A Computational Text Analysis

The main explanatory variable that we are interested in are events that indicate progress or failure of the TPP and TTIP negotiations. Rather than manually selecting some events, we decided to rely on the automated analysis of newspaper reports. The main advantage of our approach is that we do not identify turning points in a post-hoc manner that might not havebeen identifiable as such to contemporary observers. Rather, we rely on information (and the interpretation of that information as indicating progress or failure) available at the moment of the event.

We retrieved in the US published newspaper reports that represent the starting point for our approach from LexisNexis using the following algorithms:

> “DATE(=[year]) and (HEADLINE(TPP) or HEADLINE(Trans-Pacific Partnership) or HEADLINE(Transpacific Partnership)) and ((BODY(Trans-Pacific Partnership) or BODY(Transpacific Partnership) or BODY(transpacific) or BODY(TransPacific) or BODY(trade agreement)) or (HEADLINE(Trans-Pacific Partnership) or HEADLINE(Transpacific Partnership) or HEADLINE(transpacific) or HEADLINE(TransPacific) or HEADLINE(trade agreement)))”

> “DATE(=[year]) and (HEADLINE(TTIP) or HEADLINE(Transatlantic Trade and Investment Agreement) or HEADLINE(Transatlantic Trade Agreement))”

The newspaper search on TPP had to be more restrictive as TPP is an acronym for several other, not trade-related topics. We further restricted our sample to articles printed in outlets published in the United States. Using this approach, we arrived at 2,359 newspaper articles on TPP published between 1 January 2009 and 31 December 2017 and 1,193 newspaper articles on TTIP that were published between 1 January 2013 and 31 December 2017.

Figure AA.1 shows the number of articles over time. News on TPP peaked at five moments: at the end of 2009 when the United States entered the TPP negotiations, at the end of 2012 during intense negotiations and when Canada and Mexico were invited to join the negotiations, in January 2016 when the final TPP text was released, in January 2017 when the US withdrew from TPP, and at the end of 2017 as the eleven remaining members of TPP announced progress in their negotiations.

Four peaks and one longer stretch of intense news reporting characterize the development of the TTIP negotiations. The reports in July and August 2013 deal with the first round of negotiations over TTIP. At the beginning of 2014, the EU Commission consulted the public on provisions in TTIP on investment and investor-state dispute settlement. The following negotiation rounds were characterized by tensions over investment issues, standards, and agriculture. On 9 October 2014, the European Commission published the TTIP negotiation mandate. News on the negotiations peaked with the British referendum over EU membership in June 2016. In November 2016, large protests against TTIP hit the headlines. In the same month, also the elections in the United States increased reporting on TTIP.

Our analysis, however, calls for more than just a measure of attention to the negotiations. What we need is a measure of whether the news are positive or negative with respect to the chances of concluding the deals. In other words, we need a measure of sentiment on a dimension from progress to stagnation.

We decided against manually coding all articles for several reasons. For one, given the number of articles in our dataset, this would have been an enormous task. Moreover, manual coding raises the question of reliability. Manual coding thus would have required double coding all articles, making the task at hand even larger. Finally, manual coding does not allow for any simple scaling up of the study, for example to study the effects of other trade negotiations. A computational analysis of the texts helps on all of these issues.

When it comes to the question of which computational method to pick, several options exist. The computationally simplest approach relies on a dictionary, which includes character strings

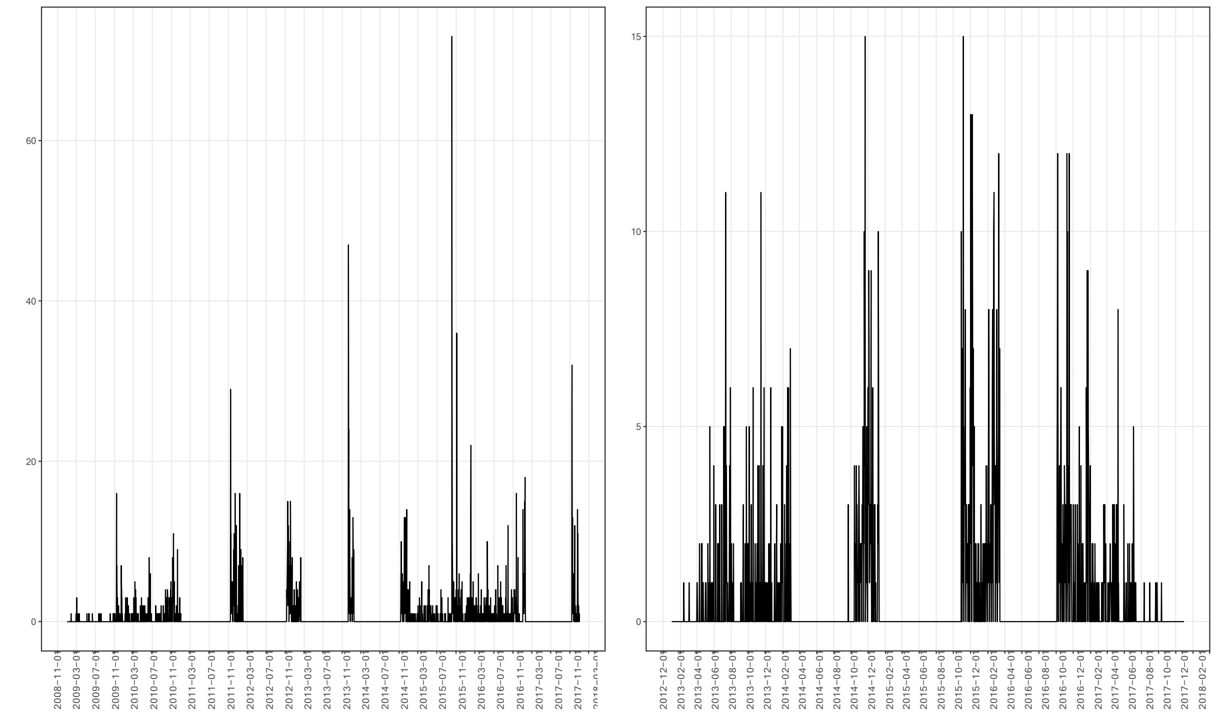


Figure AA.1: Newspaper articles on TPP (left) and TTIP (right) over time

and sentiment values that classify text (Krippendorff, 2013). Yet, professional linguistic dictionaries with values exist only for the classification of positive versus negative texts. When using existing dictionaries, we thus would have to assume that progress equals positive sentiments and stagnation negative sentiments. Positive words such as “good”, “great” or “fabulous”, however, seem to cover only parts of our concept of progress. Sentences such as “The parties finished negotiations” would be classified as negative using the positive versus negative classification, because the word “finish” comes with a negative loading. Yet, for the purpose of this study the respective sentence should be understood as indicating progress in trade negotiations. To be able to rely on a dictionary-based approach, we thus would have to generate our own dictionary. Haselmayer and Jenny (2017), for instance, did so by relying on large-scale crowd coding of text segments to generate sentiment values of texts and subsequently of words. However, we would need to code a lot of texts to generate a useful dictionary. Haselmayer and Jenny (2017) had ten coders each code 13,000 randomly selected sentences. Such a large-scale coding undermines the above mentioned advantages of automated processes in our research design.

An alternative approach is to rely on supervised machine learning algorithms (Burscheret al., 2014, SML). Kananovich (2018) applies this to a similar problem as ours, namely the classification of newspaper articles. SML learns to classify text on a subsample of text segments that were coded by humans (Grimmer and Stewart, 2013). This subsample represents thetraining set from which the computer learns and infers the coding for the remaining, not yet classified documents. This is the approach that we adopt in this paper.

Hence, we started with the manual coding of 500 newspaper texts. We asked the coder to assign a value of 1 if the text deals with events that have the potential to increase the likelihood of a successful conclusion of the negotiations. A text receives the value of -1 if it captures events that have the potential to hinder or delay the successful conclusion of the negotiations. This includes actors, such as politicians or interest groups, coming out in opposition to the agreement. A value of 0, finally, indicates a text that captures neutral events that relate to neither progress nor stagnation of the negotiations. To make this manual coding reliable, three coders looked at a subset of 100 texts to calibrate the coding. We then took 80 percent of the 500 coded texts to train the data and 20 percent to test the performance of approaches.

To make a computational analysis possible, we had to prepare and clean the texts. The aim of the preprocessing was to reduce noise while keeping the meaning of the text.[1] First, we lower-cased all words and removed punctuation. Next, we dropped extra and superfluous whitespace. Third, we lemmatized words to reduce unnecessary complexity in the text. Lemmatization is an algorithmic process that reduces the word to the *lemma*, which keeps the word's intended meaning. In contrast to stemming, lemmatization identifies the position of the word and infers therefrom the meaning. This means that lemmatization is less prone to delete substantial information from the text than stemming. We used a tool called Treetagger by Schmid and Schmid (1994) to realize the lemmatization. If the tool fails to find an appropriate lemma, we used the algorithm proposed by Porter (1980) to arrive at the word stem. Fourth, we compounded words that belong together.[2] This represents another important step to avoid a distortion of the meaning in the text. Since the machine learning algorithms rely on a bag-of-words approach, the creation of n-grams is indispensable to maintain the meaning of the texts. The input to the machine learning algorithms are document-term matrices with both 1-gram and 2-grams of the texts.

