are unspecified but that have an impact on output. These year-specific effects are omitted variables. If these omitted variables have an impact on input variables, this would cause endogeneity. Table 6.5 and table 6.5 show the results of all ten yearly regression for industry 208 and industry 371. The results help to see the variation of coefficients over time. If the variation of coefficients is large, it means that the production technologies of industries differ across years and year-specific effects have a large impact. In this case, the year-specific effects that are omitted cause endogeneity. This endogeneity results from an impact of year-specific effects that is non-linear. Applying a panel data model and including yearly fixed effects means that year-specific effects have a linear shifting effect on a production technology and can be covered by a dummy variable. If coefficients vary across years in a cross-sectional model, the yearly regressions show that year-specific effects have a non-linear impact on the production technology. Ignoring this fact and applying a panel data model including yearly fixed effects, results in a composite error term, and therefore efficiency, that partly includes year-specific effects that are omitted.

Table 6.5 shows that the truncated normal distribution of inefficiency collapses into a half-normal distribution in years 2005 and 2014. In those years, the mean efficiency is close to 1 and γ is close to zero. Both indicate that the data set for these years has not the right property to apply a SFA approach. In all the other years, the yearly regression appropriately approximates a frontier production function. The

Table 6.6: SFA incl. Yearly Fixed Effects - Industry 208 and 371

	Dependent variable:	
	Industry 208: output	Industry 371: output
(Intercept)	2.294***	1.809 ***
2006	-0.019	-0.007
2007	-0.035***	-0.003
2008	-0.118***	-0.037 ***
2009	-0.135***	-0.072 ***
2010	-0.134***	-0.056 ***
2011	-0.175***	-0.059 ***
2012	-0.213***	-0.074 ***
2013	-0.23***	-0.077 ***
2014	-0.215***	-0.104 ***
capital	0.01	0.092 ***
labor	0.474***	0.436 ***
material	0.302***	0.357 ***
capital.sqr	0.003***	0.007 ***
labor.sqr	0.088***	0.076 ***
material.sqr	0.076***	0.075 ***
capital:labor	-0.016***	-0.016 ***
labor:material	-0.144***	-0.132 ***
capital:material	0.009***	-0.006 ***
sigmaSq	0.614***	0.293 ***
gamma	0.86***	0.88 ***
mu	-1.453***	-1.015 ***
log likelihood	-10047.380	-1806.675
Observations	21,766	22,846
mean efficiency	0.799	0.854
Note:	*p<0.1; **p<0.05; ***p<0.01	

capital coefficient equals approximately zero in all yearly regressions. In most years, the coefficient is insignificant. The output elasticity of capital is on average 2% and varies between 1 and 3%. The output elasticity of labor is on average 34% and varies between 32 and 38%. The output elasticity of material is on average 65% and varies between 59 and 68%. Results of the yearly regressions are comparable to the results of the fixed effect regression. Furthermore, the yearly regressions show significant squared values of labor and material, but not for capital. At least for most years, squared values of capital are insignificant. Significant positive squared values represent increasing returns to scale for those input factors. Furthermore, the coefficients of interaction terms show that the input factors capital and labor are substitutes. The coefficients are significant in the years 2008 to 2013. In all other years, the interaction term between both input factors is insignificant. By this, the results of the yearly regressions differ from the results of the fixed effect regression. The fixed effect regression results in a highly significant negative interaction term for capital and labor. Overall, the output increase in industry 208 is mainly determined by increases in input factors labor and material. According to the results of both, yearly and fixed effect regression, an increase in capital plays a minor role in the production of beverages.

Table 6.7: Yearly SFA Regressions - Industry 208

year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
(Intercept)	1.876***	2.288***	2.824***	2.717***	1.975***	1.836***	1.937***	1.807***	1.743***	2.336***
capital	-0.033	-0.065**	-0.014	-0.056*	0.044*	0.074***	-0.005	0.002	0.025	0.174***
labor	0.552***	0.646***	0.419***	0.53***	0.481***	0.394***	0.498***	0.446***	0.384***	0.276***
material	0.334***	0.217***	0.242***	0.194***	0.313***	0.381***	0.337***	0.399***	0.441***	0.235***
capital.sqr	0.006	0.004	0.003	0.006**	0.002	4.00E-03	0.002	0.006***	0.004**	0.013**
labor.sqr	0.076***	0.065***	0.074***	0.093***	0.078***	0.09***	0.1***	0.09***	0.085***	0.073***
material.sqr	0.075***	0.084***	0.072***	0.073***	0.076***	0.075***	0.081***	0.071***	0.065***	0.076***
capital:labor	-0.006	0.002	-0.006	-0.034***	-0.01*	-0.013***	-0.017***	-0.015***	-0.011***	-0.015
labor:material	-0.142***	-0.145***	-0.125***	-0.143***	-0.136***	-0.139***	-0.165***	-0.144***	-0.132***	-0.1***
capital:material	0.003	0.002	0.006	0.026***	0.002	-0.003	0.013***	0.005	0.002	-0.027**
sigmaSq	0.145***	0.415***	0.746***	0.84***	0.774***	0.731***	0.582***	0.545***	0.408***	0.05***
gamma	0	0.763***	0.862***	0.882***	0.898***	0.891***	0.858***	0.873***	0.813***	0.001
mu	-0.007	-1.126***	-1.605***	-1.722***	-1.667***	-1.614***	-1.414***	-1.38***	-1.151***	-0.016
log likelihood	-701.359	-701.930	-1232.360	-1434.999	-1282.782	-1260.273	-1190.834	-984.772	-820.593	27.142
Observations	1548	1695	2270	2511	2591	2695	2765	2775	2572	344
mean efficiency	0.999	0.832	0.785	0.773	0.776	0.783	0.800	0.802	0.829	0.997
output elasticities in percent										
capital	3	1	3	1	2	2	2	2	2	2
labor	34	32	32	35	32	34	33	33	33	38
material	65	66	63	62	68	68	67	66	67	59

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.5 reports coefficients for industry 371. The output elasticity of capital is on average 3% and varies between -2 and 5%. The output elasticity of labor is on average 25% and varies between 22 and 34%. The output elasticity of material is on average 69% and varies between 65 and 76%. Results of the yearly regressions are comparable to the results of the fixed effect regression. The coefficients for labor and material are highly significant. The coefficient for capital square is significantly positive in the years 2007 to 2013. For this coefficient, the results of the yearly regression are comparable to the results of the fixed effect regression. Similarly comparable is the positive coefficient for squared values of labor and material. The input factors capital and labor as well as labor and material are substitutes. By this, the results of the yearly regressions are again comparable to the results of the fixed effect regression. In contrast to the fixed effect regression where input factors capital and material are significant substitutes, in the yearly regressions these input factors are significant complements in the years 2008 and 2011.

Table 6.8: Yearly SFA Regressions - Industry 371

year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
(Intercept)	1.517***	1.322***	2.133***	2.051***	1.761***	1.593***	1.541***	1.719***	1.748***	1.67***
capital	0.029*	-0.027*	0.06***	0.144***	0.074***	0.119***	0.029**	0.137***	0.091***	-0.037
labor	0.492***	0.498***	0.418***	0.429***	0.425***	0.407***	0.452***	0.422***	0.454***	0.539***
material	0.42***	0.51***	0.334***	0.259***	0.376***	0.396***	0.442***	0.331***	0.337***	0.361***
capital.sqr	-0.001	-0.003*	0.004**	0.008***	0.008***	0.01***	0.003*	0.011***	0.012***	-0.013***
labor.sqr	0.102***	0.108***	0.076***	0.061***	0.068***	0.077***	0.088***	0.08***	0.069***	0.08***
material.sqr	0.088***	0.082***	0.074***	0.08***	0.068***	0.069***	0.077***	0.081***	0.073***	0.082***
capital:labor	-0.012***	-0.017***	-0.011**	-0.004	-0.015***	-0.024***	-0.011***	-0.019***	-0.018***	0.003
labor:material	-0.184***	-0.192***	-0.132***	-0.114***	-0.118***	-0.124***	-0.157***	-0.134***	-0.12***	-0.164***
capital:material	0.009***	0.023***	-0.001	-0.024***	-0.004*	-0.005**	0.005*	-0.014***	-0.01***	0.019**
sigmaSq	0.163***	0.293***	0.348***	0.292***	0.257***	0.311***	0.365***	0.293***	0.27***	0.136***
gamma	0.838***	0.914***	0.86***	0.841***	0.848***	0.886***	0.906***	0.907***	0.882***	0.834***
mu	-0.739***	-1.035***	-1.095***	-0.992***	-0.934***	-1.049***	-1.15***	-1.031***	-0.977***	-0.675***
log likelihood	323.890	33.371	-441.402	-412.853	-198.337	-246.980	-242.311	37.460	-81.688	53.598
Observations	1867	2031	2432	2580	2646	2776	2829	2826	2616	243
mean efficiency	0.884	0.853	0.848	0.855	0.861	0.850	0.843	0.855	0.857	0.900
output elasticities in percent										
capital	1	1	3	3	5	5	4	4	5	-2
labor	24	22	26	27	25	24	24	24	25	34
material	72	76	67	66	69	68	71	70	69	65

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 6.2, 6.3 and 6.4 show output elasticity estimates and the 95% confidence interval for labor, capital and material for both industries. Output elasticity estimate is calculated according to De Loecker and Warzynski (2012) as:

$$\hat{\theta}_{it}^{j} = \hat{\beta}_j + 2\hat{\beta}_j x_{it}^{j} + \sum_k \hat{\beta}_{jk} x_{it}^{k} \tag{6.4}$$

where $i = firm$, $j, k = \{labor, capital, material\}$ and $j \neq k$.
Except for 2014, the labor output elasticity is for both industries varies little around 35%. The labor output elasticity of the industry 208 is higher than the labor output elasticity of the industry 371. Therefore, the industry 208 seems to be more labor intense. Concluding, the production of beverage needs a higher increase of labor force for each percent of sales increase than the production of motor components. This might result from the degree of automation. If the automation is high, the labor intensity is low and the capital intensity is high. This hypothesis could be supported by the estimate for capital output elasticity. Different than expected, the capital output elasticity is higher for the industry 208 in the years 2005 to 2007. Later on, until 2012, capital output elasticity is similar for both industries with a value ranging around 2%, while the industry 371 has a higher capital output elasticity than the industry 371. Compared to the labor output elasticity the capital output elasticity is relatively small. An increase of one percent of capital results in a sales increase of about one to five percent if labor and material are stable. If sales needs to be increased the investment in capital will be a subordinate instrument as the the output elasticity is small. In contrast, the material output elasticity is high. It ranges between 59% and 63% for industry 208. For industry 317, the material output elasticity is much more volatile. It ranges between 66% in 2006 to 56% in 2008. Concluding, the production of motor vehicles is confronted with a highly volatile material output elasticity which can be party traced back to volatile prizes for raw material markets such as steel, plastics and oil. Overall, material has the highest impact on output.

Efficiency

Figure 6.5 shows mean efficiency and the 95% confidence interval for both industries, 208 and 371, per year. As OLS residuals of the industry 208 are right-skewed in the years 2005 and 2014, the mean efficiency is close to one and the variance is small. Those years cannot be interpreted. Industry 208 seems to have an average efficiency loss in the years 2005 to 2008. The mean efficiency dropped from approximately 83% to 77%. Beginning in 2009 the industry recovered and mean efficiency increased back to 83% in 2013. Mean efficiency of industry 371 is on average higher than the

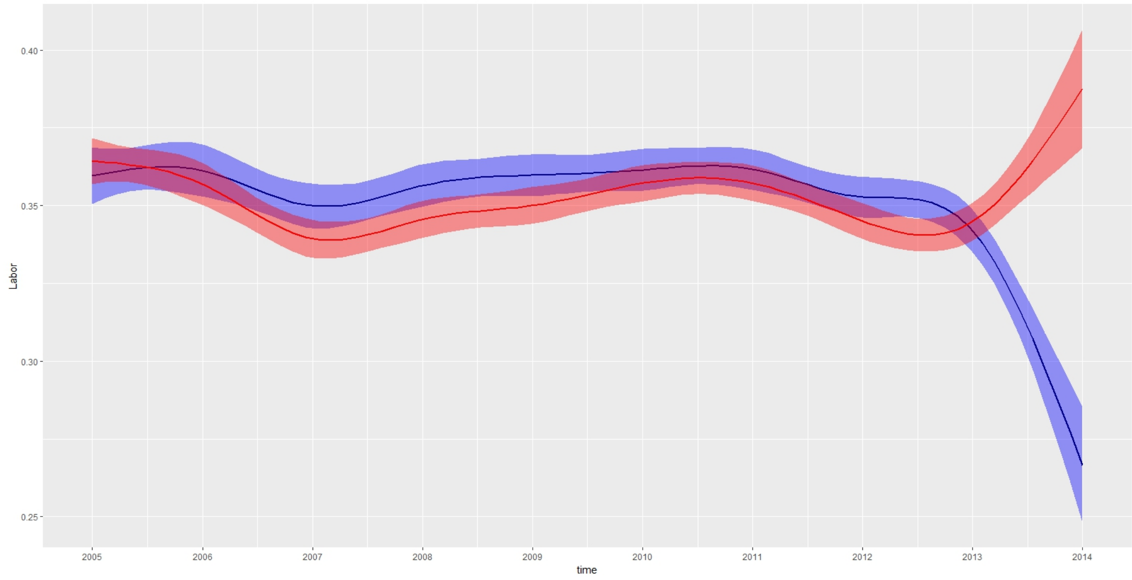


Figure 6.2: Labor Output Elasticity - Industry 208 (blue) and 371 (red)

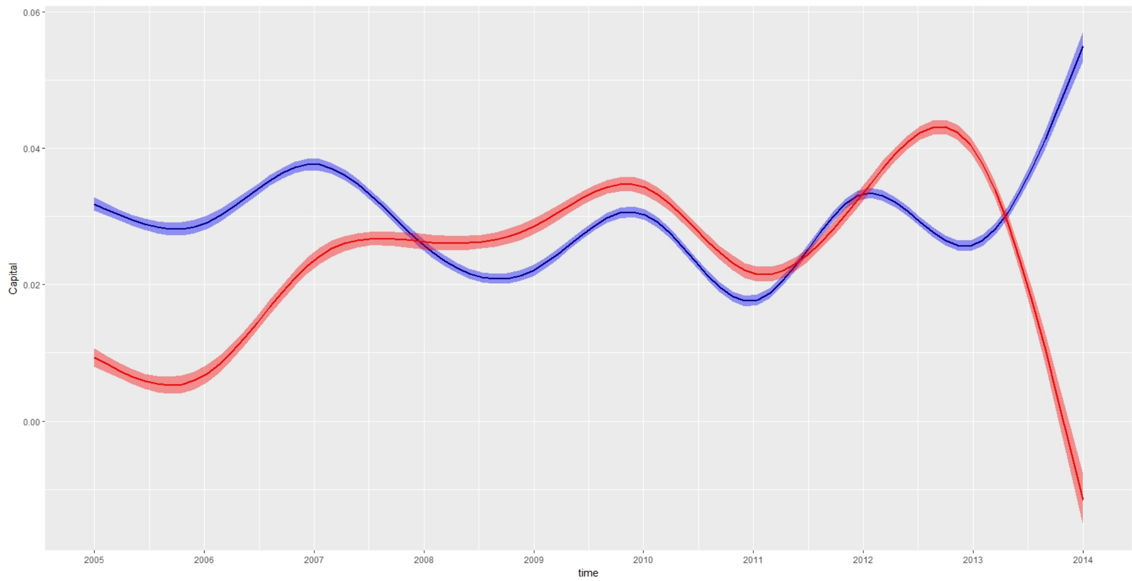


Figure 6.3: Capital Output Elasticity - Industry 208 (blue) and 371 (red)

mean efficiency of industry 208 ranging between 84% in 2011 and 89% in 2014. In general, the mean efficiency of industry 371 is more stable than the mean efficiency of industry 208. The industry of motor vehicle production shows a small efficiency loss in 2007 and 2011. Surprisingly, mean efficiency is increasing from 2007 to 2009 even though the number of sold vehicles in Europe decreased during this period as shown in figure 6.6. One possible explanation is that only firms that survived the crises can be observed. These firms were perhaps forced to increase efficiency because otherwise they had to leave the market and were not be observable.
The mean output of industry 208 of approximately 28.6 M€ equals an average efficiency of 80%. An efficiency increase of 1% equals an output increase of 2.9 M€.

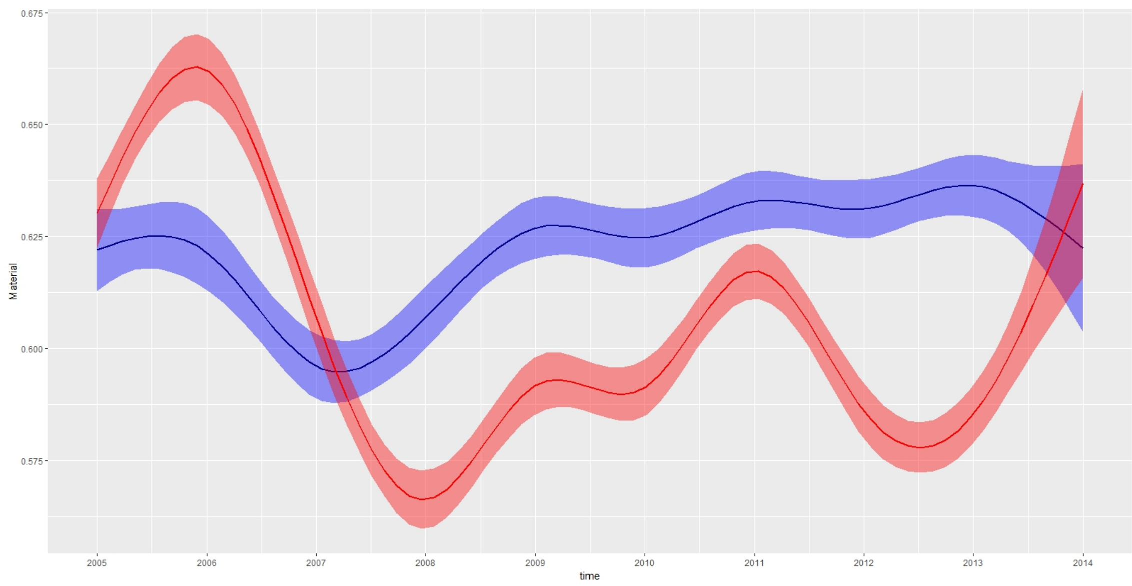


Figure 6.4: Material Output Elasticity - Industry 208 (blue) and 371 (red)

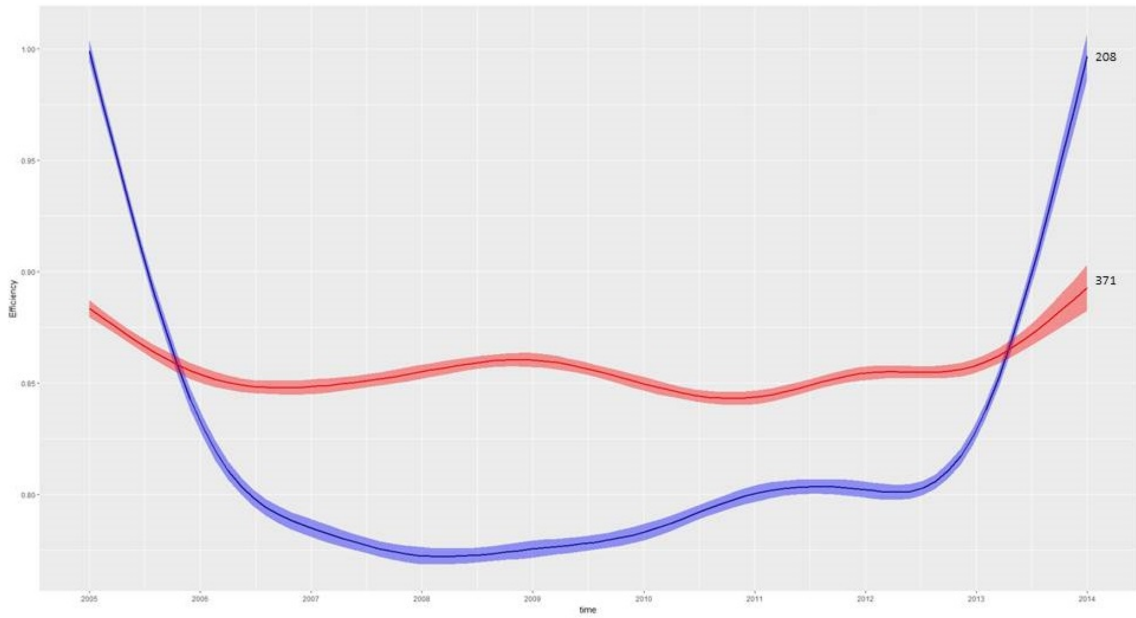


Figure 6.5: Efficiency - Industry 208 and 371

For industry 371 an efficiency increase of 1% equals an average output increase of 16.9 M€.

Horizontal Mergers

Table 6.9 shows the number of identified buyers and targets in both industries, industry 208 and industry 371.

Table 6.10 shows summary statistics for efficiency. In industry 208, the mean efficiency of buyers and targets is higher than the overall mean efficiency. Furthermore,

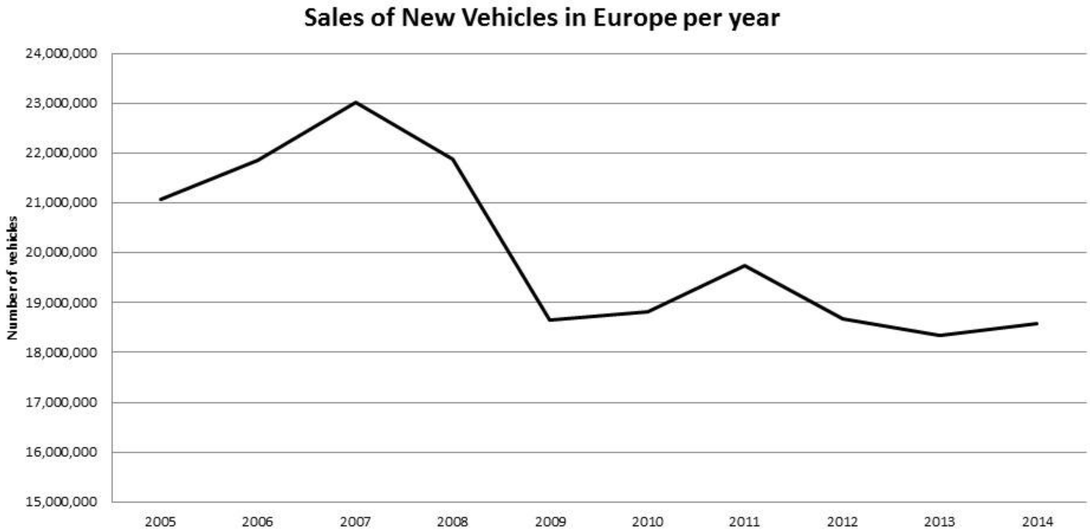


Figure 6.6: Sales of New Vehicles in Europe (OICA, 2017)

Table 6.9: Identified Buyers and Targets in Industries 208 and 371

Industry	Buyers	Targets
208	113	85
371	42	66

the mean efficiency of targets is higher than the mean efficiency of buyers. In industry 371, the mean efficiency of buyers is higher than the overall mean efficiency. In contrast, the mean efficiency of targets is lower than the overall mean efficiency and lower than the mean efficiency of non-merging firms. For both industries there exist approximately the same number of observations. The standard deviations of overall efficiency in industry 208 are higher than the standard deviations of overall efficiency in industry 371, which results mainly from the efficiency estimates in the years 2005 and 2014. The standard deviations of buyers' and targets' efficiency are smaller than the standard deviation of efficiency of the overall data set for industry 208. Especially for targets, the standard deviation is relatively small. This may indicate that the efficiency of a firm increases its probability to be a target. In contrast, the targets' standard deviation of efficiency is larger than the standard deviation of efficiency of the overall data set for industry 371. At the same time, the standard deviation of buyers' efficiency is very small. In industry 371, this may indicate that the more efficient a firm is the more likely it will be a buyer.

According to the Welch two Sample t-test, the differences in mean efficiency between buyers or targets and the overall data set for industry 208 are significant with a p-value smaller than 0.01. The same can be observed concerning the difference in mean efficiency between buyers and targets in industry 208. For industry 371, the difference in mean efficiency between buyers and the overall data set is significant, as well as the difference between buyers and targets is significant. However, the difference between targets and the overall data set is insignificant. Figure 6.7 and figure 6.8 show density functions of efficiency for industry 208 and 371. The right hand tail for industry 208 results from the efficiency estimates in the years 2005 and 2014. The figure shows once again that the mean efficiency is higher and the standard deviation is smaller in industry 371 than in industry 208. Furthermore, the figure shows the differences in means. It further shows that the overall mean efficiency of industry 371 is close to the mean efficiency of targets. Furthermore, buyers in the industry 371 seem to be highly efficient.

