Effects of ethical exclusions: An empirical assessment of conduct-based exclusions from the Government Pension Fund Global

Vegard Hanssen Ekra and Lars Thyholdt

Master's Thesis in Financial Economics Department of Economics Norwegian University of Science and Technology



Supervisor: Knut Anton Mork June 2018

Preface

This Master's Thesis is written as a final part of NTNU's Master of Science programme in Financial Economics. It is written during the spring semester of 2018.

The subject of the thesis is a result of our common interest for econometrics, financial markets and sustainable investments. The Norwegian Government Pension Fund Global is a practical and relevant case at the intersection of these fields of interest. Writing this thesis has been challenging and educational, and it has taught us a lot about practical implementation of theoretical knowledge. We want to thank our supervisor Professor Knut Anton Mork for counseling and helpful discussion throughout the writing process. We would further like to thank our families and close ones for support. Any errors are our own.

Trondheim, June 2018

Vegard Hanssen Ekra

Lars Thyholdt

Abstract (English)

In this thesis we examine whether exclusion from the Norwegian sovereign wealth fund on ethical grounds have long-term consequences for the return and return volatility of the excluded firms. Using a period of 4 years before and after the exclusion, we investigate the relationship between the returns of the excluded companies, comparable companies, and the world market at large. We do this by first examining and testing different descriptive measures of return, before using different forms of regression analysis. We use conventional statistical tools to test for shifts in regression coefficients in factor models for asset returns, and to ensure our results are robust in the face of common pitfalls in applied econometric analysis. Our Seemingly Unrelated Regression analysis unveils that the excluded firms are related, but overall our results show no obvious pattern of uniform change in return or return volatility. The general result is that several of the sample firms have significant changes in return and return volatility in the period around the exclusion, but that the exclusion in and of itself is no reliable predictor of how a firm will perform in the years following the divestment.

Abstract (Norwegian)

I denne oppgaven undersøker vi om ekskludering fra Statens Pensjonsfond Utland som følge av uetiske forhold har konsekvenser for det eksluderte selskapets aksjeavkastning og volatilitet på lang sikt. Vi benytter en periode på fire år før og etter offentliggjøring av ekskludering for å granske sammenhengen mellom avkastningen til de ekskluderte selskapene, sammenlignbare selskaper og verdensmarkedet. Dette gjøres ved først å se på og teste ulike deskriptive mål på avkastning og deretter ulike former for regresjonsanalyse. Vi anvender konvensjonelle statistiske verktøy til å teste for skifter i regresjonskoeffisienter i faktormodeller for avkastning, og for å unngå vanlige fallgruver innen økonometrisk analyse. En Seemingly Unrelated Regressionsformulering av vår modell avdekker felles impulser på tvers av firmautvalget, men det er ingen åpenbare mønstre som entydig impliserer samsvarende forandring i avkastning eller volatilitet. Resultatet er at man kan slå fast at flere i utvalget har statistisk signifikante endringer i avkastning og volatilitet fra perioden før ekskludering til perioden etter, men at ekskludering som sådan ikke kan sies å være en konsistent forutsigelse for den respektive aksjens prestasjon årene etter ekskludering.

Contents

	Pref	face	i
	Abs	tract (English)	iii
	Abs	stract (Norwegian)	v
1	Intr	roduction	1
	1.1	Background on the GPFG	3
	1.2	Literature review	4
2	Dat	a and methodology	9
	2.1	Sample data	9
	2.2	Descriptive analysis	12
	2.3	Assumptions	18
	2.4	Structural breaks	20
3	Ana	alysis	23
	3.1	Augmented Capital Asset Pricing Model	23
		3.1.1 Tests for equality between sets of coefficients	27
		3.1.2 Wald tests for an unknown structural break	30
		3.1.3 Post-estimation analysis of the ACAPM	33
		3.1.4 Robust standard errors	37
	3.2	Seemingly unrelated regression equations	42
4	Con	nclusion	49
Re	ferei	nces	55

A	Acronyms	65
B	Return data reference codes and sources	67
С	Assumptions and results	69
	C.1 Seemingly Unrelated Regressions	69
	C.1.1 Assumptions for the general SUR model	69
	C.1.2 SUR and ACAPM results	72

Chapter 1

Introduction

In the last few decades sovereign wealth funds (henceforth SWF(s)) have become goliaths in the global financial markets. The biggest among these funds is the Norwegian Government Pension Fund Global (GPFG) (Sovereign Wealth Fund Institute, 2018). Acting as a self-restrained morally conscious investor, the GPFG may choose to exclude firms due to unethical conduct or production of immoral products, based on recommendations from the Council on Ethics. The council is an independent advisory board appointed by the Norwegian Department of Finance to evaluate whether the investments are in line with the ethical guidelines of the fund. With its position as a major player in the financial markets, the signalling power of the fund is of great interest.

We seek in this thesis to illuminate the long-term quantitative effects on firms excluded by the GPFG due to poor ethical conduct. Stock returns and stock price volatility of a sample of relevant firms will be analysed to shed light on what signalling effects the exclusions may have. The ethical screening carrjes a cost to the fund, both in terms of possible foregone return and a smaller investment universe, and Norges Bank Investment Management (NBIM) state that their product-based exclusions have reduced the cumulative return on the equity index by 2, 4 percentage points. The product-based exclusions include producers of tobacco, coal and weaponry that is used in ways that violate human rights. Some of these are traditional "sin" stocks, with well-documented extraordinary returns in previous studies, e.g. Hong and Kacperczyk (2009) and Fabozzi et al. (2008). On the other hand, the conduct-based exclusions are said to have increased the cumulative return on the equity index by around 0,9 percentage points (Norges Bank Investment Management, 2018b, p.16). These exclusions are across a wide range of industries,

CHAPTER 1. INTRODUCTION

as the criteria for conduct-based exclusion can be violated by any firm regardless of industry. Breach of human rights, violation of the rights of individuals in war, severe environmental damage, gross corruption or other serious violations of fundamental ethical norms are examples of conduct that is deemed unacceptable. Our thesis will examine the effects of conduct-based exclusion on the target firm's stock return and volatility in the medium- to long-run after announcement of divestment from the GPFG. We think this is worth researching both due to the possible implications of the growing size and importance of the SWF investor class in general, but also to evaluate the effects of a core policy in the management of our collective national wealth. In researching these exclusions we seek to determine if exit as a form of fund activism has any tangible result on the target firm and its stock return. In turn, this can hopefully contribute to the discussion on whether and to which degree it is possible for SWFs to act as extensions of the nation state and use investment decisions to exert political power. There is ongoing debate on whether such strategic investments could be problematic. If there are no effects of divestment by the GPFG on the target firm, applying the same transparency and investment standards employed by the GPFG on the SFW investor class as a whole will help alleviate these concerns.

Chapter 1 provides background information and a literature review on the GPFG, SWF investments and effects of unethical conduct. In Chapter 2 we provide descriptive analysis of our sample data and illustrate what a potential structural break in mean return or volatility might look like. We look at the cumulative market-adjusted return and buy-and-hold adjusted returns to assess how the return of the excluded companies compare to a related index. Further, Chapter 3 makes up the majority of our analysis, where an augmented capital asset pricing model is presented and fitted for the sample companies, and the results are tested to identify a possible break resulting from the exclusion. Said model is then reestimated using a seemingly unrelated regression-approach in order to search for common factors for the excluded firms. Chapter 4 includes a summary of our findings and a discussion of the results.

1.1 Background on the GPFG

Norway's sovereign wealth fund, the Government Pension Fund Global, was established in 1990. The first deposits into the fund were made in 1996, and it has been growing rapidly ever since. The fund is invested globally to avoid overheating the Norwegian economy and to reduce Norway's future dependency on oil revenues. According to GPFG's strategy report for 2017-2019, the fund's mandate includes investment of wealth from Norway's petroleum reserves on behalf of current and future generations of the Norwegian people (Norges Bank Investment Management, 2017b). This clearly establishes the fund as an extraordinarily long-term investor, as most investors don't have an investment horizon beyond their own lifetime. Sethi (2005) argues that socially responsible investments are essential for long-term investors, as these companies are more likely to withstand the strains of time and thus survive longer than less responsible firms. This long-term perspective advocates an active ownership, and GPFG voted at 11 294 shareholder meetings in 2016. As a considerable stakeholder in many of these companies, an active ownership is crucial to promote healthy corporate governance and a sustainable, effective company strategy. Voting guidelines have been constructed in line with the G20/OECD Principles of Corporate Governance. In GPFG's 2016 report Norges Bank Investment Management (2016b), the purpose of the fund is defined as follows:

Our mission is to safeguard and build financial wealth for future generations. We manage the fund responsibly in order to support the investment objective of the highest possible return with a moderate level of risk. Responsible investment is integrated into our investment strategy.

Responsible investment is therefore a core aspect of the operation and management of GPFG. In recent years, focus on environmental and social issues has meant increased interest in socially responsible investments. NBIM is the arm of the Norwegian central bank that operates the fund day-to-day. NBIM in particular has in its investment mandate a set of ethical guidelines (Norges Bank Investment Management, 2016a), and a policy of divesting from companies that operate in a way that is seen to be a breach of these.

1.2 Literature review

Sovereign wealth funds are state-owned funds that include international financial assets. According to Greene and Yeager (2008), most SWFs originate from natural resource export or foreign exchange reserves. The main purpose is generally to accumulate wealth for future generations in nations where wealth originate from non-renewable resources, and to stabilize export and government income (Truman, 2009). The Sovereign Wealth Fund Institute estimate that the largest funds today are the Norwegian Government Pension Fund Global, China Investment Corporation, Abu Dhabi Investment Authority and Kuwait Investment Authority (Sovereign Wealth Fund Institute, 2018). In February 2018 the aggregated value of all SWFs were estimated to be \$7,58 trillion. Most relevant literature and research has been written and done since the turn of the millennium, possibly due to the dramatic rise in both numbers and the individual sizes of SWFs. Indicative of this is that the term "sovereign wealth fund" itself, while today considered a staple in international finance, was coined as late as May 2005 by Rozanov (2005). The number of SWFs increased with over 20 during the period of 1998-2012 as noted by Castelli and Scacciavillani (2012), and the total assets under management by SWFs rose from about \$1,3t in 1997 (Mezzacapo, 2009), to \$3,07t in December 2008, and \$6,59t in March 2017 (Pregin, 2017), and further up to \$7,58t at the time of writing (Sovereign Wealth Fund Institute, 2018). It must be stressed that these are best-guess estimates, and subject to errors, as much of the literature on SWFs is, due to their opaque nature. This could help explain the relative dearth of research done on SWFs as major financial players, a point touched upon by Bernstein et al. (2013) among others. Due to the inherent differences in nature and mandate of SWFs from more traditional mutual funds and hedge funds, the standards against which they are held differs, as noted by Dewenter et al. (2010) among others. Where most hedge funds are incentivized to not limit its investment universe due to lower possible return and less diversifying opportunities (briefly mentioned by Hong and Kacperczyk (2009)), the SWF might take other dimensions into consideration. For example, the beyond-a-generation investment horizon might result in a particular focus on environmental sustainability. These qualities can contribute to SWFs being regarded as prime market monitors, as outlined by Chen et al. (2007). Due to SWFs being owned and organized by a sovereign government, questions have been raised about the intentions of

their investment policy by Beck and Fidora (2008), Blundell-Wignall et al. (2008), Aizenman and Glick (2009), Monk (2009), and several others. There are real world examples of SWFs seemingly unduly affecting policy changes, prompting reactions and statements from both prominent politicians and the population at large. A clear case of the former is noted by Dewenter et al. (2010), who relays an article from The Wall Street Journal (2008), in which China used its State Administration of Foreign Assets (SAFE) agency to purchase \$300m in Costa Rican bonds on the condition that Costa Rica switch diplomatic allegiance from Taiwan to China. SAFE was at the time under control of a Chinese SWF, the China Investment Corporation. Most SWFs are opaque, and there is incentive to keep any instances of using them as policy pressure tools as hidden as possible. However, speculation, prediction, and theorizing is rife. Prominent European political figures such as Emmanuel Macron, Angela Merkel, and Jean-Claude Juncker are all on record expressing concern regarding the rise of cross-border state investments (see Reuters (2018), Reuters (2008), European Commission (2017)). Furthermore, SWF acquisitions of strategic assets was and is a controversial topic of public discourse: NBIM came under fire for shorting Icelandic bank bonds in 2006 (The Economist, 2008), and a government-owned company from Dubai acquiring American ports provoked debate (The Economist, 2006), among other cases. The research on whether SWF investments are solely motivated by return maximisation is conflicted: Balding (2011), Bortolotti et al. (2015), Avendaño and Santiso (2009), and Megginson et al. (2013) find that the investment strategies are consistent with what one would expect from a rational investor, while Boubakri et al. (2016), Bernstein et al. (2013) and Kotter and Lel (2011) show that SWF investments are biased by non-economic factors. Truman (2010) argue that it is naive to dismiss these concerns regardless of empirics; SWFs are creations of the state, and therefore inherently political by definition. While SWF investments and divestments as policy tools are generelly held up as a source of potential problems, the notion of socially responsible investment as fund activism hinges on SWFs being able to influence through their strategies. If not, the fund simply avoids complicity. This is a point raised by Richardson (2011) in relation to GPFG specifically.

Although there is no universally adopted best practice for SWFs, attempts have been made towards defining and implementing such a framework. Truman (2009) lays out a set of categories (structure and objectives of the fund, governance of the fund, accountability and transparency of the fund, behaviour in managing of the fund), in which an SWF can score a total of 100 points. In the version in Bagnall and Truman (2013) Norway's GPFG score a total of 98, and is the best scoring SWF. The average score of all funds included is 54.

Shleifer and Vishny (1997) document the importance of corporate governance for investors, as does subsequent research done by La Porta et al. (2002), Chhaochharia and Laeven (2009), and several others. However, divestment criteria for the GPFG include facets beyond return maximization, such as unethical labour practices, engagement in environmentally unsustainable production processes, and contribution to corruption through the target firm's way of doing business, among other things. Here we will briefly consult the literature on how the equity markets at large react to corporate social performance. Waddock and Graves (1997) find a positive relationship between the social and financial performance of companies in a variety of industries. Lourenço et al. (2012) show that social performance is positively tied to financial performance for large, profitable firms that are able to communicate their socially sustainable strategies out to the market. Inversely, it is negatively tied to the financial performance of firms that are not. Moreover, Schnietz and Epstein (2005) show that such a reputation translate to tangible financial benefit during a public relations crisis. Konar and Cohen (2001) find significant negative correlation between poor environmental record and the intangible asset value of publicly listed manufacturing firms in the S&P500 stock index. Furthermore, they decompose the loss into litigation costs and value loss as a result of toxic emissions, of which litigation costs are an economically insignificant part. Earlier research done by Dowell et al. (2000) show that US multinational enterprises that adopt a stringent global standard of environmental performance outperform those firms that adhere to a more lax standard in terms of market value. With regards to labour practices, Edmans (2011) show that the top 100 US companies ranked by employee satisfaction earned a positive and statistically significant alpha (ie. excess return over an estimated market return) of 2,1% annually in the period 1984-2009, controlling for relevant firm characteristics. In a meta-analysis of the relationship between social and financial performance, Margolis et al. (2009) find a small but positive link, and a more dominant link between revealed social misdeeds and financial performance. This is supported by the research done by Gunthorpe (1997), among others. The positive link between social and financial performance cements the results in an earlier meta-analysis by Orlitzky et al. (2003), and a literature review

by van Beurden and Gössling (2008).

Fernandes (2011) uses a broad dataset from the period 2002-2007 to document effects of SWF ownership, and finds improved financial and operational performance. He finds that SWF ownership increase long-term market value. Kotter and Lel (2011) find positive effects on stock prices of SWF target firms around the announcement date, but no long-run sizable effect on firm governance and performance. Moreover, there is a positive relation between SWF transparency and impact on firm value. Higher excess returns are found in firms with high likelihood of future financial distress. Their research indicate that large firms with high leverage, poor performance, low cash reserves and international presence are preferred. Abnormal positive returns are observed after SWF stock purchase announcements, while negative abnormal returns are seen with divestment, as in Dewenter et al. (2010), for example. However, they cannot reject the market efficiency hypothesis; that stocks earn normal returns after being procured by SWFs. The short-term reaction is in line with previous research by Sojli and Tham (2011), who also find a long-term increase in internationalization and Tobin's Q (market value of company relative to replacement cost of company assets) after SWF investment. They conclude that SWF investments are beneficial for the firms' shareholders. The effect of SWFs' acquisitions on the targeted firms' competitors was researched by Boubakri et al. (2017). They conclude that SWF acquisition of a firm has a positive impact on the target firms' competitors. The authors interpret these results as market anticipation of value-creating restructuring activities in the sector. Bertoni and Lugo (2014) study the effect on credit risk, measured by credit default swap (CDS) spreads of target companies around SWF investment announcement. The resulting lowered spread is interpreted as a market reaction to an implicit guarantee to creditors given by the SWF investment, decreasing the perceived risk associated with investing in the company. The magnitude of the reduction is amplified by the level of stability in the SWF country, the transparency of the fund, and the neutrality of political relationship between target and SWF country.

Hoepner and Schopohl (2016) investigate the operational effects of exclusion of firms from the GPFG and the Swedish government AP-funds. They construct a theoretical portfolio of the excluded firms and compare the portfolio performances to a broad, global market portfolio, namely the MSCI All Country World index. They find that the excluded firms do not generate abnormal returns relative to their benchmark, and that the risk of the exclusion portfolio is higher only in the case of GPFG. We should mention the case study on GPFG done by Beck and Fidora (2008). They investigate the impact of divestment from GPFG on 20 companies excluded in 2005-2006 for non-economic reasons. They use daily observations from year 2000 up to the date of exclusion to estimate parameters for their model, an augmented capital asset pricing model (ACAPM) controlling for the return of a domestic equity index and a sector-specific index. Estimates of the expected returns are generated for the period of exclusion, generally from 2 months before the announcement to the day of announcement. Tests whether the realized returns over the period and on the announcement date differ from the expected return based on their model is then carried out. None of the negative excess returns on the divested companies is shown to be statistically significant. Our thesis will be an interesting addition to this study, as we examine medium- to long-term differences before and after the announcement. Our data set is also extended beyond theirs, with a different selection of companies over a longer period of time. We thus pick up the baton where Beck and Fidora (2008) leave it and hope to fill in some of the blanks. This is to the best of our knowledge the most relevant research on divestment on ethical grounds from any SWE.