Similar to Kananovich (2018), we trained eight machine learning algorithms on these texts: support vector machine, generalized linear model, maximum entropy, scaled linear discriminant analysis, bagging, random forest, decision tree, and boosting.[3] We selected these algorithms to cover a wide range of assumptions and performance characteristics. Decision tree and random forest, for instance, are effective in high dimensions. Generalized linear models are better dealing with only few dimensions but are computationally effective. In contrast, the support vector machine model requires more computational power; yet it often delivers robust results. All of these algorithms are based on a single strong learner, which aims at the maximization of the correlation with the true classification. Boosting, in contrast, combines multiple weak learners, where each is only slightly correlated with the true classifier. Three of the algorithms did not run on a computer with 32 GB RAM and 16 cores because of a lack of memory. Thus, we have results for five algorithms.

By dint of the test sample (20 percent of the human coded sample), we assessed the performance of these algorithms. For this purpose, we relied on three measures: precision, recall, and F-score. Precision measures the proportion of predicted values that match the human coding. Recall represents the proportion of the correctly predicted values. The F-score captures the harmonic average of precision and recall with a value of 1 being perfect precision and recall and 0 worst precision and recall. Table AA.1 shows the results of these performance checks. We took the two best-performing algorithms, namely support vector machine and random forest, toclassify the remaining documents as indicating progress or stagnation. If these two algorithms agree, we took the respective value; if not, we used the value of the algorithm that was certain with a probability greater than 80 percent. In case both algorithms were certain with a probabil- ity greater than 80 percent and calculated different results or if both algorithms were uncertain with a probability lower than 80 percent and disagreed, we assigned a value of 0, which is our neutral category.

For our analysis, we need one value capturing the progress or stagnation of an event day. This requires an aggregation of the individual newspaper values per agreement and per day. At this point, we dropped event days that covered less than four TTIP articles or less than four TPP

[1]We used the following R-packages for preprocessing: *quanteda*, *stringr*, and *treetagger*.

[2]The compound words (after lemmatization) in the newspaper articles are the following: trans-pacif part- nership agreement, trans-atlantic, work group, trade commission, transatlantic trade agreement,civil society, european commission, european parliament, karel de gucht, michael froman, Atlantic council forum, unite king- dom, trade union, g20 summit, g8 summit, trade representative, free trade, trade area, trade talk, trans-pacif partnership, united state, trade representative, trade rep, human right, trade deal, trade chief, council of the euro- pean union, environmental protect, social right, labour standard, environmental protection, intellectual property right, european union, investor arbitration, trade in good, trade in service, preferential trade agreement, free trade agreement,trade agreement, donald trump, barack obama, hillary clinton, angela merkel, gernd lang, justin trudeau, shinzo abe, new zealand, van hollen, de gucht.

[3]For details on the different algorithms see Gibbons et al. (2017). The R-package *RTextTools* provides an efficient infrastructure to work with these algorithms.

Table AA.1: SML Performance measures

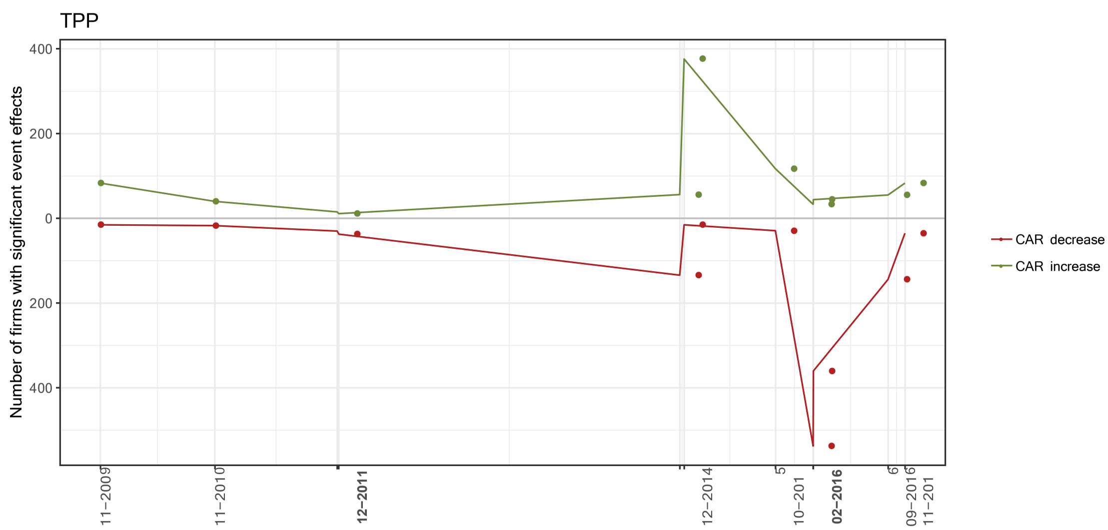
Algorithm	Precision	Recall	F-score	Ranking
Support vector machine	0.72	0.55	0.48	1
Random forest	0.61	0.38	0.32	2
Maximum entropy	0.51	0.56	0.49	3
Generalized linear model	0.44	0.39	0.38	4
Boosting	0.34	0.34	0.34	5

articles. The risk of analyzing days with too few articles is that the event is captured wrongly and that we include event-dates that are irrelevant to investors. The assumption here is that if a significant event happens, more than three newspapers report on the issue. To aggregate values for newspaper articles to values for event dates, we first weight newspaper-article-values by their probability and use these weighted values to calculate the average per day. Events with a time difference of seven or fewer days are treated as one event, where we calculate the weighted value across all these days and flag the result with the minimum date.[4] This is important to avoid overlaps in the analysis. We then selected the seven most probable progress events and all three stagnation events.[5] Finally, we assigned the value of -1 to all stagnation and the value of 1 to all progress events. We also checked whether there was any overlap between TPP and TTIP events, but this was not the case.

Table AA.2 shows the result of this process. Most of these events and their coding as progress or stagnation event seem plausible. In October 2015, for instance, the TPP negotiations were concluded and in February 2016 TPP was signed formally. Both events are classified as progress events in our sample. In September 2016, Vietnam decided to delay the ratification of TPP. This event signals stagnation in the dataset. In November 2014, the first protests on TTIP emerged and we see a stagnation event in our data. Yet, we are surprised by the progress classification of 4 December 2014, which is the date when one million signatures were reached by the anti-TTIP campaign.

[4]As we take a lead of five days and a lag of one day for the calculation of the cumulative abnormal returns, seven days represents the minimum required distance between two events.

[5]This proportion is very close to the one that we arrived at in the manual coding sample. The number results from the fact that the SML output covered 3 stagnation events for each agreement. Hence, we took all stagnation events and defined the number of progress events therefrom.



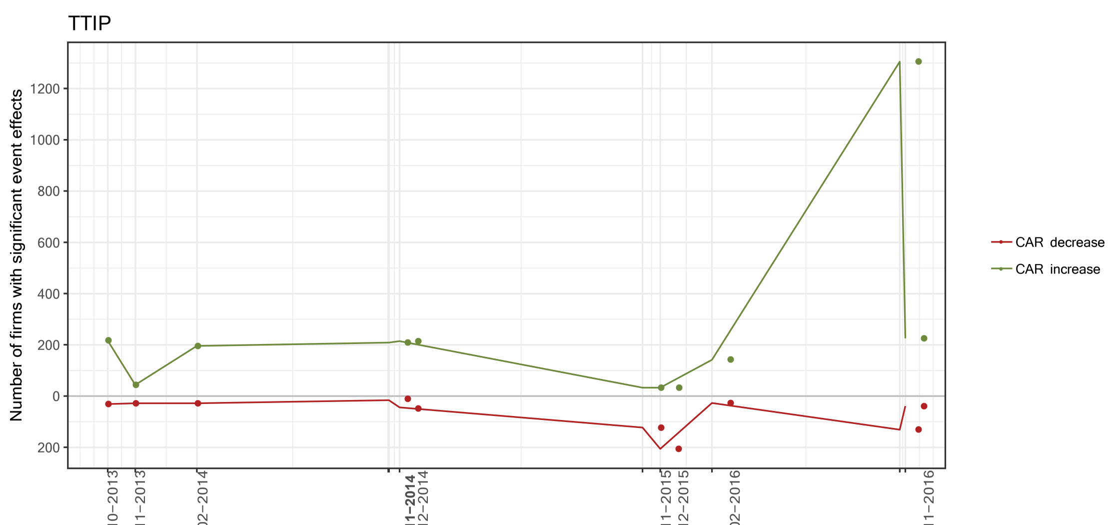


Figure AA.2: Count of firms with significant event effects

Table AA.2: Progress versus Stagnation Events

Date	Agreement	Value
2009-11-14	TPP	1
2010-11-14	TPP	1
2011-12-09	TPP	1
2011-12-14	TPP	1
2014-12-05	TPP	1
2014-12-19	TPP	-1
2015-10-06	TPP	1
2016-02-04	TPP	1
2016-09-29	TPP	-1
2016-11-22	TPP	-1
2013-10-18	TTIP	-1
2013-11-26	TTIP	1
2014-02-21	TTIP	1
2014-11-18	TTIP	-1
2014-12-04	TTIP	1
2015-11-12	TTIP	1
2015-12-07	TTIP	1
2016-02-18	TTIP	-1
2016-11-09	TTIP	1
2016-11-17	TTIP	1

B Robustness Checks

B.1 Different dependent variables: Out-of-sample market adjusted model and mean return model