Table 6.10: Summary Statistics for Efficiency

Statistic	N	Mean	St. Dev.	Min	Max
ind 208: overall	21,766	0.814	0.115	0.003	0.999
ind 208: buyers	1,640	0.824	0.112	0.106	0.999
ind 208: targets	742	0.837	0.086	0.305	0.999
ind 208: non-merging firms	20,383	0.813	0.116	0.003	0.999
ind 371: overall	22,846	0.856	0.085	0.003	0.989
ind 371: buyers	361	0.871	0.042	0.672	0.960
ind 371: targets	595	0.854	0.092	0.054	0.943
ind 371: non-merging firms	22,094	0.856	0.085	0.003	0.989

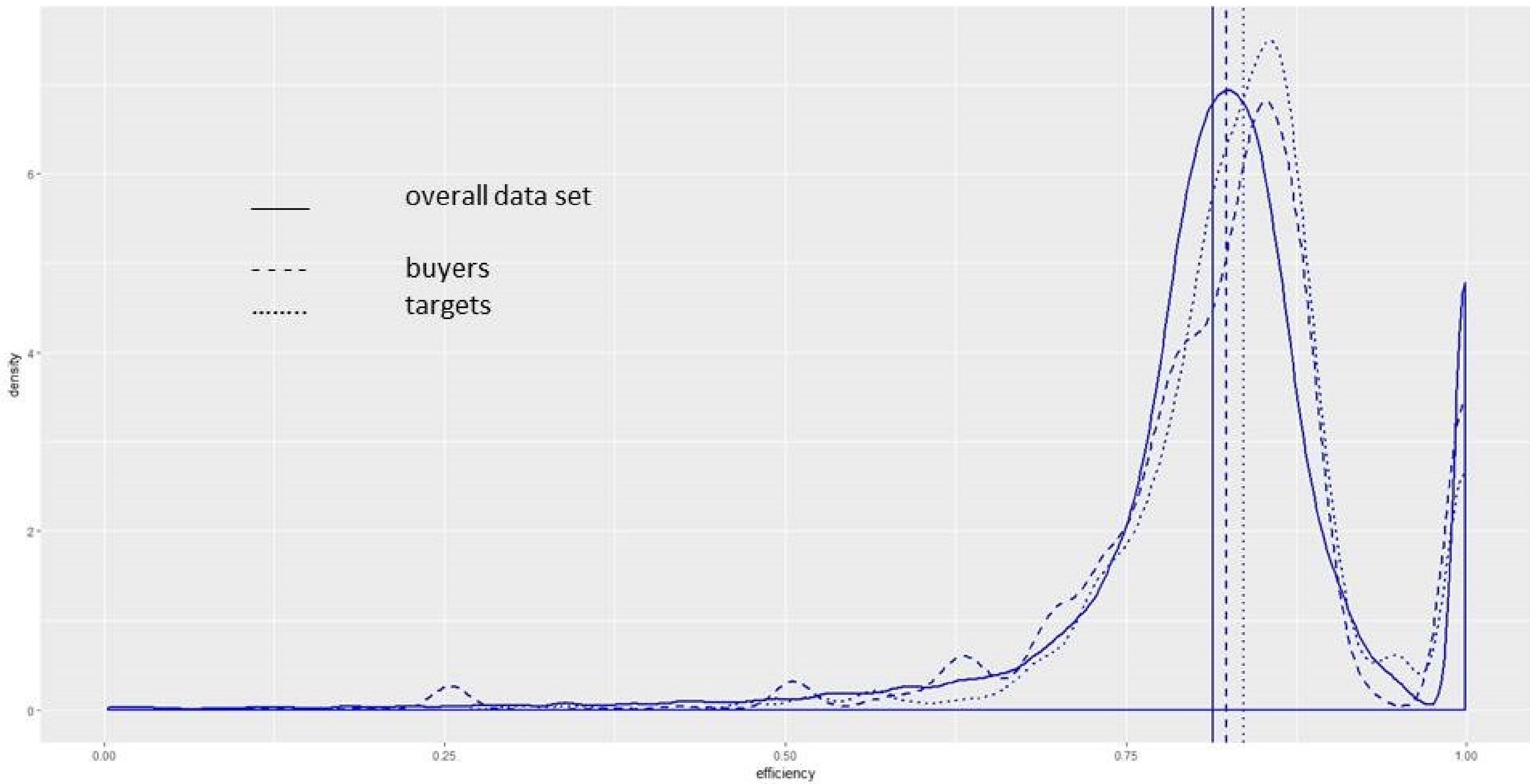


Figure 6.7: Density function of efficiency - Industry 208

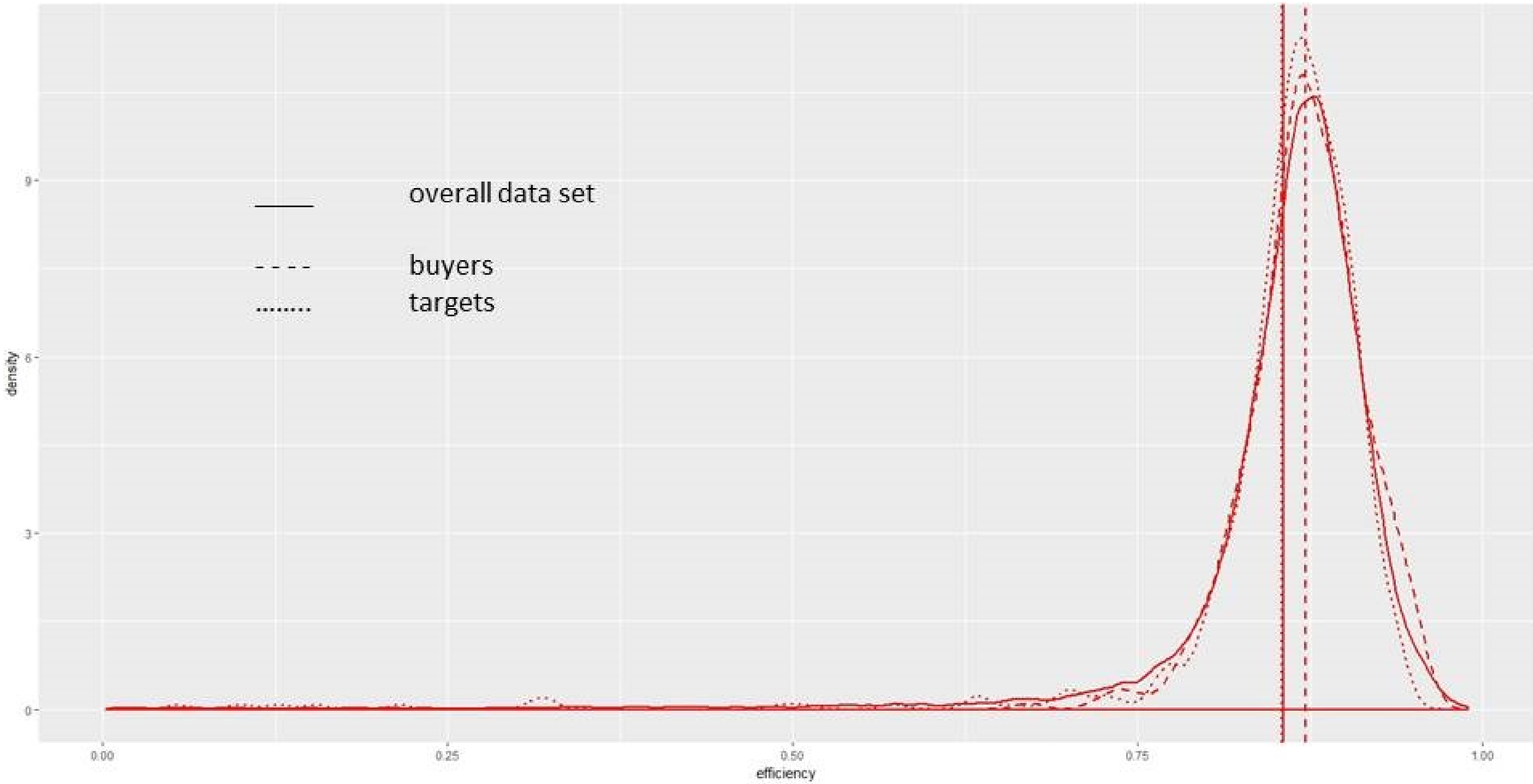


Figure 6.8: Density function of efficiency - Industry 371

Figure 6.9 and 6.10 show the development of mean efficiency over time for industry 208 and 371. For industry 208, the development of targets' mean efficiency is above and in parallel to the development of the overall mean efficiency. Buyers' mean efficiency is below the overall mean efficiency until 2007. Beginning in 2008 the development is parallel to the development of overall mean efficiency. Concluding, the significantly higher mean efficiency of buyers and targets is observable most of the time. For industry 371, the development of buyers' mean efficiency is above and parallel to the development of the overall mean efficiency. Targets' mean efficiency is below average until 2008 and above until 2011. Beginning in 2012 targets' mean efficiency is identical to overall mean efficiency. Concluding, the insignificant difference in mean efficiency between targets and the overall data set results on the one hand from a partly lower and partly higher mean efficiency over time and on the other hand from a similar mean efficiency in the years 2012 to 2014.

The density function of efficiency estimates resulting from the application of the SFA approach, as shown in figures 6.7 and 6.8, show that results of the applied SFA approach are comparable to the results of the TFP approach with regard to efficiency estimates as shown in figure 4.1. Results differ only by the fact that the applied SFA approach is a cross-sectional model while the applied TFP approach is a panel data model. Thus, the efficiency estimates in industry 208 for the years 2005 and 2014 cause a right-hand tail in the distribution of efficiency estimates for the SFA approach, while in the TFP approach the two years cause a high mean productivity.

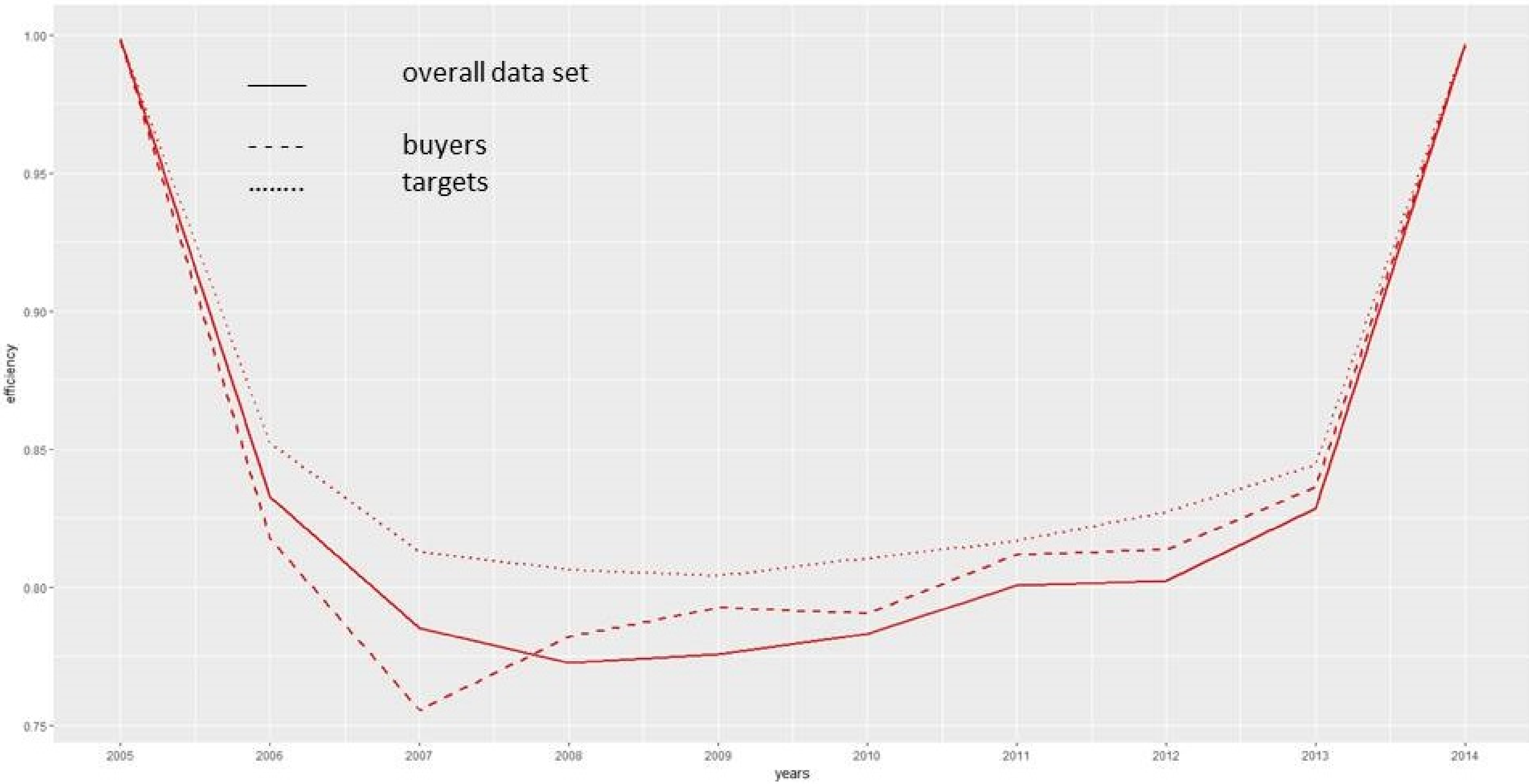


Figure 6.9: Mean Efficiency per Year - Industry 208

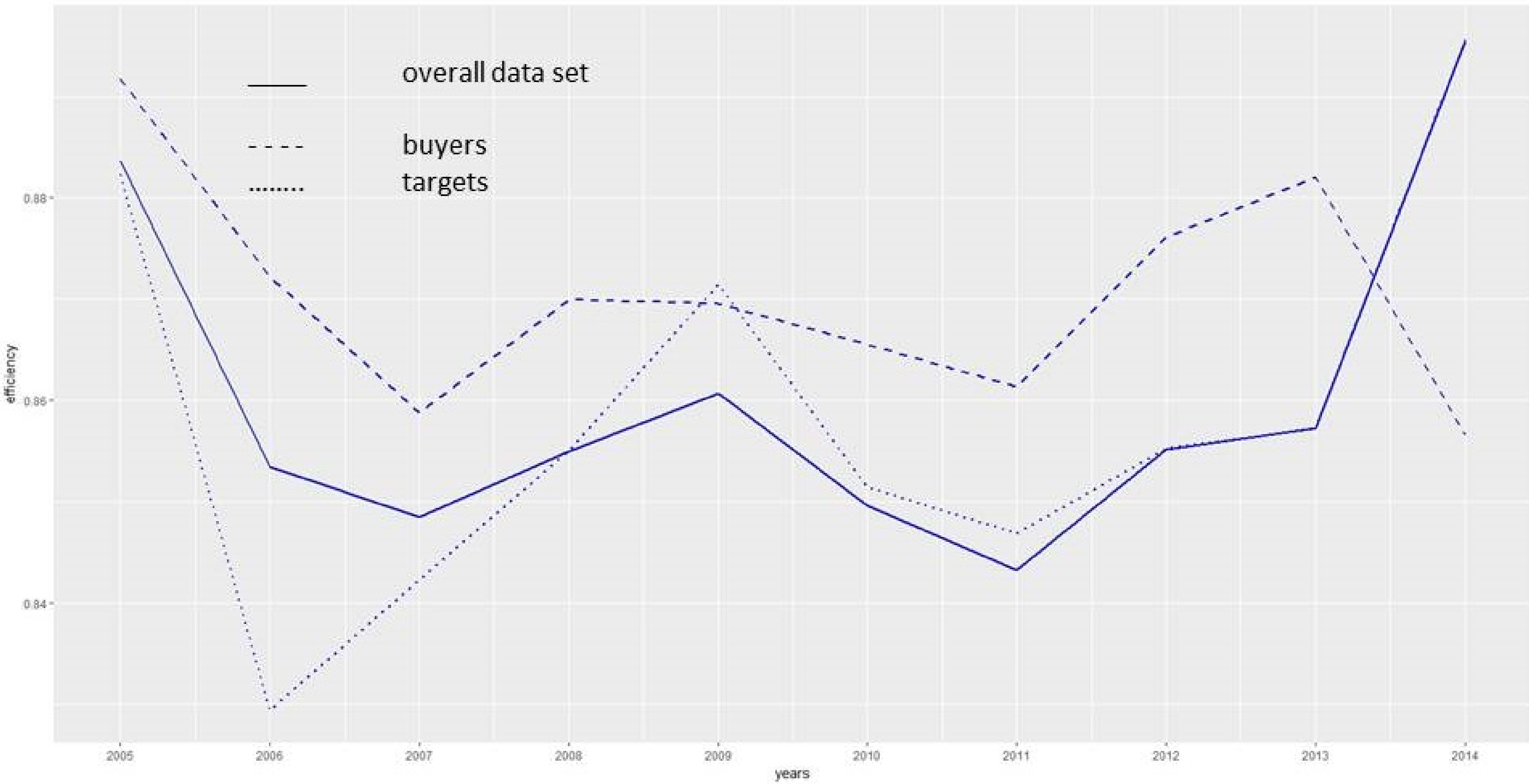


Figure 6.10: Mean Efficiency per Year - Industry 371

Table 6.11 shows the number of observations per merger period. Especially, in periods long before or after the merger, e.g. periods -9, -8, -7 and 7, 8, 9, the number of observable buyers and especially targets is rather small.

Table 6.11: Number of Buyers and Targets per Period - Industry 208 and 371

period	ind 208: buyers	ind 208: targets	ind 371: buyer	ind 371: target
-9	4	1	2	5
-8	29	5	11	10
-7	47	12	18	18
-6	67	20	21	25
-5	90	31	24	37
-4	109	39	26	43
-3	123	52	32	48
-2	147	63	34	51
-1	157	74	43	66
0	181	82	42	61
1	159	78	26	61
2	134	71	19	47
3	116	64	17	39
4	96	45	14	30
5	72	43	11	22
6	55	32	10	16
7	35	21	7	10
8	17	8	3	6
9	2	1	1	

Figure 6.11 and figure 6.12 show the development of mean efficiency of buyers and targets in industry 208 and 371 in pre- and post-merger periods. For industry 371, the figure shows that buyers are consequently above mean efficiency of the industry. In contrast, the mean efficiency of targets varies between being above and below mean efficiency of the industry. In the merger period itself, the targets' mean efficiency is below while buyers' mean efficiency is above the mean efficiency of the industry. Moreover, for the time horizon between pre-merger period -6 and post-merger period 6, targets' mean efficiency is at its lowest level and buyers' mean efficiency is at its highest level in the merger period. One possible interpretation is that buyers tend to merge at a very high efficiency level while targets are merged at a very low efficiency level. If the efficiency level was low, this might have an impact on the value of the firm and therefore on the price of the merger. A low efficiency

level is partly reflected by the profit margin (e.g. the EBITDA). The profit margin, especially the EBITDA, is a reference point for a buyer to anticipate the break-even of an investment. The lower the profit margin, the lower the price of the merger. Furthermore, if the efficiency level is partly reflected by the profit margin, one can expect high profits with firms that are highly efficient. Consequently, if buyers have high profits in the merger period, a merger may be partly explained by available fortune of buyers that can be invested in a merger. As the number of observations per period is small, without analyzing period by period, it may make sense to aggregate pre- and post-merger periods. The comparison of buyers' mean efficiency of pre- and post-merger periods shows little differences between both. Therefore, the analysis of merger-specific efficiency gains may result in insignificant coefficients for buyers. In contrast, the comparison of targets' mean efficiency in pre- and post-merger periods shows that targets are below the mean efficiency of the industry in pre-merger periods and above in post-merger periods. Concluding, the analysis of merger-specific efficiency gains may result in significant coefficients for targets.
For industry 208, the mean efficiency of targets and buyers varies a lot. This is similar to industry 371. In contrast to industry 371, targets' mean efficiency and not buyers' mean efficiency is consequently above the mean efficiency of the industry, while buyers' mean efficiency varies between being above and below mean efficiency of the industry. In the merger period itself, buyers and targets have a nearly identical mean efficiency. The comparison of buyers' pre-merger and post-merger mean efficiency shows that both are above mean efficiency of the industry. But, buyers' pre-merger mean efficiency is 83%, which is higher than their post-merger mean efficiency of 82%. The difference is even larger for targets. Their pre-merger mean efficiency is 85% while their post-merger mean efficiency is 93%. The difference may indicate that the analysis of merger-specific efficiency gains results in significant coefficients for buyers and targets.
The figure shows large differences between industries. While the industry 371 buyers tend to be more efficient than targets, industry 208 shows the opposite trend. While the difference between buyers' as well as targets' mean efficiency in pre-merger and post-merger periods is small for industry 371, those differences are large for industry 208. While the difference of buyers' and targets' mean efficiency is large for industry 371 this difference is small for industry 208. These differences between industries as well as the high variation of mean efficiency over periods may indicate that each industry and each merger is different.