Chapter 2

Data and methodology

2.1 Sample data

In order to create a list of sample companies, containing the date of announcement and reason for exclusion, we scour the information provided at Norges Bank Investment Management (2018a). This is a fragmented overview of all companies, either currently on watch or fully excluded. We whittle down the list by looking solely at companies that are excluded due to conduct rather than product - the reason being that we are interested in the incentives to change. It is unrealistic to expect any company excluded on the basis of what it produces to fundamentally change its line of business. Excluding producers of coal, tobacco, and various types of munitions and weaponry reduces the list from a total of 159 companies to 36 companies. Performing long-term analysis, we are interested in companies with a period of at least 4 years after the announcement date. Hence, we remove the companies which have been excluded from 2014 and onwards. This prunes the list further down to 23 companies. Finally we remove the companies that are under active management, rather than full-on exclusion. This returns 18 companies. Two of these have incomplete timelines: one due to being founded in less than four years before divestment, and the other being involved in a merger shortly after the divestment. We therefore discard the two respective companies, and are left with a list of 16 companies. These are our candidates for analysis. There is variation in announcement date, reason for exclusion, geography, industry and sector. The list is presented in Table 2.1 on page 11. It should be noted that some of our sample companies are separately listed divisions of the same corporation. Wal-

Mart Stores Inc (now branded as Walmart Inc) and Wal-Mart de Mexico are both divisions of Walmart Inc, and Rio Tinto Ltd and Rio Tinto Plc are two divisions of the Rio Tinto Group. These firms are trade in separate contries under different stock tickers. Furthermore, Sterlite Industries Ltd (henceforth Sterlite) is a subsidiary of Vedanta Resources Plc (Vedanta), both of which were excluded in November 2007. Sterlite was not held by the GPFG, but was excluded from GPFG's investment universe. We still choose to include the company in our analysis as the signalling effects we are interested in should still be present, even though the stock was not held by the GPFG. The fund holds small stakes in each company: the GPFG ownership of our sample the year preceding their divestment has a median of 0,27% and a mean of 0,45% of total company shares. Exclusions are announced after all held shares have been sold in order to reduce downward pressure on share prices. Therefore, in our view, the GPFG not owning a company it excludes from its investment universe should not prevent the company from being a candidate for analysis. In January 2014, Vedanta Ltd was excluded from GPFG. This company is the result of several corporate actions, namely mergers of Madras Aluminium Company and Sterlite Industries Ltd and a name change, see Norges Bank Investment Management (2018a). As the timeline of Sterlite Industries is not affected by this merger until mid 2013, we do not see this as limiting to our study. Note that Vedanta Ltd that was excluded in January 2014 is not the same as Vedanta Resources Plc, excluded in November 2007. It should further be noted that Potash Corporation of Saskatchewan underwent a merger in January 2018 (Reuters, 2017). However, this does not affect our analysis, as it is outside the scope of our timeline. Theoretically, there could be companies that fit our selection parameters but is currently included after a period of exclusion, and therefore do not appear on the list of excluded companies curated by NBIM. We contacted NBIM with a query, but was not provided with any information beyond what is available online. We therefore decide to disregard any such possible candidates.

		lable 2.1: Features of excluded companies	eu companies		
Company i	Incorporation country	Sector, industry	GPFG ownership (%)	Date of announcement	Reason for exclusion
Barrick Gold Corporation	Canada	Materials, metals and mining	0,64	30/01/2009	Pollution
Elbit Systems Ltd	Israel	Industrials, aerospace and defense	0,27	03/09/2009	Violation of ethical norms
Freeport McMoRan Copper and Gold Inc	USA	Materials, metals and mining	0,17	06/06/2006	Pollution
MMC Norilsk Nickel	Russia	Materials, metals and mining	0,32	19/11/2009	Pollution
Potash Corporation of Saskatchewan	Canada	Materials, metals and mining	0,58	06/12/2011	Violation of ethical norms
Rio Tinto Ltd	Australia	Motoriale motale and mining	0,05	00/00/000	Dollution
Rio Tinto Plc	United Kingdom		0,54	0007100100	I OIIMIOI
Shikun & Binui Ltd	Israel	Industrials, construction and engineering	0,22	15/06/2012	Violations of human rights
Sterlite Industries	India	Materials, metals and mining	0	31/10/2007	Pollution
Ta Ann Holdings Berhad	Malaysia	Materials, paper and forest products	0,56	14/10/2013	Pollution
Vedanta Resources Plc	United Kingdom	Materials, metals and mining	0,19	06/11/2007	Violations of human rights
Volcan Compañia Minera	Peru	Materials, metals and mining	0,22	14/10/2013	Pollution
Wal-Mart de Mexico	Mexico	Consumer staples,	0,09	06/06/2006	Violations of human
Wal-Mart Stores Inc	USA	food and staples retailing	0,12		and labour rights
WTK Holdings Berhad	Malaysia	Materials, paper and forest products	2,3	14/10/2013	Pollution
Zijin Mining Group	China	Materials, metals and mining	0,5	14/10/2013	Pollution
Table 2.1: Information colle	Table 2.1: Information collected from several sources. T	The companies themselves have been collected from the overview provided by Norges Bank Investment Management	llected from the overview	provided by Norges Bank Inv	vestment Management

Table 2.1: Features of excluded companies

(2018a), as have the dates of announcement and the reasons for exclusion. The reasons for exclusion are provided in Norwegian and have been translated to English by the authors of this paper. Countries in which the firms are based, GPFG's ownership percentage and on which stock exchange the stocks are traded are collected from the list of GPFG stake in the company is constant until the decision to sell is made. The Thomson Reuters Eikon database provided us with the sector and industry classification for each respective firm. The sector and industry classifications is the Global Industry Classification Standard (GICS) developed by Morgan Stanley and Standard & Poor's (MSCI, GPFG's asset holdings (Norges Bank Investment Management, 2017a). Note that the ownership percentage is only provided once a year, so we assume that the last provided 2018).

CHAPTER 2. DATA AND METHODOLOGY

2.2 Descriptive analysis

This section will give a brief overview of the descriptive statistics for our sample data and their comparable indices. We start our analysis by comparing the performance of the divested companies to comparable sector indices for each firm. We present an arithmetic measure of abnormal return and a measure using geometric sums. These are the cumulative market-adjusted return (CMAR) and the buy-and-hold market-adjusted return (BHAR), respectively. Barber and Lyon (1997) investigate the use of BHARs and cumulative abnormal returns (CARs). CMAR and CAR are conceptually similar measures, where the difference lies in which benchmarks are used to determine abnormal returns: Barber and Lyon (1997) use a market index as the measure of expected return, while we use a sector index. Continuing, they use a sample of 200 000 observations, and calculate a 12-month CAR and an annual BHAR using an equally weighted market index. They estimate the following relation:

$$BHAR_{i,12} = -0,013 + 1,041CAR_{i,12} + \epsilon$$
(2.1)

meaning CARs are biased predictors of long-run BHARs,¹ and therefore prefer the BHAR approach on conceptual grounds, since it most closely reflects the investor experience of holding stock over time. However, both the use of buy-and-hold abnormal returns and the use of cumulative abnormal returns have drawbacks. Summarizing the flaws of each method; BHAR is subject to a new listing bias, a skewness bias and rebalancing bias. CAR on the other hand, is subject to a new listing bias, a skewness bias and a measurement bias. The new listing bias is the effect of new firms included in the index that begin trading subsequent to the event, rebalancing bias arise because the reference portfolios compounded returns typically are calculated assuming periodic rebalancing, while the returns of the sample firms are compounded without rebalancing, and the skewness bias is due to the fact that long-run abnormal returns are positively skewed. The skewness bias is less severe for the CAR than for the BHAR. In conclusion, they find that by using matching sample firms in terms of size and book-to-market ratios, the biases are reduced, leading to better-specified test statistics. Due to the pros and cons of

¹This problem is referred to as a measurement bias: essentially, CARs ignore compounding returns, while BHARs reflect compounding returns.

both procedures we report both. We set the month in which announcement occurs as month 0, around which intervals for BHAR and CMAR are calculated symmetrically. We look at periods in yearly intervals before and after announcement date. In other words, we calculate for intervals [-48, -1], [-36, -1], [-24, -1] and [-12, -1] before the announcement, and [0, 12], [0, 24], [0, 36] and [0,48] after the announcement. In total we look at four-year periods before and after announcement, eight years and one month in total. The day of announcement is on varying days of the month for each respective company, but as we look at long-term effects, we disregard this and simply use the month in which the announcement is made. Monthly total return close price data for each firm was extracted from the Thomson Reuters Eikon database. Monthly price data for the sector indices for each firm country was also obtained from the Thomson Reuters Eikon database: we use the country-specific Sector Total Return Index assembled by Thomson Reuters for each given firm where these are available. From the monthly close price data for the firms and the indices we calculate arithmetic monthly return. The indices are based on Thomson Reuters Business Classification (henceforth TRBC) groupings. For instance, for Elbit Systems Ltd (Elbit), an Israeli company that produces electronics for the defense industry, we use the Thomson Reuters Israel Industrials Total Return Index. Equivalently for all other companies, we use the appropriate index depending on the country in which the company is based and to which industry it belongs. An overview of the TRBC groupings is found at Thomson Reuters (2018) and the methodology behind index construction is found at Thomson Reuters (2012). There are two exceptions to this. The first is Volcan Compañia Minera (Volcan), where the relevant Thomson Reuters index was not available. We instead use the S&P/BVL Peru Mining Index, found at Standard & Poor's (2018). It should be noted that this index was launched in May 2015, and historical returns are therefore constructed post-launch by S&P using the index methodology. Its historical monthly close price values are therefore theoretical. Moreover, it reflects an industry, ie. a subcategory of the sectors reflected in the other indices. We do not feel this hinders our research to any noteworthy extent. The second exception is the index for MMC Norilsk Nickel (Norilsk), which was unavailable before 2007, and therefore does not cover the period we're looking at. We instead use the Metals and Mining Index provided by the Moscow Stock Exchange (Moscow Exchange, 2018). The Thomson Reuters economic sector indices are selected by Thomson Reuters algorithms, and contains a minimum of 10 constituent companies (Thomson Reuters (2016)). All historical monthly close prices are adjusted for corporate actions, such as stock splits and dividends, which are reinvested. The corporate actions methodology can be found at Thomson Reuters (2015). The reference codes for data series for our sample companies and their sector indices can be found in Table B.1 in Appendix B. The returns are calculated arithmetically as

$$R_{i,t} = \left(\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}\right), \ R_{S,t} = \left(\frac{P_{S,t} - P_{S,t-1}}{P_{S,t-1}}\right)$$
(2.2)

where $P_{i,t}$ is the close price of the stock of company *i* on last trading day of month *t*, and $P_{i,t-1}$ is the close price on the equivalent day the previous month. Subscript *S* indicates sector index. Market-adjusted return for firm *i* on month *t* is defined as the net difference in return between the given firm and the index of companies operating in the same economic sector. It is defined as

$$MAR_{i,t} = R_{i,t} - R_{S,t} \tag{2.3}$$

where $R_{i,t}$ is the target firm's stock return over month t, and $R_{S,t}$ is the comparable sector's total return over month t. The cumulative market-adjusted return for firm i from month t to month m is the sum of the market-adjusted returns over this period. The intervals are given as [t, m] = [t, -1] before the announcement date, and [t, m] = [0, m] after the announcement date, where month 0 is the month of the announcement.

$$CMAR_{i,m} = \sum_{t}^{m} MAR_{i,t}$$
(2.4)

BHAR_{*i*,*m*} is the buy-and-hold marked-adjusted return for firm *i* in the interval [t, m]. This is the compounded stock return minus the compounded comparable index return over the given period.

BHAR_{*i*,*m*} =
$$\left[\prod_{t}^{m} (1 + R_{i,t}) - 1\right] - \left[\prod_{t}^{m} (1 + R_{S,t}) - 1\right]$$
 (2.5)

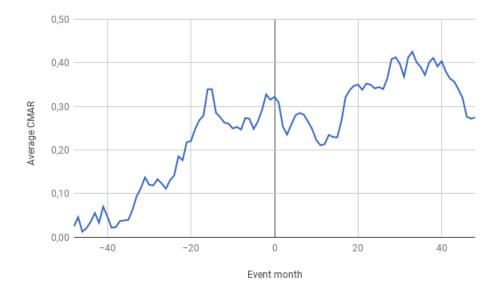


Figure 2.1: Average cumulative market-adjusted returns of all firms over the event window, [-48, 48] months around the announcement of exclusion from GPFG. Calculated as the average firm return net the average sector return cumulated from month -48 to +48 relative to the announcement.

	CMAR	BHAR	CMAR	BHAR	CMAR	BHAR	CMAR	BHAR
	[-48	8,-1]	[-3	6, -1]	[-24	,-1]	[-12,	-1]
Mean	0,3062	0,7954	0,2469	0,4942	0,1870	0,3018	0,0437	-0,0245
Median	0,1644	0,0962	0,2250	0,1734	0,1703	0,1186	0,0554	0,0588
St. dev.	0,5060	1,1833	0,4108	1,1424	0,4211	0,7357	0,2963	0,4975
Wilcoxon	2,12*	1,50	2,12*	1,34	1,82	1,40	0,93	1,03
t-test	2,42*	1,72	2,40*	1,73	1,78	1,64	0,59	-0,19
	[0,	12]	[0	,24]	[0,	36]	[0,4	8]
Mean	-0,1105	-0,1177	0,0170	-0,0478	0,0477	-0,1180	-0,0497	-0,2184
Median	-0,1110	-0,1384	0,0102	-0,0418	-0,0624	-0,1450	-0,1470	-0,2524
St. dev.	0,1953	0,1982	0,4150	0,4254	0,3654	0,4116	0,4626	0,4939
Wilcoxon	-1,97*	-2,12*	0,57	-0,41	0,41	-1,09	-0,52	-1,71
t-test	-2, 26*	-2,37*	0,16	-0,45	0,53	-1,15	-0,43	-1,77

Table 2.2: Descriptive features for the given period before and after the event month

Table 2.2: Descriptive values for the cumulative market-adjusted return and buy-and-hold adjusted return for various time periods around the announcement day for the 16 companies in our data set. The t-statistic reported is for a test of whether the mean equals zero. The median values are tested for statistically significant difference from zero with the Wilcoxon signed rank test. The statistic from this test is reported as Wilcoxon. Both the Wilcoxon and t-tests are two-tailed. Bold type indicate statistical significance at the 10% level. Significance at the 5% level or below is indicated by asterisk (*).

Figure 2.1 shows the average CMAR of all firms over the sample period. Note that this figure is for illustrative purposes only, showing the average CMAR cumulating from t = -48 to t = 48. We can see that the average CMAR visually looks like a random walk with a positive drift. A drop is observed shortly after t = 0, but this in itself is not tangible evidence of a negative shift after announcement of exclusion. Table 2.2 gives a summary of essential characteristics of the CMAR and BHAR for our sample in the years around announcement of divestment from the GPFG. All of the following analysis is done with the statistical software Stata.² The results of the Wilcoxon signed rank test³ as designed by Wilcoxon (1945) is also reported. The procedure is elaborated upon in Siegal (1956, pp. 75-83). We wish to test whether or not the target companies earned statistically significant abnormal returns in the periods before and after divestment. The calculated values are tested for a mean and median value significantly different from zero. Interpreting our results, we see that the CMAR and BHAR for several of the given intervals before the announcement date are statistically significant different from zero. We see that all observations with significant Wilcoxon test statistics also have significant t-test statistics. CMAR [-24, -1] and BHAR [0, 48] are significant at the 10% level. At the 5% level CMAR [-48, -1], [-36, -1], [0, 12] and BHAR [0, 12] are significant. It is particularly interesting that all the rejections before the divestment date is of a positive nature, in other words the abnormal return is larger than zero, while after the event date all the null rejections are due to a negative abnormal return. This is in line with the relevant research in Section 1.2.

However, there are several problems tied to the use of these tests. Most severely, our sample consists only of 16 firms, leading to a weak approximation of the normal distribution. The low sample size and the associated distribution gives our t-test lower validity than what is ideal. The Wilcoxon test does not assume a normal distribution, but it does however assume a symmetric distribution. These results should therefore be interpreted with a grain of salt. Further, there are several problems with the use of CMAR and BHAR for measurement of abnormal returns over time, but these are covered on page 12.

²URL: https://www.stata.com/

³See Stata documentation under "Signrank": https://www.stata.com/manuals13/rsignrank.pdf

			5. Duy-al	lu-noiu	aujusie	ultiu	115			
Company i	[-48, -37]	[-36, -25]	[-24, -13]	[-12, -1]	[0,12]	[13,24]	[25, 36]	[37,48]	μ	σ
Barrick Gold Corp	-0,1405	-0,3905	-0,0178	0,4553	-0,6169	-0,1766	0,1485	-0,1804	-0,1149	0,3253
Elbit Systems Ltd	-0,0299	0,1372	0,2955	0,1972	-0,1895	-0,0038	0,0424	-0,0197	0,0537	0,1517
Freeport McMoRan Copper and Gold Inc	0,2339	0,2478	-0,0835	0,4146	0,1626	0,3525	-0,1832	0,0013	0,1432	0,2122
MMC Norilsk Nickel	0,3404	0,6889	0,0058	-1,7090	0,1711	0,2628	0,1434	0,1638	0,0084	0,7227
Potash Corporation of Saskatchewan	0,1306	-0,3947	-0,0205	-0,0251	0,0688	0,1591	0,2038	-0,2432	-0,0152	0,2080
Rio Tinto Ltd	0,0074	0,1364	-0,0721	0,3182	-0,2845	0,1955	-0,0725	-0,0581	0,0213	0,1887
Rio Tinto Plc	0,0609	-0,0536	-0,0055	0,2736	-0,2541	0,0536	-0,0645	-0,1086	-0,0123	0,1529
Shikun & Binui Ltd	0,1231	0,2811	0,3338	-0,0121	0,0667	-0,2840	-0,2636	-0,2763	-0,0039	0,2497
Sterlite Industries	0,4146	-0,0600	1,1513	0,1048	-0,0172	0,2552	-0,4393	-0,0381	0,1714	0,4686
Ta Ann Holdings Bhd	0,0347	0,1605	-0,0509	-0,1815	-0,1095	0,0320	-0,0217	-0,2549	-0,0489	0,1319
Vedanta Resources Plc	-0,1131	0,1742	1,2076	0,0626	-0,1921	1,8945	-0,3734	-0,3312	0,2912	0,8196
Volcan Compañia Minera	-0,0758	0,1211	0,1813	-0,0989	-0,2656	-0,5243	-0,6712	1,2028	0,1515	0,5506
Wal-Mart de Mexico	0,1115	-0,3474	-0,0317	0,0550	-0,1375	0,0853	0,0932	0,2709	0,0124	0,1868
Wal-Mart Stores	0,0494	-0,0662	-0,1762	0,0332	-0,1392	0,4347	0,0548	-0,2798	-0,0112	0,2163
WTK Holdings Bhd	-0,3266	0,1516	-0,2484	0,0896	-0,1615	-0,0699	-0,1517	-0,5503	-0,1584	0,2254
Zijin Mining Group	-0,3922	-0,1224	0,3408	-0,3701	0,0151	0,1681	0,2408	-0,4189	-0,0673	0,3042
Mean	0,0268	0,0415	0,1756	-0,0245	-0,1177	0,1772	0,0018	-0,0700	0,0263	_
Median	0,0421	0,1287	-0,0117	0,0588	-0,1383	0,1222	0,0104	-0,1445	-	-

Table 2.3: Buy-and-hold adjusted returns

Table 2.3: Displays the BHAR for the given periods. Note that the periods consist of 12 months, except for the interval starting in the exclusion month, which is set to 13 months. The rows for mean and median display mean and median BHAR for all firms over the given interval. The μ and σ columns show the mean and standard deviation of the BHAR for the given firm over the listed intervals.