	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−1.64***	−3.20***	−0.54	−0.66	−0.20	−2.79***
	(0.08)	(0.12)	(0.30)*	(0.46)*	(0.61)	(0.71)
Market value (log)	0.01	0.01	0.17**	0.19**	0.21**	0.14
	(0.02)	(0.02)	(0.03)	(0.05)	(0.07)	(0.08)*
Capital intensity	−0.34***	−0.36***	−0.41***	−0.41***	−	*
	(0.02)	(0.06)				
			0.03	−0.02	−0.04	−0.01
			(0.03)	(0.03)	(0.04)	(0.04)
Diversification	0.06*	−0.02			0.32	−0.60
	(0.02)	(0.09)*				
Foreign sales of total sales (dummy)	−0.16	0.17***	−	0.14	0.62	−0.65
	(0.09)	(0.08)	(0.14)	(0.14)	(0.20)	(0.20)
	0.08			(0.50)	(0.67)	(0.73)
TTIP		1.96***				
		(0.12)				
Progress x TTIP		2.82***				
		(0.14)				
Progress x Market value (log)			−0.24***	−0.21**	−0.13	−0.22*
			(0.04)	(0.06)	(0.08)	(0.10)
Progress x Capital intensity			0.12	0.10	0.23	0.07
			(0.17)*	(0.17)*	(0.21)	(0.25)
Progress x Diversification			0.12**	0.12**	0.12**	0.13**
			(0.03)	(0.03)	(0.04)	(0.05)
Market value x Foreign sales				0.03	−0.14	0.12
				(0.07)	(0.09)	(0.10)
Progress x Foreign sales				0.10	0.18	0.80
				(0.56)	(0.75)	(0.86)
Progress x Market value x Foreign sales				−0.04	−0.03	−0.17
				(0.07)	(0.10)	(0.12)
Num. obs.	49797	49797	49797	49797	24826	24971
R^2 (full model)	0.08	0.08	0.08	0.08	0.09	0.13
R^2 (proj model)	0.01	0.05	0.01	0.01	0.01	0.03
Adj. R^2 (full model)	0.08	0.08	0.08	0.08	0.08	0.13
Adj. R^2 (proj model)	0.01	0.05	0.01	0.01	0.00	0.03
Num. groups: econ sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	4	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	4	5

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table AB.3: Robustness Check: Out-of-sample market adjusted model instead of within sample market adjusted model

Figure AB.3: The interaction between *Progress* and *Market value*

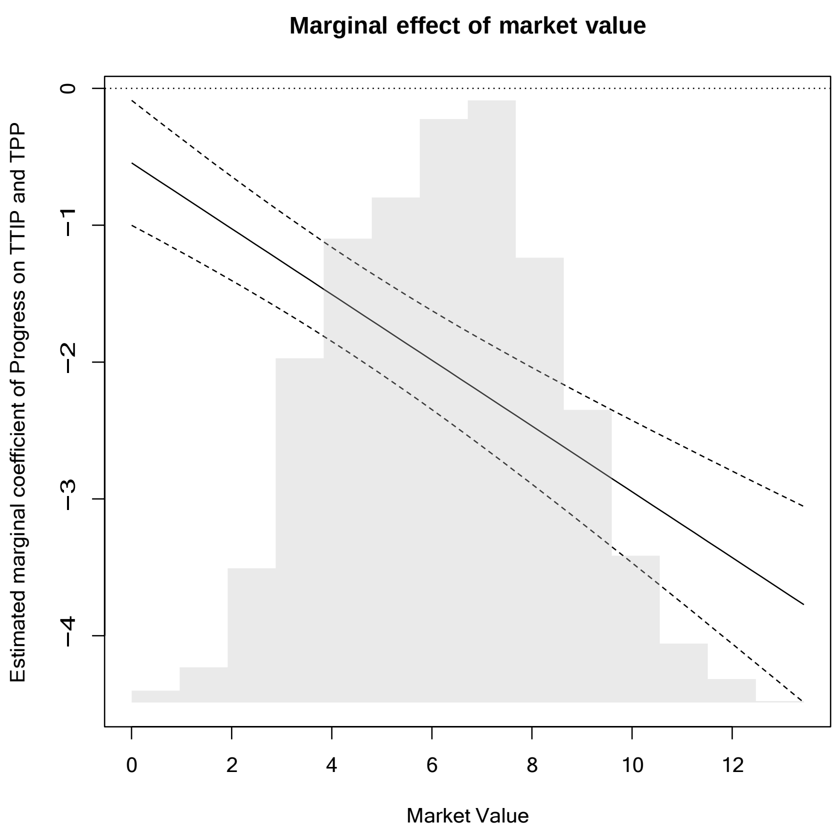


Figure AB.4: The interaction between *Progress* and *Capital intensity*

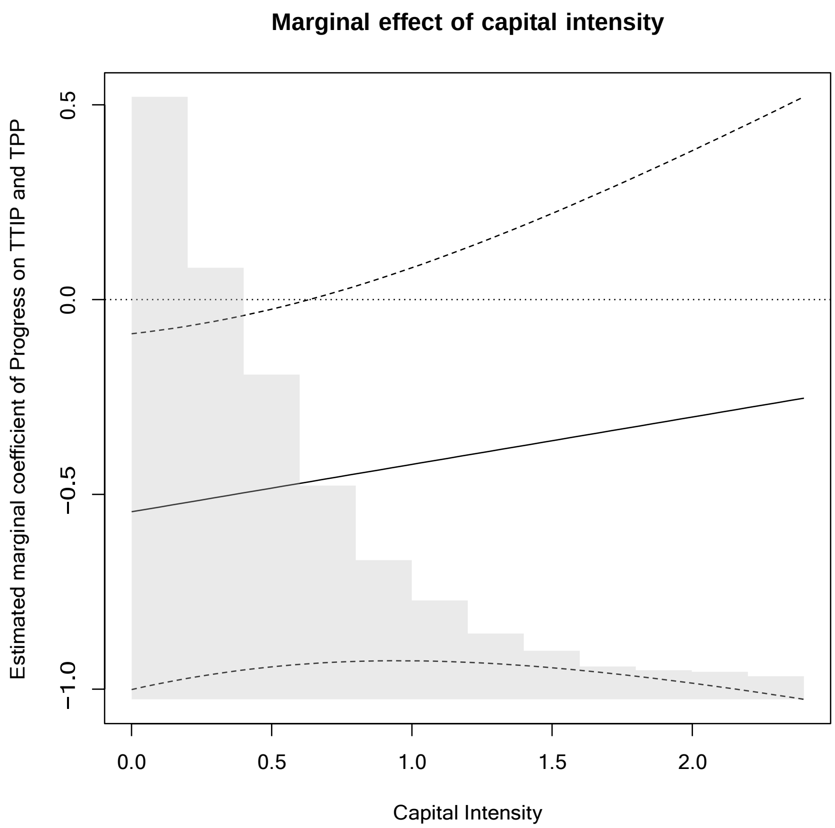
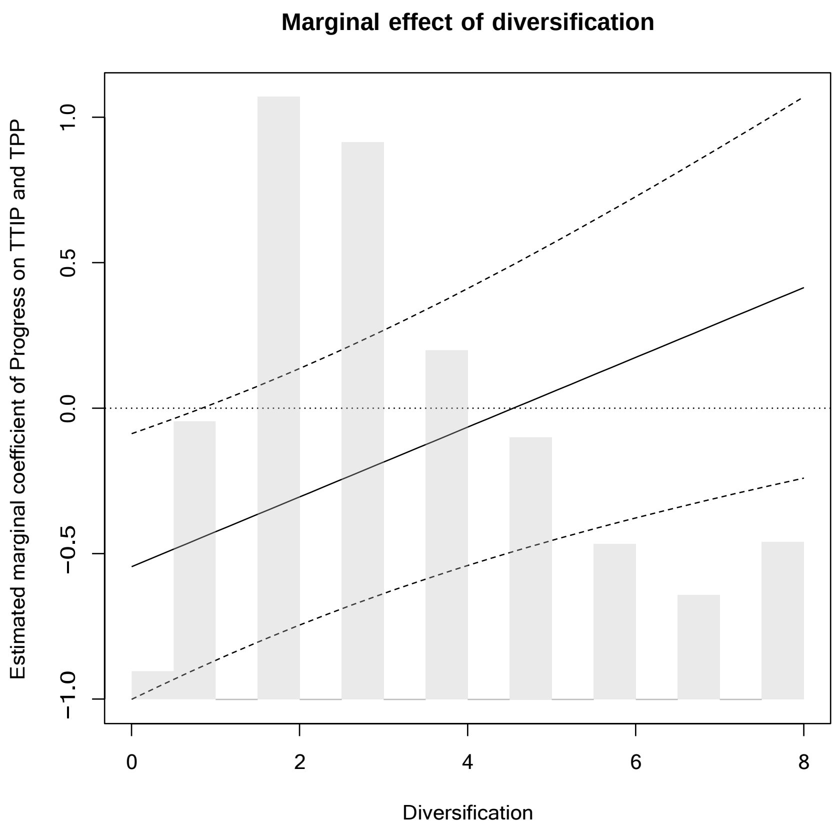