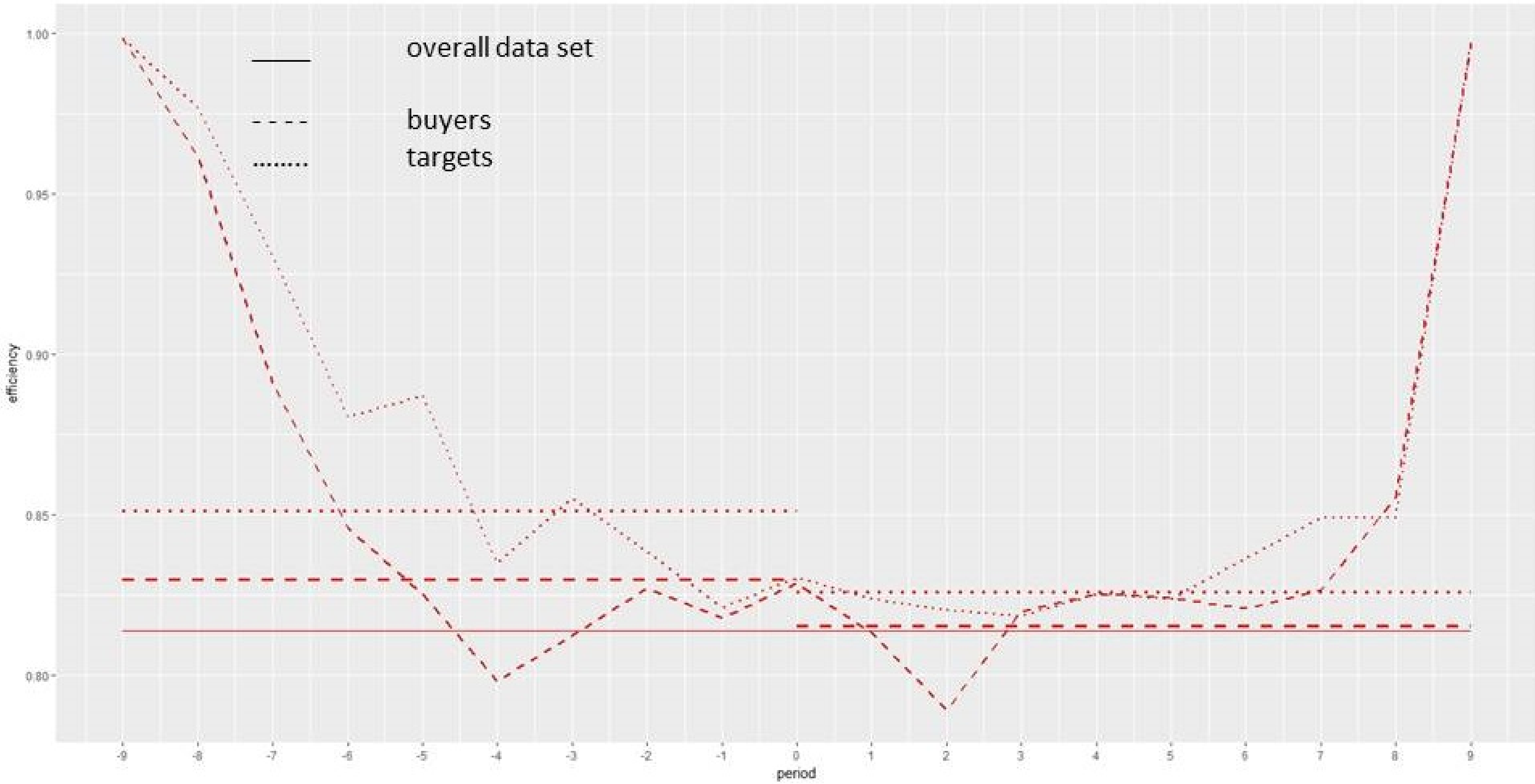


Figure 6.11: Mean Efficiency per Period - Industry 208

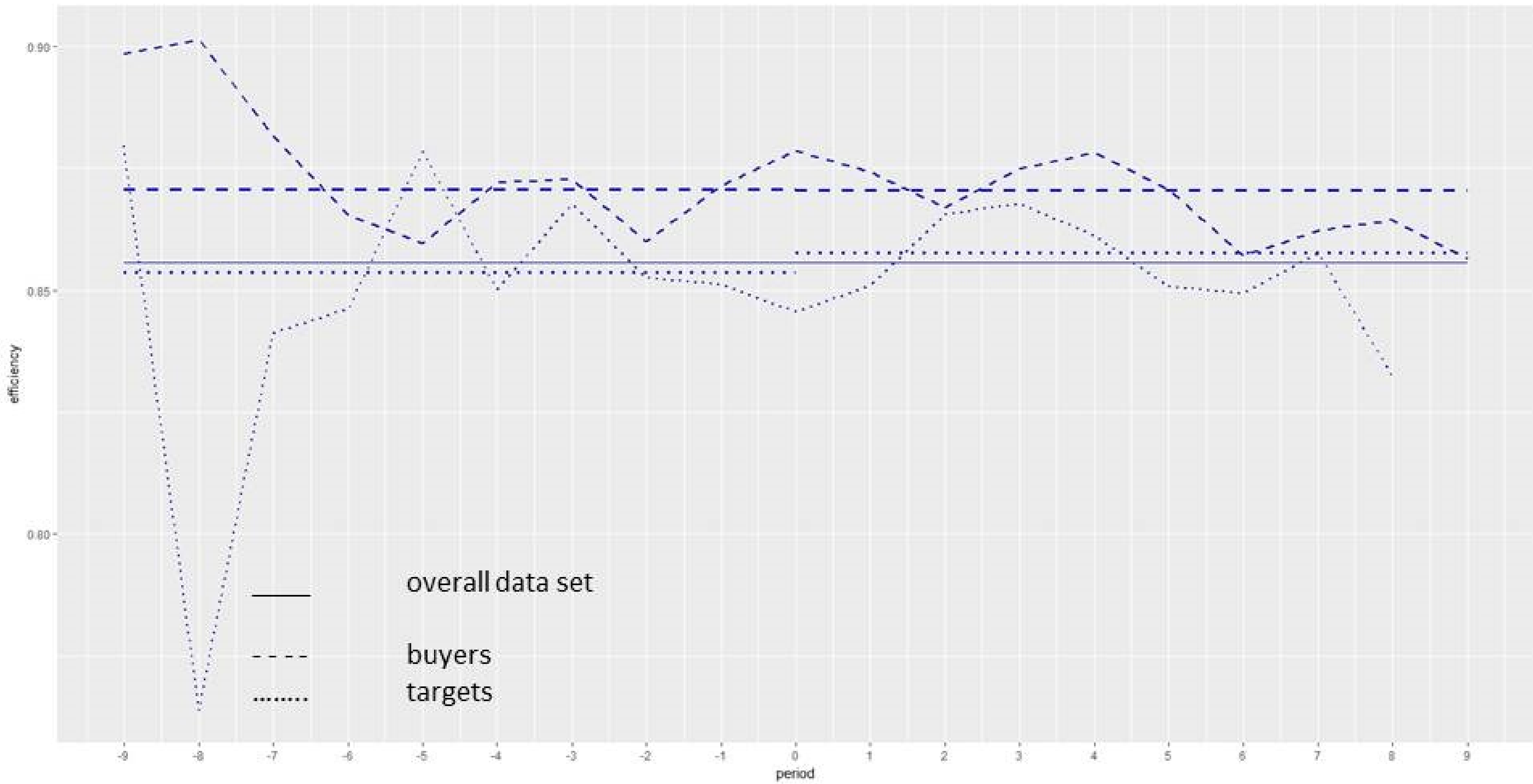


Figure 6.12: Mean Efficiency per Period - Industry 371

DID

The DID approach applied is introduced in chapter 5.[10] Table 6.12 shows results of the DID regression as introduced in equation (5.3) for industry 208 using all firms in the industry as control group. For the purpose of clarity, fixed effects are not shown. The fixed effects control for firm-size time trends and country time trends. Therefore, the DID estimates differences in efficiency after efficiency has been standardized with regard to country and firm-size effects. "Pre merger" is a dummy variable, which equals one, if the treated firm faces a merger in one of the following years, and zero otherwise. Therefore, the coefficient is an estimate for the difference between the mean pre-merger efficiency of treated firms and the overall mean efficiency of the industry. A firm is treated if it is involved into a merger as either buyer or target. For each post-merger period, the model includes one dummy variable that equals one if the treated firm was involved in a merger in one of the previous years and zero otherwise. For the first post-merger period the dummy variable is named "post.period1" and so forth.[11] The coefficient of the post-merger period dummy variables estimate the difference between the mean efficiency of treated firms in the defined period towards the mean pre-merger efficiency.
Results in table 6.12 tell that buyers' mean pre-merger efficiency does not significantly differ from the overall mean efficiency after controlling for the country and firm-size time trends. Furthermore, the post-merger mean efficiency of buyers does not differ significantly from their pre-merger efficiency. In contrast, targets are approximately 1% more efficient in pre-merger periods than other firms in the industry. In post-merger periods, the mean efficiency of targets does not differ significantly from their pre-merger efficiency.
Concluding, either mergers have an insignificant impact on mean efficiency of buyers and targets, or the available data set is insufficient to analyze the impact of mergers on targets' efficiency. The R^2-value for both regressions is about 36 to 37%. Thus, other influences except mergers may explain the variance of efficiency, and their impact may be much higher than the impact of mergers on efficiency. Furthermore, the F-statistic is highly significant, which indicates that the combination of chosen independent variables is capable to explain efficiency. Other authors, e.g. Blonigen and Pierce (2016), use fixed effects instead of yearly dummy variables to capture mean post-merger efficiency. An advantage of fixed effects towards the yearly dummy variables is the consistency of the estimate. A disadvantage of the estimate is the

[10] Efficiency changes based on efficiency estimates resulting from the application of frontier approaches can alternatively be decomposed with the help of the Malmquist Index. In the context of this study, the data set is too small to apply the analysis of merger-specific efficiency gains based on the decomposition of the Malmquist Index. For more details, see Appendix 9.14.

[11] Alternatively, post-merger periods can be aggregated. For more information, see appendix 9.14.

needed assumption that defines the beginning and end of the post-merger period. The chosen model using yearly dummy variables to capture post-merger efficiency allows to describe the merger process through out the years. Thus, the model needs less assumption for the price of statistical consistency.

Table 6.13 shows results of the DID regression for industry 371 using all firms in the industry as control group. Results show that the pre-merger efficiency of targets is approximately one percentage point below the mean efficiency of the industry. This difference is significant. In contrast, buyers' pre-merger efficiency is not significantly different compared to the mean efficiency of the other firms in the industry. Furthermore, buyers' post-merger efficiency does not differ from their pre-merger efficiency. This is the case for any post-merger period. Similarly, the difference between pre- and post-merger efficiency of targets is insignificant. Concluding, mergers seem to have no relevant impact on the efficiency of firms in the industry 371. Nevertheless, the R^2 value for both DID regressions is approximately 21%. Compared to the DID regression in industry 208, the chosen independent variables and the fixed effects explain less of the variance of efficiency. Again, the F-statistic is highly significant, which indicates that the combination of chosen dependent variables is capable to explain efficiency.

6.6 Conclusion

This chapter concentrates on the application of an SFA approach to analyze merger-specific efficiency gains. The chosen SFA model is a basic cross-sectional model. Thus, each year of the panel data set is treated as cross-sectional data set. Even though, the chosen model requires several assumptions and can be further discussed, the results allow to partly explain three common approaches that can be found in literature.

First, the majority of empirical studies that analyze merger-specific efficiency gains stochastically in the manufacturing sector apply a TFP approach. Empirical studies that apply frontier approaches are often focused on certain industries. The TFP approach might be partly preferred to a frontier approach as it allows to estimate productivity without the assumption of inefficiency.

Secondly, most empirical studies aggregate pre- or post-merger observations and analyze differences in means (e.g. Maksimovic and Phillips (2001) and Blonigen and Pierce (2016)). From a theoretical perspective, it is indefinite at which time mergers do have an impact on efficiency of merging parties. Therefore, the analysis of merger-specific efficiency gains according to periods provides more differentiated results than an aggregated approach. But, as the available data set does often not provide enough information to apply an analysis according to periods, the aggrega-

Table 6.12: DID regression for Industry 208 using all Firms as Control Group

	Dependent variable:	
	efficiency	
	Ind 208: buyer	Ind 208: target
pre.merger	0.0002	0.010***
	(-0.003)	(0.005)
post.period1	0.003	0.002
	(-0.008)	(0.012)
post.period2	−0.003	0.006
	(-0.009)	(0.012)
post.period3	0.004	−0.001
	(-0.009)	(0.013)
post.period4	0.002	0.012
	(-0.01)	(0.015)
post.period5	0.004	0.001
	(-0.011)	(0.015)
post.period6	−0.012	−0.001
	(-0.013)	(0.017)
post.period7	−0.009	0.013
	(-0.016)	(0.021)
post.period8	−0.024	0.006
	(-0.023)	(0.034)
post.period9	−0.003	−0.010
	(-0.072)	(0.095)
Observations	22,546	21,904
R^2	0.374	0.357
Adjusted R^2	0.367	0.349
Residual Std. Error	0.092 (df = 22,290)	0.093 (df = 21,648)
F-statistic	52.23*** on 255	47.13*** on 255
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6.13: DID regression for Industry 371 using all Firms as Control Group

	Dependent variable:	
	efficiency	
	Ind 371: buyer	Ind 371: target
pre.merger	0.004	-0.011^{***}
	(-0.005)	(0.004)
post.period1	0.001	0.004
	(-0.016)	(0.011)
post.period2	-0.005	0.018
	(-0.018)	(0.012)
post.period3	-0.0001	0.021
	(-0.019)	(0.013)
post.period4	0.007	0.016
	(-0.021)	(0.015)
post.period5	-0.001	0.015
	(-0.024)	(0.017)
post.period6	-0.017	0.021
	(-0.025)	(0.020)
post.period7	-0.015	0.032
	(-0.029)	(0.025)
post.period8	-0.013	0.036
	(-0.045)	(0.032)
post.period9	-0.104	
	(-0.094)	
Observations	22,918	22,960
R^2	0.208	0.207
Adjusted R^2	0.2	0.199
Residual Std. Error	0.076 (df = 22,671)	0.076 (df = 22,714)
F-statistic	24.23^{***} on 246	24.26^{***} on 245
Note:	*p<0.1; **p<0.05; ***p<0.01	

tion of periods is a possible solution.
Third, most empirical studies analyze buyers and targets separately or analyze only one of them. Instead, it would be theoretically possible to analyze both of them together and analyze the impact that a merger has on the newly aggregated firm. This analysis is possible with the decomposition of the Malmquist Index. Most empirical studies, that analyze buyers and targets of the same merger, are either case studies (e.g. Ravenscraft and Scherer (1987)[12]) or they are based on a small data set and therefore tend to apply non-stochastic approaches like the DEA approach (e.g. Zschille (2014)). This chapter suggests that the separate analysis of merging parties is also data driven as it is difficult to identify pre-merger efficiency of both, buyer and target within one merger.
Furthermore, this chapter emphasizes differences between two manufacturing industries. The detailed analysis of the two industries, 208 "Beverages" and 371 "Motor Vehicles and Motor Equipment" shows that industries differ by their production technology. On the one hand, both production technologies are characterized by increasing economies of scale. Furthermore, both industries show a decrease in technical change between the years 2005 and 2014. On the other hand, there are differences between both industries. While the coefficients of the production technology of industry 371 show substitute effect for all input factors, industry 208 is characterized by a complementary effects between material and capital. The production technology of industry 208 is dominated by the usage of labor, as an increase in labor has the largest impact on output. Furthermore, the usage of capital is insignificant. The production technology of industry 371 is dominated by labor, but material is similarly dominant. Furthermore, the material output elasticity is highly volatile. Concluding, the results strengthen the common approach to estimate production functions industry-wise as industries differ significantly.
This chapter also shows that the analysis of merger-specific efficiency gains will be limited to a few meaningful results if the underlying data set is small. The analysis of mergers in both industries shows that efficiency of buyers and targets also differ depending on the industry. After controlling for country and firm-size effects, the differences in efficiency of buyers and targets towards the overall industry is mostly insignificant. Especially differences between pre- and post-merger periods are insignificant. Table 6.14 summarizes the results of the analysis of merger-specific efficiency gains. Only pre-merger efficiency of targets differs from the overall efficiency of an industry. But, while targets in industry 208 are more efficient, targets in industry 371 are less efficient than other firms in the industry. However, the analysis of merger-specific efficiency gains according to industry does not allow to estimate significant effects. This may be partly due to the small data sets. Nevertheless,

[12] For an overview see e.g. Fisher and Lande (1983).

the results indicate that targets may be more efficient in post-merger periods than in pre-merger periods. The same is indicated for buyers. The results of the analysis of merger-specific efficiency gains based on TFP show a similar direction, and estimates are significant (see chapter 5).

Table 6.14: Summary of Merger-specific Efficiency Gains - Industry 208 and 371

Industry 208: mean efficiency		Industry 371: mean efficiency	
pre-merger	post-merger	pre-merger	post-merger
target (+1%) > overall		target (-1%) < overall	
buyer > overall		buyer > overall	
target	< target	target	< target
buyer	< buyer	buyer	= buyer

This chapter shows that using SFA efficiency estimates for the analysis of merger-specific efficiency gains result in similar results as the analysis based on TFP estimates. But, an analysis of merger-specific efficiency gains according to industry results in insignificant effects. The SFA approach can only be applied to industries for which the assumption of inefficiency holds. As the TFP approach can be applied without this assumption, the TFP approach is preferred for the analysis of a sector including several industries. This is possible, as the analysis of a sector including several industries allows to generate a data set that is large enough to estimate significant efficiency changes from mergers.

Chapter 7

Predicting Conditions

7.1 Introduction

Akhavein et al. (1997) conclude that if specific conditions can be determined, which reasonably and accurately predict when mergers are likely to result in efficiency gains, the merger approval/denial process might be improved.

This chapter intends to analyze specific conditions that predict when mergers are likely to result in efficiency gains. Empirical studies that analyze merger-specific efficiency gains often focus on whether mergers are likely to results in efficiency gains or not. Some empirical studies, like Maksimovic and Phillips (2001), analyze specific conditions that predict when mergers are likely to result in efficiency gains. The following chapter analyzes conditions that may predict when mergers result in efficiency gains by considering two viewpoints. One viewpoint is that of regulatory bodies, which are interested in conditions that help to decide if merger-specific efficiency gains of a notified merger are likely or not. Second viewpoint is that of firms, which are interested in conditions that help to decide whether and how much they are willing to invest into a merger. Thus, this chapter concentrates on testing the impact of merger categories, merger indicators and firm characteristics on short-, mid- and long-term efficiency changes of buyers and targets. The impact is tested with the help a multiple regression, which can be defined as

$$y_{it} = x_{it}'\beta + \epsilon_{it} \tag{7.1}$$

where y_{it} is a demeaned merger-specific efficiency change of merging firms in year t, and x_{it} is a vector of merger categories, merger indicators or firm characteristics. Efficiency is demeaned by industry-, country-, and firm-size-specific time trends. The multiple regression introduced in equation 7.1 focuses on efficiency changes of buyers and targets. Results are used to identify factors that have an impact on merger-specific efficiency gains.

7.2 Data

Table 7.1 summarizes efficiency changes of merging firms in a short-term, mid-term and long-term. The efficiency estimates result from the TFP approach described in chapter 4. As those efficiency estimates are demeaned by industry-, country-, and firm-size-specific time trends, the efficiency changes are further defined as merger-specific. The short-term merger-specific efficiency change is calculated as the difference between the mean pre-merger productivity and the mean productivity in the first post-merger period. A mid-term merger-specific efficiency change uses the third post-merger period, as reference, and a long-term merger-specific efficiency change is based on the fifth post-merger period. Pre-merger efficiency is defined as the average efficiency over all pre-merger periods.

Table 7.1 shows that the short-term as well as the mid-term efficiency change of buyers is negative, while the long-term is positive. Even though the number of observations is decreasing and the standard deviations are increasing from short- to long-term, the observed buyers tend to generate merger-specific efficiency losses in a short-term and merger-specific efficiency gains in a long-term. Figure 7.1 visualizes the distribution of efficiency changes. The standard deviation increases over the periods.

Table 7.1 further shows that the short-term, mid-term and long-term efficiency changes of targets are positive. The number of observations is smaller than for buyers and is decreasing from short-term to long-term. Overall, the observed targets tend to generate merger-specific efficiency gains in a short-, mid- as well as long-term perspective. Figure 7.2 visualizes the distribution of efficiency changes. Interestingly, the mean efficiency change as well as its standard deviation is much higher in a mid-term perspective than in a short- or long-term perspective. The distribution of mid-term efficiency changes shows that a lot of targets generate efficiency gains with a value larger than 0.25. For values larger 0.25 the distribution shows flatter decrease than expected.

7.3 Merger Categories

Maksimovic and Phillips (2001) show that there are differences in productivity depending on whether a firm sells its main or subordinate division and whether the buyer adds the target to its main or a subordinate division. The authors differentiate mergers by the matching of segments. They analyze whether post-merger efficiency differs from pre-merger efficiency, depending on whether the horizontal merger is a "main-to-main", "main-to-sub", "sub-to-main" or "sub-to-sub" merger. The present study adapts this approach and uses dummy variables for merger categories as in-

Table 7.1: Summary Statistics: Efficiency Change

	Obs.	Min	Max	Mean	Std. Dev.
short-term (period +1)					
Buyers	1,880	-2.9190	1.2887	-0.0095	0.1906
Targets	225	-1.1129	1.4382	0.0288	0.2668
mid-term (period +3)					
Buyers	1,192	-2.8961	1.1182	-0.0044	0.1937
Targets	154	-1.0052	5.0234	0.0662	0.5589
long-term (period +5)					
Buyers	754	1.5167	3.2712	0.0059	0.2227
Targets	81	-0.9926	1.5487	0.0003	0.3416

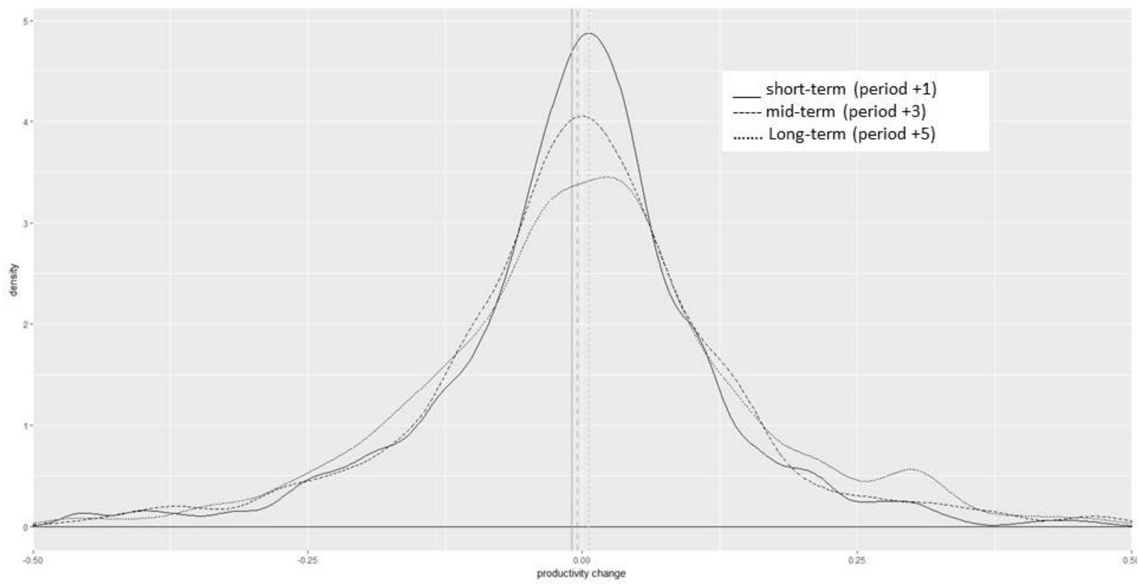


Figure 7.1: Efficiency Change of Buyers

dependent variables to explain efficiency changes.

Table 7.2 summarizes the results of applying a multiple regression to explain efficiency changes of buyers by merger categories. The intercept represents the mean efficiency change of buyers of main2main mergers when both, buyer and target, are single-segment firms. Results show, that buyers of main2main mergers generate efficiency losses in a short-term. If the buyer is a multi-segment firm it will have a positive significant impact on efficiency change. In a mid-term, the same independent variables have a significant impact, but the impact itself is higher and such are significance levels of the estimates. In a long-term, sub2sub mergers have a positive

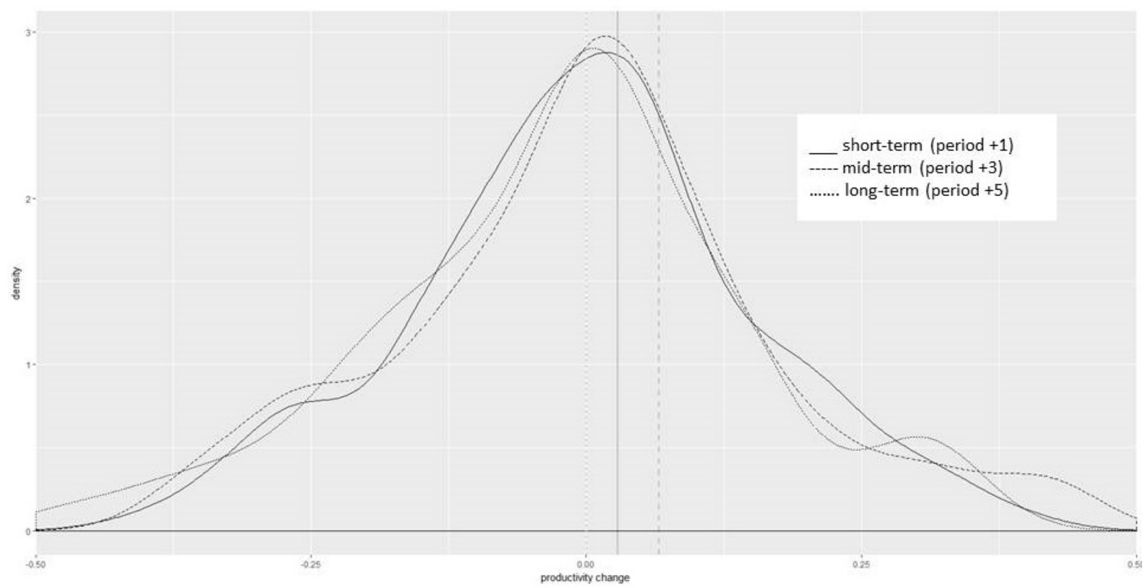


Figure 7.2: Efficiency Change of Targets

impact on buyers' efficiency change. Furthermore, the impact of main2main mergers of single-segment firms is significantly positive. For all regressions, R^2 values are between 0 and 2%. These low R^2 values can be expected as the dependent variable is a delta of residuals from a TFP regression. It is unlikely that the chosen independent variables explain the majority of variation of a delta of residuals. Overall, results indicate that buyers that are single-segment firms and merge a target that mainly operates in the same segment are capable to generate merger-specific efficiency gains. Contrarily, buyers that operate in several segments and merge a target that mainly operates in the same segment are likely to generate merger-specific efficiency losses. The F-statistic is only for mid- and long-term efficiency changes significant, which indicates that the combination of chosen independent variables has a limited capability to explain short-term efficiency changes.
Table 7.3 summarizes the results of applying a multiple regression to explain efficiency changes of target by merger categories. The table shows no significant coefficient except for one variable, which is the variable "main2main". A main2main merger of single-segment firms has a significantly positive impact on the mid-term efficiency change of targets. Again, R^2 values are low, ranging between 1 and 3%. Overall, merger categories have a little impact on efficiency changes of targets. The F-statistic is not significant, which again indicates that the combination of chosen independent variables has a no capability to explain efficiency changes.

Table 7.2: Impact of Merger Categories on Efficiency Changes of Buyers

	Short-term	**Mid-term**	**Long-term**
(Intercept)	-0.0148**	-0.0274***	-0.0089
sub2main	0.0215	0.0386	0.0251
main2sub	-0.0102	-0.0033	-0.0191
sub2sub	0.0122	-0.0002	0.0817**
is.multi.target	-0.0162	-0.0139	-0.0277
is.multi.buyer	0.0188*	0.049***	0.0345*
R^2	0.0028	0.0150	0.0165
Adj. R^2	0.0002	0.0108	0.0010
F-statistic	1.065 on 5 (1,874 DF)	3.607** on 5 (1,186 DF)	2.507* on 5 (748 DF)

Note: *p<0.1; **p<0.05; ***p<0.01

7.4 Merger Indicators

As discussed in chapter 3 the identification of a change of control on a lasting basis is difficult to identify. Thus, merger indicators are used to identify the change of control. Further, it is tested whether those indicators have an impact on efficiency changes of merging firms. Merger indicators are dummy variables, which are defined according to table 7.4.