Table 2.3 shows the buy-and-hold adjusted returns for each firm net their respective comparable sector over the listed periods. We see that the firms' performance relative to their sector varies greatly across the listed timeline. The most extreme movements (measured by σ) can be seen in Norilsk, Vedanta and Volcan. Note that both Norilsk and Volcan has a different type of reference sector than the rest of our sample, as mentioned earlier. The listed numbers can be seen as the net return on a long-short portfolio with a long position in the firm and a short position in the sector. Some firms experience extreme movements over certain intervals, affecting the means rather drastically. Examples of this is e.g. Sterlite and Vedanta in [-24, -13] with BHAR of respectively 1,1512 and 1,2076. Another example is Norilsk in [-12, -1] with -1,7090, where the buy-and-hold return of the company was 0,425 (42,5%) and the sector was 2,134 (213,4%). If we group the results in the table as [-48, -1] and [0,48] we see that 36 out of the 64 values before the break and 28 out of the 64 values after the break are positive. The average of the mean BHARs before the break is 0,0548 and after the break is -0,0022. The average across all periods is 0,0263, implying that the firms overall outperform their comparable sector.

2.3 Assumptions

In this section we will discuss the general assumptions for the ordinary least squares (OLS) regression model on time-series data. This is the estimation technique we will use for the majority of our analysis. The assumptions and properties of this model is elaborated upon in e.g. Wooldridge (2016).

The three first classical assumptions regards the unbiasedness of OLS. Failing to meet these assumptions are serious violations, leading to biased estimators. With biased estimators the results from the analysis cannot be generalized beyond the sample, as the estimates are systematically flawed. The assumption of linearity state that the model is linear in its parameters. This is generally tested by inspecting scatter plots of the data. If the data display a non-linear relationship the variables can be transformed (e.g. using logs or squares) to accommodate a better fit.

Following, we have the assumption of no perfect collinearity. This states that no independent variable is a perfect combination of other independent variables, and that no variable is constant. Perfect collinearity can cause biased estimators as there is no way to identify which variable is causing a certain movement. High multicollinearity (i.e. a high, but lower than 1 correlation between independent variables) leads to unstable estimates and increased standard errors of the affected variables. We will use a variance inflation factor test to investigate this for our regression models.

The last assumption for the unbiasedness of the model regards the zero conditional mean of the error term. The expected value of the error is zero at all times, given the independent variables for all time periods. When this holds, we have strictly exogenous explanatory variables, and following unbiased estimates. However, if the error term has a zero mean within the same period, but not for all periods, we have contemporaneous exogenity. With contemporaneous exogenity we will still have consistent OLS-estimators, but the estimates may be biased.

The following assumptions does not affect the bias of the estimators, but it does affect the variance, and thereby the inference methods for the models. The assumption of homoskedasticity states that conditional on the independent variables, the variance of the residual should be equal across all periods, i.e. the variance is constant across the time-series. Heteroskedasticity is thus the absence of homoskedasticity and it leads to biased standard errors for the estimates, which is naturally followed by bias in the test statistics and confidence intervals. OLS generally weights all observations equally, but when some observations do in fact have larger residual variance they contain less information and should ideally be weighted less than their lower variance counterparts. Hence, OLS is no long BLUE (Best Linear Unbiased Estimator) in the presence of heteroskedasticity. Heteroskedasticity can be detected by inspecting the plotted residuals against the fitted values for the model, or by various tests. Reducing the impact of heteroskedasticity can be achieved by using robust standard errors, transforming the variables, respecifying the model, or by using Weighted Least Squares (WLS) to estimate the model.

The next assumption is that of no serial correlation (sometimes referred to as autocorrelation), and this states that conditional on the independent variables, the residuals in different time periods are uncorreleated. Problems with serial correlation include inefficient estimators with erroneous standard error estimates. E.g. with positive serial correlation (a positive error in one period is followed by a positive error in the next period) and an independent variable that grows over time, the goodness to fit will be overrated and the standard errors too small. This may in turn lead to false positives, i.e. that insignificant results appear significant. Autocorrelation can be detected by various tests, or e.g. by inspecting a plot of the residuals over time to look for patterns of clustered residuals above or below zero.

Under all these five assumptions, the OLS estimators will be BLUE conditional on the explanatory variables. One final assumption regarding the inference (standard errors and test statistics) states that the errors are independent of the control variables, and that they are iid (independently and identically distributed) as $N(0, \sigma^2)$. Under all six of these assumptions the OLS estimators are normally distributed conditional on the independent variables, and under the null hypothesis each t statistic is t-distributed and each F statistic is F-distributed.

We will use one of the most common assumptions in finance, the assumption of log-normal returns. This follows from the assumption that stock prices are approximately lognormally distributed, and hence the natural log of these will be normally distributed. With the exception of the assessment of returns in Section 2.2 we will use logarithmic returns for all return-variables in this thesis. The central limit theorem states that the normal distribution will arise naturally when random variables are added. Outcomes of a stochastic process can be characterized as

sums of independent random variables with a finite variance, and the distribution of such a sum will approach the normal distribution as the number of observations approaches infinity. Using this theorem, we can assume our log-normal returns follow an approximate normal distribution. This is discussed in most basic finance and statistics textbooks, eg. McDonald (2013, p. 564).

2.4 Structural breaks

To illustrate what a structural break might look like, we use a simple random walk with drift model to simulate stock price developments. Note that this section contains simulated data, and its purpose is simply to illustrate structural breaks. This model implies that prices changes are independent of each other, so the price develops as a stochastic process where the current price depends on the previous price, a drift component and a normally distributed random error.

$$P_t = \alpha_t + P_{t-1} + \epsilon_t, \qquad \epsilon \stackrel{iid}{\sim} N(0, \sigma^2)$$
(2.6)

....

Figure 2.4 shows a simulated illustration of a structural break in the price development of a simple random walk with drift model. The break here manifests as changes in the trend, the growth rate changes from 0,4 per day, to -0,2 and then back to 0,4. The red line illustrates the trend, without any volatility. Note that the variance is constant over the timeline. Using this model, returns are given as

$$r_t = [ln(P_t) - ln(P_{t-1})]$$
(2.7)

Another form of structural break can be a change in volatility of returns. Below we have plotted the time-series of returns with breaks in volatility at two different points in time. Figure 2.3 displays an example of this, where the variance changes at day 100 and day 300.

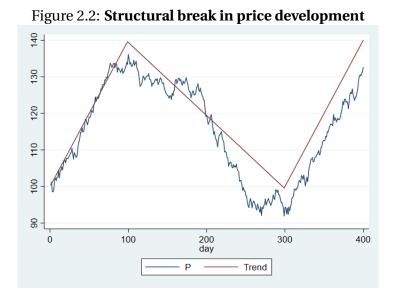


Figure 2.2: Simulated random walk with drift model for the stock price P_t . The drift parameter α_t is set to 0,4 for days [1,99] and days [300,400] and to -0,2 for [100,299]. The stochastic part of the process is normally distributed and has a constant mean of 0 and variance of 1, $\epsilon_t \stackrel{iid}{\sim} N(0,1)$. The red line indicates the trend, given as the price development with $\sigma = 0$ and the same drift as the stock, and the blue line indicates the price of the stock.

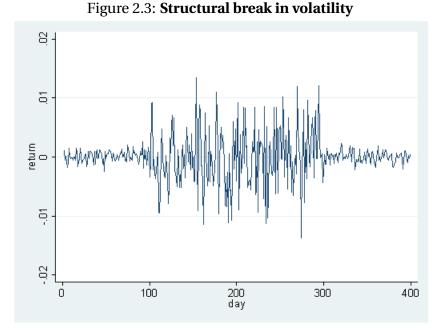


Figure 2.3: Simulated normally distributed log returns. $r_t = [ln(P_t) - ln(P_{t-1})]$. The series illustrates two structural breaks in volatility. $r_t \stackrel{iid}{\sim} (0, \sigma_t^2)$ with $\sigma_1^2 = \sigma_3^2 = 0, 1$ for days [1,99] and days [300,400] and $\sigma_2^2 = 0,5$ for [100,299].

Chapter 3

Analysis

3.1 Augmented Capital Asset Pricing Model

The capital asset pricing model (CAPM) is perhaps the most influential asset pricing model in finance. This model presented the first insight into the question of how risk should affect the expected return of investments. The original CAPM framework was first developed in the 1960s, in the seminal papers of Sharpe (1964), Lintner (1965a), Lintner (1965b) and Mossin (1966). The general formula for CAPM is given by

$$E(R_{i}) = R_{f} + \beta_{i}(E(R_{m}) - R_{f})$$
(3.1)

where $E(R_i)$ is the expected return on the capital asset, R_f is the risk-free return and $E(R_m)$ is the expected market return. $E(R_m) - R_f$ can be interpreted as the market premium (sometimes also referred to as the risk premium, i.e the difference in expected return associated with investing in risky assets contra a risk-free asset), and β_i is the sensitivity of expected excess asset return to the expected excess market return. Using OLS to estimate the beta, the beta for asset *i* is calculated as $\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$.

The model is a simple framework for pricing individual securities or portfolios. The beta offers a way to measure the portion of an asset's risk that cannot be diversified away (often called systematic risk or market risk). The model relies on several restricting assumptions, and has a poor real world empirical record (Fama and French, 2004). However, it is widely used today due

to its simple logic and straightforward explanation of the relationship between expected return and risk. Several varieties and extensions have been put forward over the years. In the following section we will employ an excess return version with an added sector-specific return variable. As a proxy for the risk-free rate in our analysis, we use the annualized 3-month U.S. Treasury bill rate presented by the St. Louis Federal Reserve Economic Data database (Federal Reserve Bank of St. Louis, 2018). The treasury rates are set daily, and is given as an annual percentage yield, so we calculate the monthly risk-free rate with the formula

$$\mathbf{R}_{f,t} = \left(1 + \frac{R_{3m,t}}{100}\right)^{\frac{1}{12}} - 1 \tag{3.2}$$

where $R_{3m,t}$ is the 3-month T-bill rate sampled at the last day of each month, resulting in a monthly rate $R_{f,t}$ as a proxy for the risk-free rate for any given month *t* in our dataset. The company, sector and market returns for company *i* at time *t* are calculated as

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \ R_{S,i,t} = ln\left(\frac{P_{S,i,t}}{P_{S,i,t-1}}\right), \ R_{M,t} = ln\left(\frac{P_{M,t}}{P_{M,t-1}}\right)$$
(3.3)

where subscripts *S* and *M* refers to sector and market respectively. The specifics of how the sector and market proxies are obtained is discussed in Section 2.2. As a proxy for the market return we use monthly data of the MSCI All Country World Index, downloaded from Thomson Reuters. In our regression we subtract the monthly risk-free rate from each observation, leaving us with the excess returns of our variables.

$$r_{i,t} = R_{i,t} - R_{f,t}, \ r_{S,i,t} = R_{S,i,t} - R_{f,t}, \ r_{M,t} = R_{M,t} - R_{f,t}$$
(3.4)

Including a sector index leads us to an augmented form of the CAPM model framework

$$r_{i,t} = \beta_{0,i} + \beta_{S,i} r_{S,i,t} + \beta_{M,i} r_{M,t}$$
(3.5)

where $\beta_{0,i}$ denotes the abnormal return, i.e. the return not explained by the explanatory variables. This constant is expected to be 0 in equilibrium in the CAPM framework. We thus interpret the constant as Jensen's alpha, the famous measure of marginal return not measured by the existing model, from Jensen (1968). $\beta_{S,i}$ is the sensitivity of excess asset return to the excess sector return, while $\beta_{M,i}$ measures the sensitivity of excess asset return to the excess market return. As before, subscript *i* denotes company *i* = 1,...,16 and *t* denotes the month *t* = -48,...,48 relative to announcement date. Subscripts *S* and *M* are indicators of sector and market variables, respectively. Note that each company has its own unique sector index $r_{S,i,t}$ as indicated by subscript *i*, while the market index $r_{M,t}$ is common for all companies. Also note that the time sequence as denoted by *t* is relative to an announcement date unique to each company, meaning that month *t* = 10 for company 1 is not necessarily equal to month *t* = 10 for company 2, for example. We will use this notation scheme throughout our analysis unless specified otherwise. Since we use a log-log model, $\hat{\beta}_S$ and $\hat{\beta}_M$ are the estimated percentage changes in the dependent variable given a 1% change in the respective independent variable.

Table 3.1 displays the results from separately fitted models for each firm before and after the hypothesized break. The difference in residual variance is discussed in Subsection 3.1.1. The results shown is this table will only be discussed briefly, as the points of interest are highlighted later in this thesis. The constant term is significant at the 5% level in only 1 out of the 16 firms in each period, namely Elbit before the break and WTK after the break. In addition, Shikun has a significant constant at the 10% level after the break. For example, in the case of Elbit Systems, the interpretation of the constant $\hat{\beta}_0$ is a positive abnormal return not explained by the sector and world market returns of 0,0125. Further we see that the sector returns have consistently significant explanatory power for all firms' returns in both periods, except in the case of Norilsk. As mentioned in Section 2.2, Thomson Reuters did not have a sector consistent with the rest of our sample firms, so the sector we use in this analysis is perhaps not the optimal choice. All significant coefficients for the sector returns are positive. In contrast, the coefficient for the world market returns have varying signs. Negative coefficients here might be due to the fact that the firm and sector have moved in opposite direction relative to the world market, or it might be due to collinearity between the world and sector returns. Inspecting the difference between the coefficient values, we see that several significant coefficients vary notably in the different subsamples. The implications of this difference will be discussed in the following subsections of this thesis.

		T	TUDIO OTOTI	out the contraction of the minimum of the second se								
			Before divestment	estment					After divestment	tment		
Company i	\hat{eta}_0	$\hat{\beta}_S$	\hat{eta}_M	Adjusted R ²	SSR	σ_1^2	\hat{eta}_0	$\hat{m{eta}}_{ m S}$	\hat{eta}_M	Adjusted R^2	SSR	σ_2^2
Barrick Gold Corp	-0,0069	1,3451**	$-1, 5113^{**}$	0,6716	0,1707	0,00379	-0,0101	1,1782**	$-0,6516^{**}$	0,6259	0, 1453	0,00316
Elbit Systems Ltd	0,0125*	0,6890**	-0,1020	0,5234	0,0757	0,00168	-0,0042	0,8768**	0,0229	0,6770	0,0566	0,00123
Freeport McMoRan Copper and Gold Inc	0,0103	1,1735*	0,2685	0,3062	0, 4365	0,00970	-0,0017	1,9822**	-0,2140	0, 6458	0,4495	0,00977
MMC Norilsk Nickel	0,0117	0,1517	1,7291**	0,5318	0,4123	0,00916	-0,0029	-0,1752	0,6498*	0,0985	0,2617	0,00569
Potash Corporation of Saskatchewan	-0,0004	0,7849**	0,0420	0,3536	0,4976	0,01106	-0,0100	0, 3098*	0,2328	0,0729	0,2422	0,00526
Rio Tinto Ltd	0,0061	$1,1646^{**}$	-0,4304	0, 5335	0, 1305	0,00290	-0,0033	1,6892**	-0,4293	0,5057	0, 3647	0,00793
Rio Tinto Plc	0,0020	1,3204**	-0,3587	0, 7981	0,0648	0,00144	-0,0042	$1,4596^{**}$	-0,6123	0,7177	0, 2943	0,00640
Shikun & Binui Ltd	0,0168	$1,4211^{**}$	$-0,4840^{*}$	0,5547	0,2774	0,00617	-0,0158	0,9574**	0,2042	0, 3361	0, 1455	0,00316
Sterlite Industries	0,0035	1,10287**	0, 9729	0,4449	0,6379	0,01418	-0,0053	0, 7999**	0,7460**	0,8158	0, 2414	0,00525
Ta Ann Holdings Bhd	-0,0027	1,0526**	0, 1920	0,3806	0, 1923	0,00427	-0,0026	0,9826**	-0,4872	0, 1690	0, 1229	0,00267
Vedanta Resources Plc	0,0059	1,5581**	-0,2540	0,5097	0,2590	0,00575	-0,0093	0,9422**	0,8499*	0, 7396	0,3872	0,00842
Volcan Compañia Minera	0,0001	0,8685**	-0,0834	0,3406	0, 3066	0,00681	-0,0073	1,4237**	-0,1230	0, 3108	0, 8739	0,01900
Wal-Mart de Mexico	-0,0010	1,0217**	$-0,3078^{*}$	0,6884	0,0309	0,00069	0,0023	$1,4266^{**}$	$-0,3848^{**}$	0, 7506	0,0733	0,00159
Wal-Mart Stores	0,0033	$1,4052^{**}$	$-0,9045^{**}$	0,5360	0,0563	0,00125	-0,0002	0,5263**	-0,2878	0, 1734	0,0915	0,00199
WTK Holdings Bhd	-0,0154	1,8558**	0,1110	0,5887	0,2260	0,00502	-0,0202*	1,2801**	-0,1792	0,2708	0,1396	0,00303
Zijin Mining Group	-0,0171	1,0299**	0,1141	0,4703	0,5170	0,01149	0,0085	1,1739**	$-1,0343^{*}$	0, 4549	0, 2487	0,00541
Table 3.1: Displays the results from separately fitted regression equations for the sample firms in the periods $[-48, -1]$ and $[0, 48]$ around the announcement of exclusion. $\hat{\beta}_0$ denotes the estimated constant term, $\hat{\beta}_S$ gives the estimated elasticity of the sector return on the return of the excluded firms, $\hat{\beta}_M$ gives the elasticity of the market return on the return of the excluded firms, Adjusted R^2 is the adjusted measure of goodne	ie results f lusion. $\hat{\beta}_0$ ves the ela	rom separa , denotes th asticity of th	ntely fitted ra ne estimatec ne market re	fitted regression equations for the sample firms in the periods $[-48, -1]$ and $[0, 48]$ around the stimated constant term, $\hat{\beta}_S$ gives the estimated elasticity of the sector return on the return of the narket return on the return of the excluded firms, Adjusted R^2 is the adjusted measure of goodness	luations f β_{S} g return of	for the sar ives the e f the exclu	nple firms stimated e ıded firms	in the peri lasticity of Adjusted	lods [–48, – the sector 1 R ² is the ad	1] and [0,48 eturn on the justed meas] around e return o ure of go	the if the odness
										•	'ī	

Table 3.1: Regression results before and after divestment

CHAPTER 3. ANALYSIS

of fit. SSR is the sum of the squared residuals, σ^2 is the mean square error of the regression, and is a measure of the residual variance. The tests performed on the estimated coefficients are standard two-tailed t-tests for statistically significant difference from zero. Bold indicate 10% sign-

ificance, (*) = 5% significance, (**) = 1% significance.