Figure AB.5: The interaction between positive event and diversification



	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
		(0.12)***	(0.29)	(0.43)	(0.57)	(0.68)
Market value (log)	−0.09	−0.09*				
Progress	−1.36***	−2.63***	−0.69*	−0.86*	0.03	−3.26***
	(0.08)***	0.40	0.50 / 0.03	0.48 / −0.01	0.07	0.64 / 0.13
	0.02)***					
Capital intensity	−0.39	(0.02)***	(0.03)***	(0.05)***	0.07	(0.08)***
	(	−0.06			0.42	
			0.03	−0.03	(−0.04*)	−0.02
	0.09)*	(0.09)***	(0.13)	(0.13)	(0.18)	(0.19)
Diversification	0.06**					
Foreign sales of total sales (dummy)	0.12 / 0.03)	−0.12 / (0.02)	(0.02)	−0.39 / (0.32)	0.02 / (0.03)	−1.06 / (0.08)
	(−0.08)	(0.08)***		(0.45)	(0.60)	(0.68)
TTIP		2.01				
		(0.11)				
Progress x TTIP		2.30***				
		(0.14)	***	*		
			0.04)	(0.06)	(0.07)	(0.10)
Progress x Market value (log)			−0.18	−0.13	−0.10	−0.10
Progress x Capital intensity			0.18	0.14	0.29	0.09
			(0.16)*	(0.16)*	(0.20)	(0.24)
Progress x Diversification			0.12**	0.13**	0.12**	0.15**
			(0.03)	(0.03)	(0.04)	(0.05)
Market value x Foreign sales				0.07	−0.03	0.22*
				(0.06)	(0.08)	(0.09)
Progress x Foreign sales				0.16	0.64	0.50
				(0.34)	(0.70)	(0.84)
Progress x Market value x Foreign sales				−0.07	−0.11	−0.13
				(0.07)	(0.09)	(0.11)
Num. obs.	49798	49798	49798	49798	24827	24971
R^2 (full model)	0.08	0.09	0.08	0.08	0.10	0.12
R^2 (proj model)	0.01	0.04	0.01	0.01	0.00	0.03
Adj. R^2 (full model)	0.08	0.09	0.08	0.08	0.10	0.12
Adj. R^2 (proj model)	0.01	0.04	0.01	0.01	0.00	0.03
Num. groups: econ sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	4	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	4	5

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table AB.4: Robustness Check: Mean return model instead of within sample market adjusted model

Figure AB.6: The interaction between *Progress* and *Market value*

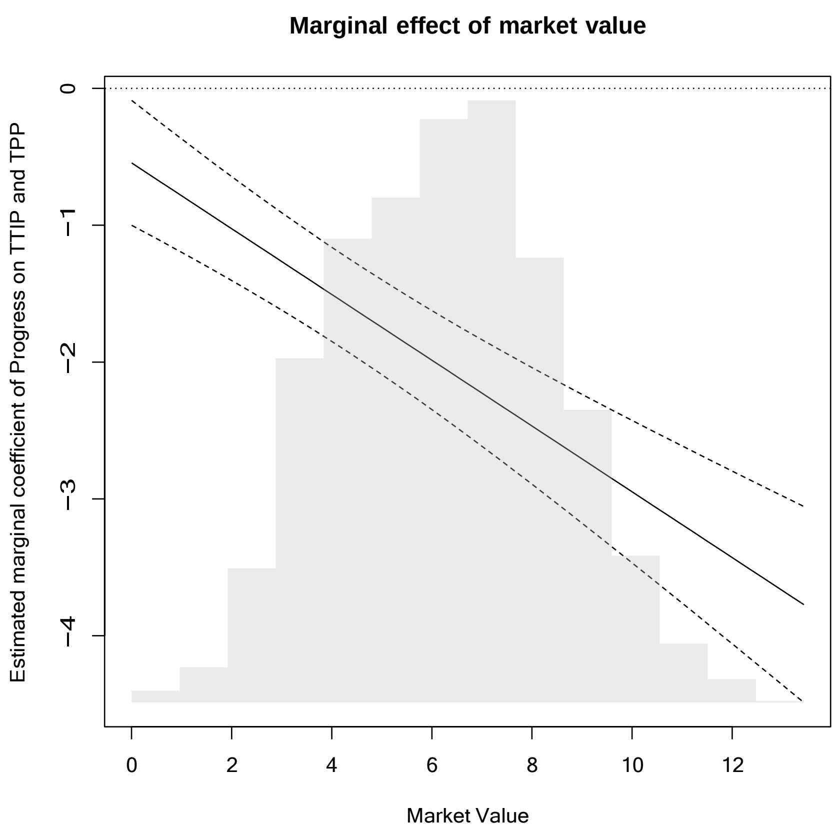


Figure AB.7: The interaction between *Progress* and *Capital intensity*

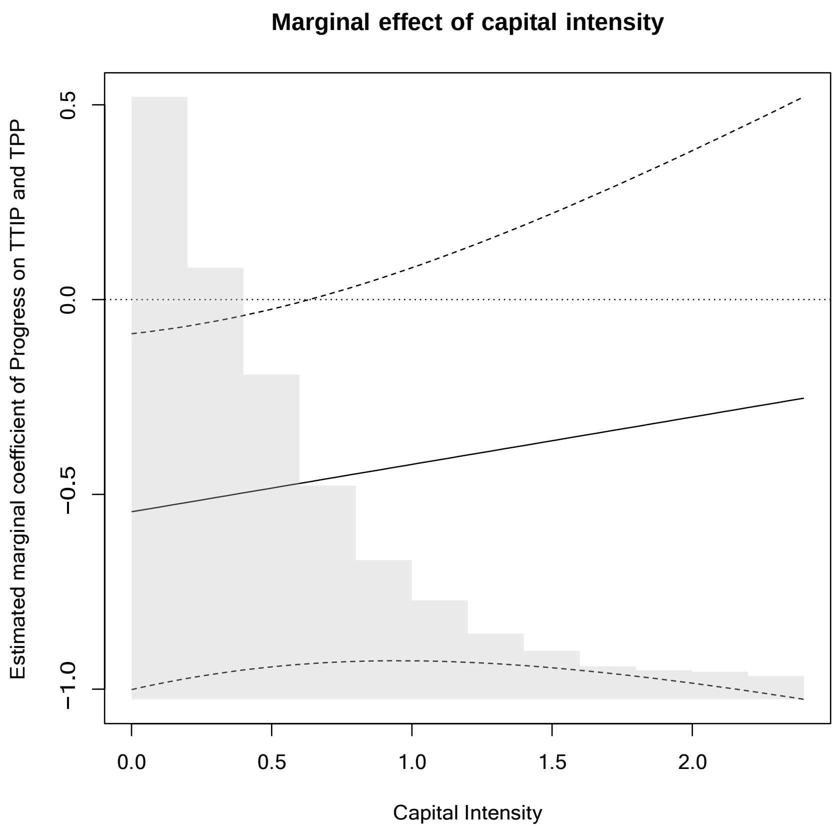
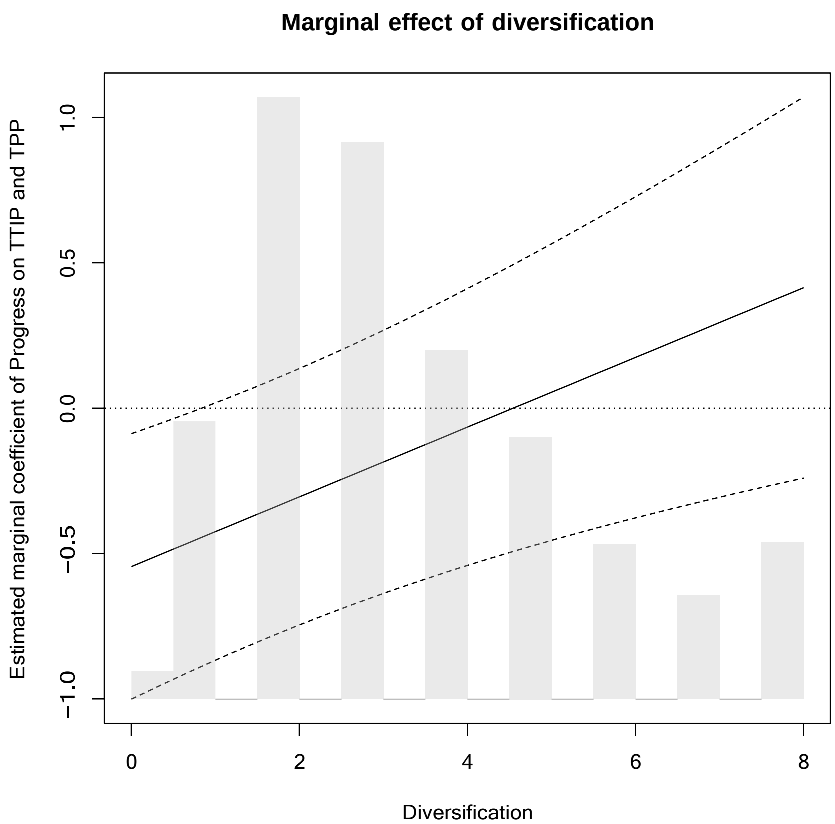