Table 7.5 summarizes the results of applying a multiple regression to explain buyers' efficiency changes by merger indicators. Results show that the merger characteristic "primary source" has a significantly positive impact in a short- and mid-term, while it has a significantly negative impact on efficiency changes of buyers in a long-term. In a short-term, a notification to the EC as well as a notification in the EU has a low significant impact on efficiency changes of buyers. Whereas the impact of the notification to the EC is negative, the notification in the EU is positive. Especially "status", meaning that a merger has been completed, has a significant negative impact on efficiency changes of buyers in a long-term. In a long-term, the intercept, which equals mean efficiency change of mergers that have a zero value for all merger indicators, is significant. Again, R^2 values are low, ranging between 0 and 2%. The R^2 values indicate that the regressions explain little of the variation of efficiency changes of buyers. The F-statistic is only for short- and long-term efficiency changes significant, which indicates that the combination of chosen independent variables has a limited capability to explain mid-term efficiency changes.

There may be various interpretations of the results shown in table 7.5. The following interpretations are a possible way to explain results. Short-term results indicate that a notification in the EU or to the EC has an impact on the efficiency change of buy-

Table 7.3: Impact of Merger Categories on Efficiency Changes of Targets

	Short-term	**Mid-term**	**Long-term**
(Intercept)	0.0337	0.1355**	-0.0313
sub2main	-0.0683	0.0833	0.1212
main2sub	0.0641	0.0189	-0.1286
sub2sub	0.063	0.1385	0.0275
is.multi.target	0.0046	-0.1547	-0.0298
is.multi.buyer	-0.0338	-0.072	0.1014
R^2	0.0126	0.0184	0.0282
Adj. R^2	-0.0099	-0.0148	-0.0366
F-statistic	0.5599 on 5 (219 DF)	0.5547 on 5 (148 DF)	0.4356 on 5 (75 DF)
Note:	*p<0.1; **p<0.05; ***p<0.01		

ers. Assuming that mergers that are notified in the EU meet the merger definition of the European Merger Regulation, this result shows that horizontal mergers that meet the definition are likely to result in efficiency changes of buyers. Further, results indicate that buyers that publish the information about the merger themselves seem to realize efficiency gains in a short-, mid- and long-term.[1] These efficiency gains may result from the fact that firms that announce a merger are willing to put effort into a post merger integration process that is necessary to increase efficiency. Nevertheless, the negative impact of 'primary.source' in a long-term perspective may indicate that the post-merger integration is not substantial. In practice, firms often reduce personal costs in a short-term after a merger. This may increase efficiency in short- and even in a mid-term, but not in a long-term perspective. The significant intercept in the long-term regression as well as the R^2 values indicate that the minority of efficiency changes of buyers can be explained by merger indicators.
Table 7.6 summarizes the results of applying a multiple regression to explain efficiency changes of targets by merger indicators. Results show that the merger indicators have nearly no impact on efficiency changes of targets. The only merger characteristic that has a significant impact is the fact that a merger information is given by a primary source. This fact has a positive impact on short-term efficiency changes. The small impact of merger indicators on efficiency changes is also represented by the R^2 value between 0 and 3%. The F-statistic is not significant, which indicates that the combination of chosen independent variables has no capability to explain efficiency changes.

[1] The efficiency change is defined as an efficiency gain if the intercept plus the relevant coefficient results in a value larger than zero.

Table 7.4: Merger Characteristics

variable	1	0
EC	The merger has been notified to the EC.	otherwise
merger	The merger is defined as "merger".	The merger is defined as "acquisition".
completed	The merger is listed with the deal status "completed".	The merger has the deal status "assumed completed".
notified.in.the.EU	The merger has been notified to a regulation body of a country in the EU.	otherwise
primary.source	The merger information has been provided by a "primary source"	otherwise

7.5 Firm Characteristics

So far, firm characteristic have been used in chapter 5 as covariates in the PSM approach to explain the likelihood of a firm to participate in a merger. Covariates are assumed to satisfy the condition that the outcome is independent of the treatment conditional on the propensity score (PSM 1). Thus, firm characteristics are expected to explain the probability of a firm to participate in a merger. The post-merger efficiency change is assumed to be independent of the merger conditional on the characteristics of a firm.

In contrast to the DID approach, the applied multiple regression concentrates on efficiency changes of treated firms without adding a control group of firms. Consequently, merger-specific efficiency gains are approximated by observing a change of demeaned efficiency of treated firms instead of using the difference in efficiency changes of both groups, treatment and control group, as an approximation.

Thus, the applied DID model and the following multiple regression model differ by the definition of merger-specific efficiency gains. The following multiple regression simply ignores whether firm characteristics explain the treatment, and thereby the efficiency gains or whether firm characteristics directly explain post-merger efficiency changes. Therefore, it can be discussed whether the treatment is an omitted variable in the following multiple regression and whether the model suffers from endogeneity.

The following five categories of firm characteristics are chosen as independent variables in the multiple regression.

First, merger year, which is a vector of dummy variables for each year except one, is

Table 7.5: Impact of Merger Indicators on Efficiency Changes of Buyers

	Short-term	**Mid-term**	**Long-term**
(Intercept)	-0.0035	0.0027	0.0609***
merger	0.0252	-0.0043	0.0192
status	-0.0156	-0.0200	-0.0541***
notified.in.EU	0.0624*	-0.0083	-0.0186
notified	-0.02292	0.0300	0.0301
EC	-0.1297***	0.0185	-0.0822
primary.source	0.0203**	0.0215*	-0.0391**
R^2	0.0109	0.0055	0.0184
Adj. R^2	0.0078	0.0005	0.0105
F-statistic	3.448*** on 6 (1,873 DF)	1.098 on 6 (1,185 DF)	2.331** on 6 (747 DF)
Note:	*p<0.1; **p<0.05; ***p<0.01		

chosen as independent variable. For short-term efficiency changes, the merger years 2005 to 2013 are analyzed; for the mid-term efficiency change calculation the years 2005 to 2011, and for the long-term efficiency change calculation the years 2005 to 2009 are analyzed. Choosing the merger year as independent variable is based on the assumption that the merger year is exogenous. Firms choose the year they are merging and therefore the merger year may provide information about efficiency changes.

Second, firm size, which is a vector of dummy variables for each firm size category, namely micro, small, medium-sized and large firms[2], expect one, is chosen as independent variable. Choosing firm size as independent variable is based on the assumption that the size of a firm has an impact on kind of post merger integration.

Third, country, which is a vector of dummy variables for each country except one, is chosen. Choosing country as independent variable is based on the assumption that the culture, legal environment, etc. of firms has an impact on the firms' operations.

Fourth, industry, which is a vector of dummy variables for each 2-digit US SIC Code industry, is chosen as independent variable. Choosing industry is based on the assumption that industries are differently qualified for mergers depending on competition, regulations, etc..

Fifth, capital intensity, which is the ratio of capital to sales, is chosen as independent variable. Choosing capital intensity is based on the assumption that the possibility of firms to react in short-term decrease with the capital intensity.

[2]Firms are characterized according to the definition of the European Commission (Commission, 2017a) as either micro, small, medium-sized or large firms based on their revenue.

Table 7.6: Impact of Merger Indicators on Efficiency Changes of Targets

	Short-term	**Mid-term**	**Long-term**
(Intercept)	-0.0387	-0.0696	0.0075
merger	0.0899	0.1346	-0.0033
status	0.0576	0.126	-0.0174
status	-0.0789	0.208	0.1338
notified	-0.0186	-0.194	-0.1306
EC	-0.0907	-	-
primary.source	0.0824**	0.1149	0.0491
R^2	0.0273	0.0151	0.0058
Adj. R^2	0.0006	-0.0182	-0.0605
F-statistic	1.021 on 6 (218 DF)	0.4527 on 5 (148 DF)	0.08764 on 5 (75 DF)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.7 summarizes the results of running a regression of efficiency changes of buyers on firm characteristics.[3] The table is reduced to significant results according to the t-test, which means that the coefficient of the model has a significant impact on the dependent variable. The intercept represents the mean efficiency change of large firms in Austria of industry 20 that merged in 2005.

Results show that the merger year has no impact on efficiency changes, same is observed for most firm size categories as well as for most countries. Interestingly, medium firm size has a highly significant impact on efficiency change in a short term. The fact that a firm is located in Netherlands has a negative impact in a short-, mid- and a long-term perspective.

Industries 23 "Apparel, Finished Products from Fabrics and Similar Materials" and 32 "Stone, Clay, Glass, and Concrete Products" have a highly significant negative impact on efficiency changes in a short-term. Industry 38 "Measuring, Photographic, Medical, and Optical Goods, and Clocks" has a highly significant negative impact on efficiency changes of buyers in a mid-term. Industries 25 "Furniture and Fixtures", 32, 38 have a highly significant impact on efficiency changes of buyers in a long-term. Except for the industry 25 the effect is negative. The impact for industries 27 "Printing, Publishing and Allied Industries", 32, 33 "Primary Metal Industries" and 38 is for all time perspectives significant. Capital intensity has a highly significant positive impact in a mid- and a long-term perspective.

The R^2 values show that the firm characteristics explain 6 to 18% of efficiency changes of buyers. The longer the time perspective, the higher the R^2 value. The F-statistic is significant, which indicates that the combination of chosen independent

[3]See appendix 9.14 for a modified model.

variables has the capability to explain efficiency changes.
Thus, firm characteristics may be predicting conditions for merger-specific efficiency gains. However, as already mentioned, it can be discussed whether the treatment itself is an omitted variable in the multiple regression. Assuming the merger is an omitted variable, firm characteristics may explain the merger and thereby the efficiency change instead of explaining the efficiency change itself. Furthermore, it can be discussed whether demeaned efficiency changes are merger-specific.[4]
Table 7.8 summarizes the results of running a regression of efficiency changes of targets on firm characteristics. The table is reduced to significant results.
In a short-term, the merger years between 2007 and 2010 have a negative impact on efficiency changes of targets. Capital intensity has a highly positive impact on efficiency changes of targets. The table shows that the coefficient for industry 32 is the only significant coefficient in the multiple regression to explain mid-term efficiency changes of targets.
In a long-term, similar to efficiency changes of buyers, some industries have a significant impact on efficiency changes of targets. The R^2 values of all regressions are much higher than the values of the regressions for buyers. Firm characteristics explain 36% of short-term efficiency changes, 26% of mid-term and even 57% of long-term efficiency changes. The F-statistic is significant for short- and long-term efficiency changes, which indicates that the combination of chosen independent variables has a capability to explain mid-term efficiency changes.

7.6 Conclusion

In this chapter, three multiple regressions are applied to explain the short-, mid- and long-term efficiency changes of buyers and targets. By doing so, the chapter analyzes whether merger categories, merger indicators or firm characteristics are predicting conditions for merger-specific efficiency gains.
For buyers, the merger categories have only small explanatory power. Results show that "main2main" mergers have a negative impact, but this impact will be less if the buyer is a multi-segment firm. Furthermore, buyers seem to benefit from a "sub2sub" merger in a long-term perspective. Thus, to merge a firm that operates within the same industry as the buyer seems to result in efficiency losses. One explanation might be that the pressure of competition is a better way to increase efficiency than

[4] An alternative approach could be to use the ATE from the DID regression as dependent variables. Applying a multiple regression to explain differences in the ATE by firm characteristics is to result in insignificant coefficients for firm characteristics that are used as covariates in the PSM. These firm characteristics are assumed to be independent of post-merger efficiency changes and thereby independent of ATE. However, this analysis of the impact of firm characteristics on ATE is left open to further studies.

Table 7.7: Impact of Firm Characteristics on Efficiency Changes of Buyers

	Short-term	**Mid-term**	**Long-term**
(Intercept)	0.0561	0.0302	-0.1013
firm.sizemedium	0.0290***	0.0231	0.0193
countryBE	-0.0957**	-0.0121	0.1099
countryCH	-0.1616**	-0.0509	-0.0289
countryDE	-0.0680*	-0.03	0.1568**
countryES	-0.0584	0.0088	0.1340*
countryFR	-0.0681*	-0.0407	0.0654
countryHU	-0.11	-0.1774**	0.0023
countryNL	-0.0755*	-0.2014***	-0.7103***
countryNO	-0.0529	0.0233	0.1960***
countryPT	-0.1348***	-0.0841	0.0156
countryRO	-0.1125**	-0.0373	0.0706
ind21	0.2117	0.4384**	0.2569
ind23	-0.1861***	-0.1106	-0.1983**
ind25	0.0551	0.0896*	0.2028***
ind26	-0.0174	-0.0159	-0.0600*
ind27	-0.0529**	-0.0803**	-0.0984*
ind28	0.017	0.0049	-0.0535*
ind29	0.1705**	0.1479	0.0611
ind30	-0.0553**	0.0033	-0.0188
ind32	-0.0707***	-0.0720***	-0.1654***
ind33	-0.0616**	-0.0599*	-0.0986**
ind36	0.0112	0.0181	-0.0697**
ind37	-0.0227	-0.0679	-0.1722***
ind38	-0.0549**	-0.1202***	-0.1715***
capital.intensity	0.0149	0.0520***	0.1070***
R^2	0.0640	0.0840	0.1754
Adj. R^2	0.0368	0.0447	0.1229
F-statistic	2.38***	2.183***	3.273***
	on 53 (1,826 DF)	on 49 (1,142 DF)	on 45 (708 DF)
Note:	*p<0.1; **p<0.05; ***p<0.01		

merging. But, if buyers operate in several segments this has a positive impact on efficiency changes. This positive impact might be caused by the fact that the negative effect generated by the "main2main" merger is compensated by the subordinate divisions. If firms extent their subordinate activities by a merger it seems to have a positive effect on a long-term perspective, especially if the merged firm also operates only subordinately in the matched segment. Merging the subordinate divisions

Table 7.8: Impact of Firm Characteristics on Efficiency Changes of Targets

	Short-term	**Mid-term**	**Long-term**
(Intercept)	0.1025	-0.0504	-0.2237
merger.year2007	-0.1418*	-0.2749	-0.0718
merger.year2008	-0.1228*	-0.1372	-0.0399
merger.year2009	-0.1585**	-0.1515	-
merger.year2010	-0.1937***	-0.0813	-
countryRO	-0.0559	0.0397	0.7499**
ind24	-0.1885**	-0.1914	-0.0819
ind32	0.0053	0.7925***	0.2103
ind34	0.0432	0.206	0.3978**
ind35	-0.0839	-0.194	-0.3046*
ind36	-0.0239	-0.1697	-0.6471**
capital.intensity	0.1629***	0.0518	-0.0253
R^2	0.358	0.255	0.5689
Adj. R^2	0.201	0.001	0.2662
F-statistic	2.281*** on 44 (180 DF)	1 on 39 (114 DF)	1.879** on 33 (47 DF)

Note: *p<0.1; **p<0.05; ***p<0.01

of two firms might generate efficiency gains as it allows the subordinate division to grow in size in relation to the main divisions and thereby to receive managerial attention, for example, which then leads to activities that increase efficiency.

The explanatory power of merger indicators is similarly small as that of merger indicators. But, results indicate that it might have an impact, especially in the short run, if firms announce the merger themselves. This might be caused by the fact that the announcement indicates that firms are willing to invest in a post-merger integration and by this into activities that have a positive impact on efficiency.

Firm characteristics indicate that buyers that are medium-sized firms are likely to generate efficiency gains in a short-run. Medium-size firms might have the possibility to react to organizational changes. For small firms, there might be only a few changes possible due to a merger, and for large firms the reaction time is longer, due to the complexity of processes. Furthermore, capital intensity might indicate the appearance of a mid- to long-term efficiency gains.

For targets, the merger categories again have only small explanatory power. In contrast to buyers, the main2main merger indicates efficiency gains for targets at least on a mid-term perspective.

Similar to merger categories, the explanatory power of merger indicators is small. On a short-term perspective, the announcement of the merger via a primary source indicates efficiency gains for targets. Thus, the announcement of a merger might cause an awareness at the merging parties that allows both, buyer and target, to generate efficiency gains in a short-term perspective.

Firm characteristics have the highest explanatory power. For targets, capital intensity has a positive impact on efficiency gains in a short-term perspective. Interestingly, Romania has a positive impact on long-term efficiency changes of targets. Romania joined the European Union in 2007. This might indicate that the accession to the EU goes in line with beneficial circumstance that increased the possibilities of targets to generate long-term efficiency gains.

Overall, results show that the chosen independent variables explain more of the variation of efficiency changes of targets than of buyers. Furthermore, firm characteristics explain more of the variation of efficiency changes than merger categories or merger indicators. Thus, merger-specific efficiency gains rather depend on firms themselves than on the kind of the merger. Furthermore, for buyers, the analyzed predicting conditions have a higher explanatory power on long-term efficiency changes than short- or mid-term efficiency changes. For targets, the explanatory power of merger categories and firm characteristics is the highest for long-term efficiency changes. But, merger indicators have the highest explanatory power for short-term efficiency changes. Therefore, merger-specific efficiency gains are long-term effects which as such should be analyzed on a long-term perspective. Especially for buyers, the effects appear on a long-term. On a short-term perspective, targets' post-merger efficiency seems to depend on merger indicators.

Chapter 8

Conclusion

The present study empirically analyzes merger-specific efficiency gains. The analysis concentrates on horizontal mergers of European manufacturing firms between 2005 and 2014. Efficiency is estimated with the help of financial data such as costs and revenues.

The analysis deals with several problems. Among others, the present study discusses and solves the problem of merger identification. Furthermore, it deals with the limitations of efficiency measurement if only financial data are available. It discusses and solves the problem of endogneity that is caused by the fact that efficiency is unobserved. The study applies an approach to control for the selection bias that is caused by the non experimental environment of mergers.

However, each applied solution has potential to be improved. The merger identification process can be improved by finding a way to identify a change of control on a lasting basis. The efficiency measurement can be improved with a higher data quality that allows to apply a frontier approach. Furthermore, the efficiency estimation can be improved by the implementation of the approach of Ackerberg et al. (2015) in combination with Wooldridge (2009) into Stata or R, which would allow researches to conveniently apply a gross output approach assuming a translog production function. Furthermore, selection bias that results from the fact that firms do not merge randomly could be improved by identifying covariates that are capable to predict a merger.

The reporting and discussion of results is concentrated on the measured quantitative effects. However, answering 'why do things happen?' would be the appropriate next step. Due to the mentioned difficulties there is a lot of potential to improve the findings of the study. For two reasons, the answer to this question is left open to further research. On the one hand, robustness checks of results are recommended before starting a qualitative discussion. On the other hand, this study shows that mergers are ambiguous processes. They are idiosyncratic and difficult to be explained by external effects. Furthermore, efficiency changes underlie firm-, industry-, and country-specific as well as yearly effects. Mergers as well as efficiency changes and thereby merger-specific efficiency gains are complex. The complexity limits the possibilities of a qualitative discussion to explain observed effects. Therefore, deducting general conditions that predict merger-specific efficiency gains would be speculative. However, competition policy wants to improve the merger regulation process, and firms want to improve their target setting with regard to efficiency gains. Thus, the present study suggest to be aware of the following findings.

When do customers or consumers benefit from efficiency gains? First, efficiency gains need to be substantial. The present study shows that the efficiency changes of targets are much more likely to be substantial than the efficiency changes of buyers. Thus, first finding is that targets are much more interesting than buyers regarding the substantial impact of mergers on efficiency.

Second, efficiency gains should appear timely. If timely means in the first year after the merger, there is nearly no chance to observe any substantial efficiency change. Thus, second finding is that timely efficiency gains of a merger appear the earliest in the second year after the merger.

Third, efficiency gains should benefit customers and/ or consumers in the relevant market. One could expect that the main2main mergers, meaning if merging firms are similar with regard to their main operations, generate efficiency gains due to an overlap of similar activities. Furthermore, these firms are expected to have an interest in decreasing prices in the relevant market. However, main2main mergers have a negative impact on efficiency at least for buyers. Thus, third finding is that firms and their costumers might be better off when firms remain competitive instead of merging if they both operate mainly in the same industry.

Fourth, efficiency gains should result from a reduction in marginal costs. Marginal costs are determined by labor and material costs. Capital has a minor impact. Furthermore, capital is a dynamic variable that depends on an investment. Therefore, a reduction in capital costs rather has a long-term than a short-term impact on efficiency. Fourth finding is that a timely reduction in marginal costs occurs most likely due to a reduction in labor or material costs. Which one of both has the higher marginal impact on output differs across industries.

Are efficiency gains a direct consequence of a merger? First of all, it is difficult to explain why firms merge. Thus, it is difficult to define an efficiency gain to be a direct consequence of a merger and why it could not have been achieved in a different way. However, the comparison of merged firms to non-merged firms shows that observed targets generate efficiency gains shortly after the merger. Furthermore, targets are capable to continuously improve their efficiency. For buyers, substantial efficiency gains appear in a long-term perspective. Thus, fifth finding is that efficiency gains are on average a direct consequence of a merger. Targets, which maintain in the

market after a merger, are continuously improving. For buyers, substantial merger-specific efficiency gains appear in a long-run.
How is it possible to verify merger-specific efficiency gains? Efficiency of manufacturing firms can be measured with the help of a TFP approach. For some industries, it is even possible to apply an SFA approach. However, the question of how to verify that efficiency gains result from a merger requires predicting conditions. First, merger-specific efficiency gains rather depend on firm characteristics than on merger characteristics. But, firms that announce the merger themselves likely generate merger-specific efficiency gains. One explanation is that firms put themselves on the spot with an announcement and are therefore willing to put effort into efficiency improvements. Second, efficiency gains are substantial for mid-sized buyers. For larger firms, it might be difficult to measure substantial changes. For smaller firms, potential or resources might be limited. Third, capital intensity has a positive impact on merger-specific efficiency gains for both, buyers as well as targets.

Einav and Levin (2010) emphasize

> "focusing on the elegance of the solution can lead one to gravitate towards less important questions."

Most of the time, working on the answer to the question 'Whether - and if so, under which conditions - do horizontal mergers in the European manufacturing sector result in merger-specific efficiency gains?' I spent on the understanding of methods to estimate efficiency. Even though, a lot of important methodological issues such as endogeneity come along with efficiency estimation, the solution of those issues provides little input to the overall purpose of this study.
Moreover, Einav and Levin (2010) argue that richer data may substitute methods. This study shows that generalizing the answer towards the appearance of merger-specific efficiency gains is difficult as mergers are ambiguous processes. Nevertheless, the outcome of this study rather results from the rich data set than from modifications of methodologies. The large data set allows e.g. to disaggregate post-merger periods and to separate buyers from targets.
The difficulty of the research question is to balance the claim of generalizing merger-specific effects and to consider individual merger-specific effects. On the one hand, the large data set allows the econometric analysis of merger-specific efficiency gains under a large amount of assumptions. On the other hand, results show that mergers are idiosyncratic processes, and that assumptions needed for the econometric analysis suffer from anticipating individual merger-specific effects. The trade-off between generalizing and individualizing merger-specific effects can be solved in two ways. One possible way is to leave the path of generalization and to go into details of

mergers by applying constraints on e.g. industry or firms. As result, the analysis will be a case study or an industry-specific study. To generalize the outcome it is necessary to aggregate the results of many case studies or industry-specific studies. The other possible way is to leave the path of individualization and to rework the general frameworks so that it considers individual effects. As result, the analysis will be e.g. a cross-industry study. To individualize the outcome it is necessary to implement e.g. instrumental variables that capture individual effects.
Many studies on merger-specific efficiency gains decided to apply restrictions on industries. By this, they rather analyze industries or firms than mergers in general. This study, as well as the study of e.g. Blonigen and Pierce (2016), decide to aggregate industries and thereby concentrate rather on mergers than on individual effects. Thereby, this study goes in line with the statement of Einav and Levin (2010) that by choosing the second way it is necessary to concentrate empirical industrial organization studies on the overall organization of production in the economy.

Chapter 9

Appendix

9.1 Merger Definition

The EC Merger Regulation defines a merger of previously independent firms (or parts of firms) as a process that leads to a concentration. This process is initiated by a change of control based on legal rights, treaties, and/or contracts. Control contains the possibility of exercising decisive influence on a firm (Art 3 no 2 EC Merger Regulation (RL [EC] No 139/2004)).
Therefore, a merger is defined as process, where a firm exercises influence on another firm after legal rights, treaties, and/or contracts constituted a change of control.[1]

> "The Commission in principle only examines larger mergers with an EU dimension, meaning that the merging firms reach certain turnover thresholds. There are two alternative ways to reach turnover thresholds for EU dimension.
> The first alternative requires:
>
> (i) a combined worldwide turnover of all the merging firms over €5 000 million, and

[1]

> "[A] merger of two or more previously independent undertakings or parts of undertakings"

is a concentration.
(Art 3 no 1a EC Merger Regulation (RL [EC] No 139/2004))

> "A concentration shall be deemed to arise where a *change of control* on a lasting basis results [...]."