3.1.1 Tests for equality between sets of coefficients

In this section we employ a test for equality between sets of coefficients in two linear regressions from Chow (1960). The test assumes a known breakpoint, a linear model, independent Gaussian-distributed residuals and constant residual variance within subsamples, as well as constant residuals across the structural breaks. We use OLS to estimate three models for each firm, using the whole dataset for our overarching model, and the subsamples with months t = -48, ..., -1 as model 1 and t = 0, ..., 48 as model 2. From equation (3.5), we get a regression equation on the form

$$r_{i,t} = \beta_{0,i} + \beta_{S,i} r_{S,i,t} + \beta_{M,i} r_{M,t} + u_{i,t} \quad \text{with} \quad u_{i,t} \stackrel{iid}{\sim} N(0,\sigma^2)$$
(3.6)

The results of the regressions for the pre- and post-announcement subsamples are presented in Table 3.1 on page 26. The results of the regressions for the whole sample is presented in Table 3.2 on page 28. The residual sum of squares (RSS) are kept for each regression in order to calculate the following test statistic

$$F = \frac{(RSS - (RSS_1 + RSS_2))/k}{(RSS_1 + RSS_2)/(T_1 + T_2 - 2k)} \sim F_{k,T-2k}$$
(3.7)

where *RSS* equals the residual sum of squares, *T* equals the number of observations, and *k* equals the number of parameters in the regression. Variables for the unrestricted model are noted by lack of subscript, while subscript 1 and 2 indicate period 1 and period 2, respectively. For all of our regressions we have $T_1 + T_2 = 48 + 49 = 97$ and k = 3. This results in critical values $F_{0,10} = 2,145$, $F_{0,05} = 2,705$ and $F_{0,01} = 4,004$ for the respective significance levels, given $(v_1, v_2) = (3,91)$ degrees of freedom.

The null hypothesis for the test is that the data set can be represented in a single regression line, i.e. that there is no break point separating subsample 1 and 2. The null hypothesis is rejected if the test statistic exceed the critical value from an F-table. The result of the Chow test is presented in Table 3.2. However, if the assumption of homoskedasticity is broken the variance of the residuals are not constant over the sample. Toyoda (1974) calculates the appropriate significance levels for a Chow test under heteroskedasticity given different T_1, T_2 , k and $\theta = \frac{\sigma_2^2}{\sigma_1^2}$, where θ is the relative variance of the two periods. Using the root mean square error (RMSE) from the Stata regression output as a proxy for error term standard deviation for each regression, we can calculate the error variance, and the respective θ . Given $\theta \neq 1$ we have heteroskedasticity, and the assumed significance level under homoskedasticity ($\alpha_{0,05}$) is adjusted for the different input factors, resulting in an approximate true significance level (α^*). Note also that θ values above 1 indicate a higher mean variance for the period after announcement, while the opposite is true for values below 1.¹ Using the rounded values for each θ we find the corresponding α^* , i.e. the

			Chow test results						
Company i	\hat{eta}_0	\hat{eta}_S	\hat{eta}_M	Adjusted R^2	SSR	F-value	p-value	θ	α^*
Barrick Gold Corp	-0,0051	1,1790**	-0,9208**	0,6293	0,3457	2,8503*	0,0417	0,8329	0,054
Elbit Systems Ltd	0,0044	0,7966**	-0,1020	0,5873	0,1448	2,8846*	0,0400	0,7313	0,054
Freeport McMoRan Copper and Gold Inc	0,0054	1,5865**	0,1209	0,5349	0,9069	0,7164	0,5447	1,0073	0,05
MMC Norilsk Nickel	0,0033	0,0593	1,2713**	0,3437	0,7866	5,0683**	0,0027	0,6208	0,072
Potash Corporation of Saskatchewan	-0,0022	0,5966**	0,1722	0,2722	0,7711	1,2830	0,2850	0,4761	0,072
Rio Tinto Ltd	-0,0019	1,3630**	-0,2415	0,5174	0,5171	1,3406	0,2662	2,7330	0,093
Rio Tinto Plc	-0,0016	1,4072**	-0,5234	0,7454	0,3614	0,1974	0,8998	4,4474	0,134
Shikun & Binui Ltd	-0,0005	1,1736**	-0,2487	0,4624	0,4629	2,8694*	0,0408	0,5130	0,072
Sterlite Industries	0,0034	0,9403**	0,6269*	0,6466	0,9158	1,2591	0,2932	0,3702	0,111
Ta Ann Holdings Bhd	-0,0039	1,0652**	-0,0216	0,2959	0,3305	1,4714	0,2276	0,6253	0,072
Vedanta Resources Plc	-0,0029	1,1146**	0,6181*	0,6818	0,6738	1,3015	0,2788	1,4625	0,062
Volcan Compañia Minera	-0,0007	1,1292**	-0,1044	0,3155	1,2173	0,9430	0,4233	2,7882	0,094
Wal-Mart de Mexico	-0,0006	1,2567**	-0,3419**	0,7168	0,1139	2,7978*	0,0445	2,3227	0,083
Wal-Mart Stores	0,0002	0,8160**	-0,4991**	0,3035	0,1652	3,5710*	0,0167	1,5893	0,065
WTK Holdings Bhd	-0,0194	1,6709**	0,0588	0,4931	0,3859	1,6822	0,1764	0,6043	0,072
Zijin Mining Group	-0,0050	1,1082**	-0,2783	0,4605	0,8003	1,3719	0,2564	0,4707	0,072

Table 3.2: Regression results for the entire sample and results from Chow tests

Table 3.2: Regression results for the various companies over the whole period [-48, 48]. Regression coefficients ($\hat{\beta}_0$, $\hat{\beta}_S$, $\hat{\beta}_M$) are tested for statistically significant difference from zero with a standard two-tailed t-test. Adjusted R^2 is the goodness-of-fit for the regression. Sum of squared residuals (SSR) is the sum of differences between predicted and empirical values. The reported F-value is for a Chow-test for differences in coefficients between periods before and after announcement. The p-value is a standard statistical measure of the significance of the results. θ is a relative measure of variance between periods adapted from Toyoda (1974), and it gives an adjusted significance level α^* . Bold type indicate rejection of the null hypothesis at 10% significance, while asterisk (*) and double asterisk (**) indicate rejection of the null at 5% and 1% significance, respectively.

¹We use k = 3, $T_1 = 48$ and $T_2 = 49$, while Table 1(b) in Toyoda (1974, pp. 606) uses $T_1 = T_2 = 50$, which we consider approximately similar. For the firms with θ above 1 (except Freeport), we use a linear approximation of the α^* based on the values for θ of 1, 3 and 5 from Toyoda. For the firms with θ below 1, we use the nearest values from the table. We do this as the intervals from a θ of 1 to 3 and 5 are substantial, and as the α^* seems to increase in a close to linear fashion.

adjusted significance level under heteroskedasticity. For example, Freeport McMoRan Copper and Gold Inc has a θ = 1,0073, meaning a value very closely tied to homoskedasticity, which leads to $\alpha_{0.05} = \alpha^*$. For others, such as Rio Tinto Plc, we have $\theta = 4,4474 \neq 1$, ie. a value indicating heteroskedasticity, and an adjusted $\alpha^* = 0,148$. This increases the size of the test, leading to an increased chance of rejecting the null hypothesis when not adjusting for heteroskedasticity. Note that this adjustment is subject to minor inaccuracies, as not all θ values are provided for in the said paper. We can see heteroskedasticity has several consequences for our analysis: the true significance level always becomes higher than under homoskedasticity, meaning the results are less robust and the probability of committing Type 1 errors increases. Intuitively this means that the probability of rejecting a true null hypothesis increases. For example, under the assumption of homoskedasticity Wal-Mart de Mexico has a p-value of 0,0167, meaning one could reject the null hypothesis of no change in SSR between subsamples at 1,67% significance. At 5% significance the null hypothesis would therefore be rejected. When the assumption of homoskedasticity is broken ($\theta = 2,3227 \neq 1$), the significance level that was thought to be 5% turns into a significance level of 8,3%. To reject the null hypothesis at the 5% significance level under heteroskedasticity, we would need a higher F-value and a following lower p-value than we would need under homoskedasticity. The tests thus lose predictive power.

Inspecting the results in Table 3.2 we see that the difference in variance as measured by θ varies greatly among the sample firms. As mentioned, Rio Tinto Plc has the highest θ of 4,45 meaning the average variance is more than 4 times larger in the subsample after the break. On the other end of the spectrum we have Sterlite Industries, with a θ of 0,37. Overall 9 out of 16 sample firms have lower mean variance and 6 out of 16 have a higher mean variance in the post period, while Freeport is just about unchanged. Looking at the firms with significant test statistics at the 5% level for the Chow test, we see that 4 out of these 6 have θ below 1, the exceptions being Wal-Mart de Mexico and Wal-Mart Stores. It should be noted that 5 out of the 6 companies that show a higher mean variance in the period after announcement, the exception being Volcan, were excluded between 06.06.2006 and 09.09.2008, suggesting that the financial crisis of 2008 probably inflated their volatility. However, Elbit, Freeport, Sterlite and Barrick were also excluded in the mentioned time period (and Norilsk, if one extends the period until 19.11.2009), and all these firms have θ below 1, so the time of exclusion cannot entirely be attributed the

direction of heteroskedasticity.

Note that the Chow-test can be achieved by respecifying the model with dummy variables separating the different sub-periods for each explanatory variable and the constant term, and thereafter conduct an F-test for the significance of these dummy variables. We modify equation (3.5) by adding dummy variables, resulting in equation (3.8). We subsequently test $H_0: \delta_0 = \delta_S = \delta_M = 0$ for each company *i*.

$$r_{i,t} = \beta_{0,i} + \delta_{0,i}D_t + \beta_{S,i}r_{S,i,t} + \delta_{S,i}D_tr_{S,i,t} + \beta_{M,i}r_{M,t} + \delta_{M,i}D_tr_{M,t} + u_{i,t}$$
with $(i = 1, ..., 16; t = -48, ..., 48)$ and $D_t = \begin{cases} 0 & \text{if } t < 0 \\ 1 & \text{otherwise} \end{cases}$
(3.8)

where δ_0 , δ_s and δ_M denote dummy coefficients (i.e. the difference between the periods) for the constant term, r_s and r_M . Subscripts are defined as before. This model is used in most of the following analysis.

3.1.2 Wald tests for an unknown structural break

As the Chow test in the preceding subsection only checks whether there is a difference between the pre- and post-period of the divestment, we want to see if a test for an unknown break date can identify a break close to the announcement date, or whether the breaks in the time series are on other points in time and thereby most likely due to something else than the GPFG divestment. We extend the analysis of our Augmented CAPM model using Stata's built-in test for structural breaks, the "estat sbsingle"-test for an unknown structural break.² We run the tests on the ACAPM regression equation (3.6). The test statistic is constructed by combining the computed test statistics from a Wald test for each possible break date in the sample. The asymptotic distribution (the hypothetical distribution of a sequence of distributions) for each test is not standard - but it is however still known. Each test statistic is a function of several sample statistics, and each of these statistics depend on the unknown break date. The unknown break point is not identified under the null hypothesis. Even though all computed tests are functions of sample statistics computed over a range of potential breaks, the dates close to the beginning

²See Stata documentation under "estat sbsingle": https://www.stata.com/manuals14/tsestatsbsingle.pdf

and the end of the series cannot be tested. This is due to the lack of respectively preceding and following observations. This problem is solved by a default trimming of 15% from the beginning and end of the series, as recommended by Andrews (1993). We employ two tests for the data. The first is a supremum test that uses the maximum of sample Wald tests. The maximum sample test is compared with what could be expected under the null hypothesis of no structural break. Quandt (1960) and Andrews (1993) among others explain the intuition behind these tests. The supremum test statistic is the maximum of the test statistic values from a series of Wald tests over the range of possible break dates, where *b* denotes a possible break date in the range [b_1 , b_2], and *T* denotes the total sample size. The null hypothesis for the supremum version is that there are no structural breaks in the *k* coefficients, and the test statistic is found as

supremum
$$S_T = \sup_{b_1 \le b \le b_2} S_T(b)$$
 (3.9)

with the limiting (asymptotic) distribution of the test statistic given by

supremum
$$S_T \to d \sup_{\lambda \in [\varepsilon_1, \varepsilon_2]} S(\lambda)$$
 (3.10)

Here $B_k(\lambda)$ denotes a vector of *k*-dimensional independent Brownian motions, with $\varepsilon_1 = b_1/T$, $\varepsilon_2 = b_2/T$ and $\lambda = \varepsilon_2(1 - \varepsilon_1)/\{\varepsilon_1(1 - \varepsilon_2)\}$. And $S(\lambda)$ is given by

$$S(\lambda) = \frac{\{B_k(\lambda) - \lambda B_k(1)\}' \{B_k(\lambda) - \lambda B_k(1)\}}{\lambda(1-\lambda)}$$
(3.11)

The second test is an average test that uses the average of the sample statistics. This test is considered optimal when only minor changes in the parameter values of the model is the alternative hypothesis. Andrews and Ploberger (1994) discuss the properties of average tests. The test statistic for the average test is

average
$$S_T = \frac{1}{b_2 - b_1 + 1} \sum_{b=b_1}^{b_2} S_T(b)$$
 (3.12)

where the limiting distribution is

average
$$S_T \to d \quad \frac{1}{\varepsilon_2 - \varepsilon_1} \int_{\varepsilon_1}^{\varepsilon_2} S(\lambda) d\lambda$$
 (3.13)

For the reported p-values, Stata uses the method from Hansen (1997).

		Supremum test	Average test		
Company <i>i</i>	Month	Test statistic	p-value	Test statistic	p-value
Barrick Gold Corp	-3	13,17	0,0663	1,80	0,7617
Elbit Systems Ltd	-10	12,65	0,0811	3,06	0,3893
Freeport McMoRan Copper and Gold Inc	-	9,39	0,2599	3,18	0,3606
MMC Norilsk Nickel	10	16,72*	0,0154	8,74**	0,0071
Potash Corporation of Saskatchewan	_	4,54	0,8582	2,23	0,6196
Rio Tinto Ltd	_	4,30	0,8849	1,34	0,9078
Rio Tinto Plc	_	4,13	0,9027	0,78	1,0000
Shikun & Binui Ltd	-29	13,43	0,0597	9,46**	0,0041
Sterlite Industries	_	5,99	0,6640	2,97	0,4092
Ta Ann Holdings Bhd	_	9,00	0,2941	4,17	0, 1923
Vedanta Resources Plc	_	9,57	0,2452	4,29	0,1782
Volcan Compañia Minera	27	12,64	0,0815	4,88	0,1192
Wal-Mart de Mexico	-12	13,52	0,0577	8,27**	0,0102
Wal-Mart Stores	4	16,30*	0,0184	10,27**	0,0015
WTK Holdings Bhd	27	13,97*	0,0482	5,32	0,0875
Zijin Mining Group	_	9,95	0,2154	3,38	0,3189

Table 3.3: Results from Wald tests

Table 3.3: Summary table for the Wald test for an unknown structural break. "Month" shows the reported month for the significant supremum tests. The remaining columns show the test statistics and p-values for the supremum tests and average tests, respectively. Bold type indicate rejection of the null hypothesis at the 10% significance, while (*) and (**) indicate rejection at the 5% and 1% significance.

Table 3.3 gives a summary of the test results. We see that the supremum test rejects the null hypothesis of no structural change in parameter values in 8 of the 16 sample firms using a significance level of 10%. However, at the 5% level only 3 firms have significant results. As the test reports the maximum test statistic from a series of tests for each break, it can identify the month the break was most likely to occur in. We see a wide variety of break points in our significant re-

sults. The time series is set as the monthly range [-48, 48] with 0 as the month of announcement, -48 being 4 years prior and 48 being 4 years and 1 month post announcement. Our results range from -29 to 27. Barrick and Wal-Mart have reported breaks closest to the divestment announcement, with respective breaks 3 months prior and 4 months after the divestment announcement. Looking at the results from Table 3.1 on page 26 we see that both of these firms have negative shifts in $\hat{\beta}_0$ and $\hat{\beta}_S$ and positive shifts in $\hat{\beta}_M$ from the period before the announcement to the period after.

The average test shows significant results in 5 out of the 16 firms using a 10% significance level, and 4 using the 5% level. We see that all the firms with significant results in the average test also have significant results in the supremum test. Furthermore, combining these results with the results from our initial Chow test in Table 3.2 on page 28, we see that significant results at the 10% level in all three tests occur only in only 4 firms. These firms are Wal-Mart, Wal-Mart de Mexico, Norilsk Nickel and Shikun & Binui Ltd. At the 5% level only Wal-Mart and Norilsk Nickel show significant results in all tests. However, looking at the identified break months from the supremum test, we see that the estimated break dates are far from the hypothesized break in t = 0. These results indicate that there is not clear trend of structural breaks in the returns of the companies directly following the announcement of unethical conduct by the GPFG.