Figure AB.8: The interaction between positive event and diversification



B.2 Different event window range: 3 and 1 day window

	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−1.38***	−2.92***	−0.43	−0.71	−0.28	−2.55***
	(0.08)	(0.12)	(0.27)*	(0.41)	(0.48)	(0.65)
Market value (log)	−0.00	−0.01	0.14**	0.13**	0.12*	0.10
	(0.02)*	(0.02**)*	(0.03)	(0.05)	(0.05)	(0.08)*
Capital intensity	−0.22	0.24	−0.14	−0.14	0.00	−0.37
	(0.09)*	(0.09)	(0.13)	(0.13)	(0.17)	(0.18)
Diversification	0.06**	0.06***	−0.04	−0.04	−0.04	−0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Foreign sales of total sales (dummy)	−0.12	−0.12		−0.12	0.36	−0.91
	(0.07)	(0.07**)*		(0.41)	(0.53)	(0.63)
TTIP		1.85				
		(0.10)				
Progress x TTIP		2.79***				
		(0.13)				
Progress x Market value (log)			−0.21***	−0.15**	−0.10	−0.15
			(0.04)	(0.05)*	(0.06)*	(0.09)*
Progress x Capital intensity			−0.10	−0.12**	−0.04**	−0.11**
			(0.15)	(0.16)	(0.19)	(0.22)
Progress x Diversification			0.15***	0.15	0.13	0.18
			(0.03)	(0.03)	(0.04)	(0.04)
Market value x Foreign sales				0.02	−0.07	0.15
				(0.05)	(0.07)	(0.09)
Progress x Foreign sales				0.42	0.29	1.22
				(0.50)	(0.65)	(0.76)
Progress x Market value x Foreign sales				−0.09	−0.07	−0.20*
				(0.07)	(0.08)	(0.10)
Num. obs.	49798	49798	49798	49798	24825	24973
R^2 (full model)	0.07	0.08	0.08	0.08	0.10	0.14
R^2 (proj model)	0.01	0.05	0.01	0.01	0.00	0.03
Adj. R^2 (full model)	0.07	0.08	0.08	0.08	0.10	0.14
Adj. R^2 (proj model)	0.01	0.05	0.01	0.01	0.00	0.02
Num. groups: econ sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	4	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	4	5

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table AB.5: Robustness Check: Different event window range: 3-day window

Figure AB.9: The interaction between *Progress* and *Market value*

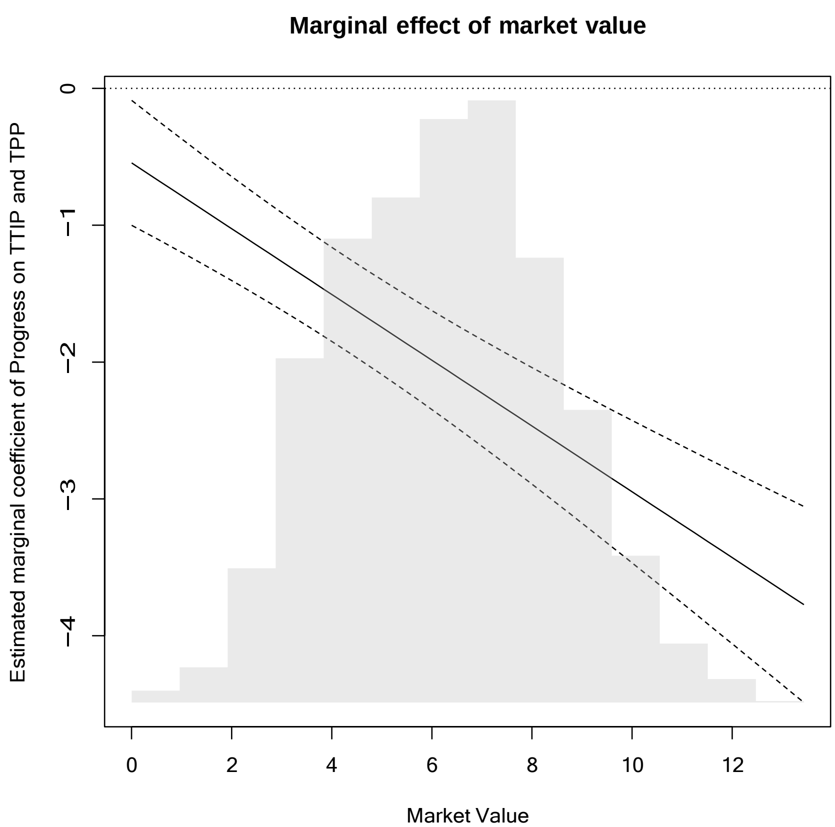


Figure AB.10: The interaction between *Progress* and *Capital intensity*

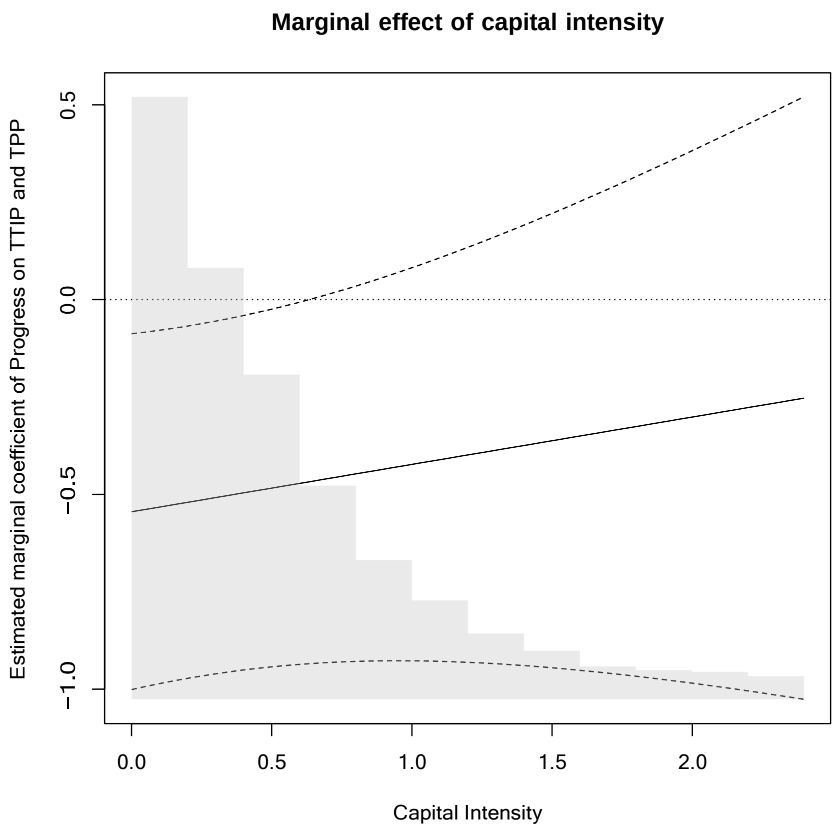
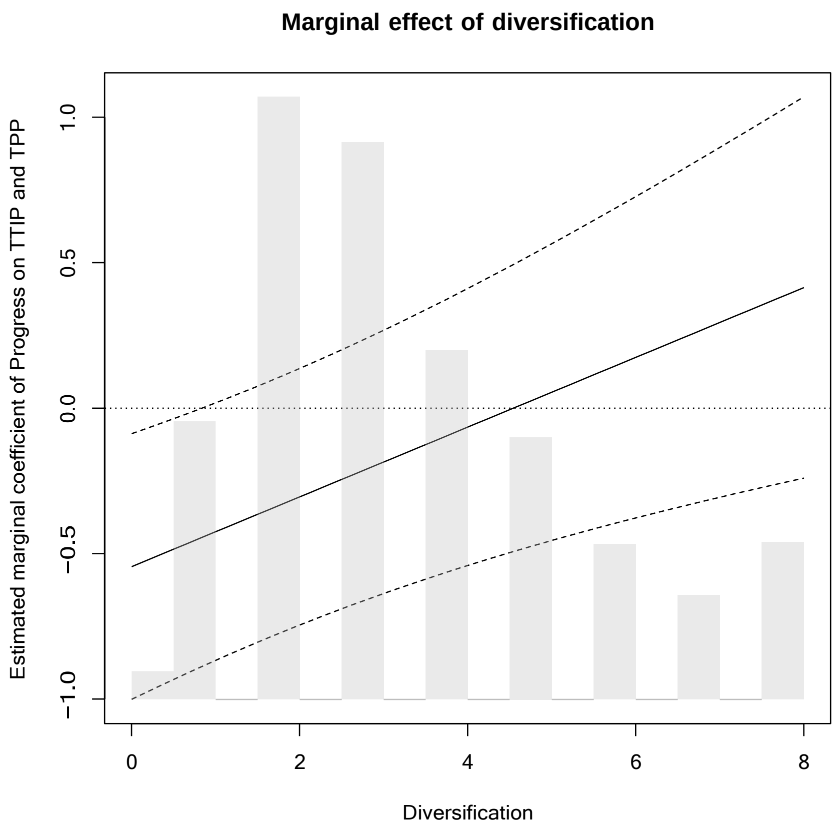