(Art 3 no 1a EC Merger Regulation (RL [EC] No 139/2004))

> "Control shall be *constituted* by rights, contracts or any other means which, [...] confer the possibility of exercising decisive influence on an undertaking [...]."

(Art 3 no 2 EC Merger Regulation (RL [EC] No 139/2004))

(ii) an EU-wide turnover for each of at least two of the firms over €250 million.

The second alternative requires:

(i) a worldwide turnover of all the merging firms over €2 500 million, and

(ii) a combined turnover of all the merging firms over €100 million in each of at least three Member States,

(iii) a turnover of over €25 million for each of at least two of the firms in each of the three Member States included under ii, and

(iv) EU-wide turnover of each of at least two firms of more than €100 million."

(Commission, 2017c)

9.2 The Assessment of Horizontal Mergers

Figure 9.1 illustrates the general assessment of horizontal mergers according to the Horizontal Merger Guidelines. The assessment can be divided into three steps. In a first step, the European Commission calculates the market share and the concentration level of the notified merger to evaluate whether the merger is likely to increase market power of the merging firms. An affirmation of the increase in market power leads to an assessment of possible anti-competitive effects in a second step. The two possible cases that cause a negative welfare effect are introduced in subsection 1. The assessment of countervailing effects follows in a third step if the merger is likely to cause anti-competitive effects. One of the countervailing effects are merger-specific efficiency gains, named efficiencies (EC Merger Regulation (RL [EC] No 139/2004), recital 29).
The European Commission takes efficiency claims into account if the claimed efficiency gains fulfill three conditions. These conditions are cumulative. (Horizontal Merger Guidelines (2004), C 31/13, at 78.)
The first condition requires that *consumers benefit* from efficiency gains. This is the primary condition, on which the Commission decides whether or not it considers claimed efficiency gains. Four sub-conditions define whether efficiency gains are likely to benefit consumers. First, efficiency gains should be *substantial*. Second, they should be *timely*. Third, they should *benefit consumers in relevant markets* where it is otherwise likely that competition concerns would occur. Fourth, efficiency gains are most likely to be beneficial for the consumer, if they lead to *reductions in variable or marginal costs*. (Horizontal Merger Guidelines (2004), C 31/13, at 79.)

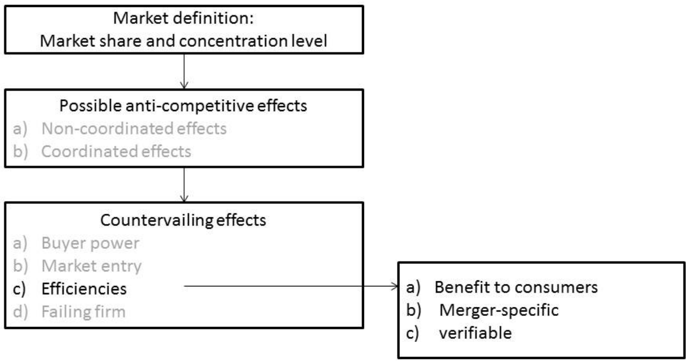


Figure 9.1: The Assessment of Horizontal Mergers

The second condition requires that efficiency gains are a *direct consequence of the notified merger* and cannot be achieved to a similar extent by less anti-competitive alternatives. (Horizontal Merger Guidelines (2004), C 31/13, at 85.)
The third condition requires that efficiency gains are *verifiable* in a way that the Commission can be reasonably certain that the efficiency gains are likely to materialize. For this purpose, efficiency gains should be quantified. (Horizontal Merger Guidelines (2004), C 31/13, at 86.) Verifiable efficiency gains have evidence such as internal documents, historical examples, and external experts' studies. (Horizontal Merger Guidelines (2004), C 31/13, at 88.)

9.3 Reasons for Merger-specific Efficiency Gains

Röller et al. (2006) distinguish five reasons for merger-specific efficiency gains: rationalism, economies of scale, technological progress, purchasing economies and reduction of slack.
Rationalism[2] causes allocative efficiency gains due to a reallocation of output between production plants. It is merger-specific if the possibility to allocate output is only possible between dependent firms.
Economies of scale can be realized if a firm's average costs decreases while output increases. (Röller et al., 2006) They can be realized either in a short-run or in a long-run. Economies of scale appear if the production function has the property of IRS. Economies of scope are a generalization of the concept of economies of scale

[2]Definition of rationalism according to Röller et al. (2006): "Rationalism of production refers to the cost savings that may be realized from shifting output from one plant to another, without changing the firms' joint production possibilities."

to the case of the multi-product firm. (Röller et al., 2006) Economies of scale are merger-specific if the possibility to grow in size in a similar extent is only possible due to the merger.
A technical progress is either a process or a product innovation.[3] An efficiency gain resulting from a technological process is a technical efficiency change. A technical progress is merger-specific if it is caused by the merger.
Purchasing economies arise in imperfectly competitive factor markets.[4] They cause a technical efficiency change due to a decrease of input prices. Purchasing economies are merger-specific if they could not have been realized without the merger.
Slack, also called X-inefficiency, is defined as the "failure of the management to maximize the profits". (Röller et al., 2006) A merger may increase efficiency by disbanding the separation of ownership and control. The reduction of slack is also a technical efficiency change.

9.4 TFP Models: Problems and Solutions

In TFP models, five major econometrical problems may cause biased estimates. These major econometrical problems are endogeneity, measurement errors, missspecification, multicollinearity and selection bias. The following introduction to these problems and their solution closely follows Aguirregabiria (2009).

Endogeneity

First, as introduced in chapter 4, endogeneity may cause biased estimates. Besides the introduced Control Function approach there are three other approaches to solve endogeneity in efficiency estimation, namely an instrumental variable, a fixed effect and a dynamic panel approach.

Instrumental Variables: The basic idea of IV is to find a variable that can be used as instrument to capture all endogenous variations of $\mathbf{x}_{it}$. Let $\mathbf{z}_{it}$ be a vector of $1 \times M$ instrumental variables. To be capable of capturing endogenous variation of $\mathbf{x}_{it}$, $\mathbf{z}_{it}$ needs to fulfill two criteria:
(IV1) $E[\omega_{it}|\mathbf{z}_{it}] = \mathbf{0}$ (Strict Exogeneity), and
(IV2) $E[\mathbf{x}_{it}|\mathbf{z}_{it}] \neq \mathbf{0}$ (Relevance).
The first assumptions implies that the instrument is assumed to be exogenous and

[3] According to Röller et al. (2006) a technical progress is either "process innovation [that] reduces the cost of producing an existing product [...] [or a] product innovation [that] increases the value (quality) of an existing product."

[4] According to Röller et al. (2006) purchasing economies are "costs savings [...] [which arise] because of the presence of imperfectly competitive factor markets. Small firms often need to purchase their inputs [...] at prices above marginal costs."

therefore not correlated with productivity. The second assumption implies that the instrument is relevant as it is highly correlated with inputs.
Estimation is done in a two step approach. In a first step $\mathbf{x}_{it}$ is regressed on $\mathbf{z}_{it}$:

$$\mathbf{x}_{it} = \alpha \mathbf{z}_{it} + \xi_{it} \tag{9.1}$$

which results in estimates for $\mathbf{x}_{it}$ as $\hat{X} = Z(Z'Z)^{-1}Z'X$.
In a second step $\mathbf{y}_{it}$ is regressed on estimates for $\mathbf{x}_{it}$, $\hat{\mathbf{x}}_{it}$:

$$\mathbf{y}_{it} = \hat{\mathbf{x}}'_{it}\beta + \epsilon_{it} \tag{9.2}$$

which results in unbiased estimates for β as $\hat{\beta}_{IV} = (\hat{X}'\hat{X})^{-1}\hat{X}'Y$.
Input prices are often suggested as instruments in the context of TFP estimation. One problem of input prices is the data availability. Mostly, input prices are not observable, or if they are observable they will not be precise. Moreover, an instrumental variable needs cross-sectional variation to be useful. If input markets are strongly competitive there will be no reason why prices should differ between firms. And if input prices differ it will be hard to argue that input prices are uncorrelated with productivity.

Fixed Effects: The basic idea of FE is to implement a time invariant and firm-specific effect that captures all endogenous variation of $\mathbf{x}_{it}$. Let α_i be the fixed effect. The basic panel data model can be rewritten into:

$$\mathbf{y}_{it} = \alpha_i + \mathbf{x}'_{it}\beta + \xi_{it} \tag{9.3}$$

with

$$\xi_{it} = \omega^*_{it} + \nu_{it} \tag{9.4}$$

whereas
ξ_{it} is the new error term, including
ω^*_{it}, an idiosyncratic productivity shock, and
ν_{it}, the random error.
Productivity is a composite term:

$$\omega_{it} = \alpha_i + \omega^*_{it} \tag{9.5}$$

To be capable of capturing endogenous variation of $\mathbf{x}_{it}$, the following assumptions must hold:
(FE1) α_i is time invariant,
(FE2) $E[\xi_{it}|\mathbf{x}_{it}] = 0$, and

(FE3) $E[\xi_{it}|\alpha_i] = 0$.
The first assumption implies, as mentioned, that the fixed effect is time invariant and firm-specific. The second assumption includes that the idiosyncratic productivity shock is realized after the input decision and is therefore uncorrelated with the inputs. The third assumption will hold if all endogeneity is captured by the fixed effects.
Estimation is done after eliminating the fixed effect by a subtracting means over time in equation (9.4):

$$(y_{it} - \overline{y_{it}}) = (\mathbf{x}_{it} - \overline{\mathbf{x}}_{it})'\beta + (\xi_{it} - \overline{\xi_{it}}) \tag{9.6}$$

whereas

$$\overline{m}_i = \frac{1}{T}\Sigma_{t=1}^{T} m_{it} \forall m_{it} = y_{it}, \mathbf{x}_{it} \tag{9.7}$$

Regression results in $\hat{\beta}_{FE} = ((X - \overline{X}_i)'(X - \overline{X}_i))^{-1}(X - \overline{X}_i)'(Y - \overline{Y}_i)$.
Although the FE model has several advantages from a theoretical side, it is rarely applied in practice. One reason is that the number of observed periods are normally small and therefore T consistency of α_i is not possible. Another reason is that even if T consistency of α_i is possible, the assumption of partly time invariant productivity will be a strong one. In the context of analyzing merger-specific productivity changes this means that pre- and post-merger fixed effect are needed. The impact of the merger on productivity must be large to get significant differences. Furthermore, the within-variation in capital and labor is often very small. If e.g. capital is very persistent over time and therefore within-variation is small while the within-variation of the error term is large, this may amplify the measurement error problem. Therefore, FE often provides small estimates for input factors according to Aguirregabiria (2009).

Dynamic Panel (Generalized Method of Moments): The basic idea is to apply GMM in the context of dynamic panel. Assuming that:
(GMM1) α_i is time invariant,
(GMM2) $E[\xi_{it}|\alpha_i] = 0$,
but instead of (FE2) $E[\xi_{it}|\mathbf{x}_{it}] = 0$, endogeneity results from $E[\xi_{it}|\mathbf{x}_{it}] \neq 0$. Partial derivatives of inputs for at least one input are assumed to be nonzero and depend on productivity:
(GMM3) $\mathbf{x}_{it} = f_x(\mathbf{x}_{i,t-1}, \omega_{it})$.
In contrast to FE equation (9.4) the first difference removes α_i:

$$\Delta \mathbf{y}_{it} = \Delta \mathbf{x}_{it}'\beta + \Delta \xi_{it} \tag{9.8}$$

Assumption (GMM3), which tells that inputs of period t depend on inputs of period t-1, but not on inputs of period t-2 and those before, helps to solve the endogenity problem. As inputs of t-1 correlate with inputs of t-2, inputs and output of t-2 can be used as instrument to capture endogeneity of first differences of inputs. Furthermore, lagged first difference as instrument for period t.
Instead of applying a two step approach, moment conditions resulting from the instruments can be used:

$$E[\Delta\xi_{it} \otimes \begin{pmatrix} \mathbf{x}_{i,t-2} \\ ... \\ \mathbf{x}_{i,t-T} \end{pmatrix}] = 0 \tag{9.9}$$

and

$$E[\xi_{it} \otimes \begin{pmatrix} \Delta\mathbf{x}_{i,t-1} \\ ... \\ \Delta\mathbf{x}_{i,t-T+1} \end{pmatrix}] = 0 \tag{9.10}$$

Regression results in $\hat{\beta}_{GMM} = (\Delta X' P_Z \Delta X)^{-1} \Delta X' P_Z Y$, whereas $P_Z = Z(Z'Z)^{-1}Z'$. The problems of GMM are similar to the problems of the FE. It often provides small estimates for input factors.

Measurement Error and the Fixed Effects Approach

Second, measurement errors are an issue. For example, TFP estimation is often based on financial data and e.g. "total fixed assets" is the proxy of the value of capital. The annual financial statement of a firm includes the value of "total fixed assets". Each country has legal regulations of annual financial statements. For example, in Germany, the legal regulations impose that any information provided in financial statements needs to follow a risk-averse scheme. This scheme intends to minimize the risk that shareholders overestimate the value of a firm. However, it also results also in relatively high depreciation rates, which cause that firms often generate hidden assets. A risk-averse capital value and hidden assets cause a measurement error in estimation as they lead to an underestimated impact of capital on output and an overestimated impact of productivity.
The following three approaches partly solve the problem of measurement errors:

1. A composite error term with distributional assumptions,
2. the Decomposition of efficiency changes,
3. Fixed Effects (FE).

First, a composite error term with distributional assumptions for both components, productivity, ω_{it}, as well as random error, ν_{it}, allows to decompose the residual into a measurement error and a productivity term. A Stochastic Frontier Analysis (SFA) approach does this decomposition. As mentioned by Syverson (2011), in a simple TFP model we cannot distinguish between both components of the error term, ϵ_{it}, neither productivity, ω_{it}, nor random error, ν_{it}. Therefore, the residual, which is the estimate for productivity, include measurement errors. SFA adds distributional assumptions on both, the random error, ν_{it}, as well as productivity, ω_{it}, which allows to decompose the residual into a term that includes measurement errors and a term that represents inefficiency. The SFA approach can only be applied if the available data quality is high and indicates the existence of inefficiency.

Second, the decomposition of efficiency changes according to the Malmquist Index allows to distinguish different sources that influence efficiency. It is possible to eliminate some effects caused by omitted variables. More precisely, it is possible to separate "Technical Efficiency Change", which is the inefficiency of a firm, from "Technical Change", which is an industry wide effect, and "Economies of Scale", which is influenced by the characteristics of a production technology in combination with the size of a firm. The efficiency change can be adjusted to the part of most interest. In the context of merger-specific efficiency gains, the "Technical Efficiency Change" is of most interest. The "Technical Change" is comparable to a mean efficiency effect of all firms. And the "Economies of Scale" is comparable to size-specific effect given a certain production technology.

Third, the Fixed Effect (FE) approach can be applied as control for omitted variables, and therefore - at least partly - can reduce the bias caused by measurement errors. The approach is related to the idea of the decomposition of efficiency changes according to the Malmquist Index. But, instead of calculating the geometric mean, the FE approach eliminates mean efficiency effects related to firm, time, size, country, etc. by adding dummy variables, also named FE. An often applied version of FE is the implementation of a time-invariant, firm-specific fixed effect that captures all endogenous variation of $\mathbf{x}_{it}$.

In a addition to a firm-specific fixed effect it is possible to add e.g. a time-specific effect, a country- or a size-specific fixed effect effect. A time-specific FE allows to eliminate mean efficiency effects of each period and therefore captures 'Technical Change' of an industry. A size-specific FE allows to eliminate mean efficiency effects that are related to the size of a firm and therefore captures 'Economies of Scale'. A country-specific FE allows to eliminate mean efficiency effects of a country and therefore can partly eliminate the described impact of e.g. the risk-averse scheme of German financial statements on the efficiency estimate. Most empirical studies that analyze merger-specific efficiency gains using a TFP approach add FE to net out the effects of omitted variables that may cause biased estimates (e.g. Blonigen and Pierce (2016)).

Misspecification and the Nonparametric Approach

Third, another problem might be the misspecification of the functional form of the production function. Mostly, literature assumes either a Cobb Douglas or a translog production function. Misspecification is a consequence if the true production function is neither a Cobb Douglas nor a translog function. Thus, some literature suggests semi or nonparametric approaches to approximate the functional form of production functions. The nonparametric approach allows to assume an unknown production technology, so that:

$$y_{it} = g(\mathbf{x}_{it}) + \epsilon_{it} \tag{9.11}$$

where $g(\mathbf{x}_{it})$ is the unspecified production function. The distribution of ϵ_{it} is known. Assuming that ϵ_{it} $i.i.d.N(0, \sigma^2)$ the nonparametric regression is based on the following moment condition:

$$E[\epsilon_{it}|\mathbf{X} = \mathbf{x}_{it}] = -E[\epsilon_{it}] = -\sigma\sqrt{\frac{2}{\mu}} = 0 \Rightarrow E[Y|\mathbf{X} = \mathbf{x}_{it}] = g(\mathbf{x}_{it}) - \sigma\sqrt{\frac{2}{\mu}} = g(\mathbf{x}_{it}) \tag{9.12}$$

The unknown production function $g(\mathbf{x}_{it})$ can be estimated as:

$$\hat{g}(\mathbf{x}_{it}) = \hat{E}[Y|\mathbf{X} = \mathbf{x}_{it}] \tag{9.13}$$

where $\hat{E}[Y|\mathbf{X} = \mathbf{x}_{it}]$ is unknown.
$\hat{E}[Y|\mathbf{X} = \mathbf{x}_{it}]$ can be estimated by using nonparametric regression, e.g. kernel regression[5]. Applying e.g. the Nadaraya-Watson estimator[6] results in:

$$\hat{E}[y_{it}|\mathbf{x}_{it}] = \frac{\frac{\sum_{j=1}^{J} y_{jt} K(\mathbf{x}_{it} - \mathbf{x}_{jt})}{h}}{\frac{\sum_{j=1}^{J} K(\mathbf{x}_{it} - \mathbf{x}_{jt})}{h}} \tag{9.14}$$

Fan et al. (1996), Kumbhakar et al. (2007), and Martins-Filho and Yao (2015) introduce semi- and nonparametric approaches in the context of SFA. In the analysis of merger-specific efficiency gains, the nonparametric approach has not been applied to the best of knowledge. As the analysis of merger-specific efficiency gains concentrates on the efficiency estimate, the approximation of the functional form

[5] According to Fan et al. (1996) the kernel regression is the most studied nonparametric estimator.

[6] Any other kernel estimator would work as well.

of the production technology plays a minor role. Nevertheless, the definition of the function form of the production technology has an impact on the productivity estimate.

Multicollinearity and the Choice of Variables

Fourth, multicollinearity might be an issue. If we e. g. approximate labor via wage, number of employees and personnel costs, we expect that at least one of them is redundant and we therefore cannot identify at least one of the parameters.
Several values may indicate multicollinearity, e.g. the correlation coefficient or the coefficient of determination. Also, the variance inflation factor (VIF) test can be applied to test for multicollinearity. The VIF value is calculated as:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{9.15}$$

where R_j is the coefficient of determination from the regression of $\mathbf{x}_j$ on the other independent variables. Commonly, a VIF value of larger than 10 indicates a high multicollinearity.
Multicollinearity can be solved by the choice of variables. Most empirical studies that apply a TFP approach do not discuss the problem of multicollinearity. However, the choice of variables differs across studies, which may partly be driven by data availability and the purpose to avoid multicollinearity.

Selection Bias and the Anticipation of Firm Behavior

Fifth, a selection bias may occur. Mostly, an unbalanced panel data set is used for estimation. A firm's exit in a panel data set cannot be treated as random according to Olley and Pakes (1996). They assume that firms exit markets depending on a trade off between expected future profits and a payoff that can be generated by leaving the market.
According to Olley and Pakes (1996) firms have three decisions at the beginning of each period. First, they decide whether to exit the market and receive a sell-off of Φ or to continue in the market; if they continue, they secondly choose the input variable factor and third, they chose the amount of investment, i_t, which together with their current capital stock, k_t, define the capital stock at the beginning of the next period, k_{t+1}:

$$k_{t+1} = (1 - \delta)k_t + i_t \tag{9.16}$$

Firms are assumed to maximize their expected discounted value of future net cash flows. The expected discounted value of future net cash flow depends on the productivity, ω_t, as well as the available capital stock and some other control variables, e.g. age in the model of Olley and Pakes (1996), which are in the following renounced for the purpose of clearness. Productivity is known to the firms and is assumed to evolve over time. The choice of firms can be written as:

$$\begin{aligned} V_t(\omega_t, k_t) = \max\{\Phi, \sup_{i_t \geq 0} \phi_t(\omega_t, k_t) - c(i_t) \\ + \beta E[V_{t+1}(\omega_{t+1}, k_{t+1}|J_t]\} \end{aligned} \tag{9.17}$$

where $\phi(\cdot)$ is the restricted profit function, $c(i_t)$ is the cost of investment, β is a discount factor and J_t is the information available at t.

A firm sells off if the expected discounted value of future net cash flows is lower than the payoff from the sell-off, Φ. Therefore, from equation (9.17) results in an exit rule and an investment demand function:

$$\chi_i = \begin{cases} 1, \text{ if } \omega_t \geq \underline{\omega_t}(k_t) \\ 0 \text{ otherwise} \end{cases} \tag{9.18}$$

and

$$i_t = i_t(\omega_t, k_t) \tag{9.19}$$

Concluding, a firm will continue in the market if its productivity, ω_t, is larger than a certain threshold, $\underline{\omega_t}(k_t)$. Furthermore, the investment decision of a firm depends on its productivity. Anticipating firms behavior concerning entry and exit of markets allows to control for a selection bias and generate unbiased estimates.

9.5 TFP in the Context of Markup Analysis

Recently, the production function estimation receives - among others - large attention in the context of markup estimation (e.g. Blonigen and Pierce (2016), De-Loecker and Eeckhout (2017)). The concept of De Loecker and Warzynski (2012) allows to distinguish between markups and productivity. Furthermore, their approach allows to estimate markups based on financial data, which are largely available.

The authors assume that firms produce output using the following production technology

$$Q_{it} = Q(X_{it}^1, ..., X_{it}^V, K_{it}, \omega_{it}) \tag{9.20}$$

where Q_{it} is the output of firm i in period t, $X_{it}^1, ..., X_{it}^V$ are variable input choices, K_{it} is the input factor capital and ω_{it} is the productivity of firm i in period t.

Furthermore, assuming firms minimize costs gives the Lagrangian function:

$$L(X_{it}^1, ..., X_{it}^V, K_{it}, \lambda_{it}) = \Sigma_{v=1}^V P_{it}^{X^V} X_{it}^V + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)) \tag{9.21}$$

where $P_{it}^{X^V}$ and r_{it} are the firm's input prices.
Minimizing the Lagrangian function by setting the first order condition (FOC) equal to zero gives

$$\frac{\partial L_{it}}{\partial X_{it}^V} = P_{it}^{X^V} - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^V} = 0 \tag{9.22}$$

where $\lambda_{it} = \frac{\partial L_{it}}{\partial Q_{it}(\cdot)}$ is the marginal cost of production. Multiplying both sides of equation (9.22) with $\frac{X_{it}^V}{Q_{it}}$ gives:

$$\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^V} \frac{X_{it}^V}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X^V}}{Q_{it}} \tag{9.23}$$

where $\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^V} \frac{X_{it}^V}{Q_{it}}$ is the output elasticity of any variable input. Therefore, the optimal input is chosen if the output elasticity of any variable input equals $\frac{1}{\lambda_{it}} \frac{P_{it}^{X^V}}{Q_{it}}$.
Furthermore, DeLoecker and Eeckhout (2017) define markup, μ_{it}, as the ratio of price to marginal cost:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} \tag{9.24}$$

This allows to rewrite equation (9.23) as

$$\theta_{it}^X = \mu_{it} \frac{P_{it}^X X_{it}}{P_{it} Q_{it}} \tag{9.25}$$

where θ_{it}^X denotes the output elasticity of any variable input and $\alpha_{it}^X = \frac{P_{it} Q_{it}}{P_{it}^X X_{it}}$ denotes the expenditure share.
Markup is defined as

$$\mu_{it} = \theta_{it}^X (\alpha_{it}^X)^{-1} \tag{9.26}$$

Expenditure shares are observable. Therefore, the approach of DeLoecker and Eeckhout (2017) allows to estimate markups by using observable expenditure shares in combination with the output elasticity that can be obtained from the estimation of the production function.
The production function estimation as introduced requires the log version of the production technology:

$$Q_{it} = F(X_{it}^1, ..., X_{it}^V, K_{it}; \beta) exp(\omega_{it}) \tag{9.27}$$

The output elasticities, $\theta_{it}^{X^V}$, are now given by $\frac{\partial ln F_{it}}{\partial ln X_{it}^V}$ being independent of productivity, ω_{it}. The authors apply the approach of Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) to estimate the parameters of the production function. They assume a translog gross output production function. The output elasticity of e.g. labor is defined as:

$$\hat{\theta}_{it}^{L} = \hat{\beta}_{l} + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it} \tag{9.28}$$

Expenditure shares are defined as:

$$\hat{\alpha}_{it}^{X} = \frac{P_{it}^{X} X_{it}}{P_{it} \frac{\tilde{Q_{it}}}{exp(\hat{\epsilon_{it}})}} \tag{9.29}$$

Concluding, markup for e.g. labor is estimated as:

$$\mu_{it} = \hat{\theta}_{it}^{L} (\hat{\alpha}_{it}^{X})^{-1} \tag{9.30}$$

9.6 Variable Selection for Efficiency Estimation

Table 9.1 shows all variables, which are available in AMADEUS, that are considered to match data requirements. Available data are information according to the balance sheet and profit & loss account.