3.1.3 Post-estimation analysis of the ACAPM

In this subsection we will analyze the results of the dummy-specification of the model, see equation (3.8) on page 30. This section should be seen in context of the assumptions and possible problems regarding OLS-estimation discussed in Section 2.3. Our model is designed to shed light on some of the prime movers for the returns of our sample companies. As there are many contributing factors to the returns, we cannot realistically create a model explaining the returns entirely. A possible signal effect from the announcement of exclusion by the GPFG could change the firm's constant term, i.e. the abnormal return, the return sensitivity to the exogenous variables in our model, or it could impact the residual term. The residual term picks up any effects left out by the explanatory variables. Any signal effect is then likely to manifest as a change in the residual term. This section is therefore dedicated to shedding light on common problems in OLS-models, and explain to what extent they might tamper with our results. We will investigate the classical assumptions for OLS and assess the extent to which these are broken in our model. Further we will infer how this affects the validity of our results. The problems of possible heteroskedasticity for the Chow test were partly discussed in Subsection 3.1.1. OLS assumes $Var(u_i) = \sigma^2 \forall i$, i.e. that the variance of the error term is constant. A structural break could alter a firm's return, and it can change the variance for the model's error term, resulting in heteroskedasticity. Consider our specified model

$$r_{i,t} = \beta_{0,i} + \delta_{0,i}D_t + (\beta_{S,i} + \delta_{S,i}D_t)r_{S,i,t} + (\beta_{M,i} + \delta_{M,i}D_t)r_{M,t} + u_{i,t}$$
(3.14)

While heteroskedasticity does not lead to biased parameter estimates, it leads to bias in the standard errors, which in turn will lead to bias in the test statistics. Generally heteroskedasticity is treated by respecifying the model, using robust standard errors or using another estimation technique (e.g. Weighted Least Squares). We will employ two tests for heteroskedasticity on our estimated models. One of these is a test for linear heteroskedasticity, and the other test for more general forms of heteroskedasticity. Both tests are elaborated upon in Stata's manuals.³ The Breusch-Pagan/Cook-Weisberg ((Breusch and Pagan, 1979), (Weisberg and Cook, 1982)) tests the null hypothesis of constant variance over time. This is a linear specification of variance, i.e. it tests if bigger predicted values of the independent variable leads to bigger standard errors. More formally, it tests t = 0 in Var(e) = $\sigma^2 exp(zt)$, where z is the independent variables in the model. Stata thus runs the regression $\hat{e}_i^2/\hat{\sigma}^2 = a + z_i t + v_i$. This test is χ^2 -distributed with x degrees of freedom, where x is the number of parameters. The other test is White's test for heteroskedasticity from White (1980). This is a more general test, testing for other non-linear forms of heteroskedasticity. This test is therefore able to pick up heteroskedasticity not identified in the Breusch-Pagan/Cook-Weisberg test, and it performs better with non-normal errors. Being a general test, it will however have less power in cases where the heteroskedasticity is in fact linear, and thereby makes it less likely to produce a significant result in this case. The test statistic is computed as nR^2 from regressing the saved residuals \hat{u}^2 from equation (3.14) on the explanatory variables and all their cross products. nR^2 is χ^2 -distributed with x - 1 degrees of freedom, where x is the number of parameters in the auxiliary regression. We see that the tests

³See Stata documentation under "hettest" and "imtest": https://www.stata.com/manuals13/rregresspostestimation.pdf

show significant results in several firms. The consequences of this will be elaborated upon in the following subsection.

DA denotes the p-values for the Durbin alternative test for serial correlation in the disturbance term,⁴ as described by Durbin (1970). Applying the test procedure on our regression equation (3.14) we have

$$\hat{u}_{i,t} = \gamma_{1,i}\hat{u}_{i,t-1} + \beta_{0,i} + \delta_{0,i}D_t + (\beta_{S,i} + \delta_{S,i}D_t)r_{S,i,t} + (\beta_{M,i} + \delta_{M,i}D_t)r_{M,t} + \epsilon_{i,t}$$
(3.15)

$$H_0: \,\gamma_{1,i} = 0 \tag{3.16}$$

where equation (3.15) is the residual term $\hat{u}_{i,t}$ regressed on its own lag of order one, and the rest of the explanatory variables. Hence, equation (3.16) is the null hypothesis of no serial correlation of order one for company i = 1, ..., 16 in our specified model. The intuition is clear: the coefficient for the lagged fitted residual is tested for statistical significance. The p-values are presented in Table 3.4 under *DA*. We see that none of the values are significant at the 5% level, and we therefore reject any instances of serial correlation in our model. While there are other tests that aim to determine serial correlation, we choose this as it is less cumbersome. Our results being unambivalent in their ability to not reject the null of no serial correlation, we disregard serial correlation as an issue.

To search for multicollinearity we use Stata's variance inflation factor (VIF) test⁵. This is simply given as

$$VIF(x_i) = \frac{1}{1 - \hat{R}_i^2}$$
(3.17)

where \hat{R}_i^2 is the R^2 from a regression of x_i against the other explanatory variables. Multicollinearity can potentially be a problem for us if the sector and world indices for a firm are highly correlated. We run this test on the model without the dummy variables as these will inflate the results. According to Chatterjee and Hadi (2012) most researchers use informal rules to judge whether a VIF score indicate problematic multicollinearity. These guidelines say that there is evidence of multicollinearity if the average VIF is well above 1, and if the largest VIF in the regression is greater than 10. More liberal analysts use 30 as their limit. Note that as we use the model without

⁴See Stata documentation under "durbinalt": https://www.stata.com/manuals13/rregresspostestimationtimeseries.pdf ⁵See Stata documentation under "vif": https://www.stata.com/manuals13/rregresspostestimation.pdf

dummy variables to measure the VIF, the \hat{R}_i^2 for each test will simply be the coefficient of correlation between the sector and the world indices, and hence there is only one VIF to report from each regression. The results presented in Table 3.4 indicate that the level of multicollinearity in our models do not pose a problem.

Tuble 5.4. Results Holl	Post could				egreosiono
Company <i>i</i>	BP	W	DA	VIF	Adjusted R ²
Barrick Gold Corp	0,0000**	0,0072**	0,1254	1,53	0,6500
Elbit Systems Ltd	0,5968	0,9305	0,2341	1,81	0,6107
Freeport McMoRan Copper and Gold Inc	0,0018**	0,0061**	0,9688	5,66	0,5307
MMC Norilsk Nickel	0,0000**	0,0003**	0,8244	1,00	0,4192
Potash Corporation of Saskatchewan	0,0003**	0,0045**	0,8525	1,29	0,2787
Rio Tinto Ltd	0,0000**	0,8190	0,8407	2,37	0,5226
Rio Tinto Plc	0,0000**	0,8526	0,5797	2,79	0,7387
Shikun & Binui Ltd	0,2618	0,9362	0,1619	1,72	0,4927
Sterlite Industries	0,0000**	0,1199	0,1920	2,28	0,6495
Ta Ann Holdings Bhd	0,0221*	0,1439	0,9518	1,54	0,3064
Vedanta Resources Plc	0,1606	0,1550	0,9257	2,72	0,6849
Volcan Compañia Minera	0,0006**	0,2954	0,5138	1,23	0,3142
Wal-Mart de Mexico	0,0014**	0,0013**	0,2639	2,04	0,7321
Wal-Mart Stores	0,1121	0,1670	0,4302	3,39	0,3566
WTK Holdings Bhd	0,0000**	0,0351*	0,1329	1,54	0,5039
Zijin Mining Group	0,1319	0,0776	0,2194	1,68	0,4668

Table 3.4: Results from post-estimation tests for the ACAPM-regressions

Table 3.4: Displays the results for the post-estimation tests on the augmented capital asset pricing model with dummy variables separating the period before and after announcement of exclusion. The reported values for BP, W and DA in the table represents the p-values of the associated tests. BP denotes the Breusch-Pagan/Cook-Weisberg test for normally distributed, constant variance errors. W denotes White's test for assessing general forms of heteroskedasticity not picked up by the BP-formulation. *DA* is the p-value for Durbin's alternative test for serial correlation of the residual, lagged of order one. *VIF* is the variance inflation factor for the model without dummy variables. *R*² is the adjusted *R*² of the evaluated model. Bold type indicate rejection of null at the 10% level. Asterisks (*) and (**) indicates a rejection of the null at the 5% and 1% level, respectively.

These tests are used to evaluate how well our model is suited to the task of explaining the sample firms' returns around the announcement of divestment from the GPFG, and to what

extent our results are valid and reliable. Ideally we would have a broader data set (more firms and longer time series), and a model that could explain the mechanisms of the returns better. However, as short-term stock returns are a result of multiple factors, e.g. fundamental firm characteristics, various macroeconomic factors, market psychology etc. establishing a perfect model for stock returns is an impossible task, well beyond the scope of this thesis. Nevertheless, as a robustness test we estimated several other specifications of models, the regular capital asset pricing model, the Fama-French 3-factor model, and the Fama-French 3-factor plus sector returns (as in our ACAPM) model, and Carhart's four-factor model. Using adjusted R^2 to assess the goodness-of-fit of the models, we see that the original CAPM model was severely underpowered compared to the augmented version, while the more complex models showed little to no improvement over the simple, yet decent ACAPM. We therefore choose to base our main analysis on this model.

3.1.4 Robust standard errors

Table 3.4 shows that most of our models are prone to heteroskedasticity. This change in variance can in itself be a result of the exclusion from the GPFG, as previous research has found increased risk associated with exclusion (Hoepner and Schopohl, 2016). In this Subsection we want to investigate to what degree heteroskedasticity robust standard errors affect our analysis. The idea here is to isolate the change in return sensitivity coefficients and the constant term, without the interference of changing variance. To supplement our results in Table 3.2 and Table 3.3 we will run the regressions using a heteroskedasticity-robust formulation of standard errors. This lets us isolate and partly separate the effects of changing volatility and returns. The results can be either more or less significant with the robust formulation, depending on the direction of correlation between the residual variance and the explanatory variable. With positive correlation giving too small OLS standard errors, and negative correlation giving OLS too large standard errors. The direction and degree to which the standard errors change in the robust formulation vary between the different firms.

In order to correct for heteroskedasticity of the error terms shown in Table 3.4, we make use of the robust standard errors, developed by White (1980). The method is readily available in

Stata.⁶ Without deriving the results, we have the following matrix expressions for the general case

$$y = \mathbf{X}'\boldsymbol{\beta} + \boldsymbol{u} \tag{3.18}$$

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{y} \tag{3.19}$$

$$Var(\hat{\beta}) = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' Var(y)\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$$
(3.20)

$$Var(\hat{\beta}) = \begin{cases} (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\sigma^{2}\mathbf{I}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} = \sigma^{2}(\mathbf{X}'\mathbf{X})^{-1} & \text{under homoskedasticity} \\ (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'E(uu')\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} & \text{under heteroskedasticity} \end{cases}$$
(3.21)

Where (3.18) is the fitted model, (3.19) is the estimated betas, and (3.20) is the variance of the betas. We see that given $\sigma^2(\mathbf{X}'\mathbf{X}) \neq \mathbf{X}' E(uu')\mathbf{X}$, heteroskedasticity will lead to incorrect OLS estimates of the variance, resulting in biased standard errors, biased inference and potentially wrong test results. Table 3.5 on page 39 displays the results from the tests described in Subsection 3.1.2. Comparing these to the results from the same tests using traditional standard errors in Table 3.3 on page 32 we see that the impact of the robust standard errors are affecting the inference notably. Using the robust formulation we see that 4 firms have significant results at the 1% with the supremum test, opposed to 0 in the non-robust formulation. Looking at all firms significant at the 10% level or below, there are 8 firms with significant results in both formulations. Barrick goes from significant to insignificant at the 10% level using the robust formulation, while Vedanta does the opposite. The remaining 7 significant companies experience varying degrees of changed significance, with Elbit, Volcan and WTK gaining astonishing improvements in significance values. As the test tries to identify the exact time a break takes place, we can judge whether the significant results indicate a break possibly resulting from GPFG's announcement of divestment. In both the robust and the standard formulations, we see that Wal-Mart Stores is identified as the firm with a break closest following after the hypothesized break in t = 0. Looking at the firms with breaks in the period [-6, 6] around the announcement and looking at the estimates for the ACAPM models in Table 3.6 on page 41, we see that Norilsk have negative $\hat{\delta}_0$, $\hat{\delta}_S$ and $\hat{\delta}_M$. This translates into a negative shift in the abnormal return, as well as reduced sensitivity to sector and market excess returns. Wal-Mart have negative $\hat{\delta}_0$ and $\hat{\delta}_S$, but positive $\hat{\delta}_M$. These results indicate that many of the sample firms do in fact experience structural breaks in

⁶See test documentation: https://www.stata.com/manuals14/u20.pdf#u20.21Obtainingrobustvarianceestimates

their return series, however, it is not likely that the exclusion from the GPFG is the source of these changes.

In the average test the number of companies with significant results at the 10% level or below goes from 5 to 7 using the robust formulation. Again, we can see from the difference in p-values that some firms experience a rise in significance, while others experience a decline. Further we see that all firms with significant results in the average test also have significant results in the supremum test, but on the contrary, not all firms significant in the supremum test have significant results in the average test.

		Supremum test	Average test		
Company <i>i</i>	Month	Test statistic	p-value	Test statistic	p-value
Barrick Gold Corp	_	8,97	0,2975	2,01	0,6916
Elbit Systems Ltd	-10	31,42**	0,0000	4,28	0,1793
Freeport McMoRan Copper and Gold Inc	_	5,97	0,6672	2,83	0,4458
MMC Norilsk Nickel	-5	15,20*	0,0292	8,30**	0,0100
Potash Corporation of Saskatchewan	_	3,95	0,9204	2,15	0,6427
Rio Tinto Ltd	_	6,44	0,6006	3,13	0,3733
Rio Tinto Plc	_	3,32	0,9683	1,41	0,8874
Shikun & Binui Ltd	-29	13, 12	0,0675	8,02*	0,0123
Sterlite Industries	_	7,28	0,4865	2,71	0,4767
Ta Ann Holdings Bhd	_	11,44	0,1278	6,16*	0,0482
Vedanta Resources Plc	32	12, 12	0,0993	4,62	0,1422
Volcan Compañia Minera	-32	37,38**	0,0000	8,80**	0,0068
Wal-Mart de Mexico	-12	12,11	0,0995	6,45*	0,0391
Wal-Mart Stores	4	20,85**	0,0025	13,44**	0,0002
WTK Holdings Bhd	25	36,12**	0,0000	6,12*	0,0497
Zijin Mining Group	_	6,04	0,6562	3,30	0,3351

Table 3.5: Results from Wald tests with robust standard errors

Table 3.5: Summary table for the Wald test for an unknown structural break with robust standard errors. "Month" shows the reported month for the significant supremum tests. The remaining columns show the test statistics and p-values for the supremum tests and average tests, respectively. These are the comparable results under robust standard errors to those presented in Table 3.3. Specific months for the supremum test are left out if the p-values are insignificant. Bold indicate rejection of the null at the 10% significance, while (*) and (**) denotes rejection at the 5% and 1% level.

Table 3.6 displays the results from the ACAPM dummy with traditional and robust standard errors. Again we see mixed results in the difference between the standard errors, with some increasing and other decreasing using the robust specification. Note that the coefficients and the R^2 is unchanged using the robust regression, as it is only the standard error, and hence the inference that is affected by the robust formulation. Looking at the coefficients in the table, we see that the constant and the dummy for the constant are hardly ever significant. These constants can be interpreted as the abnormal return of the company, not explained by the sensitivity of the sector and market excess returns, as discussed in Section 3.1. $\hat{\delta}_0$ is thus the difference between periods of abnormal return.

An interesting observation is that a total of 13 out of the 16 sample firms have negative δ_0 , implying reduced abnormal returns after the break. However, out of the 16 sample firms only 2 have significant values coefficients at the 5% level. These are Shikun (-0,0326) and Elbit (-0,0167), both having significant coefficients at the 5% level under the standard and the robust standard error formulation. Using the original CAPM framework, each firm's α (equivalent to our β_0) is hypothesized to be 0 in an efficient market in equilibrium, so non-significant values are hardly surprising. The $\hat{\delta}_S$ and $\hat{\delta}_M$ denote the coefficient explaining the difference in periods between the firm's excess return's sensitivity to the sector and market excess returns. These coefficients do not have an equally intuitive interpretation as the constant, as the sector and market excess return variables might pick up some of the same signals (collinearity). However, isolating the effects of each variable, one can consider coefficients $\hat{\beta}_S$ and $\hat{\beta}_M$ the expected percentage excess return for the company after a 1% increase in the excess return of the sector and market. The $\hat{\delta}_S$ and $\hat{\delta}_M$ thus gives the difference in $\hat{\beta}_S$ and $\hat{\beta}_M$ between t = [-48, -1] and t = [0, 48]. Comparing the results in Table 3.1 and Table 3.6 we see that the difference between sample 1 and 2 in Table 3.1 equals the dummy-coefficient separating the periods in Table 3.6.

The reported p-value is the result of an F-test for joint significance of the dummy variables, i.e. that $\delta_0 = \delta_S = \delta_M = 0$. Note that the column for "p-value, standard" is equal to the p-value for the Chow test in Table 3.2. This test is thus for a difference between the period before and after the hypothesized break in t = 0. With the standard specification of standard errors, where heteroskedasticity is assumed, the hypothesis of no difference between the periods is rejected in 6 out of the 16 sample firms using a 5% level of significance. Under the robust formulation that