Figure AB.11: The interaction between positive event and diversification



	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−0.49***	−1.53***	0.37	0.19	0.88*	−2.06***
	(0.06)	(0.10)	(0.23)*	(0.39)	(0.41)	(0.59)
Market value (log)	−0.01	−0.01	0.12**	0.10*	0.08	0.09
	(0.02)*	(0.01)*	(0.02)*	(0.04)*	(0.05)	(0.07)*
Capital intensity	−0.15	−0.02	0.29	0.29	0.18	−0.47
	(0.01)***	(0.17)	(0.11)	(0.11)	(0.15)	(0.16)
Diversification	0.04	0.04	−0.03	−0.03	−0.02	−0.03
	(0.07)	(0.07)*	(0.02)	(0.02)	(0.03)	(0.03)
Foreign sales of total sales (dummy)	−0.14	0.14		0.46	−0.09	−1.07
	(0.06)	(0.06)***		(0.35)	(0.46)	(0.57)
TTIP		0.05				
		(0.09)				
Progress x TTIP		1.89				
		(0.11)				
Progress x Capital intensity			0.03***	0.05**	0.05**	0.08
			(0.21)	(0.20)	(0.19)	(0.26)
Progress x Market value (log)			−0.20	−0.15	−0.15	−0.12
			(0.13)*	(0.13)*	(0.16)	(0.20)*
Progress x Diversification			0.00	0.00	0.00	0.02
			(0.02)	(0.02)	(0.03)	(0.03)
Market value x Foreign sales				0.05	0.01	0.16*
				(0.45)	(0.4)	(0.58)
Progress x Foreign sales				0.45	0.28	1.08
				(0.06)	(0.07)	(0.09)
Progress x Market value x Foreign sales				−0.08	−0.04	−0.18*
Num. obs.	49803	49803	49803	49803	24827	24976
R^2 (full model)	0.04	0.05	0.04	0.04	0.08	0.07
R^2 (proj model)	0.00	0.01	0.00	0.00	0.00	0.02
Adj. R^2 (full model)	0.04	0.05	0.04	0.04	0.08	0.07
Adj. R^2 (proj model)	0.00	0.01	0.00	0.00	0.00	0.02
Num. groups: econ sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	5	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	5	5

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table AB.6: Robustness Check: Different event window range: 1-day window

Figure AB.12: The interaction between *Progress* and *Market value*

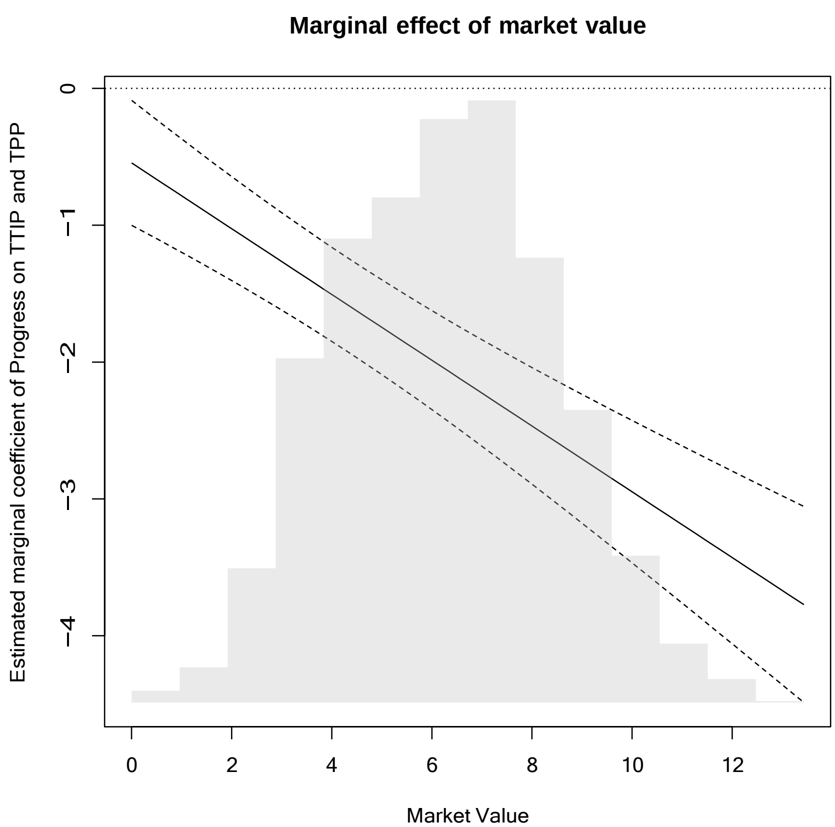


Figure AB.13: The interaction between *Progress* and *Capital intensity*

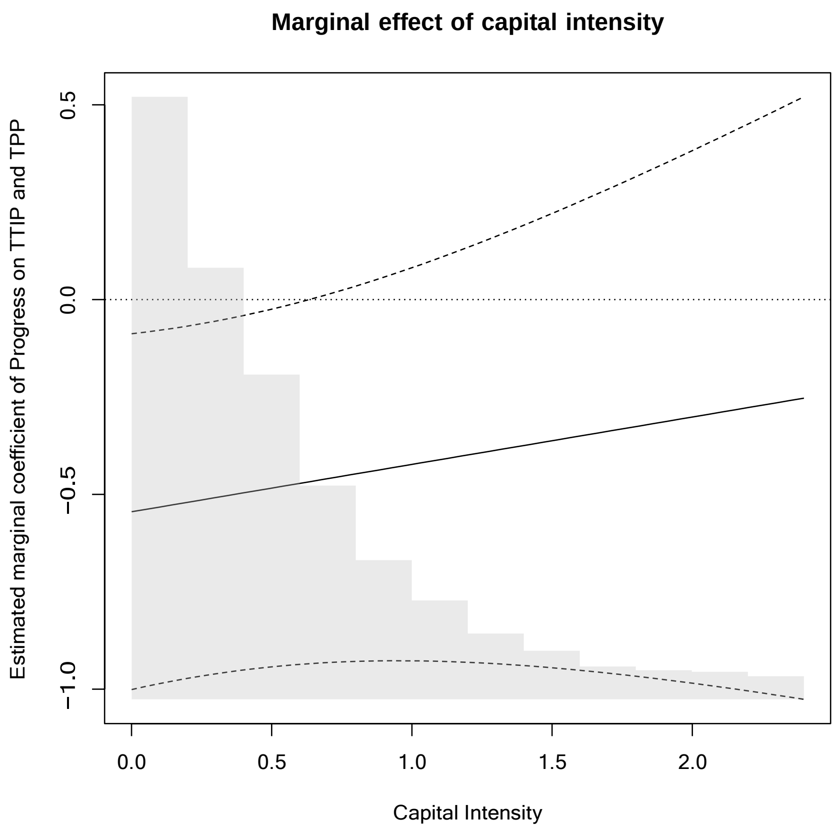
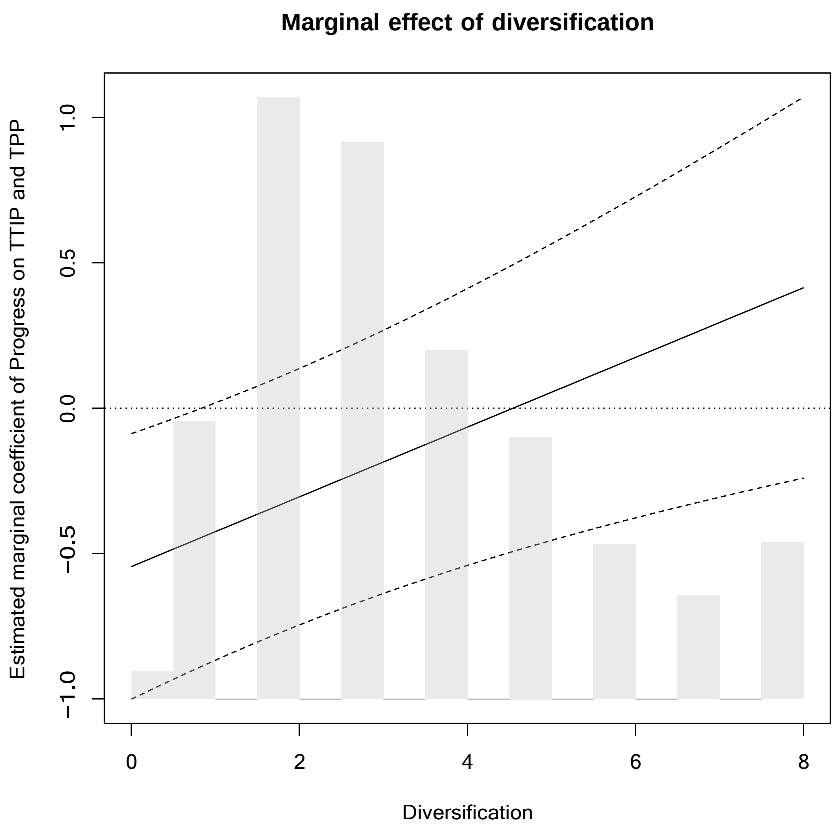