Output could be either described by "sales" or "turnover". "Sales" is selected because of both available variables it describes best the output of production. According to Konings et al. (2001) sales needs to be deflated by a three digit producer price index available from Eurostat.

Although, "costs of sold goods" summarizes all variable costs and would therefore be useful as variable to describe input, this value is not preferred in a production function estimation as it cannot be segregated into its components, labor, material, etc..

Labor could either be described by "cost of employees" (STAF) or "number of employees" (EMPL). Dividing "cost of employees" by "number of employees" generate an average wage per firm, $w_{Lit} = STAF/EMPL$. Due to data available "cost of employees" is chosen as value to describe labor.

Several values may describe capital, e.g. "Total fixed assets", "Fixed assets" etc.. "Tangible fixed assets" (TFAS) is selected because of all available data it describes best the capital stock that is used in production. As capital stock depreciates over time, capital is defined as "tangible fixed assets" minus "depreciation" (DEPR), $y_{Cit} = TFAS - DEPR$. (Konings et al., 2001)

Material is described by 'material' costs (MATE) as this is the only one variable that can be considered.

Labor is the only factor for which available data would allow to generate a price and an amount value. To be consistent in all factors, perfect competition that leads to prices, w_t, that equal marginal costs c_t is assumed. According to this prices are

unique for all firms in each period, $w_{it}/c_{it} = 1 \forall i$. Thus, the amount of each input and output factor equals the financial value $y_{kit} = y_{kit} * w_{kit} \forall k, j, i$ and $x_{jit} = x_{jit} * w_{jit} \forall i$.
Output Deflation: Eurostat describes the producer price index as follows:

> "[T]he industrial producer price index [(PPI)] measures the gross monthly change in the trading price of industrial products. [...] [PPI as] a deflator is a figure expressing the change in prices over a period of time for a product or a basket of products, which is used to 'deflate' (price adjust) a measure of value changes for the same period, thus removing the price increases or decreases and leaving only volume changes. [...] The deflator of sales adjusts for inflation in retail price developments, and is used to calculate real increases or decreases in retail sales over a specific period of time."

Sales of each firms is deflated according to the core activity of firms. Sales deflation, $y_{it} * PPI_{it}/100 = y_{it,deflated}$, uses the three-digit EU28 PPI on index basis 2010.

Table 9.1: Possible Variables for Efficiency Estimation

Required	**Available**	**Explanation** (according to the handbook of "AMADEUS")
y_{it}	1. TURN, 2. OPRE	1. Sales is the value of sold products (net sales), 2. Operating revenue (Turnover) includes net sales, other operating revenues and stock variations
	COST	costs of sold goods, production, services, which includes costs directly related to the production of goods sold such as commercial costs, administrative expenses, etc. and depreciation of those costs
x_{Lit}	1. STAF, 2. EMPL	1. costs of employees is the sum of all wages payed, 2. number of Employees included in the company's payroll
x_{Cit}	1. TOAS 1.a FIAS = IFAS + TFAS + OFAS 1.b CUAS = STOK + DEBT + OCAS, 2. DEPR	1. total assets, including 1.a fixed assets = intangible fixed assets are formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect + tangible fixed assets are buildings, machinery, etc. Other fixed assets are long term investments, shares and participations, pension funds etc + other fixed assets 1.b current assets = stocks are the value of total inventories including raw materials, material in progress and finished goods + debtors are trade receivables from clients and customers only + other current assets are receivables from other sources (taxes, group companies), short term investment of money and Cash at bank and in hand, 2. depreciation is the total amount of loss of value and amortization of the assets.
x_{Mit}	MATE	material costs

9.7 Restrictions on the AMADEUS Data Set

Four restrictions need to implemented to allow to estimate efficiency. First restriction requires that firms are manufacturing according to NACE Rev. 2 as well as US SIC Code. This restriction is needed as industries are classified based on 3-digit US SIC Code, but output values are deflated by a PPI that is based on a 3-digit NACE Code. The restriction reduces the data set by 46%, from 6,031,020 to 3,264,620 observations. The restriction eliminates the following industries from the analysis:

- US SIC industries:
  - 241 'Logging',
  - 270 'Printing, Publishing, and Allied Industries',
  - 271 'Newspaper',
  - 272 'Periodicals',
  - 273 'Book Publishing and Printing' and
  - 274 'Miscellaneous Publishing',
- NACE Rev. 2 Industries:
  - 2441 'Precious metals production',
  - 3312 'Repair of machinery',
  - 3300 'Repair and installation of machinery and equipment',
  - 3313 'Repair of electronic and optical equipment',
  - 3314 'Repair of electrical equipment',
  - 3315 'Repair and maintenance of ships and boats',
  - 3316 'Repair and maintenance of aircraft and spacecraft',
  - 3317 'Repair and maintenance of other transport equipment' and
  - 3319 'Repair of other equipment'.

Available observations are spread over 112 3-digit US SIC coded manufacturing industries.
Second restriction requires that firms are located in a Member State of the European Union. This restriction allows to apply the merger definition of the European Merger Regulation on the data set. This restriction reduces the data set to 2,485,010 observation.
Third restriction requires the output deflation. Deflated values are proxies for quantities. (Van Beveren, 2012) Productivity or efficiency estimates are usually based

on deflated output values (e.g. De Loecker (2007), Konings et al. (2001), Maksimovic and Phillips (2001)). Table 9.2 shows output values before and after deflation. Deflation reduces the number of observations for output by 2%, from 1,230,922 to 1,204,187.

Table 9.2: Output Deflation

Variable	**Obs.**	**Min**	**Max**	**Mean**	**Std. Dev.**
$y_{nondeflated}$	1,230,922	-21,910	202,458,000	31,130	763,659.4
$y_{deflated}$	1,204,187	-21,740	197,600,000	30,550	759,638.7

Fourth restriction requires that input and output values are positive due to the logarithm. Table 9.3 shows the summary statistics for each variable if only positive values are allowed.

Table 9.3: Summary Statistics: Input and Output Variables

Variable	**Obs.**	**Min**	**Max**	**Mean**	**Std. Dev.**
y	1,194,881	0	197,577,828	30,785	762,586.3
x_L	1,172,599	1	33,835,000	5,558	137,062.8
employees	1,425,983	0	566,278	130.5	2,215.997
x_C	1,178,018	1	62,002,000	6,879	209,617.8
x_M	941,300	1	298,700,068	16,916	437,797.2

Material is the variable that indicates the highest reduction of available observations when limiting the data set to observations with available, positive values for all variables.

Material is a value that is not covered by profit & losses accounts according to IFRS. Therefore, it might be that firms that publish according to IFRS, e.g. firms in Great Britain, are excluded from the data set if material is required as variable. Table 9.4 shows the theoretical number of observations per country based on the number of available firms located in the country in contrast to number of available observations after restricting the data set to positive material values. The table shows that no firms in e.g. Great Britain (GB) with positive material values can be observed. The requirement of positive material values reduces the data set by 62%.

Table 9.4: Observations per Country with and without Restriction on Material

Country	theoretical no. of obs.	obs. with positive material value
AL	2440	
AT	49780	6383
BA	13330	6495
BE	53140	22222
BG	53720	31233
CH	87300	126
CY	1090	
CZ	104350	62422
DE	451320	64997
DK	22240	
EE	11890	6800
ES	235190	151779
FI	36390	24976
FR	299400	228077
GB	183810	
GR	28740	
HU	55220	17955
IE	11390	
IS	2370	
KV	810	
LI	1070	9
LT	20380	
LU	2750	917
LV	13040	320
ME	480	172
MK	10440	
MT	1460	
NL	62790	1022
NO	36830	26629
PL	304390	54452
PT	87820	64200
RO	91840	68180
RS	27300	21477
SE	68860	47082
SI	16300	11838
SK	35340	21537
total	**2,485,010**	**941,300**

Other empirical studies apply restrictions that guarantee that firms have a certain size. Those restrictions are that firms e.g. have a minimum of:

- sales of 10 M€ (Maksimovic and Phillips, 2001),
- total employees of 100 (Konings et al., 2001),
- total assets of at least 10 M€ (Konings et al., 2001).

The present study follows Blonigen and Pierce (2016) and does not apply any restrictions that guarantee a certain size of analyzed firms as especially targets of mergers are often small enterprises and would be eliminated from the data set. Therefore, these restrictions would cause a selection bias in the merger data set. Instead the present study implements, similar to Blonigen and Pierce (2016), a dummy that controls for firm-size in the analysis of merger-specific efficiency gains. Table 9.5 shows summary statistics after implying these further restrictions.[7] These restrictions reduce the data set by approximately 80%. It can be concluded that the data set consists of mainly small enterprises according to the definition of the European Commission. (Commission, 2017a) The fifth restriction requires that each indus-

Table 9.5: Summary Statistics: Input and Output Variables after Implementing Restrictions

Variable	**Obs.**	**Min**	**Max**	**Mean**	**Std. Dev.**
minimum of sales of 10 M€					
$y_{deflated,restr.}$	241,573	10,000	197,600,000	140,300	1,710,108
minimum of 100 employees					
$x_{L,restr.}$	212,425	-373,100	33,840,000	24,330	322,287.1
$employees_{restr.}$	259,206	100	566,300	564.2	5,257.1
minimum of total assets of 10 M€					
$x_{C,restr.}$	252,847	-3,779,000	62,000,000	28,960	456,254.4

try consists of at least 60 observations per year. This restriction intend to avoid a small sample problem, especially when including year dummies in the analysis of merger-specific efficiency gains. Table 9.6 shows the summary statistics and number of observations per industry before and after implementing all five restriction. The restrictions eliminate 28 industries, meaning 23% of the available industries.

[7]The table shows summary statistics after implementing restrictions on a data set covering firms that are located in a Member State of the EU. Before implementing restrictions the data set consists of 231,775 firms and 1,149,771 output observations.

Table 9.6: Number of Observations per Industry Before and After Implementing Restrictions

Variable	no. of ind	Min	Max	Mean	Std. Dev.
before	121	6	63,110	7,127	10,233.05
after	93	396	63,110	9,221	10,831.72

9.8 TFP Estimation: Endogeneity of Instruments

Table 9.7 reports Hansen's J values and their significance level for all industries. For 70 % of all industries the Hansen's J test show insignificant values, which tells that the chosen instruments are exogenous. Thus, for the majority of industries the applied TFP approach results in valid estimates. However, it can be discussed whether those industries that suffer from endogeneity should be excluded from an analysis of merger-specific efficiency gains or whether a different approach or instruments should be chosen to estimate the production function and thereby productivity.

Table 9.7: Hansen's J Value for All Industries

ind	Hansens'J	ind	Hansens'J	ind	Hansens'J	ind	Hansens'J	ind	Hansens'J
201	19.99 ***	243	3.69	289	2.54	333	21.93 ***	357	3.97
202	12.66 **	244	1.08	299	5.47	334	8.38 **	361	5.78
203	12.01 **	249	12.58 **	301	3.94	336	4.92	363	0.81
204	8.08 **	251	9.25 **	302	6.63 *	339	7.49 *	364	2.01
205	11.86 **	252	0.55	306	8.39 **	341	2.62	366	7.93 *
206	5.19	262	1.1	308	6.82 *	342	1.17	367	10.76 **
207	3.08	265	5.13	311	5.1	343	3.52	369	1.22
208	30.58 ***	267	3.18	316	12.83 **	344	0.68	371	4.72
209	9.83 **	271	2.19	321	2.91	345	4.75	373	5.67
211	0.53	275	0.61	322	0.53	346	8.31 **	374	4.46
221	3.21	278	1.96	323	2.66	348	2.83	375	5.34
225	3.56	279	2.15	324	6.79 *	349	12.73 **	381	14.17 ***
227	3.83	281	0.87	325	4.15	350	6.7 *	382	3.56
228	3.41	282	7.44 *	326	5.76	351	1.2	384	2.54
229	3.74	283	1.34	327	12.37 **	352	5.21	391	3.44
232	20.94 ***	284	4.81	328	3.51	353	2.61	394	0.99
238	5.1	285	2.65	329	2.83	354	5.45	399	3.63
239	5.96	286	7.73 *	331	14.66 ***	355	2.45		
242	4.22	287	5.48	332	2.65	356	2.89		

Note: *p<0.1; **p<0.05; ***p<0.01

9.9 Matching the Efficiency and Merger Data Sets

This section provides details about the impact of matching the efficiency and the merger data set on the merger data. Furthermore, it describes the impact of restricting the merger data set to mergers of manufacturing firms in Europe, whereas manufacturing means manufacturing according to US SIC as well as NACE Rev. 2 and Europe means countries of the EU, SAA, EFTA and EEA.

Matching the ZEPHYR data to the AMADEUS data, meaning implementing the requirement that the Identification Numbers of ZEPHYR are available in the AMADEUS data set, reduces the merger data set to 8,517 mergers with an identified buyer (17% of the original data set) and 4,610 mergers with an identified target (9% of the original data set).

This reduction is mainly caused by two facts. First, AMADEUS is a database for European firms. Therefore, all firms involved in a merger that are not located in Europe are nevertheless eliminated. According to the Institute for Merger, Acquisitions and Alliances 39% of mergers worldwide from 2005 to 2014 (422,576 mergers) took place in Europe (162,934 mergers). (IMAA-Institute, 2017a) This partly explains the reduction.

Second, the AMADEUS data set is limited to manufacturing firms. This eliminates all non-manufacturing merger. According to the Institute for Merger, Acquisitions and Alliances approximately 40% of mergers worldwide from 1985 to 2016 (916,697 mergers) took place in manufacturing industries (389,406 mergers). (IMAA-Institute, 2017b) Therefore, most of the reduction of the ZEPHYR data set can be explained by the fact that the analysis focuses on manufacturing firms in Europe.

Moreover, a detailed look at the ZEPHYR data set shows that some firms, like e.g. Schaeffler, which merged with Continental in 2008, are classified as manufacturing according to ZEPHYR, but not according to AMADEUS. The reason for this is that the merging party is often the mother company, e.g. Schaeffler Holding AG, which is classified as non-manufacturing in AMADEUS as the activities of these firms are administrative. Especially large firms often consist of several legal entities that are subsumed under the roof of a firm that mainly operates as administration. These firms are not included in the data set. Therefore, mergers of large firms are partly excluded from the data set. The exact number of eliminated mergers due to this problem cannot be identified.

Implementing the restriction that firms are manufacturing according to US SIC Code as well as NACE Rev. 2 results in data sets with 5,736 mergers with an identified buyer (33% further reduction) and 3,303 mergers with an identified target

(28% further reduction). The restriction causes a reduction of 28 to 33%, which is comparable to the reduction in the AMADEUS data set (reduction of 54%).
Implementing the restriction that firms are located countries that are part of EU, SAA, EFTA or EEA results in data sets with 5,327 mergers with an identified buyer (7% further reduction) and 2,772 mergers with an identified target (16% further reduction).
Table 9.8 shows the number of identified buyers and targets per country in Europe according to the restriction. Most merging parties are located in Great Britain, Germany and Spain. As firms in Great Britain do not report any material costs, mergers with merging parties located in Great Britain are eliminated from the data set when requiring material costs as variable for efficiency estimation.

Table 9.8: Number of Merger Parties per Country

country	Buyer	Target	country	Buyer	Target
AL			HR		
AT	65	46	HU	28	30
BA	3	7	IE	14	10
BE	111	100	IS	5	2
BG	20	29	IT		
CH	120	96	KV		
CY	2		LI	3	1
CZ	53	80	LT	14	20
DE	466	359	LU	3	5
DK	115	72	LV	13	10
EE	31	15	ME		
ES	460	174	MK	1	1
FI	233	80	MT	1	3
FR	295	338	NL	137	86
GB	658	485	NO	111	77
GR	33	9	PL	115	158

9.10 Proxy for Productivity: Material vs. Invest

Productivity estimation according to Olley and Pakes (1996) and Levinsohn and Petrin (2003) additionally requires either information about investment (Olley and Pakes, 1996) or material (Levinsohn and Petrin, 2003) to build a CF for productivity. Even though, the value of investment is not available in AMADEUS, it can be generated. The variable "investment" is created by applying the following equation based on Olley and Pakes (1996):

$$k_{it} = (1 - \delta_{i,t-1})k_{i,t-1} + i_{i,t-1} \Leftrightarrow i_{i,t-1} = k_{it} - k^*_{i,t-1} \tag{9.31}$$

whereas
$k_{it} = log(TOAS_{it})$ is the non depreciated capital,
$k^*_{i,t-1} = log(TOAS_{i,t-1} - DEPR_{i,t-1})$ is depreciated capital,
$\delta_{i,t-1}$ is a depreciation rate, whereas $\delta_{i,t-1} \geq 1$ and
$i_{i,t-1} = log(I_{i,t-1})$ is a multiplier for investment, whereas $I_{i,t-1} \geq 1$.
Investment is the rate by which capital from period t-1 to period t increases, taking into account that capital depreciates at the end of period t-1 and does not depreciate at the beginning of period t.
Alternatively to investment, material can be used to build a CF for productivity. (Levinsohn and Petrin, 2003) As mentioned in 4.4 the requirement of the variable "material" causes a significant reduction in the data set. If one ignores material as variable this would lead to a data set, which would be 8% larger than the data set including material. The data set excluding material includes 924,634 observations of 136,608 firms in 95 industries. On average each firm appears 6.8 times in the data set.
As the necessity of material reduces the data set significantly it can be considered to generate the investment variable and use it instead of material as proxy for productivity. As investment is created using a lag of capital, observations for one year are eliminated from the data set. Furthermore, the investment variable can only be generated if the capital value of a firm is observed two years in a row. The lag needed for the calculation of investment as well as the requirement of a firm to appear two times in a row in the data set reduces the data set significantly. While literature discusses the truncation of over 50% resulting from using investment as proxy (e.g. Levinsohn and Petrin (2003)), the available data set experiences a reduction of 15 to 20 %, which is less. Nevertheless, the reduction is less when choosing material as proxy for productivity instead of investment. Therefore, material is favored against investment. The decision to choose material instead of investment as proxy for productivity is mainly data driven.
Additionally, investment may cause a multicollinearity problem. Using investment as proxy for productivity and generating it out of capital is based on the assumption that there is a deviation between capital at the beginning of a period and capital at the end of the previous period. What might happen, especially in capital intense industries, is that firms do not invest. In these cases, investment would be zero. This would result in perfect multicollinearty and the model would collapse.

Then again, generating investment never gives zero values as deviations between capital values are never zero. This rather happens because of data quality than real investment. In other words, there is as an error term if capital at the beginning of each period is explained by capital at the end of the previous period. This error term is used as investment. It can be expected, caused by data quality or any other influences, that deviations in the two capital values are never zero in several cases. Using investment as proxy might cause multicollinearity. If it cannot be expected, large differences in estimated coefficients because of a large variation in investment might be another problem.
The data set shows both, multicollinearity as well as large differences in coefficients. Applying a VIF test to test for multicollinearity shows large values for all variables.[8] The problem of multicollinearity can partly be avoided by choosing material instead of investment as proxy for productivity.

9.11 An Alternative DID Approach

Including a Vector of Dummy Variables for Pre-merger Periods: If we consider pre-merger periods as non aggregated we receive the results shown in table 9.11.
Figure 9.2 shows the common trend of productivity of targets of treatment and control group in pre-merger periods, especially in period -4 to the merger period.

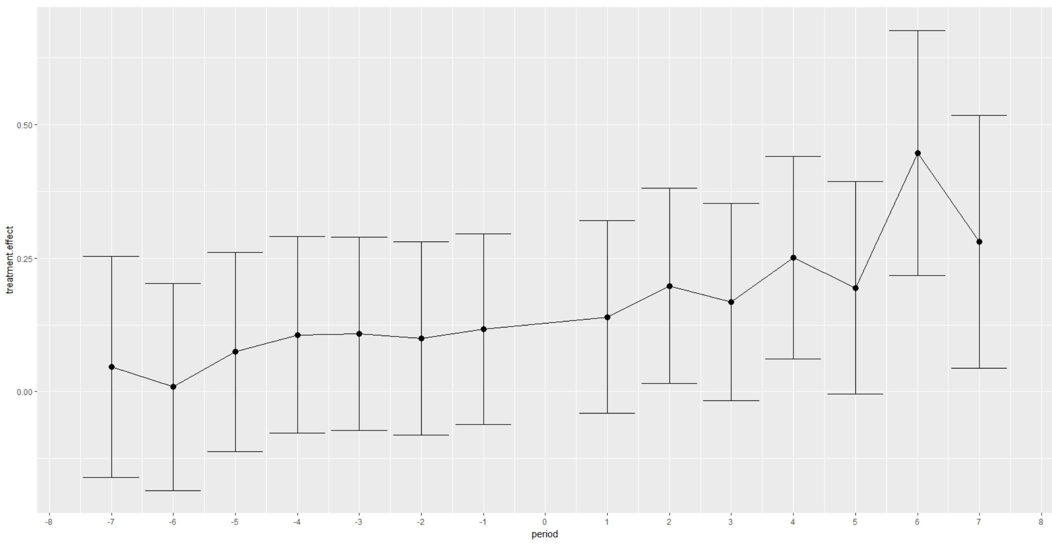


Figure 9.2: Productivity of Targets: Treatment Effects incl. Premerger Periods

Figure 9.3 shows the common trend of productivity of buyer of treatment and control

[8]Testing multicollinearity in a simple OLS regression, $y_{it} = \beta_k k_{it} + \beta_{kl} k_{it} l_{it} + \beta_{kk} k_{it} k_{it} + \beta l_{it} + \beta_{ll} l_{it} l_{it} + \beta_m m_{it} + \beta_{m,lag} m_{i,t-1} + \beta_{k,lag} k_{i,t-1}$, for the 2-digit US SIC industry 'Food Products' results in VIF values of 1.45 for invest and VIF values larger 10 for all other coefficients.

Table 9.9: Results DID incl. Dummies for Pre-Merger Periods

	Dependent variable:	
	efficiency	
	target	buyer
Treatment	-0.137 (0.088)	0.044 (0.095)
post.merger 1	0.140 (0.092)	-0.037 (0.096)
post.merger 2	0.198** (0.093)	-0.024 (0.096)
post.merger 3	0.168* (0.094)	-0.017 (0.096)
post.merger 4	0.251*** (0.097)	-0.017 (0.096)
post.merger 5	0.194* (0.052)	0.011 (0.096)
post.merger 6	0.447*** (0.117)	0.000 (0.097)
post.merger 7	0.281** (0.121)	-0.018 (0.098)
post.merger 8	-	-0.003 (0.126)
post.merger 9	-	-
Adj. R^2	0.93	0.95
obs.	4,543	41,198
Note:	*p<0.1; **p<0.05; ***p<0.01	

group in pre-merger periods. As results in table 9.11 and this figure show, buyers are not capable to generate merger-specific efficiency gains. However, targets are continuously improving by generating merger-specific efficiency gains.