	$\hat{\beta}_0$	$\hat{\delta}_0$	βs	$\hat{\delta}_S$	\hat{eta}_M	$\hat{\delta}_M$	p-value	Ie	n2
Company i	(s.e) (r.s.e)	(s.e) (r.s.e)	(s.e) (r.s.e)	(s.e) (r.s.e)	(s.e) (r.s.e)	(s.e) (r.s.e)	standard	robust	4
Barrick Gold Corp	-0,0069 (0,0087) (0,0085)	-0,0032 (0,0122) (0,0131)	1,3451 (0,1348)** (0,1655)**	-0,1670 (0,1916) (0,2069)	-1,5113 (0,2643)** (0,3421)**	0, 3597 (0, 3150)** (0, 4333)*	0,0417*	0,2139	0,6682
Elbit Systems Ltd	0125 (0,0061)*	-0,016 (0,0079)* (0,6890 (0,1131)** (0,1345)**	0,1878 (0,1670) (0,1857)	,10	0, 1249 (0, 2046) (0, 2158)	0, 0400*	0,0221*	0,6310
Freeport McMoRan Copper and Gold Inc	103 (0,0139)	-0,0085 (0,0203) (0,0193)	1,1735 (0,5358)* (0,5597)*	0,8088 (0,7581) (0,7819)	0,2685 (0,6829) (0,7415)	-0,4824 (0,9434) (1,1127)	0,5447	0, 5479	0,5351
MMC Norilsk Nickel	0,0117 (0,0125) (0,0129)	-0,0147 (0,0179) (0,0166)	0, 1517 (0, 0888) (0, 0930)	-0,3269 (0,1920) (0,1904)	1,7291 (0,2107)** (0,2796)**	-1,0793 (0,3524)** (0,3845)**	0,0027** (0,0054**	0,4494
Potash Corporation of Saskatchewan	$\begin{array}{c} -0,0005\\ (0,0131) & (0,0144) \end{array}$	-0,0095 (0,0190) (0,0175)	0,7849 (0,1611)** (0,2513)**	-0,4751 (0,2489)* (0,2863)	0,0420 (0,2369) (0,3695)	0, 1908 (0, 4728) (0, 5011)	0,2850	0, 3533	0,3163
Rio Tinto Ltd	0,0061 (0,0111) (0,0088)	-0,0095 (0,0154) (0,0167)	1,1646 (0,2508)** (0,1193)**	0,5246 (0,3844) (0,3506)	-0,4304 (0,4532) (0,4556)	0,0011 (0,5397) (0,6473)	0,2662	0,0999	0,5475
Rio Tinto Plc	0,0020 (0,0095) (0,0056)	-0,0061 (0,0131) (0,0129)	1,3204 (0,1856)** (0,1364)**	0,1392 (0,2434) (0,2443)	-0,3587 (0,3640) (0,3798)	-0,2536 (0,4464) (0,5041)	0, 8998	0,8211	0,7323
Shikun & Binui Ltd	0,0168 (0,0100) (0,0116)	-0,0326 (0,0145)* (0,0141)*	1,4211 (0,1842)** (0,2439)**	-0,4637 (0,3172) (0,3444)	-0,4839 (0,2063)* (0,2592)	0,6881 (0,3945) (0,3898)	0, 0408*	0,0703	0,5191
Sterlite Industries	$\begin{array}{c} 0,0035\\ (0,0159) & (0,0142) \end{array}$	-0,0088 (0,0213) (0,0174)	1,1029 (0,2067)** (0,2051)**	$\begin{array}{c} -0,3030 \\ (0,2686) & (0,2410) \end{array}$	0,9729 (0,7159) (0,8203)	-0,2370 (0,7952) (0,8596)	0,2932	0, 5696	0,6677
Ta Ann Holdings Bhd	-0,0027 (0,0087) (0,0094)	0,0001 (0,0124) (0,0126)	1,0526 (0,2531)** (0,3656)**	$\begin{array}{c} -0,0701 \\ (0,4130) & (0,5062) \end{array}$	0,1920 (0,2477) (0,2881)	-0,6792 (0,4134) (0,4011)	0,2276	0,0783	0,3425
Vedanta Resources Plc	0,0059 (0,0136) (0,0107)	-0,0151 (0,0182) (0,0173)	1,5581 (0,3033)** (0,3067)**	-0,6159 (0,3588) (0,3479)	$\begin{array}{c} -0,2540\\ (0,6743) & (0,5051) \end{array}$	1, 1040 (0, 7435) (0, 6324)	0,2788	0, 2373	0,7013
Volcan Compañia Minera	0,0001 (0,0171) (0,0130)	-0,0074 (0,0240) (0,0249)	0,8685 (0,2491)** (0,2249)**	0,5551 (0,3732) (0,3416)	-0,0838 (0,3977) (0,2474)	-0,0396 (0,7759) (1,0241)	0,4233	0, 2338	0,3500
Wal-Mart de Mexico	$\begin{array}{c} -0,0010 \\ (0,0052) & (0,0034) \end{array}$	0,0033 (0,0072) (0,0070)	1,0217 (0,1507)** (0,1866)**	0,4050 (0,1918)* (0,2239)	-0,3078 (0,1746) (0,1815)	-0,0770 (0,2091) (0,2191)	0, 0445*	0,0925	0,7461
Wal-Mart Stores	0,0033 (0,0061) (0,0065)	-0,0035 (0,0084) (0,0091)	1,4051 (0,2338)** (0,2049)**	-0,8789 (0,2853)** (0,2744)**	-0,9042 (0,2626)** (0,3335)**	0,6165 (0,3179)* (0,3721)	0, 0167* (0,0056**	0,3901
WTK Holdings Bhd	-0,0154 (0,0093) (0,0095)	-0,0048 (0,0134) (0,0126)	1,8558 (0,2726)** (0,4649)**	-0,5756 (0,4449) (0,6040)	0,1110 (0,2668) (0,3561)	$\begin{array}{c} -0,2902\\ (0,4452) & (0,5012) \end{array}$	0,1764	0, 2307	0,5298
Zijin Mining Group	-0,0170 (0,0138) (0,0176)	0,0256 (0,0193) (0,0207)	1,0299 (0 ,1 88 4)** (0 ,2947)**	0,1440 (0,2982) (0,3463)	$\begin{array}{c} 0,1141\\ (0,4010) & (0,6405) \end{array}$	-1,1484 (0,6809) (0,7175)	0,2564	0, 1799	0,4946

Table 3.6: Regression results for the entire sample and results from Chow tests

CHAPTER 3. ANALYSIS

theses. The p-values presented are for an F-test of $\delta_0 = \delta_S = \delta_M = 0$ under standard and robust standard errors, while R^2 is the explanatory power

for the regression. Bold type indicate rejection of the null hypothesis of the coefficient being equal to zero at 10% significance, while asterisk (*)

and double asterisk (**) indicate rejection of the null at 5% and 1% significance.

take potential heteroskedasticity into account, the hypothesis is rejected for only 3 companies. Again, we see little evidence of a clear structural change in target firms' returns as a result of being excluded by the GPFG.

Barrick and Wal-Mart de Mexico prove an interesting case. Both have significant tests at the 5% level for the dummy-variables, but neither are significant in the robust formulation. In addition, both firms show clear signs of heteroskedasticity in the Breusch-Pagan and White test in Subsection 3.1.3. This indicates that the significance of the Chow test in Subsection 3.1.1 is due to changes in variance, i.e. heteroskedasticity. Using the θ from Table 3.2, we see that the average volatility (as measured by RMSE for each sub-period) is lower after the break in Barrick, and higher in Wal-Mart de Mexico. In contrast to this, we have Elbit and Wal-Mart Stores, with significant results in the Chow-test using both traditional and robust standard errors, and no significant results in the Breusch-Pagan and White-tests for heteroskedasticity. This implies that the rejection of the null hypothesis of no difference between periods is due to changing coefficients, not changing variance. Norilsk on the other hand, has significant results in all of the four mentioned tests, i.e. the Chow test with traditional and robust standard errors, and the heteroskedasticity tests. This implies both heteroskedasticity and a change in coefficients causing the rejection of the Chow-test using the robust formulation. The remaining firms have either non-significant results for all tests, significant test(s) for heteroskedasticiy but not enough difference in RSS to reject the Chow-test, or significant results for the Chow-test using the traditional standard errors but no other significant tests, the last of which is only the case for Shikun. It should be noted that the Chow-test for Shikun is significant at the 10% level with the robust formulation and at the 5% level using traditional standard errors.

3.2 Seemingly unrelated regression equations

Seemingly unrelated regression equations (henceforth SUR or SURE) is an econometric model developed by Zellner (1962), comprised of several linear multiple regression equations. While the equations that form the system are valid to regress on their own, the point of the SUR model is to account for possible interactions between the equations through possible correlations of their respective residual terms. In other words, while the equations are seemingly un-

related, they might be related through forces that affect more than one of the respective random disturbances. Jointness of the error terms' distribution and resulting non-diagonal variancecovariance matrix links the system of equations statistically. While each individual equation could be estimated with OLS in turn, the notion is that exploiting the additional information inherent in the SUR framework could improve the inferences drawn from analysis. More specifically, we wish to examine the possible effects common for all excluded firms. For this purpose the SUR approach would yield sharper results than OLS estimation for each regression separately. For there to be any exploitable information justifying the use of SUR rather than OLS, there needs to be some covariance between error terms across equations, as well as some difference in regressors across equations. Given our data set, consisting of 16 companies and 97 observations per company and using the method of Srivastava and Giles (1987) on our regression equation (3.8), we have the following system of equations

$$y_{i,t} = \beta_{0,i} + \delta_{0,i}D_t + \beta_{S,i}r_{S,i,t} + \delta_{S,i}D_tr_{S,i,t} + \beta_{M,i}r_{M,t} + \delta_{M,i}D_tr_{M,t} + u_{i,t}$$
with $(i = 1, ..., 16; t = -48, ..., 48)$ and $D_t = \begin{cases} 0 & \text{if } t < 0 \\ 1 & \text{otherwise} \end{cases}$
(3.22)

where notation for excess firm return is changed from $r_{i,t}$ to $y_{i,t}$ due to ease of formatting. Everything else is unchanged from before: $r_{S,i,t}$ is the excess sector return, $r_{M,t}$ is the excess market return, and $u_{i,t}$ is the random disturbance term, all for company *i* at time *t*. Additionally, D_t is a dummy variable equal to zero in the period before announcement (t < 0) and one after the announcement ($t \ge 0$), meaning the period before announcement is the base condition. The equations for each period is then given as

Before:
$$y_{i,t} = \beta_{0,i} + \beta_{S,i} r_{S,i,t} + \beta_{M,i} r_{M,t} + u_{i,t}$$
 (3.23)

After:
$$y_{i,t} = \beta_{0,i} + \delta_{0,i} + (\beta_{S,i} + \delta_{S,i})r_{S,i,t} + (\beta_{M,i} + \delta_{M,i})r_{M,t} + u_{i,t}$$
 (3.24)

If we stack all 97 observations for the *i*'th company from equation (3.22) we have

$$\begin{bmatrix} y_{i,-48} \\ \vdots \\ y_{i,48} \end{bmatrix} = \begin{bmatrix} 1 & r_{S,i,-48} & r_{M,-48} \\ \vdots & \vdots & \vdots \\ 1 & r_{S,i,48} & r_{M,48} \end{bmatrix} \begin{bmatrix} \beta_{0,i} \\ \beta_{S,i} \\ \beta_{M,i} \end{bmatrix} + \begin{bmatrix} D_{-48} & D_{-48}r_{S,i,-48} & D_{-48}r_{M,-48} \\ \vdots & \vdots & \vdots \\ D_{48} & D_{48}r_{S,i,48} & D_{48}r_{M,48} \end{bmatrix} \begin{bmatrix} \delta_{0,i} \\ \delta_{S,i} \\ \delta_{M,i} \end{bmatrix} + \begin{bmatrix} u_{i,-48} \\ \vdots \\ u_{i,48} \end{bmatrix} (3.25)$$

$$\begin{bmatrix} y_{i,-48} \\ \vdots \\ y_{i,0} \\ \vdots \\ y_{i,48} \end{bmatrix} = \begin{bmatrix} 1 & r_{S,i,-48} & r_{M,-48} \\ \vdots & \vdots \\ 1 & r_{S,i,0} & r_{M,0} \\ \vdots & \vdots & \vdots \\ 1 & r_{S,i,48} & r_{M,48} \end{bmatrix} \begin{bmatrix} \beta_{0,i} \\ \beta_{S,i} \\ \beta_{M,i} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & r_{S,i,0} & r_{M,0} \\ \vdots & \vdots & \vdots \\ 1 & r_{S,i,48} & r_{M,48} \end{bmatrix} \begin{bmatrix} \delta_{0,i} \\ \delta_{N,i} \\ \delta_{M,i} \end{bmatrix} + \begin{bmatrix} u_{i,-48} \\ \vdots \\ u_{i,0} \\ \vdots \\ u_{i,48} \end{bmatrix} (3.26)$$

$$y_{i} = \mathbf{R}_{i}\beta_{i} + \mathbf{R}_{i}^{*}\delta_{i} + u_{i} \qquad (3.27)$$

where equation (3.25) reduces to equation (3.26) due to $D_t = 0 \forall t < 0 \lor D_t = 1 \forall t \ge 0$. Equation (3.27) is equation (3.26) written in matrix notation, where normal type indicate a vector and bold type indicate a matrix. We have y_i as a (97 × 1) vector of dependent variables, \mathbf{R}_i as a (97 × 3) matrix of ones in the first column (accommodating the constant $\beta_{0,i}$) and independent variables in columns 2 and 3, β_i as a (3 × 1) vector of coefficients, and u_i as a (97 × 1) vector of random disturbance terms. Additionally, we have \mathbf{R}_i^* as a (97 × 3) matrix of zeroes from row 1 down to and including row 48. Further, from row 48 to row 97 we have ones in column 1 (accommodating the constant $\delta_{0,i}$) and independent variables in column 2 and 3. Finally, we have δ_i as a (3 × 1) vector of coefficients. Using equation (3.27), we stack on 16 individual companies, which yields

$$\begin{bmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{16} \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{1} & 0 & \cdots & 0 \\ 0 & \mathbf{R}_{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots \\ 0 & 0 & \cdots & \mathbf{R}_{16} \end{bmatrix} \begin{bmatrix} \beta_{1} \\ \beta_{2} \\ \vdots \\ \beta_{16} \end{bmatrix} + \begin{bmatrix} \mathbf{R}_{1}^{*} & 0 & \cdots & 0 \\ 0 & \mathbf{R}_{2}^{*} & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots \\ 0 & 0 & \cdots & \mathbf{R}_{16}^{*} \end{bmatrix} \begin{bmatrix} \delta_{1} \\ \delta_{2} \\ \vdots \\ \delta_{16} \end{bmatrix} + \begin{bmatrix} u_{1} \\ u_{2} \\ \vdots \\ \delta_{16} \end{bmatrix}$$
(3.28)
$$y = \mathbf{R}\beta + \mathbf{R}^{*}\delta + u$$
(3.29)

where, as before, equation (3.29) is equation (3.28) in matrix notation. We have that 97 * 16 = 1552, meaning that in equation (3.29) *y* is on the form (1552×1), **R** is on the form (1552×16),

 β is the form (16 × 1), **R**^{*} is on the form (1552 × 16), δ is the form (16 × 1) and *u* is on the form (1552 × 1). Assumptions for the general case of *M* equations and *T* observations are provided in Appendix C.1.1. A way to check non-diagonality of the variance-covariance matrix is by running a Breusch-Pagan test. The reported Breusch-Pagan test of independence is used to assess whether the equations are independent, i.e. that that the residual covariance matrix is diagonal. The test is elaborated upon in Breusch and Pagan (1980). The χ^2 -statistic for this test is distributed as χ^2 with M(M-1)/2 degrees of freedom. It is computed as

$$\lambda = T \sum_{m=1}^{M} \sum_{n=1}^{m-1} r_{mn}^2$$
(3.30)

where the estimated correlation between the residuals of the *M* equations is given by r_{mn} . The number of observations is denoted as *T*.

The results from our regression can be found in Appendix C.1 and Appendix C.2. Interpreting these results, we see that all equations are significant (p = 0,0000), meaning that at least some of the dependent variables are significant in each regression equation. Further, we see that both the Breusch-Pagan test for independence and the coefficient test for the dummies (the dummy-equivalence of a Chow-test described in Subsection 3.1.1) is highly significant. The Breusch-Pagan test tells us that the variance-covariance matrix is non-diagonal, meaning that we do not reject the null hypothesis of independent equations. This indicates that running the regressions as an interconnected system (as is done in the SUR-estimation), provides valuable information that is otherwise left out when running the system as single, separate equations. The non-diagonality of the variance-covariance matrix also suggest something else: since the equations our SUR model is comprised of span different timelines, the non-zero covariances are between residual terms from different calendar dates. Thus, the non-diagonality of the variance-covariance matrix of residuals goes counter to one of the assumptions of the tests performed throughout the paper, namely no intertemporal cross-equation residual covariance. However, since we look at relative timelines, these covariances are the sort of common impulse we seek to examine by employing the SUR model.

The test for the period-determined dummy-variables rejects the hypothesis of all dummies being equal to zero. This indicates that there is in fact a difference in the coefficients between the periods prior and post announcement. The reported "R-sq" cannot be directly compared to the R^2 from OLS-regressions. As SUR is estimated with the feasible generalized least squares method (FGLS), R^2 cannot be computed as it is with OLS. See Appendix C.1.1 for a brief discussion of FGLS. The "R-sq" denotes the percent of variance explained by the predictors.

	SI	JRE	Separate equations		
Company <i>i</i>	χ^2	Prob > χ^2	F	Prob > F	
Barrick Gold Corp	9,87*	0,0197	2,85*	0,0417	
Elbit Systems Ltd	8,69*	0,0337	2,88*	0,0400	
Freeport McMoRan Copper and Gold Inc	2,16	0,5398	0,72	0,5447	
MMC Norilsk Nickel	19,32**	0,0002	5,07**	0,0027	
Potash Corporation of Saskatchewan	4,88	0, 1805	1,28	0,2850	
Rio Tinto Ltd	7,28	0,0635	1,34	0,2662	
Rio Tinto Plc	1,54	0,6738	0,19	0,8998	
Shikun & Binui Ltd	8,84*	0,0315	2,87*	0,0408	
Sterlite Industries	8,22*	0,0417	1,26	0,2932	
Ta Ann Holdings Bhd	5,73	0,1254	1,47	0,2276	
Vedanta Resources Plc	3,06	0,3828	1,30	0,2788	
Volcan Compañia Minera	3,15	0,3685	0,94	0,4233	
Wal-Mart de Mexico	8,24*	0,0413	2,80*	0,0445	
Wal-Mart Stores	19,08**	0,0003	1,68*	0,0167	
WTK Holdings Bhd	6,85	0,0768	1,68	0,1764	
Zijin Mining Group	4,63	0,2013	1,37	0,2564	
Joint $\hat{\delta}_0$	19,01	0,2681	_	_	
Joint $\hat{\delta}_S$	48,30**	0,0000	_	_	
Joint $\hat{\delta}_M$	49,17**	0,0000	_	_	

 Table 3.7: Coefficient tests for SURE and separately fitted models

Table 3.7: Results from significance tests for the dummy variables (equivalent to the Chow test described in Subsection 3.1.1 for the SUR model and the separately fitted models. The results under "Separate equations" are from Table 3.2, and are included here for comparative and illustrative means. Bold type indicate rejection of the null hypothesis at 10% significance, while asterisk (*) and double asterisk (**) indicate rejection of the null at 5% and 1% significance, respectively.

Table 3.7 displays the results from the coefficient tests for SURE next to the the results of the regressions estimated separately. We see that the tests from the SURE-estimates are more often

statistically significant with lower significance levels, apart from Vedanta Resources. However, we run different tests on SUR and on the separately fitted equations, so we cannot compare p-values directly. The results are expected, given non-diagonal variance-covariance matrix between residuals, and different independent variables across equations. The degree to which the significance improves in the SURE estimation varies greatly. Using the SURE approach, the coefficient test for differences between the periods becomes significant at the 10% level for Rio Ltd and WTK, in addition to the firms that had significant results with the separate regressions. Sterlite has the most dramatic increase in significance, going from a p-value of 0,2932 to 0,0417. The reported "joint δ_0 , joint δ_S and joint δ_M " are tests for the dummy coefficients ($\delta_0, \delta_S, \delta_M$) of all equations in the SUR for respectively the constant, the sector and the market. We see that the test shows highly significant results for the overall difference between periods for the firms' return sensitivity to sector and market returns, but that the overall difference in the constant term is non-significant. This is hardly surprising, as the constant term β_0 and the dummy for difference in the constant between periods seldom is significant, both for the separately fitted equations and for the SUR, as seen in Table 3.1, Table 3.2, Appendix C.1 and Appendix C.2. Inspecting said appendices we see that the dummy for change in the constant term is significant at the 5% level in only 2 out of the 16 sample firms, namely Elbit and Shikun. A point of interest is that these two also are among the firms with the most significant constant terms as well, where the firms with significant constant terms at the 10% level are Elbit with a P > |z| of 0,021, WTK with 0,066 and Shikun with 0,098. Both Elbit and Shikun have positive and significant $\hat{\beta}_0$'s and negative and significant dummy coefficients, implying an abnormal return that is reduced after the break.