Figure AB.14: The interaction between positive event and diversification



B.3 Only US listed firms

	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−1.82***	−3.58***	−0.35	−0.73	−0.91	
	(0.09)	(0.13)*	(0.32)* **	(0.50) **	(0.79)	
Market value (log)	−0.05	−0.05	0.16	0.17	0.10	
	(0.02)***	0.34		0.46		
Capital intensity	−0.32	(0.02)***	(0.04)*	(0.06)*	0.08	−0.05
		−	−0.47*	−	0.40	
	(0.09)*	(0.09)*	(0.15)*	(0.15)*	(0.17)*	(0.15)*
Diversification	0.04	0.04	−0.06	−0.06	−0.07	0.07
	(0.07)	(−0.07)***		0.06	−0.22	0.88
Foreign sales of total sales (dummy)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
	−0.08	0.08		(0.57)	(0.67)	(0.60)
TTIP		2.00				
		(0.11)				
Progress x TTIP		3.18**				
		(0.14)	***	***	*	
Progress x Market value (log)			−0.30	−0.24	−0.22	−0.04
			(0.04)	(0.07)	(0.11)	(0.06)
Progress x Capital intensity			0.22	0.21	0.04	
			( ) ***			
Progress x Diversification			0.17	(0.18)***	(0.25)***	
			0.14	0.14	0.24	
			(0.03)	(0.03)	(0.05)	*
Market value x Foreign sales				−0.01	0.02	−0.15
				(0.07)	(0.09)	(0.08)
Progress x Foreign sales				0.62	1.19	
				(0.64)	(0.94)	
Progress x Market value x Foreign sales				−0.11	−0.16	
				(0.08)	(0.12)	
Num. obs.	43588	43588	43588	43588	19461	12971
R^2 (full model)	0.10	0.11	0.10	0.10	0.04	0.10
R^2 (proj model)	0.01	0.06	0.01	0.01	0.01	0.00
Adj. R^2 (full model)	0.10	0.11	0.10	0.10	0.04	0.10
Adj. R^2 (proj model)	0.01	0.06	0.01	0.01	0.01	0.00
Num. groups: econ_sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	5	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	5	5

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table AB.7: Baseline Model

Figure AB.15: The interaction between *Progress* and *Market value*

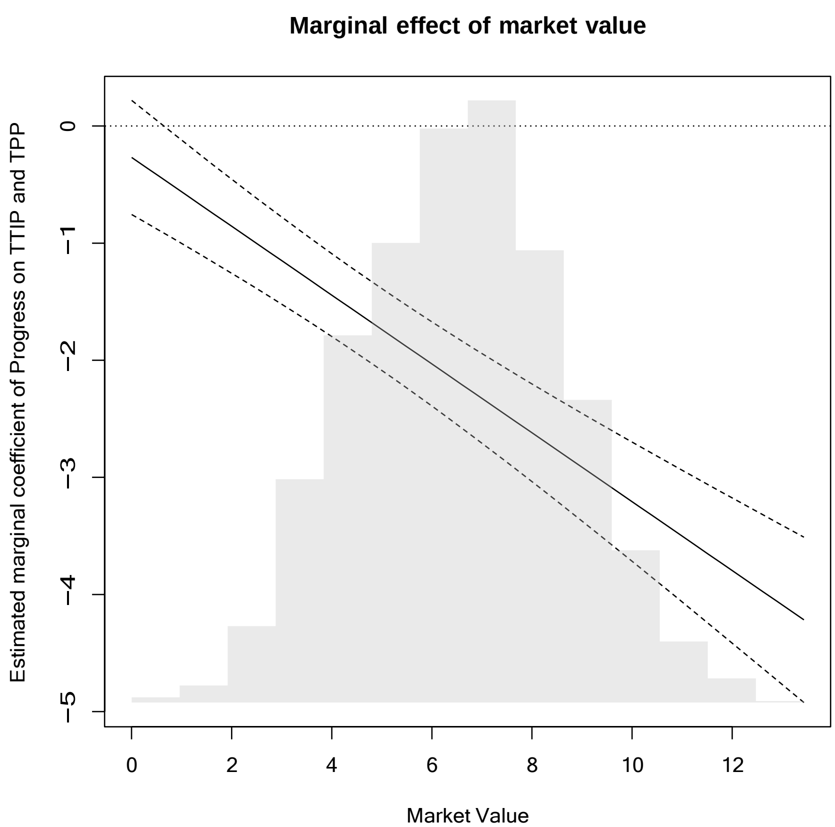


Figure AB.16: The interaction between *Progress* and *Capital intensity*

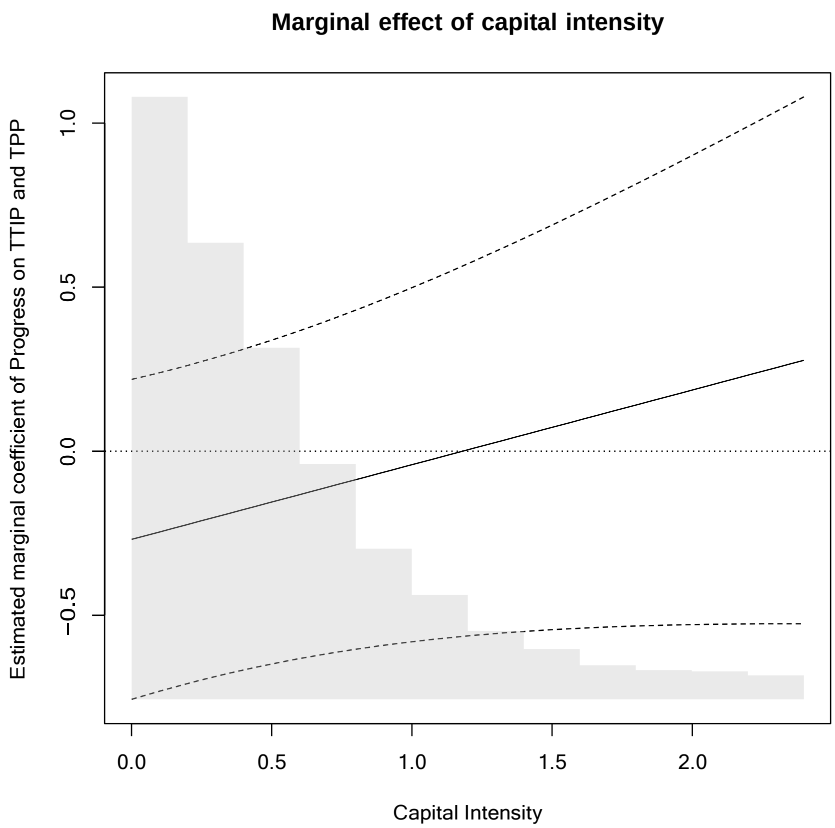
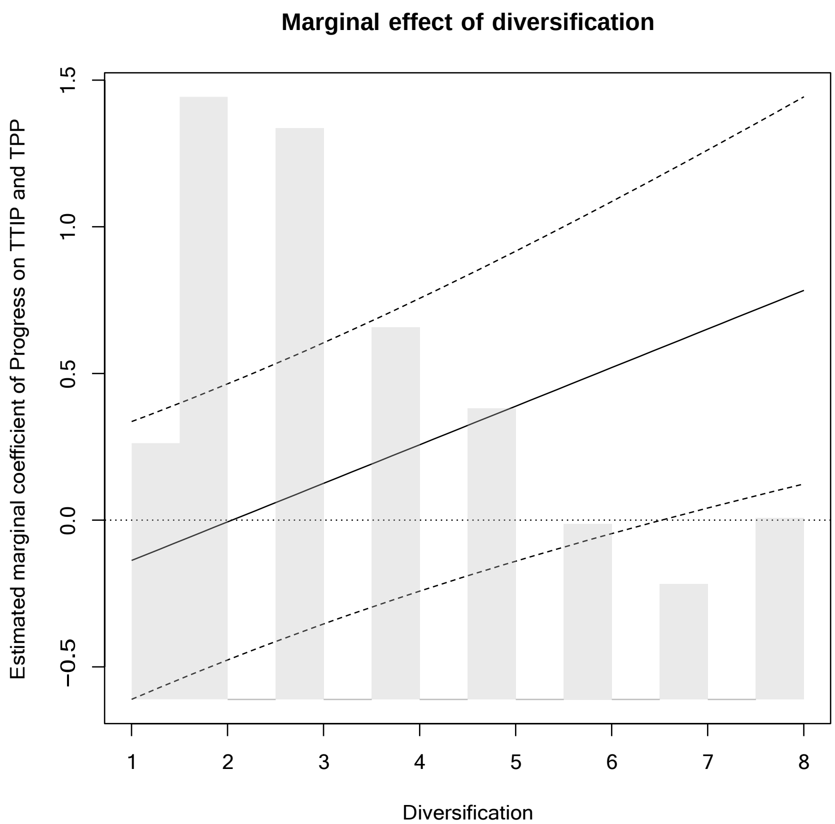


Figure AB.17: The interaction between positive event and diversification



B.4 Dropping 2016-11-09 as event day, which caused extreme reactions

	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−2.14***	−3.09***	−1.13***	−1.14*	−0.50	−3.92***
	(0.09)	(0.13)	(0.30)	(0.47)	(0.58)	(0.88)
Market value (log)	0.02	0.02	0.17**	0.18**	0.28**	−0.04
		0.33				
Capital intensity	−0.31					0.11
	(0.02)*	(0.02)**	(0.04)*	(0.06)*	(0.07)*	( )
	*	−*	−0.44*	−0.44*	−0.47*	−0.44
Diversification	0.04* (0.10)	0.05** (0.10)	−0.03 (0.15)	−0.03 (0.15)	−0.01 (0.18)	−0.03 (0.27)
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Foreign sales of total sales (dummy)	−0.11	−0.12		0.07	0.72	−1.66
	(0.08)	(0.08)**		(0.51)	(0.63)	(0.91)
TTIP		1.04				
		(0.12)				
Progress x TTIP		1.76***				
		(0.14)				
Progress x Market value (log)			−0.23***	−0.21**	−0.25**	−0.04
			(0.04)	(0.06)	(0.08)	(0.12)
Progress x Capital intensity			0.20	0.18	0.62**	−0.14
			(	0.11	0.01	0.16
Progress x Diversification			0.10 (0.17)	(0.17)	(0.20)	(0.31)
			(0.03)**	0.02** (0.03)	−0.15 (0.04)	0.30** (0.06)*
Market value x Foreign sales				(−0.07)	(0.08)	(0.12)
Progress x Foreign sales				−0.05	−0.35	1.86
				(0.59)	(0.74)	(1.05)
Progress x Market value x Foreign sales				−0.01	0.09	−0.35*
				(0.08)	(0.10)	(0.14)
Num. obs.	47309	47309	47309	47309	22356	22477
R^2 (full model)	0.08	0.08	0.08	0.08	0.06	0.14
R^2 (proj model)	0.01	0.03	0.01	0.01	0.01	0.03
Adj. R^2 (full model)	0.08	0.08	0.08	0.08	0.06	0.13
Adj. R^2 (proj model)	0.01	0.03	0.01	0.01	0.01	0.03
Num. groups: econ sector	10	10	10	10	10	10
Num. groups: year	6	6	6	6	4	5
Num. groups: agreement	2		2	2		
Num. groups: weekday	5	5	5	5	4	5