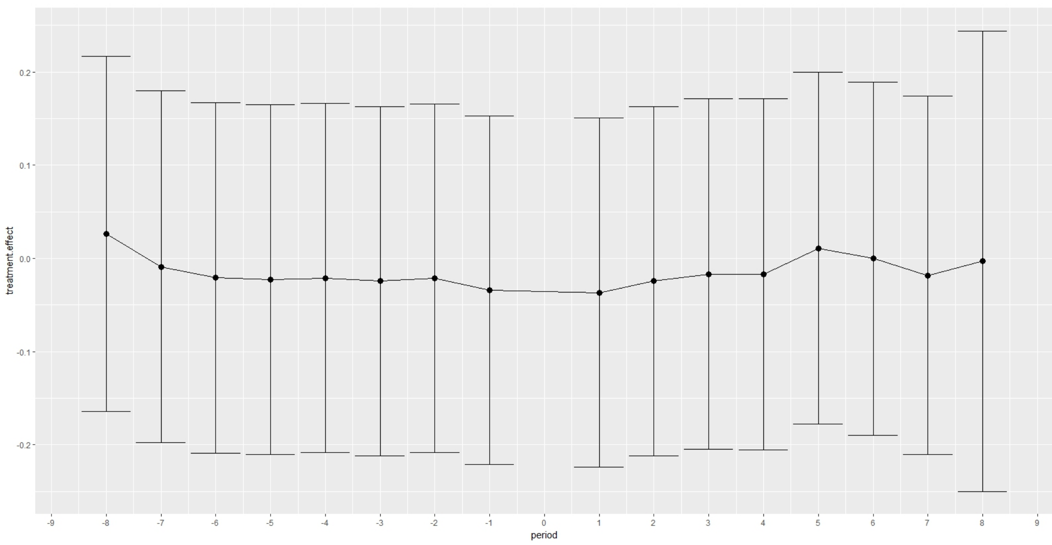


Figure 9.3: Productivity of Buyers: Treatment Effects incl. Premerger Periods

9.12 An Alternative PSM Approach

Matching in Period -1: Figure 5.2 in chapter 5 indicate that productivity differs between treatment and control group already in pre-merger periods. Thus, it can be discussed whether both groups show a common trend before the merger. Furthermore, treatment effects for productivity of targets as shown in figure 9.2 slightly increase in premerger period 1. Treatment effects of productivity of buyers as shown in figure Figure 9.3 slightly decreases. The deviation from a common trend in a pre-merger period close to the merger goes together with the concern of Blonigen and Pierce (2016) that firms find targets that are tending towards higher future productivity search for targets if they are tending towards a lower future productivity. To anticipate this effect, I match at period -1. As productivity is the left-hand variable in the DID approach, I use difference in productivity between pre-merger period -2 and -1 as covariate in the PSM instead of productivity itself.

Figure 9.4 and 9.5 shows the development of productivity per period of buyer and targets per merger category when matching at pre-merger period -1. While the trend of productivity of treated targets seems to nearly identically with the trend of the control group, the trend of productivity of treated buyers is parallel to the trend of the control group.

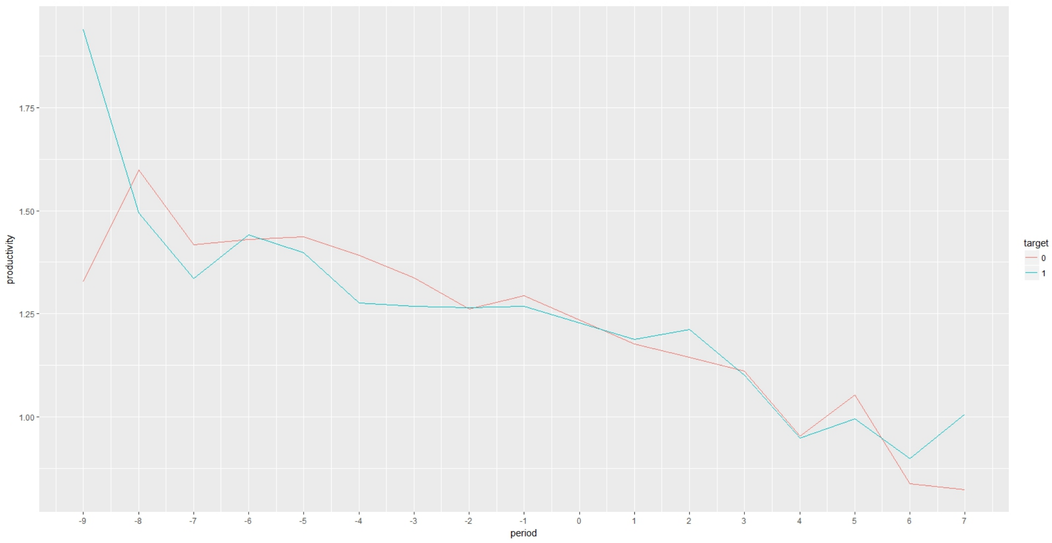


Figure 9.4: PSM: Mean Efficiency of Targets and Control Group - Matched at Period -1

Table 9.10 summarizes results of the DID model using those firms as control group that are matched in period -1 according to the propensity score matching. Results for buyers are comparable to those when matching the control group in the merger year, except the fact that the coefficient for buyers is not significant. But results for targets differ completely when matching in pre-merger period -1. Results show that

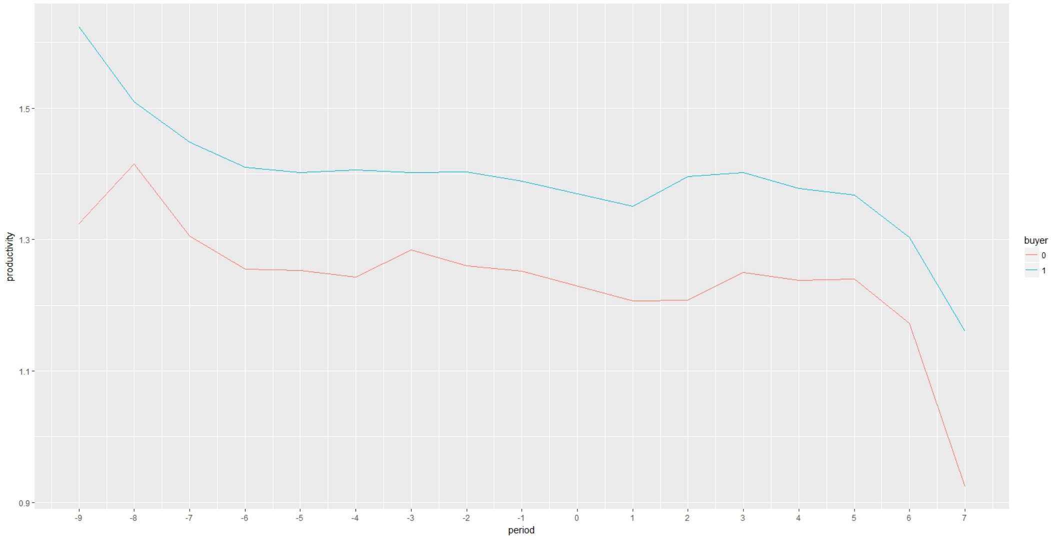


Figure 9.5: PSM: Mean Efficiency of Buyers and Control Group - Matched at Period -1

Table 9.10: Results DID after Matching at Period -1

	Dependent variable:	
	efficiency	
	target	buyer
Treatment	0.470** (0.193)	0.113 (0.070)
post.merger 1	-0.539*** (0.196)	-0.099 (0.071)
post.merger 2	-0.522*** (0.197)	-0.072 (0.072)
post.merger 3	-0.520*** (0.198)	-0.081 (0.073)
post.merger 4	-0.565*** (0.200)	-0.108 (0.073)
post.merger 5	-0.104854	-0.117 (0.075)
post.merger 6	-0.121632	-0.156* (0.081)
post.merger 7	-	-0.168 (0.146)
Adj. R^2	0.91	0.90
obs.	3,598	30,024
Note:	*p<0.1; **p<0.05; ***p<0.01	

targets are significantly more productive than their control group in a pre-merger period, but after the merger they loose this advantage. All values for post-merger periods are significant.

Figure 9.6 and figure 9.7 shows that while targets do not seem to have a common trend with their control group in period -9 but then after, buyers seem to have a stable common trend with their control group in pre-merger periods when matching at pre-merger period -1.

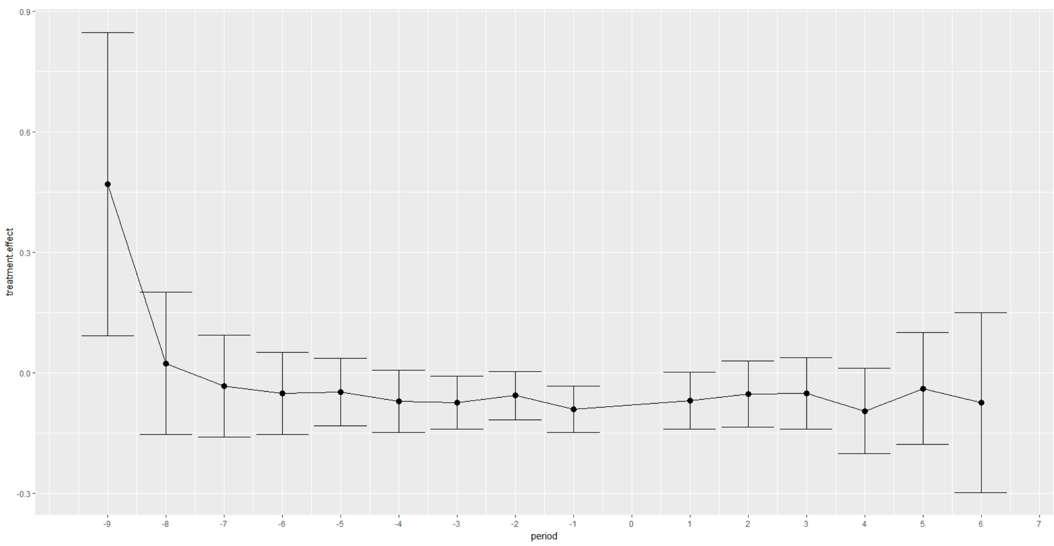


Figure 9.6: Productivity of Targets: Treatment Effects incl. Premerger Periods - Matched at Period -1

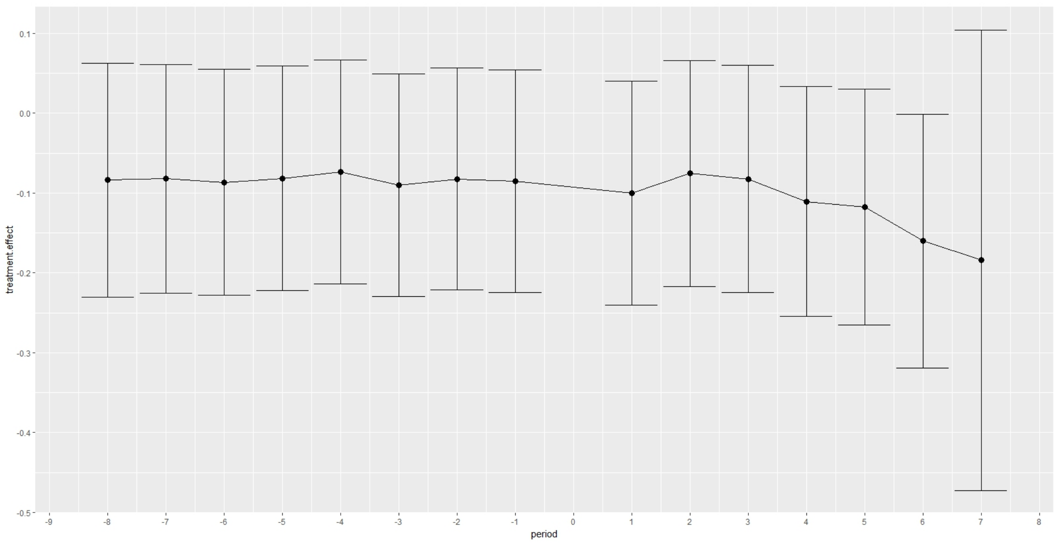


Figure 9.7: Productivity of Buyers: Treatment Effects incl. Premerger Periods - Matched at Period -1

9.13 SFA: Estimation of Technical Efficiency in a Cross-Sectional Model

Kumbhakar and Lovell (2003) describe the estimation of technical efficiency in a cross-section SFA model using a maximum log likelihood approach. To apply a maximum log likelihood approach, the joint density function of the combined error term, $\epsilon = v - u$, and inefficiency term, u, is needed, f(u, ϵ). The joint density function

can be generated by multiplying the density function of the normal distributed random error term, v, and the density function of the truncated normal distributed inefficiency term, u. Applying a maximum log likelihood approach results in the conditional distribution of inefficiency given the combined error term. The mean or mode of this conditional distribution allows to estimate inefficiency.
The cross-sectional SFA production function can be generalized as

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + v_i - u_i \tag{9.32}$$

where v_i is a random error term and u_i is an inefficiency term. u_i and v_i are assumed to be independently distributed of each other, and the regressors. In the following v_i $i.i.d.N(0, \sigma_v^2)$ is normal distributed and u_i $i.i.d.N^+(\mu, \sigma_u^2)$ is assumed to be truncated normal distributed.
The density function of the normal distributed v, f(v), is

$$\mathrm{f}(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \exp - \frac{v^2}{2\sigma_v^2} \tag{9.33}$$

The density function of the truncated distributed u, f(u), is

$$\mathrm{f}(u) = \frac{1}{\sqrt{2\pi}\sigma_u \Phi(-\mu/\sigma_u)} \exp - \frac{(u-\mu)^2}{2\sigma_u^2} \tag{9.34}$$

where μ is the mode of the normal distribution, which is truncated below zero, and $\Phi(\cdot)$ is a standard normal cumulative distribution function.
The joint density function of u and v, f(v, u), can be generated by a multiplication of both density functions

$$\mathrm{f}(u,v) = \mathrm{f}(u) \times \mathrm{f}(v) = \frac{1}{2\pi\sigma_u\sigma_v\Phi(-\mu/\sigma_u)} \exp - \frac{(u-\mu)^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2} \tag{9.35}$$

Furthermore it is possible to replace v by $v = u + \epsilon$. The joint density function of u and ϵ is

$$\mathrm{f}(u,\epsilon) = \frac{1}{2\pi\sigma_u\sigma_v\Phi(-\mu/\sigma_u)} \exp - \frac{(u-\mu)^2}{2\sigma_u^2} - \frac{(u+\epsilon)^2}{2\sigma_v^2} \tag{9.36}$$

The marginal density function of ϵ is

$$\begin{aligned} f(u,\epsilon) &= \int_0^{\mathrm{inf}} \mathrm{f}(u,\epsilon) \\ &= \frac{1}{\sqrt{2\pi}\sigma\Phi(-\mu/\sigma_u)} \Phi(\frac{-\mu}{\lambda\sigma} - \frac{\epsilon\lambda}{\sigma}) \exp - \frac{(\epsilon-\mu)^2}{2\sigma^2} \\ &= \frac{1}{\sigma}\phi\left(\frac{\epsilon+\mu}{\sigma}\right)\Phi\left(\frac{\mu}{\sigma\lambda}\right)\left[\Phi\left(-\frac{\mu}{\sigma_u}\right)\right]^{-1} \end{aligned} \tag{9.37}$$

with $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$ and $\lambda = \sigma_u/\sigma_v$. $\phi(\cdot)$ is a standard normal density function. The mean of the combined error, $E(\epsilon)$, is

$$E(\epsilon) = -E(u) = -\frac{\mu a}{2} - \frac{\sigma_u a}{\sqrt{2\pi}} \exp -\frac{1}{2}\left(\frac{\mu}{\sigma_u}\right)^2 \tag{9.38}$$

The variance of the combined error, $V(\epsilon)$, is

$$V(\epsilon) = \mu^2 \frac{a}{2}\left(1 - \frac{a}{2}\right) + \frac{a}{2}\left(\frac{\pi - a}{\pi}\right)\sigma_u^2 + \sigma_v^2 \tag{9.39}$$

with $a = [\Phi(-\mu/\sigma_u)]^{-1}$.
The log likelihood function with i firms is

$$\ln \text{L} = constant + I \ln \sigma - I \ln \Phi\left(-\frac{\mu}{\sigma_u}\right) + \sum_i \ln\Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\epsilon_i\lambda}{\sigma}\right) - \frac{1}{2}\sum_i\left(\frac{\epsilon_i + \mu}{\sigma}\right)^2 \tag{9.40}$$

with $\sigma_u = \lambda\sigma/\sqrt{1+\lambda^2}$.
Maximizing the log likelihood function results in the conditional distribution of u given ϵ, f$(u|\epsilon)$

$$\begin{aligned}\text{f}(u|\epsilon) &= \frac{\text{f}(u,\epsilon)}{\text{f}(\epsilon)} \\ &= \frac{1}{\sqrt{2\pi}\sigma_* \left[1 - \Phi(-\tilde{\mu}/\sigma_*)\right]} \exp -\frac{(u - \tilde{\mu})}{2\sigma_*^2}\end{aligned} \tag{9.41}$$

The conditional function is normal distributed $N^+(\tilde{\mu}_i; \sigma_*^2)$ with $\tilde{\mu}_i = (-\sigma_u^2\epsilon_i + \mu\sigma_v^2)/\sigma$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.
To approximate inefficiency the mean or mode of the conditional distribution is useful

$$E(u_i|\epsilon_i) = \sigma_*\left[\frac{\tilde{\mu}_i}{\sigma_*} + \frac{\phi(\tilde{\mu}_i/\sigma_*)}{1 - \Phi(-\tilde{\mu}_i/\sigma_*)}\right] \tag{9.42}$$

with $M(u_i|\epsilon_i) = \tilde{\mu}_i$ if $\tilde{\mu}_i > 0, 0$ otherwise. If $\tilde{\mu}_i \leq 0$ the truncated normal distribution collapses to a half normal distribution.
Technical efficiency can be estimated as

$$\begin{aligned}TE_i &= E(exp{-}u|\epsilon_i) \\ &= \frac{1 - \Phi\left[\sigma_* - (\tilde{\mu}_i/\sigma_*)\right]}{1 - \Phi(-\tilde{\mu}_i/\sigma_*)} exp{-}\tilde{\mu}_i + \frac{1}{2}\sigma_*^2\end{aligned} \tag{9.43}$$

The estimate of technical efficiency is unbiased but inconsistent.

9.14 The Malmquist Index

An alternative approach to DID to analyze merger-specific efficiency gains is the decomposing efficiency gains. An efficiency gain can be measured as negative growth rate of inefficiency from period $t-1$ to t:

$$\frac{D^t(\mathbf{y}^t, \mathbf{x}^t)}{D^{t-1}(\mathbf{y}^{t-1}, \mathbf{x}^{t-1})} < 1 \tag{9.44}$$

The efficiency gain can be interpreted as percentage that inefficiency decreased. If equation (9.44) is larger than one, the efficiency change is an efficiency loss. If equation (9.44) is one efficiency stagnates.
Taking into account that an environment influences efficiency change, Malmquist (1953) defines a relative efficiency change as

$$M = (M^t M^{t-1})^{1/2} \tag{9.45}$$

which is the geometric mean of

$$M^t = \frac{D^t(\mathbf{y}^t, \mathbf{x}^t)}{D^t(\mathbf{y}^{t-1}, \mathbf{x}^{t-1})} \tag{9.46}$$

and

$$M^{t-1} = \frac{D^{t-1}(\mathbf{y}^t, \mathbf{x}^t)}{D^{t-1}(\mathbf{y}^{t-1}, \mathbf{x}^{t-1})} \tag{9.47}$$

Färe et al. (1994) decompose the Malmquist Index as introduced in equation (9.45) into three components, namely 'Economies of Scale', 'Technical Change' and 'Technical Efficiency Change'. Zschille (2014) identifies a merger-specific efficiency change by a further decomposition of the Malmquist Index. The author assumes that two firms, A and B, which are independent in a pre-merger period, *pre*, merge into one firm named M in a post-merger period, *post*. He distinguishes a merger-specific efficiency change by assuming that firms A and B can be hypothetically merged into firm ADD by simply adding their pre-merger inputs and outputs. The predicted values for firm ADD gives the needed information about how firm A and B would have performed if they had not lost their independence.

$$M_{CRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD}, \mathbf{y}_M, \mathbf{x}_M) = \left[\frac{1}{D^{post}_{VRS}(\tilde{\mathbf{y}}^{post}_{ADD}, \mathbf{x}_{ADD})}\right] \tag{9.48a}$$

$$* \left[\frac{D^{post}_{VRS}(\mathbf{y}_M, \mathbf{x}_M)}{\frac{D^{pre}_{VRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}{D^{pre}_{VRS}(\tilde{\mathbf{y}}^{pre}_{ADD}, \mathbf{x}_{ADD})}}\right] \tag{9.48b}$$

$$* \left[\frac{D^{pre}_{VRS}(\tilde{\mathbf{y}}^{post}_{ADD}, \mathbf{x}_{ADD})}{D^{pre}_{VRS}(\tilde{\mathbf{y}}^{pre}_{ADD}, \mathbf{x}_{ADD})} * \frac{D^{post}_{VRS}(\tilde{\mathbf{y}}^{post}_{ADD}, \mathbf{x}_{ADD})}{D^{post}_{VRS}(\tilde{\mathbf{y}}^{pre}_{ADD}, \mathbf{x}_{ADD})}\right]^{1/2} \tag{9.48c}$$

$$* \left[\frac{\frac{D^{pre}_{VRS}(\mathbf{y}_M, \mathbf{x}_M)}{D^{post}_{VRS}(\mathbf{y}_M, \mathbf{x}_M)}}{\frac{D^{pre}_{VRS}(\tilde{\mathbf{y}}^{post}_{ADD}, \mathbf{x}_{ADD})}{D^{post}_{VRS}(\tilde{\mathbf{y}}^{post}_{ADD}, \mathbf{x}_{ADD})}} * \frac{\frac{D^{pre}_{VRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}{D^{post}_{VRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}}{\frac{D^{pre}_{VRS}(\tilde{\mathbf{y}}^{pre}_{ADD}, \mathbf{x}_{ADD})}{D^{post}_{VRS}(\tilde{\mathbf{y}}^{pre}_{ADD}, \mathbf{x}_{ADD})}}\right]^{1/2} \tag{9.48d}$$

$$* \left[\frac{\frac{D^{pre}_{CRS}(\mathbf{y}_M, \mathbf{x}_M)}{D^{pre}_{VRS}(\mathbf{y}_M, \mathbf{x}_M)}}{\frac{D^{pre}_{CRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}{D^{pre}_{VRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}} * \frac{\frac{D^{post}_{CRS}(\mathbf{y}_M, \mathbf{x}_M)}{D^{post}_{VRS}(\mathbf{y}_M, \mathbf{x}_M)}}{\frac{D^{post}_{CRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}{D^{post}_{VRS}(\mathbf{y}_{ADD}, \mathbf{x}_{ADD})}}\right]^{1/2} \tag{9.48e}$$

The Malmquist Index as defined in equation (9.48) can be decomposed into a "Merger Effect" (cf. subequation (9.48a)), "Technical Efficiency Change" (cf. subequation (9.48b)), "Technical Change" (cf. subequation (9.48c)), a "Bias of Technical Change" (cf. subequation (9.48d)) and a "Economies of Scale", named "Post-merger Scale Effect" (cf. equation (9.48e)).

The "Merger Effect" measures the reversed distance of $\tilde{\mathbf{y}}^{post}_{ADD}$ to the VRS frontier function in a post-merger period. $\tilde{\mathbf{y}}^{post}_{ADD}$ equals the sum of the efficient outputs of firms A and B in a post-merger period. The merger effect can be interpreted as the percentage an efficient output of two dependent firms exceeds or falls below the added efficient outputs of two independent firms in a post-merger period. The difference between these two values is caused by the dependency of the two merging firms and therefore identifies merger-specific efficiency change.

"Technical Efficiency Change" measures the the change of producers' performances that could have been achieved without the merger. It is based on the assumption that producers use an available production technology differently, whereas the usage is differently efficient and producers may change the way they use a technology.

"Technical Change" is based on the assumption that the environment, i.e. the industry, changes. Technical change measures the impact of a shift and/or a rotation of the VRS and/or CRS frontier function on efficiency change. A "Bias of Technical Change" has an impact on the efficiency change, as the measurement of a technical change may differ if it is calculated based on the added input and output or on observed input and output values of the merged firm.

"Economies of Scale" are based on the assumption that the production function has Variable Returns to Scale (VRS). Therefore, for each input vector there is certain percentage by which the Constant Returns to Scale (CRS) production frontier function exceeds or falls below the VRS production function. If the CRS frontier function exceeds the VRS frontier function, the production function is characterized by Decreasing Returns to Scale (DRS). If the VRS frontier function exceeds the CRS frontier function, the production function is characterized by Increasing Returns to Scale (IRS). "Economies of Scale" or - as defined in the context of a merger - the 'Post-merger Scale Effect' measure the percentage by which the CRS frontier function exceeds or falls below the VRS frontier function as defined in equation (9.48e). The advantage of the approach of Zschille (2014) it that it considers an explicit merger effect without assuming that merging firms would behave like non merging firms if they do not merge.[9] Overall, the decomposition of the Malmquist Index has been applied in the analysis of efficiency change in merger analysis, e.g. Lang and Welzel (1999), Bogetoft and Wang (2005) and Zschille (2014).

Data for the Decomposition of the Malmquist Index

The decomposition of efficiency gains according to Zschille (2014) requires the identification of mergers with input and output information of both, buyer and target. In the following, the combination of identified buyer and target are named buyer-target-combination. As a merger may consist of more than one buyer and/or target[10], a merger may consist of more than one buyer-target-combination.
At this point both data sets, the merger data set based on "ZEPHYR" data and the efficiency data set based on "AMADEUS" data, needs to be matched. Comparable to other authors who analyze effects of mergers in Europe (e.g. Oberhofer and Pfaffermayr (2011), Stiebale and Trax (2011), Oberhofer (2013)), the matching is based on a Identification Number assigned by the Bureau van Dijk (BvD ID).
After matching the efficiency data set to the merger data set, out of 51,128 mergers can be identified 388 buyer-target combinations. This shows that the decomposition of the Malmquist Index can be applied to a minority of mergers. For more mergers, either buyer or target can be identified in the efficiency data set. Nevertheless, for most mergers, neither buyer nor target can be identified in the efficiency data set.
Table 9.11 summarizes input and output variables after matching. Comparing mean sales and mean number of employees of buyer and targets shows that buyers are in average larger than their targets.