Chapter 4

Conclusion

Throughout this thesis we have gathered evidence to answer the question of whether GPFG's announcements of unethical conduct in public companies have any signalling effects to the financial markets. To investigate this we identified 16 sample companies for which GPFG have made a public statement of exclusion from their investment universe due to poor ethical conduct. These companies have widely dissimilar characteristics in geography, time of exclusion, industry, and size. In Section 2.2 we looked at the returns of the sample companies relative to a comparable sector for each firm. Using cumulative market-adjusted returns and buy-and-hold adjusted returns we found evidence indicating an overall outperformance of the sectors in the years before the exclusion, and mixed or weak performance relative to the sectors in the years following the exclusion. The mean BHAR for all firms over sub-periods of 12-13 months over the sample timeline was found to be 0,0263, indicating that the firms generally have a higher return than their comparable sector. Some earlier research have also found similar results, e.g. Kotter and Lel (2011), who finds positive effects on the stock prices of SWF investment targets and negative abnormal returns for SWF divestment targets. Negative abnormal returns for SWF divestment targets.

In Section 3.1 and Subsection 3.1.1 we established the model on which the remainder of our analysis is built, and presented initial results from a Chow-test for differences between the subsamples before and after exclusion. Using the augmented capital asset pricing model framework, we found mixed results in the degree of difference between the periods. Further, we looked at the difference in mean variance between the periods, again finding mixed results. In

6 out of the 16 companies we have higher mean volatility, while 1 firm has virtually unchanged mean volatility. The remaining 9 companies show reduced mean volatility after the exclusion. Using the 5% level of significance, 6 companies have significant F-statistics for the Chow test of difference in periods. Of these 6 firms, 4 have lower and 2 have higher volatility in the post-exclusion period. Due to the trend of decreased credit spread after SWF investment, as shown by Bertoni and Lugo (2014), we expected increased volatility after the break, but our results show no clear sign of this.

Following, in Subsection 3.1.2 we use Stata's built-in test to detect a structural break at an unknown place in time. Both a supremum test measuring the month in which there is most likely to be a break in the series and an average test checking for an overall change in the model is applied. The supremum test gives significant results at the 5% level in 3 firms, and the average test in 4 firms. Out of these only 2 firms (Norilsk Nickel and Wal-Mart Stores) overlap, being significant in both tests. However, most months identified as breakpoints by the supremum test seem unrelated to the exclusion from the GPFG, with identified breakpoints ranging from t = -29 to t = 27 relative to the hypothesized break in t = 0. In Subsection 3.1.3 we evaluate the ACAPM-regressions estimated thus far, and identify heteroskedasticity as a potential problem. As heteroskedasticity is a possible result of a structural break in the return series of the excluded companies, we investigate this further in Subsection 3.1.4. Here we repeat the tests from Subsections 3.1.1 and 3.1.2 using robust standard errors for our regression models. The difference between these robust results and the results using the traditional formulation of standard errors is that the robust formulation takes the heteroskedasticity into consideration, giving more reliable standard errors when the assumption of homoskedasticity is broken. The inference from these tests are thus more reliable than their traditional standard error counterpart. Using the robust formulation, 5 out of the 16 sample firms have significant results from the supremum test, and 7 have significant results with the average test. The break months from the supremum test are however still scattered, ranging from t = -32 to t = 25. Wal-Mart Stores is the only firm with a consistent and significant break closely following the exclusion, with a significant break 4 months after exclusion using both the standard and the robust formulation.

Next we compare the separately fitted regressions with traditional and robust standard errors. This allows for more precise inference, and thus more valid results in the presence of heteroskedasticity. The Chow-test has significant results at the 5% level in 6 and 3 out of the 16 sample firms using respectively traditional and robust standard errors. This implies that the presence of heteroskedasticity is the source of difference between periods for some of the sample companies.

We round off our analysis with a Seemingly Unrelated Regression formulation of our model. By allowing correlation between the firms' residuals, we are able to distinguish if there is any connection between the firms on the relative timeline defined by their time of exclusion from the GPFG. A potential common impulse would manifest as a covariance between the residual terms in the months following GPFG's announcement. Using this framework for the models fitted separately (i.e. without allowing for cross-equation residual correlation), we find more significant results for the hypothesis of inequality between the periods. All firms with significant results at the 5% level in the separately fitted equations are significant at the 5% or below using the SURE-model. In addition, Sterlite goes from a P > F of 0,2932 to a $P > \chi^2$ of 0,0417 in the test of significant dummies. We see that Vedanta and Zijin are the only firms in our sample with insignificant results in all break- and post-estimation tests, i.e. Chow or Chowequivalent dummy-testing using the standard, robust and SUR-formulation, both formulations of the supremum and average tests, and the heteroskedasticity and autocorrelation tests. Here we also test the joint significance of the dummies separating the pre- and post-exclusion periods, finding non-significant change in the constant term and a highly significant change in the estimated sensitivity to sector and market returns. The signs of these coefficients are mixed, with 9 firms having a negative $\hat{\delta}_S$, and 9 firms having negative $\hat{\delta}_M$. We see no clear pattern here, with 10 firms having opposite signs for $\hat{\delta}_S$ and $\hat{\delta}_M$, while the remaining 6 firms have similar signs for these coefficients. We thus conclude that the difference is significant, i.e. non-zero, but the effect differs between the companies.

At the company specific level we see that the firms with the highest indicators of breaks as measured by the number of significant tests at the 5% level, are Norilsk Nickel, Wal-Mart de Mexico and Wal-Mart Stores. Norilsk have significant results in all break-test formulations (i.e. all tests besides the test for serial correlation, the Durbin alternative test), indicating a clear shift in stock return mechanisms over the sample period. Wal-Mart de Mexico have significant results for the effect of dummies (i.e. the Chow-test) using the basic formulation of standard errors and using the SUR-approach. The tests for heteroskedasticity are significant, and the Chow-equivalent test for the robust formulation is however not significant. The supremum test for these firms does not yield significant results with neither the standard nor robust errors. Wal-Mart Stores have significant results for all break-tests except the heteroskedasticity tests in the post-estimation Subsection 3.1.3. The companies showing little evidence of changing mechanisms over the sample timeline are Freeport, Potash, Rio Tinto Ltd, Rio Tinto Plc, Vedanta and Zijin. These firms show significant results only for heteroskedasticity or no tests at all.

We have looked at our data from different angles and controlled for possible problems, and we thus feel confident in our results. The results are mixed and show no obvious significant pattern. All in all we cannot conclude that the exclusion from the GPFG cause a clear, unison change in the sample firms' stock prices. We see that the returns of the sample companies experience changes in both volatility, return and sensitivity to sector and market returns, but as the changes vary widely both in size, direction and time relative to the exclusion, we cannot attribute these changes to GPFG's announcement of said firms' unethical conduct. The structural changes we observe around the announcement dates are not unique, larger or even extraordinary relative to changes observed at other points in time, as pointed out by the supremum tests in Subsection 3.1.2 and 3.1.4. We therefore cannot conclude that exclusion from GPFG on ethical grounds is in itself an incentive to operate in a socially responsible manner.

Our thesis is an addition to the body of literature on the impact of exclusion from the GPFG. As per the results from Hoepner and Schopohl (2016) and Beck and Fidora (2008) we expected to find mostly insignificant long-term results for our hypothesis of structural changes stemming from exclusion. The mentioned studies found no abnormal returns in a portfolio of excluded companies relative to GPFG's returns, and no significant negative abnormal return in the period after divestment. Thus, our overall results of no clear effect is of no surprise. The mentioned studies use another time-interval, other methods of estimation and a different subsample of divested companies, i.e. not only conduct-based exclusion. Yet our results are quite similar. However, we see our study as relevant in the grand scheme of things, as it to our knowledge the only study examining the medium- to long-term effects of divestment from GPFG on ethical grounds. Furthermore, in the debate about SWFs being used as political tools, our results can be used as an example of an investment mandate that do not entail long-term results. In other words, our

results show that the transparency of the GPFG and the self-imposed limit of a maximum 10% ownership share, could be used as a basis for some sort of regulatory framework if SWF influence is of concern. A suggestion for future research would be to control for company-specific variables such as size, earnings per share, volume, price-earnings, price-book, and other fundamental variables to isolate effects of SWF divestment. Another possibility is to use the return of a portfolio consisting of stocks the given SWF is invested in as an independent variable. Ideally we would have a broader data set with more firms, longer time series and more details about each firm (e.g. an overview of total SWF-ownership in each firm).

References

- Aizenman, J. and Glick, R. (2009). Sovereign wealth funds: Stylized facts about their determinants and governance. *International Finance*, 12(3):351–386.
- Andrews, D. W. K. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61(4):821–856.
- Andrews, D. W. K. and Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica*, 62(6):1383–1414.
- Avendaño, R. and Santiso, J. (2009). Are sovereign wealth funds' investments politically biased? A comparison with mutual funds. *OECD Development Centre Working Papers*, (283).
- Bagnall, A. E. and Truman, E. M. (2013). Progress on sovereign wealth fund transparency and accountability: An updated SWF scoreboard. *Policy Brief*, (13-19):1–29.
- Balding, C. (2011). A portfolio analysis of sovereign wealth funds. In *Sovereign Wealth*, pages 43–70. Imperial College Press.
- Barber, B. M. and Lyon, J. D. (1997). Detecting long-run abnormal stock returns: the empirical power and specification of test statistics. *Journal of Financial Economics*, 43(3).
- Beck, R. and Fidora, M. (2008). The impact of sovereign wealth funds on global financial markets. *Intereconomics*, 43(6):349–358.
- Bernstein, S., Lerner, J., and Schoar, A. (2013). The investment strategies of sovereign wealth funds. *Journal of Economic Perspectives*, 27(2):219–238.

- Bertoni, F. and Lugo, S. (2014). The effect of sovereign wealth funds on the credit risk of their portfolio companies. *Journal of Corporate Finance*, 27:21 35.
- Blundell-Wignall, A., Hu, Y.-W., and Yermo, J. (2008). Sovereign wealth and pension fund issues. *OECD Journal: Financial Market Trends*, 2008(1):117–132.
- Bortolotti, B., Fotak, V., and Megginson, W. L. (2015). The rise of sovereign wealth funds: Definition, organization, and governance. In *Public Private Partnerships for Infrastructure and Business Development*, pages 295–318. Springer.
- Boubakri, N., Cosset, J.-C., and Grira, J. (2016). Sovereign wealth funds targets selection: A comparison with pension funds. *Journal of International Financial Markets, Institutions and Money*, 42:60–76.
- Boubakri, N., Cosset, J.-C., and Grira, J. (2017). Sovereign wealth funds investment effects on target firms' competitors. *Emerging Markets Review*, 30:96–112.
- Breusch, T. S. and Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5):1287–1294.
- Breusch, T. S. and Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1):239–253.
- Castelli, M. and Scacciavillani, F. (2012). *The New Economics of Sovereign Wealth Funds*. Wiley, Chichester, West Sussex.
- Chatterjee, S. and Hadi, A. S. (2012). *Regression Analysis by Example*. Wiley, Hoboken, NJ, 5th edition.
- Chen, X., Harford, J., and Li, K. (2007). Monitoring: Which institutions matter? *Journal of Financial Economics*, 86(2):279–305.
- Chhaochharia, V. and Laeven, L. (2009). Corporate governance norms and practices. *Journal of Financial Intermediation*, 18(3):405–431.
- Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, 28(3):591–605.

- Dewenter, K. L., Han, X., and Malatesta, P. H. (2010). Firm values and sovereign wealth fund investments. *Journal of Financial Economics*, 98(2):256 278.
- Dowell, G., Hart, S., and Yeung, B. (2000). Do corporate global environmental standards create or destroy market value? *Management Science*, 46(8):1059–1074.
- Durbin, J. (1970). Testing for serial correlation in least-squares regression when some of the regressors are lagged dependent variables. *Econometrica*, 38(3):410–421.
- Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, 101(3):621–640.
- European Commission (2017). State of the Union 2017 Press release. http://europa.eu/ rapid/press-release_IP-17-3183_en.htm. Accessed: 2018-02-03.
- Fabozzi, F., Ma, K. C., and Oliphant, B. (2008). Sin stock returns. *Journal of Portfolio Management*, 35(1):82–94.
- Fama, E. F. and French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, 18(3):25–46.
- Federal Reserve Bank of St. Louis (2018). 3-Month Treasury Bill: Secondary Market Rate. https://fred.stlouisfed.org/series/DTB3. Accessed: 2018-03-22.
- Fernandes, N. (2011). Sovereign wealth funds: Investment choices and implications around the world. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1341692. Accessed: 2018-02-12.
- Greene, E. and Yeager, B. (2008). Sovereign wealth funds a measured assessment. *Capital Markets Law Journal*, 3(3):247–274.
- Gunthorpe, D. L. (1997). Business ethics: A quantitative analysis of the impact of unethical behavior by publicly traded corporations. *Journal of Business Ethics*, 16(5):537–543.
- Hansen, B. E. (1997). Approximate asymptotic p values for structural-change tests. *Journal of Business & Economic Statistics*, 15(1):60–67.

- Hoepner, A. and Schopohl, L. (2016). On the price of morals in markets: An empirical study of the Swedish AP-funds and the Norwegian Government Pension Fund. *Journal of Business Ethics*, pages 1–28.
- Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36.
- Jensen, M. (1968). The performance of mutual funds in the period 1945–1964. *Journal of Finance*, 23(2):389–416.
- Konar, S. and Cohen, M. A. (2001). Does the market value environmental performance? *The Review of Economics and Statistics*, 83(2):281–289.
- Kotter, J. and Lel, U. (2011). Friends or foes? Target selection decisions of sovereign wealth funds and their consequences. *Journal of Financial Economics*, 101(2):360–381.
- La Porta, R., Lopez-De-Silanes, F., Shleifer, A., and Vishny, R. (2002). Investor protection and corporate valuation. *Journal of Finance*, 57(3):1147–1170.
- Lintner, J. (1965a). Security prices, risk, and maximal gains from diversification. *Journal of Finance*, 20(4):587–615.
- Lintner, J. (1965b). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1):13–37.
- Lourenço, I. C., Branco, M. C., Curto, J. D., and Eugénio, T. (2012). How does the market value corporate sustainability performance? *Journal of Business Ethics*, 108(4):417–428.
- Margolis, J. D., Elfenbein, H. A., and Walsh, J. P. (2009). Does it pay to be good... and does it matter? A meta-analysis of the relationship between corporate, social and financial performance. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1866371. Accessed: 2018-02-15.
- McDonald, R. L. (2013). *Derivatives Markets*. Pearson Education Limited, Edinburgh Gate, Harlow.

- Megginson, W. L., You, M., and Han, L. (2013). Determinants of sovereign wealth fund crossborder investments. *Financial Review*, 48(4):539–572.
- Mezzacapo, S. (2009). The so-called "sovereign wealth funds": Regulatory issues, financial stability and prudential supervision. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.
- Monk, A. (2009). Recasting the sovereign wealth fund debate: Trust, legitimacy, and governance. *New Political Economy*, 14(4):451–468.
- Moscow Exchange (2018). Sectoral Indices of Moscow Exchange: Metals & mining. https://www.moex.com/en/index/MICEXM%26M/. Accessed: 2018-03-18.
- Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica*, 34(4):768–783.
- MSCI (2018). The global industry classification standard. https://www.msci.com/gics. Accessed: 2018-03-06.
- Norges Bank Investment Management (2016a). Guidelines for observation and exclusion from the fund. https://www.nbim.no/en/the-fund/governance-model/ guidelines-for-observation-and-exclusion-from-the-fund/. Accessed: 2018-01-24.
- Norges Bank Investment Management (2016b). Responsible investment. https://www.nbim.no/contentassets/2c3377d07c5a4c4fbd442b345e7cfd67/ government-pension-fund-global---responsible-investment-2016.pdf. Accessed: 2018-02-09.
- Norges Bank Investment Management (2017a). Holdings as at 31.12.2017. https://www.nbim. no/en/the-fund/holdings/holdings-as-at-31.12.2017/?fullsize=true. Accessed: 2018-03-06.
- Norges Bank Investment Management (2017b). Strategy 2017-2019. https: //www.nbim.no/contentassets/86f28b52bbe348baace73ad550a36861/ norges-bank-investment-management---2017-2019-strategy.pdf. Accessed: 2018-01-25.

- Norges Bank Investment Management (2018a). Observation and exclusion of companies. https://www.nbim.no/en/responsibility/exclusion-of-companies/. Accessed: 2018-01-10.
- Norges Bank Investment Management (2018b). Return and risk: Government Pension Fund Global 2017. https://www. nbim.no/contentassets/db0b28dc13934aa6a56596d81d47a33a/ return-and-risk-2017---government-pension-fund-global.pdf. Accessed: 2018-03-06.
- Orlitzky, M., Schmidt, F. L., and Rynes, S. L. (2003). Corporate social and financial performance: A meta-analysis. *Organization Studies*, 24(3):403–441.
- Preqin (2017). Preqin special report: Sovereign wealth funds. http://docs.preqin.com/ reports/Preqin-Special-Report-Sovereign-Wealth-Funds-August-2017.pdf. Accessed: 2018-01-22.
- Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, 55(290):324–330.
- Reuters (2008). Sarkozy vows to defend France against wealth funds. https://www.reuters.com/article/us-france-sarkozy-funds/ sarkozy-vows-to-defend-france-against-wealth-funds-idUSL0872968320080108. Accessed: 2018-02-03.
- Reuters (2017). Potash Corp, Agrium win final approval to merge, forming Nutrien. https://www.reuters.com/article/us-potashcorp-agrium-m-a/ potash-corp-agrium-win-final-approval-to-merge-forming-nutrien-idUSKBN1EL1EB. Accessed: 2018-03-07.
- Reuters (2018). In China, Macron presses EU for united front on foreign investments. https://www.reuters.com/article/us-china-france-europe/ in-china-macron-presses-eu-for-united-front-on-foreign-takeovers-idUSKBN1EZOQP. Accessed: 2018-02-03.

Richardson, B. (2011). Sovereign wealth funds and the quest for sustainability: Insights from Norway and New Zealand. *Nordic Journal of Commercial Law*, 2(Fall):1–27.

Rozanov, A. (2005). Who holds the wealth of nations? Central Banking Journal, 15(4):52-57.

- Schnietz, K. E. and Epstein, M. J. (2005). Exploring the financial value of a reputation for corporate social responsibility during a crisis. *Corporate Reputation Review*, 7(4):327–345.
- Sethi, S. P. (2005). Investing in socially responsible companies is a must for public pension funds: Because there is no better alternative. *Journal of Business Ethics*, 56(2):99–129.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.
- Shleifer, A. and Vishny, R. W. (1997). A survey of corporate governance. *The Journal of Finance*, 52(2):737–783.
- Siegal, S. (1956). Nonparametric Statistics for the Behavioral Sciences. McGraw-Hill.
- Sojli, E. and Tham, W. (2011). The impact of foreign government investments: Sovereign wealth fund investments in the United States. *International Finance Review*, 12:207–243.
- Sovereign Wealth Fund Institute (2018). Preqin special report: Sovereign wealth funds. https://www.swfinstitute.org/sovereign-wealth-fund-rankings/. Accessed: 2018-01-22.
- Srivastava, V. K. and Giles, D. E. (1987). *Seemingly Unrelated Regression Equations Models: Estimation and Inference*, volume 80. CRC Press.
- Standard & Poor's (2018). S&P/BVL Mining Index (PEN). https://us.spindices.com/ indices/equity/sp-bvl-mining-index-pen. Accessed: 2018-03-07.
- The Economist (2006). The Dubai ports deal. http://www.nytimes.com/2006/03/02/ opinion/the-dubai-ports-deal.html. Accessed: 2018-02-12.
- The Economist (2008). Asset-backed insecurity. http://www.economist.com/node/ 10533428. Accessed: 2018-02-10.

- The Wall Street Journal (2008). China used reserves to sway Costa Rica. https://www.wsj.com/articles/SB122121919505927749. Accessed: 2018-02-03.
- Thomson Reuters (2012). Thomson Reuters Business Classification Methodology. https://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/ financial/trbc-methodology.pdf. Accessed: 2018-03-15.
- Thomson Reuters (2015). Thomson Reuters Indices: Corporate Actions Methodology.https://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/ financial/corporate-actions-methodology.pdf. Accessed: 2018-03-15.
- Thomson Reuters (2016). Thomson Reuters Global Equity Indices. https:// financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/ global-equity-index-methodology.pdf. Accessed: 2018-03-12.
- Thomson Reuters (2018). Thomson Reuters Business Classification. https:// financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/ trbc-fact-sheet.pdf. Accessed: 2018-03-15.
- Toyoda, T. (1974). Use of the Chow test under heteroscedasticity. *Econometrica: Journal of the Econometric Society*, pages 601–608.
- Truman, E. M. (2009). A blueprint for sovereign wealth fund best practices. *Revue d'économie financière (English ed.)*, 9(1):429–451.
- Truman, E. M. (2010). *Sovereign Wealth Funds: Threat or Salvation?* Peterson Institute for International Economics.
- van Beurden, P. and Gössling, T. (2008). The worth of values: A literature review on the relation between corporate social and financial performance. *Journal of Business Ethics*, 82(2):407.
- Waddock, S. A. and Graves, S. B. (1997). The corporate social performance-financial performance link. *Strategic Management Journal*, 18(4):303–319.
- Weisberg, S. and Cook, R. D. (1982). Residuals and Influence in Regression. Chapman & Hall.

- White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, pages 817–838.
- Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin*, 1(6):80–83.
- Wooldridge, J. M. (2016). Introductory Econometrics: A Modern Approach. Cengage Learning.
- Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, 57(298):348–368.

Appendix A

Acronyms

- BHAR Buy-and-Hold Market-Adjusted Return or Buy-and-Hold Abnormal Return
- **CAPM** The Capital Asset Pricing Model
- CAR Cumulated Abnormal Return
- CMAR Cumulated Market-Adjusted Return
- FGLS Feasible Generalized Least Squares
- **GLS** Generalized Least Squares
- GPFG Government Pension Fund Global
- iid Independent and Identically Distributed
- **NBIM** Norges Bank Investment Management
- **OLS** Ordinary Least Squares
- **RIC** Reuters Instrument Code
- SUR / SURE Seemingly Unrelated Regression Equations
- SWF Sovereign Wealth Fund
- WLS Weighted Least Squares

For our analysis in Stata we use abbreviations for variable names. Following is the list of our widely used variable names:

- *i* Denotes a firm-specific variable
- s Denotes a sector-specific variable
- *m* Denotes a market-specific variable
- d directly followed by a variable name indicates a dummy for said variable
- bar Barrick Gold Corporation
- elb Elbit Systems Ltd
- fre Freeport McMoRan Copper and Gold Inc
- nor MMC Norilsk Nickel PJSC
- pot Potash Corporation of Saskatchewan
- ril Rio Tinto Ltd
- rip Rio Tinto Plc
- shi Shikun & Binui Ltd
- ste Sterlite Industries
- taa Ta Ann Holdings Berhad
- ved Vedanta Resources Plc
- vol Volcan Compañia Minera
- mex Wal-Mart de Mexico
- wal Wal-Mart Stores Inc
- wtk WTK Holdings Berhad
- zij Zijin Mining Group

Appendix B

Return data reference codes and sources

Company <i>i</i>	Company code (RIC)	Sector code (RIC)
Barrick Gold Corp	ABX.TO	TRXFLDCATMAT
Elbit Systems Ltd	ESLT.TA	TRXFLDILTIND
Freeport McMoRan Copper and Gold Inc	FCX.N	TRXFLDUSTMAT
MMC Norilsk Nickel	GMKN.MM	See references
Potash Corporation of Saskatchewan	POT.TO^A18	TRXFLDCATMAT
Rio Tinto Ltd	RIO.AX	TRXFLDAUTMAT
Rio Tinto Plc	RIO.L	TRXFLDGBTMAT
Shikun & Binui Ltd	SKBN.TA	TRXFLDILTIND
Sterlite Industries	STRL.NS^L13	TRXFLDINTMAT
Ta Ann Holdings	TAA.KL	TRXFLDMYTMAT
Vedanta Resources Plc	VED.L	TRXFLDGBTMAT
Volcan Compañia Minera	VOL_pb.LM	See references
Wal-Mart de Mexico	WALMEX.MX	TRXFLDMXTNCY
Wal-Mart Stores	WMT.N	TRXFLDUSTNCY
WTK Holdings Bhd	WTKH.KL	TRXFLDMYTMAT
Zijin Mining Group	2899.HK	TRXFLDHKTMAT
Risk free rate	_	See references
World market	_	dMIWD00000GUS

Table B.1: Sources for return series

Table B.1: Sources for return series for companies, their respective sector indices, the world market and the risk free rate. Where RIC codes are not available, see the references for URLs.

Appendix C

Assumptions and results

C.1 Seemingly Unrelated Regressions

C.1.1 Assumptions for the general SUR model

Mathematical assumptions underpinning a SUR model, given by Srivastava and Giles (1987, pp. 4–5). We have M equations, K independent variables and T observations. The model is expressed in compact form as

$$y = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{u} \tag{C.1}$$

where $y_{TM\times 1}$ is a vector of independent variables, $\mathbf{X}_{TM\times K^*}$ is a matrix of dependent variables, $\beta_{K^*\times 1}$ is a vector of coefficients and $u_{TM\times 1}$ is a vector of random disturbance terms. In addition, $K^* = \sum_{i=1}^{M} K_i$, i = 1, ..., M and t = 1, ..., T. Treating each of the M equations as classical linear relationships, we assume

$$r(\mathbf{X}_i) = K_i < T \tag{C.2}$$

$$r(\mathbf{X}) = K \tag{C.3}$$

$$\lim_{T \to \infty} \left(\frac{1}{T} \mathbf{X}'_i \mathbf{X}_i \right) = \mathbf{Q}_{ii} \text{ with } i = 1, \dots, M$$
(C.4)

where \mathbf{X}_i is fixed, nonstochastic and with no measurement errors, and \mathbf{Q}_{ii} is a nonsingular matrix with fixed and finite elements. Further, there are some assumptions about the error terms,

across individual *i* we have

$$E(u_{it}) = 0 \forall t \Longrightarrow E(u_i) = 0 \tag{C.5}$$

$$E(u_{it}u_{is}) = \sigma_{ii}$$
 if $t = s$ and 0 otherwise (C.6)

$$E(u_i u_i') = \sigma_{ii} \mathbf{I}_T \tag{C.7}$$

where *E* is the expectations operator, σ_{ii} is the variance of the error term in the *i*'th equation for each observation and \mathbf{I}_T is an identity matrix of order T. In other words, there is no direct autocorrelation, and homoskedasticity within individuals. Across individuals, we have

$$E(u_{it}u_{js}) = \sigma_{ij} \text{ if } t = s \text{ and } 0 \text{ otherwise}$$
(C.8)

$$E(u_i u'_j) = \sigma_{ij} \mathbf{I}_T \tag{C.9}$$

$$\lim_{T \to \infty} \left(\frac{1}{T} \mathbf{X}'_i \mathbf{X}_j \right) = \mathbf{Q}_{ij} \text{ with } i, j = 1, \dots, M$$
 (C.10)

meaning that there is heteroskedasticity, or contemporaneous correlation, across individuals, but no cross autocorrelation, or intertemporal correlation. σ_{ij} represents the covariance between the i'th and j'th equation for each observation in the dataset. Using equations (C.5), (C.7) and (C.9) we have

$$E(u) = 0 \tag{C.11}$$

$$E(uu') = E \begin{bmatrix} u_1 \\ \vdots \\ u_M \end{bmatrix} \begin{bmatrix} u'_1 & \dots & u'_M \end{bmatrix} = E \begin{bmatrix} u_1u'_1 & \dots & u_1u'_M \\ \vdots & \ddots & \vdots \\ u_Mu'_1 & \dots & u_Mu'_M \end{bmatrix}$$
(C.12a)
$$E(uu') = \begin{bmatrix} \sigma_{11}\mathbf{I}_T & \dots & \sigma_{1M}\mathbf{I}_T \\ \vdots & \ddots & \vdots \\ \sigma_{M1}\mathbf{I}_T & \dots & \sigma_{MM}\mathbf{I}_T \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1M} \\ \vdots & \ddots & \vdots \\ \sigma_{M1} & \dots & \sigma_{MM} \end{bmatrix} \otimes \mathbf{I}_T = \mathbf{\Psi}$$
(C.12b)

where \otimes indicates the usual Kronecker product, meaning Ψ is a matrix on the form ($MT \times MT$). Looking at equation (C.12b) we see that, as previously touched upon, variance of u_{ti} is constant for all *t*; contemporaneous covariance between u_{ti} and u_{tj} ($i \neq j$) is constant for all *t*; intertemporal covariance between u_{ti} and u_{sj} ($t \neq s$) are 0 for all *i* and *j*. In other words, there is constant variance within individuals, constant contemporaneous covariance between individuals over time, and no intertemporal covariance within or between individuals.

It should also be mentioned that since we assume there is some additional information to be utilized by running our data through a SUR model, we cannot use the OLS method, as estimators generated by OLS does not take the non-constant variance of the error terms into account. Generalized least squares (GLS) does, and feasible generalized least squares (FGLS) estimators are then the results of using our data to estimate residual terms, and using these estimates to mimic the unknown error term process.

C.1.2 SUR and ACAPM results

Seemingly unrelated regression

	E	Equation		Obs	Parms	RMSE	"R-sq"	chi2	P	
	ł	oar i		97	5	.0571105	0.6679	220.15	0.0000	
		elb_i		97	5	.0370884	0.6277	188.22	0.0000	
	f	[re_i		97	5		0.5519	133.30		
		nor_i		97	5		0.4483	90.11	0.0000	
		ot_i		97	5		0.3051	45.70	0.0000	
		:i1_i		97 97	5		0.5398	151.80 335.36	0.0000	
		rip_i shi i		97	5		0.5163		0.0000	
		ste i		97	5		0.6657	236.31		
		aa i		97	5		0.3406	64.09	0.0000	
		red i		97	5		0.6992	270.37	0.0000	
	7	701_i		97	5	.1103606	0.3495	55.27	0.0000	
	n	nex_i		97	5	.032908	0.7441	313.28	0.0000	
	v	val_i		97	5		0.3868	77.09	0.0000	
		vtk_i		97	5		0.5241	139.38	0.0000	
	2	ij_i		97	5	.088882	0.4942	105.85	0.0000	
		Coef.	Std. Err.	z	P> z		Coef.	Std. Err.	z	P> z
bar i						- rip_i				
201_1	bar_s	1.374985	.124765	11.02	0.000	rip_s		.1346987	7.58	
	bar_m	-1.557221	.2447401	-6.36		rip_m drip s		.3095554	-0.42	
	dbar_s dbar m	1879464 .8691259	.1774433		0.290	drip_s drip_m		.3653614		
	dbar_m d	0025065	.0118321		0.832	d		.0125623		
	_cons	0072891	.0084112	-0.87	0.386	_ ^{cons}	.0063612	.0090529	0.70	0.482
elb i						shi i				
	elb_s	.7161911	.1019137	7.03	0.000			.1669342		
	elb_m	161254		-1.36		shi_m		.1870047		
	delb_s delb m		.1502599		0.163	dshi_s dshi_m		.2879517 .3574451	-0.90 1.90	
	dern ^{_m}		.0076349		0.043	d		.0139728		
	_cons	.0123755	.0053475	2.31	0.021	_ ^{cons}	.0159892	.0096537	1.66	0.098
fre i										
	fre_s	1.148219	.4786803	2.40	0.016	ste_s		.1854475		
	fre_m	.4248786			0.486	ste_m	1.129747		1.76	0.078
	dfre_s dfre_m	.9387306	.6763794 .841722		0.165 0.275	dste_s dste_m	4218211	.2408635 .7115473	-1.75 -0.52	0.080
	diric_m d	0083917	.019597	-0.43	0.668	d d	0041529			
	_cons	.0093085	.0139946	0.67	0.506	_cons	0010532			
nor i						taa i				
-	nor_s	.1694141	.0802644	2.11		_ taa_s	1.139342		4.96	
	nor_m dnor s	1.733859	.1906485 .1735523	9.09 -1.67		taa_m dtaa s	.1406375		0.62	0.533 0.916
	dnor_s dnor_m	-1.161824	.3188812	-1.6/		dtaa_s dtaa m	7260649		-0.11	0.916
	d	0130472	.0172887	-0.75	0.450	d	.0001036	.0119796	0.01	0.993
	_cons	.0114461	.0120973	0.95	0.344		0030922	.0083981	-0.37	0.713
pot_i						ved_i				—
	pot_s	.7547319	.142654	5.29 -0.58		ved_s	1.435825	.277803	5.17	
	pot_m dpot_s	1220455	.2099557		0.561	ved_m dved s	0403876		-0.07	0.948
	dpot_m	.62864	.4174839	1.51	0.132	dved_m	.9759975		1.43	
	d		.0182994		0.545	d	0145859	.0175512	-0.83	0.406
	_cons	0010735	.0126698	-0.08	0.932		.0058281	.0130551	0.45	0.655
ril_i		.9404118	.1796425	E 20	0.000	vol_i				
	ril_s ril m	2497485		-0.67		vol_s vol_m	.8575468		3.76 -0.36	
	dril_s	.5190042	.265136	1.96	0.050	dvol s		.3414364	1.60	
	dril_m	.0526985	.4328736			dvol_m	0729033	.7164626	-0.10	0.919
1	d _cons	0139585 .0089285	.0147861 .010611	-0.94 0.84		d		.0231299		
	_00118	.0009200	.010011	0.04	0.100	_cons	.0004258	.0164819	0.03	0.3/3

Figure C.1: Results from the SUR for our Augmented CAPM. This presents the main results from the regression, as well as the coefficients for 12/16 sample firms. The remaining 4 can be found on the next page.

	Coef.	Std. Err.	z	P> z		Coef.	Std. Err.	z	P> z
mex_i					wtk_i				
mex_s	.9710282	.1357145	7.15	0.000	wtk_s	1.782389	.2460007	7.25	0.000
mex_m	2045262	.1579087	-1.30	0.195	wtk_m	.3492003	.2421287	1.44	0.149
dmex_s	.386812	.1728995	2.24	0.025	dwtk_s	3760424	.4014658	-0.94	0.349
dmex_m	1238893	.189252	-0.65	0.513	dwtk_m	5728616	.4042655	-1.42	0.15
d	.003791	.0069343	0.55	0.585	d	0043637	.0129014	-0.34	0.73
_cons	0009148	.0050297	-0.18	0.856	_ ^{cons}	016658	.009045	-1.84	0.06
wal_i					zij_i				
wal_s	1.511688	.208968	7.23	0.000	zij_s	1.067836	.1756739	6.08	0.000
wal_m	9908767	.2356819	-4.20	0.000	zij_m	.0367284	.3754651	0.10	0.92
dwal_s	-1.069151	.2555103	-4.18	0.000	dzij_s	.1414771	.2777163	0.51	0.61
dwal_m	.7932165	.2854227	2.78	0.005	dzij_m	-1.148933	.6355414	-1.81	0.07
d	0042795	.008134	-0.53	0.599	d	.0251704	.0186878	1.35	0.17
_cons	.003949	.0059096	0.67	0.504	_cons	0162716	.013337	-1.22	0.223

Figure B.2: Results from SUR for ACAPM (continued)

Correlation matrix of residuals:

elb_i fre_i nor_i pot_i ril_i vol_i mex_i wal_i wtk_i bar i rip i shi i ste i taa i ved i zij i bar i 1.0000 elb_i 0.1121 1.0000 fre i -0.0818 -0.0471 1.0000 0.0448 -0.0150 0.1499 1.0000 nor i pot_i 0.0024 -0.1177 -0.0264 -0.0337 1.0000 ril i -0.0492 -0.1468 0.0743 -0.1874 0.1263 1.0000 rip_i 0.0206 -0.0305 0.0402 -0.2015 0.0710 0.8389 1.0000 0.0604 0.1578 -0.0061 0.0414 -0.2242 -0.0772 -0.0446 1.0000 shi i ste_i 0.1488 -0.0631 -0.0376 0.0100 -0.0883 0.0225 0.1139 0.0437 1.0000 taa_i -0.1073 -0.0633 -0.1811 0.1359 0.0518 -0.0770 -0.1153 -0.0644 0.0775 1.0000 ved 1 0.0292 0.0726 -0.1495 0.0701 -0.1611 -0.1298 -0.0839 0.0321 0.0598 0.0795 1.0000 vol 1 -0.0239 0.0919 -0.1732 0.0288 -0.0301 0.0595 0.0581 -0.0122 -0.1122 0.0706 -0.0973 1.0000 mex i 0.0791 0.1387 -0.0891 -0.0694 0.1073 -0.0368 0.0192 -0.0454 0.1935 0.1131 -0.1163 0.0452 1.0000 0.0725 0.0624 0.0207 -0.0951 0.0534 -0.1166 -0.0659 -0.1913 wal i 0.0081 -0.0848 -0.0129 -0.0685 0.1212 1.0000 wtki 0.0235 -0.1335 0.0545 -0.0312 0.2265 -0.0261 -0.0554 0.0474 0.1297 0.3186 -0.0404 -0.1546 0.0080 -0.0959 1.0000 zij_i -0.0703 0.0327 0.0183 -0.0439 0.0354 0.0836 0.0585 -0.0501 0.0617 0.0195 -0.0460 -0.0347 0.0048 0.2103 -0.0249 1.0000

Breusch-Pagan test of independence: chi2(120) = 177.675, Pr = 0.0005

. test d 'ds' 'dm'

chi2(48) = 125.23 Prob > chi2 = 0.0000

Figure C.2: Results from the SUR for our Augmented CAPM, as well as a Breusch-Pagan test for independence, and a coefficient test for the dummy variables separating the periods pre- and post exclusion. The coefficients for 4/16 sample firms are presented here, for the remaining 12, see the previous page.