[9] A Difference-in-Difference (DID) approach is based on this assumption. The DID approach is a common approach in the analysis of merger-specific efficiency changes and has been applied by e.g. Ikeda and Doi (1983), Akhavein et al. (1997), Ferrier and Valdmanis (2004), Kwoka and Pollitt (2010).

[10] See subsection 3.3 for a description of the merger data set

Table 9.11: Buyer-Target-Combinations: Positive Input and Output Values of Merger Parties

Variable	**BTC**	**firms**	**Obs.**	**Min**	**Max**	**Mean**	**Std. Dev.**
Buyer							
y	325	298	2,176	345.9	2,009,307.4	134,918.4	219,742.4
x_L				12	370,600	20,966	34,284.58
employees	289	265	1,787	2	6,030	589.5	895.91
x_C				5	2,232,129	50,248	186,944.4
x_M				7	1,023,985	71,565	118,364.1
Target							
y	325	315	2,176	6	677,752	33,380	68,333.7
x_L				4	91,394	4,663.4	8,176.07
employees	301	292	1,816	1	2,250	158.4	227.6
x_C				1	193,954	8,092.2	16,904.44
x_M				1	537,915	20,685	50,470.23

Furthermore, the decomposition of the Malmquist Index according to Zschille (2014) requires:

1. the availability of pre-merger efficiency data of both, buyer and target, and

2. the availability of post-merger efficiency data of the buyer.

The first requirement ensures that it is possible to create a hypothetical merger by adding the pre-merger values of buyer and target. The second requirement ensures that it is possible to compare the hypothetical merger to the real merger.
The requirements cause a reduction of the data set to 184 buyer-target combinations.
Table 9.12 summarizes the input and output values for buyers and targets. The reduction has a small impact on mean values compared to values shown in table 9.11.
Implementing both requirements results in a data set that includes not only pre-merger but also post-merger values of targets. Pre- and post-merger values of targets allows not only to analyze the difference between buyers' pre- and post-merger efficiency, but also to analyze the difference between targets' pre- and post-merger efficiency. In the available data set the buyer and the target are observable as legal entity after the merger and the target never merges into the buyer in the sense that the target disappears as legal entity.

Table 9.12: Buyer-Target-Combinations: Input and Output Values of Merger Parties after Implementing Restrictions

Variable	**BTC**	**firms**	**Obs.**	**Min**	**Max**	**Mean**	**Std. Dev.**
Buyer							
y	184	175	1,769	345.9	2,009,307.4	134,026.6	233,410.2
x_L				108	259,885	20,884	39,415.38
employees	172	164	1,451	3	5,831	496.6	777.74
x_C				5	2,232,129	72,356	276,759.7
x_M				7	978,437	71,039	119,214.1
Target							
y	184	177	1,518	32.5	677,752	31,763.8	68,996.81
x_L				4	91,394	4,556	9,706.33
employees	174	168	1,281	1	2,250	145.6	220.85
x_C				1	193,954	9,661.2	20,749.01
x_M				1	537,915	19,709	49,837.33

DID Modified Model - Aggregated Post-merger Periods

As the beginning and ending of a merger process are vague, this study separates the post-merger period by years and includes each year of this period as independent variable into the DID regression. The advantage of this differentiation is that the significance of the effect of each post-merger period on efficiency may indicate the beginning and ending of a merger process. The disadvantage of this approach is that the effects of the post-merger periods are likely to be correlated. The reason for this is the fact that a merger is process, meaning a development, that builds a post-merger effect over time. Thus, the effects of post-merger periods are likely to be correlated with e.g. the effect of the period before and after.

In the following the DID model is modified. Post-merger periods 1 to 3 are aggregated as short-term, periods 4 to 6 as mid-term and 6 to 9 as long-term.

Table 9.13 shows the results of a DID regression using all firms as control group. The modified model shows similar results as the results shown in table 5.1. Targets generate significant efficiency gains in a short- and mid-term perspective after the merger. Buyers are significantly more efficient than other firms and generate efficiency gains in a mid-term perspective after the merger.

Table 9.13: DID Regression using All Firms as Control Group - Modified Model

	Dependent variable:	
	efficiency	
	target	buyer
pre.merger	0.001	0.062^{***}
	(0.011)	(0.004)
post.period.short	0.037^{*}	-0.002
	(0.020)	(0.007)
post.period.mid	0.071^{***}	0.018^{**}
	(0.026)	(0.009)
Observations	857,662	865,417
R^2	0.800	0.801
Adjusted R^2	0.800	0.801
Residual Std. Error	0.408 (df = 856524)	0.409 (df = 864279)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9.14 shows the results of a DID regression using matched firms as control group. The modified model shows similar results as the results shown in table 5.5. Targets are less efficient than their control group before a merger. They generate significant efficiency gains in a short- and mid-term perspective after the merger. Buyers are significantly more efficient than their control group. They generate efficiency gains in a mid-term perspective after the merger.

Table 9.14: DID Regression using Matched Firms as Control Group - Modified Model

	Dependent variable:	
	efficiency	
	target	buyer
pre.merger	-0.040^{***}	0.024^{***}
	(0.013)	(0.004)
post.period.short	0.068^{***}	-0.006
	(0.022)	(0.006)
post.period.mid	0.162^{***}	0.017^{**}
	(0.032)	(0.009)
Observations	4,543	41,198
R^2	0.941	0.955
Adjusted R^2	0.930	0.954
Residual Std. Error	0.278 (df = 3876)	0.252 (df = 40125)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Predicting Conditions: Modified Model for Firm Characteristics

The model in chapter 7.5 for buyers is modified as only countries and industries are used as independent variables if minimum 100 mergers took place in in those countries and industries; for targets the model is modified to a minimum of 20 mergers in each countries and industries. All other countries and industries are aggregated as "others". This allows to reduce the number of independent variables. Furthermore, the results for targets show whether countries and/or industries with more than 100 mergers for buyers respectively 20 mergers for targets differ from others.

Table 9.15 shows the results of the modified model for buyers. Similar to the results shown in table 7.7, the impact of merger years are insignificant (and thus not listed in the table). Also comparable, industry 32, the industry for "Stone, Clay, Glass, and Concrete Products", differs significantly. Furthermore, the impact of capital intensity remains the comparable. Differently to the results shown in table 7.7 the impact of countries and firm size changes. Thus, it might be that the independent variables chosen for country and firm size may suffer from multicollinearity.

Table 9.15: Impact of Firm Characteristics on Efficiency Changes of Buyers - Modified Model

	Short-term	**Mid-term**	**Long-term**
firm.sizemedium	0.024**	0.020	0.012
	(0.010)	(0.014)	(0.020)
firm.sizemicro	−0.028	0.005	0.111
	(0.032)	(0.053)	(0.079)
firm.sizesmall	−0.034**	−0.036*	0.039
	(0.015)	(0.022)	(0.033)
country.ES	0.014	0.054**	−0.001
	(0.017)	(0.021)	(0.030)
country.FI	0.021	−0.008	−0.071**
	(0.017)	(0.021)	(0.030)
country.FR	−0.001	−0.007	−0.094***
	(0.018)	(0.022)	(0.031)
country.NO	0.015	0.051**	0.012
	(0.021)	(0.026)	(0.036)
country.other	−0.001	−0.014	−0.103***
	(0.016)	(0.020)	(0.030)
ind.28	0.028	−0.0003	−0.0005
	(0.023)	(0.028)	(0.037)
ind.32	−0.064***	−0.061**	−0.108***
	(0.024)	(0.030)	(0.040)
ind.34	−0.004	−0.009	−0.006
	(0.025)	(0.033)	(0.048)
ind.35	0.004	0.026	0.030
	(0.023)	(0.030)	(0.041)
ind.36	0.023	0.021	−0.004
	(0.025)	(0.032)	(0.043)
ind.other	−0.008	−0.011	0.025
	(0.019)	(0.024)	(0.032)
capital.intensity	0.023*	0.051***	0.109***
	(0.012)	(0.017)	(0.023)
Constant	−0.019	−0.012	0.012
	(0.029)	(0.034)	(0.044)
Observations	1,880	1,192	754
R^2	0.026	0.039	0.094
Adjusted R^2	0.014	0.022	0.071
Residual Std. Error	0.189 (df = 1856)	0.192 (df = 1170)	0.215 (df = 734)
F Statistic	2.180***	2.274*** (df = 21; 1170)	4.026*** (df = 19; 734)
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 9.16 shows the results for a modified model for targets. The impact of merger

year 2007 and 2010 and of capital intensity remains significant at a comparable level for short-term efficiency gains, which indicates that those independent variables does not suffer from multicollinearity. Onla the F-statistic of the modified model for short-term efficiency changes is significant. The R^2 value of this model is half as large as the non-modified model. The estimation modified model for long-term efficiency changes results in no significant estimates. Overall, the modified models show that the model chosen does not majorly suffer from multicollinearity. Thus, the results shown in 7.8 allows to identify firm characteristics that may have an impact on post-merger efficiency changes.

Table 9.16: Impact of Firm Characteristics on Efficiency Changes of Targets - Modified Model

	Short-term	**Mid-term**	**Long-term**
firm.sizemedium	0.024**	0.020	0.012
	(0.010)	(0.014)	(0.020)
firm.sizemicro	−0.028	0.005	0.111
	(0.032)	(0.053)	(0.079)
firm.sizesmall	−0.034**	−0.036*	0.039
	(0.015)	(0.022)	(0.033)
country.ES	0.014	0.054**	−0.001
	(0.017)	(0.021)	(0.030)
country.FI	0.021	−0.008	−0.071**
	(0.017)	(0.021)	(0.030)
country.FR	−0.001	−0.007	−0.094***
	(0.018)	(0.022)	(0.031)
country.NO	0.015	0.051**	0.012
	(0.021)	(0.026)	(0.036)
country.other	−0.001	−0.014	−0.103***
	(0.016)	(0.020)	(0.030)
ind.28	0.028	−0.0003	−0.0005
	(0.023)	(0.028)	(0.037)
ind.32	−0.064***	−0.061**	−0.108***
	(0.024)	(0.030)	(0.040)
ind.34	−0.004	−0.009	−0.006
	(0.025)	(0.033)	(0.048)
ind.35	0.004	0.026	0.030
	(0.023)	(0.030)	(0.041)
ind.36	0.023	0.021	−0.004
	(0.025)	(0.032)	(0.043)
ind.other	−0.008	−0.011	0.025
	(0.019)	(0.024)	(0.032)
capital.intensity	0.023*	0.051***	0.109***
	(0.012)	(0.017)	(0.023)
Constant	−0.019	−0.012	0.012
	(0.029)	(0.034)	(0.044)
Observations	1,880	1,192	754
R^2	0.026	0.039	0.094
Adjusted R^2	0.014	0.022	0.071
Residual Std. Error	0.189 (df = 1856)	0.192 (df = 1170)	0.215 (df = 734)
F Statistic	2.180*** (df = 23; 1856)	2.274*** (df = 21; 1170)	4.026*** (df = 19; 734)
Note:	*p<0.1; **p<0.05; ***p<0.01		

Bibliography

Daniel A. Ackerberg, Kevin Caves, and Garth Frazer. Identification properties of recent production function estimators. *Econometrica*, 83(6):2411 – 2451, 2015. ISSN 00129682.

Victor Aguirregabiria. Econometric issues and methods in the estimation of production functions. 2009.

Jalal D. Akhavein, Allen N. Berger, and David B. Humphrey. The effects of megamergers on efficiency and prices: Evidence from a bank profit function. *Review of Industrial Organization*, 12(1):95 – 139, 1997. ISSN 0889938X.

Joshua Angrist and Jorn-Steffen Pischke. *Mastering Metrics: The Path from Cause to Effect*. Princeton University Press, 1 edition, 2014.

John Ashton, Khac Pham, et al. Efficiency and price effects of horizontal bank mergers. *Centre for Competition Policy Working Paper, University of East Anglia*, 2:07–9, 2007.

BCG. How successful m & a deals split the synergies, 2017.

Olivier Bertrand and Habib Zitouna. Domestic versus cross-border acquisitions: Which impact on the target firms' performance?. *Applied Economics*, 40(17):2221 – 2238, 2008. ISSN 00036846.

André Bielecki. *Efficient Frontier Analysis*. Zusätzliche Beiträge zu Methodik der empirischen Forschung. Gabler, 2011.

Bruce A. Blonigen and Justin R. Pierce. Evidence for the effects of mergers on market power and efficiency. Working Paper 22750, National Bureau of Economic Research, October 2016.

Peter Bogetoft and Lars Otto. *Benchmarking with DEA, SFA and R*, volume 157. 01 2011.

Peter Bogetoft and Dexiang Wang. Estimating the potential gains from mergers. *Journal of Productivity Analysis*, 23(2):145 – 171, 2005. ISSN 0895562X.

Marco Caliendo and Sabine Kopeinig. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72, 2008. ISSN 1467-6419.

David Cardwell. The role of the efficiency defence in eu merger control proceedings following ups/tnt, fedex/tnt and ups v commission. *Journal of European Competition Law & Practice*, pages 1–10, June 2017.

Richard E. Caves. Mergers, takeovers, and economic efficiency. *International Journal of Industrial Organization*, 7(1):151–174, 1989. ISSN 0167-7187.

J. T. Coelli. A guide to frontier version 4.1: A computer program for stochastic frontier production and cost function estimation. *CEPA Working Paper*, (07), 1996.

J. Timothy Coelli, D.S. Prasada Rao, Christopher J. O'Donnell, and George E. Battese. *An introduction to efficiency and productivity analysis*. Springer, New York, 2005. ISBN 0387242651 9780387242651 038724266X 9780387242668 0387258957 9780387258959.

Allan Collard-Wexler and Jan De Loecker. Reallocation and technology: Evidence from the us steel industry. *American Economic Review*, 105(1):131 – 171, 2015. ISSN 00028282.

European Commission. *Towards more effective EU merger control*. 2014.

European Commission. What is an sme?, 2017a.

European Commission. Merger statistics, 2017b.

European Commission. Merger control procedures, 2017c.

Jan De Loecker. Do exports generate higher productivity? evidence from slovenia. *Journal of International Economics*, 73(1):69 – 98, 2007. ISSN 00221996.

Jan De Loecker and Frederic Warzynski. Markups and firm-level export status. *American Economic Review*, 102(6):2437 – 2471, 2012. ISSN 00028282.

Jan De Loecker, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. Prices, markups, and trade reform. *Econometrica*, 84(2):445 – 510, 2016. ISSN 00129682.

Rajeev Dehejia and Sadek Wahba. Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84(1):151–161, 2002.

Jan DeLoecker and Jan Eeckhout. The rise of market power and the macroeconomic implications. (23687), August 2017.

Robert DeYoung, Douglas D Evanoff, and Philip Molyneux. Mergers and acquisitions of financial institutions: a review of the post-2000 literature. *Journal of Financial services research*, 36(2-3):87–110, 2009.

Liran Einav and Jonathan Levin. Empirical industrial organization: A progress report. *Journal of Economic Perspectives*, 24(2):145–62, June 2010.

Competition Directorate General European Commission. Minority power - eu merger control and the acquisition of minority shareholdings. *Competition policy brief*, 15, October 2014.

Eurostat. Annual detailed enterprise statistics for industry (nace rev. 2, c) - by country, 2017a.

Eurostat. Annual detailed enterprise statistics for industry (nace rev. 2, c) - by industry, 2017b.

Yanqin Fan, Qi Li, and Alfons Weersink. Semiparametric estimation of stochastic production frontier models. *Journal of Business & Economic Statistics*, 14(4): 460–468, 1996.

Rolf Färe, Shawna Grosskopf, Mary Norris, and Zhongyang Zhang. Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1):66–83, March 1994.

Joseph Farrell and Carl Shapiro. Horizontal mergers: An equilibrium analysis. *The American Economic Review*, 80(1):pp. 107–126, 1990. ISSN 00028282.

G. D. Ferrier and V. G. Valdmanis. Do mergers improve hospital productivity? *Journal of the Operational Research Society*, 55(10):1071 – 1080, 2004. ISSN 01605682.

Alan A. Fisher and Robert H. Lande. Efficiency considerations in merger enforcement. *California Law Review*, 71(6):1582, 1983. ISSN 00081221.

Lucia Foster, John Haltiwanger, and Chad Syverson. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1):394–425, March 2008.

Matilda Gjirja. Assessing the efficiency effects of bank mergers in sweden: A panel-based stochastic frontier analysis. *Goteborg University, Department of Economics*, 2003.

William H. Greene. *The Econometric Approach to Efficiency Analysis*. The Measurement of Productive Efficiency: Techniques and Applications. Oxford University Press, 2007. ISBN 9780198040507 0198040504 9781435619968 143561996X 9780195183528 0195183525.

Klaus Gugler, Dennis C. Mueller, B. Burcin Yurtoglu, and Christine Zulehner. The effects of mergers: An international comparison. *International Journal of Industrial Organization*, 21(5):625, 2003. ISSN 01677187.

Katsuhiko Ikeda and Noriyuki Doi. The performance of merging firms in japanese manufacturing industry. *Journal of Industrial Economics*, 31(3):257 – 266, 1983. ISSN 00221821.

IMAA-Institute. M & a statistics: Number and value and largest m & a transactions by region, 2017a.

IMAA-Institute. Number and value of m & a by industry, 2017b.

U. Klumpp. *Die "Efficiency Defense" in der Fusionskontrolle: eine rechtsvergleichende Untersuchung über die Berücksichtigung von Effizienzgewinnen bei der Zusammenschlusskontrolle nach deutschem, europäischem und US-amerikanischem Recht*. Wirtschaftsrecht und Wirtschaftspolitik. Nomos, 2006. ISBN 9783832918941.

Jozef Konings, Patrick Van Cayseele, and Frederic Warzynski. The dynamics of industrial mark-ups in two small open economies: Does national competition policy matter? *International Journal of Industrial Organization*, 19(5):841 – 859, 2001. ISSN 0167-7187. Competition Policy in Dynamic Markets.

S.C. Kumbhakar and C.A.K. Lovell. *Stochastic Frontier Analysis*. Stochastic Frontier Analysis. Cambridge University Press, 2003. ISBN 9780521666633.

Subal C. Kumbhakar, Byeong U. Park, Léopold Simar, and Efthymios G. Tsionas. Nonparametric stochastic frontiers: A local maximum likelihood approach. *Journal of Econometrics*, 137(1):1 – 27, 2007. ISSN 0304-4076.

John Kwoka and Michael Pollitt. Do mergers improve efficiency? evidence from restructuring the us electric power sector. *International Journal of Industrial Organization*, 28(6):645–656, 2010. ISSN 0167-7187.

Guenter Lang and Peter Welzel. Mergers among german cooperative banks: A panel-based stochastic frontier analysis. *Small Business Economics*, 13(4):273–286, 1999. ISSN 0921-898X.

James Alan Levinsohn and Amil Petrin. Estimating production functions using inputs to control for unobservables. *The review of economic studies*, (2), 2003. ISSN 0034-6527.

Frank Lichtenberg and Donald Siegel. Productivity and changes in ownership of manufactoring plants. *Brookings Papers on Economic Activity*, 18(3):643–684, 1987.

Vojislav Maksimovic and Gordon Phillips. The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *The Journal of Finance*, 56(6):2019–2065, 2001. ISSN 1540-6261.

Vojislav Maksimovic, Gordon Phillips, and Liu Yang. Private and public merger waves. *Journal of Finance*, 68(5):2177 – 2217, 2013. ISSN 00221082.

Sten Malmquist. Index numbers and indifference surfaces. *Trabajos de Estadistica*, 4(2):209–242, 1953. ISSN 0490-219X.

Carlos Martins-Filho and Feng Yao. Semiparametric stochastic frontier estimation via profile likelihood. *Econometric Reviews*, 34(4):413–451, 2015.

Robert H. Mcguckin and Sang V. Nguyen. Post-reform industrial productivity performance of china: New evidence from the 1985 industrial census data. *Economic Inquiry*, 31(3):323–341, 1993. ISSN 1465-7295.

Robert H. McGuckin and Sang V. Nguyen. On productivity and plant ownership change: New evidence from the longitudinal research database. *RAND Journal of Economics (RAND Journal of Economics)*, 26(2):257 – 276, 1995. ISSN 07416261.

Vincenzo Mollisi and Gabriele Rovigatti. Theory and practice of tfp estimation: The control function approach using stata. *CEIS Working Paper*, (399), February 2017.

Massimo Motta. *Competition Policy: Theory and Practice*. Cambridge Univ. Press, Cambridge [et al.], 1. publ. edition, 2004.

Harald Oberhofer. Employment effects of acquisitions: Evidence from acquired european firms. *Review of Industrial Organization*, 42(3):345 – 363, 2013. ISSN 0889938X.

Harald Oberhofer and Michael Pfaffermayr. Lohn- und beschäftigungseffekte von europäischen unternehmensfusionen. In Josef Nussbaumer, Gerald Pruckner, Rupert Sausgruber, and Hannes Winner, editors, *Gesundheits- und Sozialpolitik im Diskurs*, pages 59–80. Springer Vienna, 2011. ISBN 978-3-7091-0553-5.

OICA. Sales statistics of new vehicles, 2017.

G. Steven Olley and Ariel Pakes. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263 – 1297, 1996. ISSN 00129682.

David J. Ravenscraft and F. M. Scherer. The profitability of mergers. *International Journal of Industrial Organization*, 7(1):101–116, 1989.

David J. Ravenscraft and Frederic M. Scherer. *Mergers, Sell-offs, and Economic efficiency*. Brookings Institution, Washington, D.C., 1987. ISBN 0815773471 9780815773474.

Lars-Hendrik Röller, Johan Stennek, and Frank Verboven. Efficiency gains from mergers. In Fabienne Ilzkqvitz and Roderick Meiklejohn, editors, *European Merger Control: Do We Need an Efficiency Defense?*, pages 84–201. Edward Elgar, 2006. ISBN 978 1 84542 491 6.

Joel Stiebale and Michaela Trax. The effects of cross-border m&as on the acquirers' domestic performance: firm-level evidence. *Canadian Journal of Economics*, 44 (3):957 – 990, 2011. ISSN 00084085.

Chad Syverson. What determines productivity? *Journal of Economic literature*, 49 (2):326–365, 2011.

Ilke Van Beveren. Total factor productivity estimation: A practical review. *Journal of Economic Surveys*, 26(1):98–128, 2012. ISSN 09500804.

Oliver E. Williamson. Economies as an antitrust defense: The welfare tradeoffs. *The American Economic Review*, 58(1):18–36, 1968. ISSN 00028282.

Jeffrey M. Wooldridge. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3):112 – 114, 2009. ISSN 0165-1765.

Jinghua Yan. Merger waves: Theory and evidence. *Quarterly Journal of Finance*, 01(03):551–606, 2011.

Gian Luca Zampa. The role of efficiency under the eu merger regulation. *European Business Organization Law Review*, 4(4):573–622, Dec 2003. ISSN 1741-6205.

Michael Zschille. Firm performance and industry structure: Nonparametric efficiency analysis in the water sector, 2014.

Lebenslauf

Claudia Christina Maria Margareta Demmer

Berufliches

Seit Apr 2019	Mubea Präzisionsstahlrohr AG, Arbon, Schweiz Supply Chain Management Rohre
März 2018 - März 2019	Mubea Fahrwerksfedern GmbH, Attendorn & Weißensee, Deutschland Order Team Leitung Stabilisatoren
Okt 2013 - Feb 2018	Mubea KG, Attendorn, Deutschland Assistenz der Geschäftsführung
Apr 2012 - März 2013	Mubea KG, Attendorn; Mubea Inc., Florence, KY USA Kooperation für die Masterthesis, Einkauf & Produktionsplanung
März - Aug 2010	BMW Group, München, Deutschland Praktikum, Strategisches Marketing

Ausbildung

Okt 2013 - Juli 2018	Julius-Maximilians-Universität Würzburg Promotion - cum laude Wirschaftswissenschaftliche Fakultät, Industrieökonomik Thema: Merger-specific Efficiency Gains
März 2011 - Sept 2013	Julius-Maximilians-Universität Würzburg Master of Science, Business Management - 2.5 Schwerpunkte: Industrieökonomik, Industriebetriebslehre, Personalwesen
Okt 2007 - März 2011	Julius-Maximilians-Universität Würzburg Bachelor of Science - 2.7
1998 - 2007	St. Franziskus Gynmasium Olpe Abitur - 2.5

Kenntnisse

Sprachen	Deutsch (Muttersprache), Englisch, Französisch, Latein
IT	MS Office, Latex, SAP, R, Stata