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table AB.8: Baseline Model

Figure AB.18: The interaction between *Progress* and *Market value*

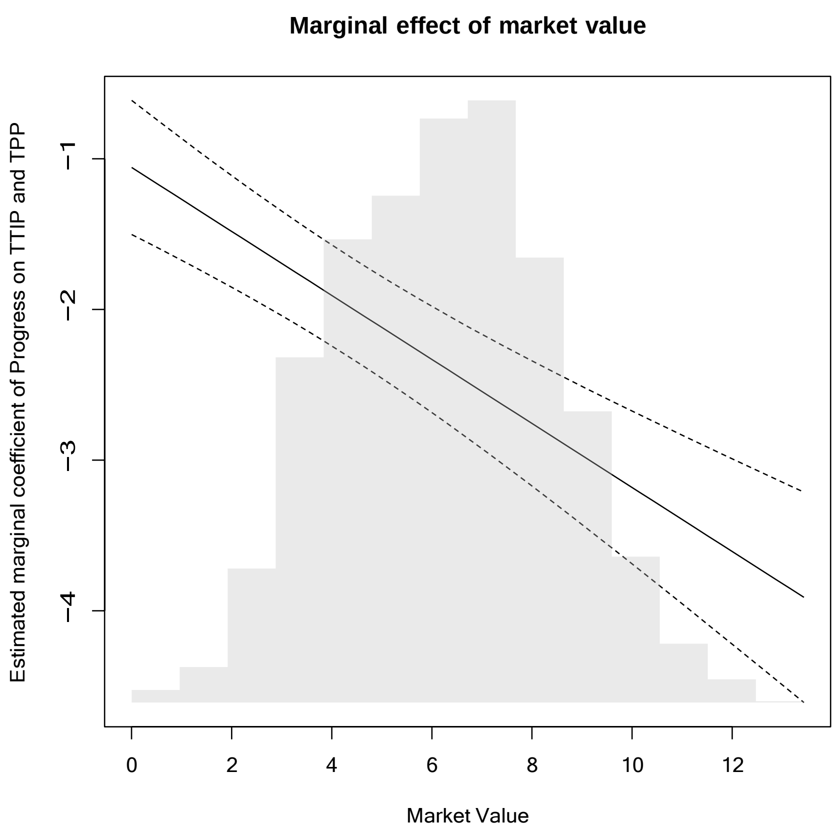


Figure AB.19: The interaction between *Progress* and *Capital intensity*

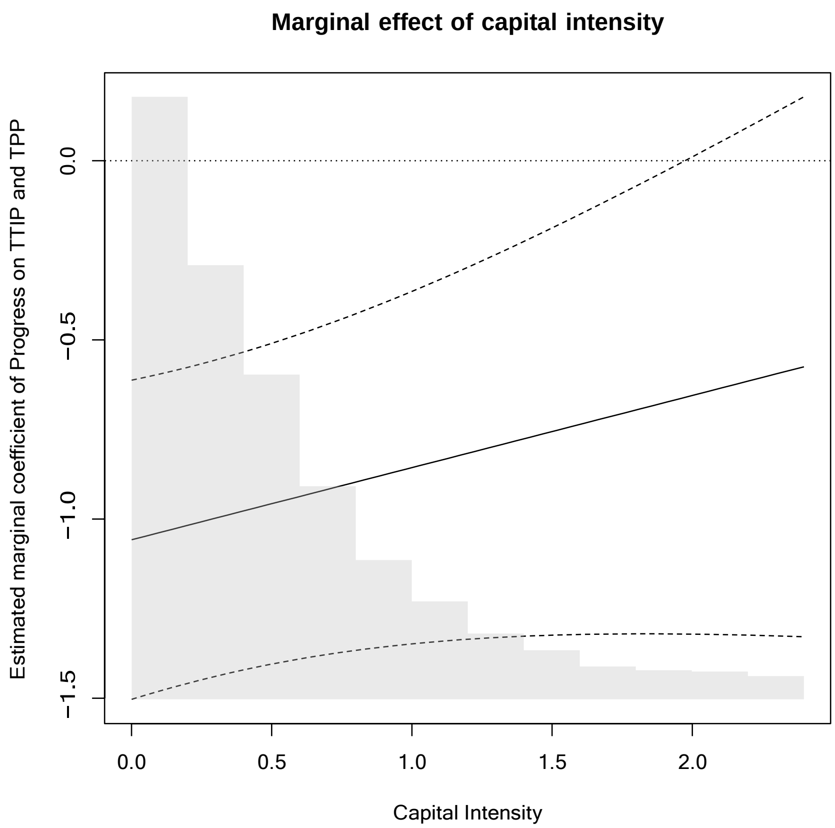
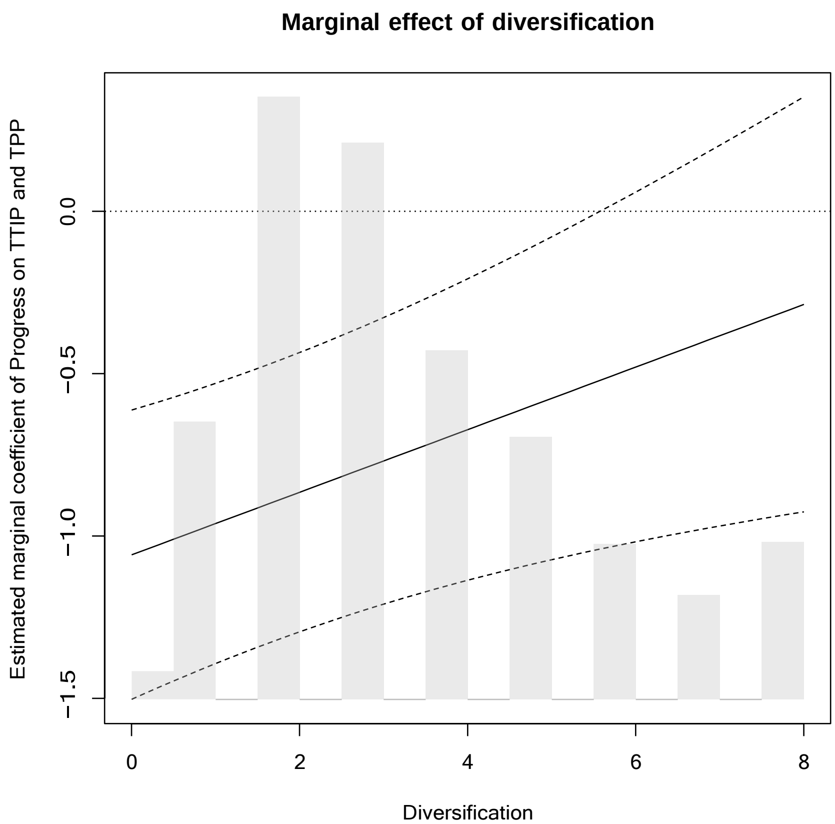


Figure AB.20: The interaction between positive event and diversification



B.5 TPP and TTIP Separately

Figure AB.21: The interaction between *Progress* and *Market value* (TPP on the left and TTIP on the right)

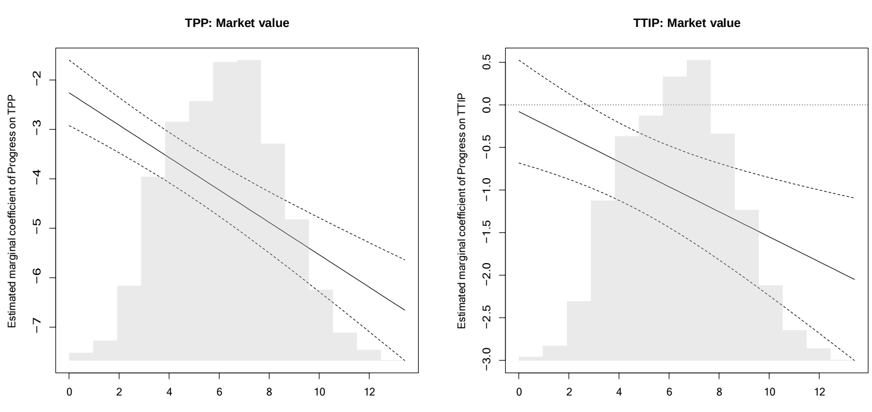


Figure AB.22: The interaction between *Progress* and *Capital intensity* (TPP on the left and TTIP on the right)

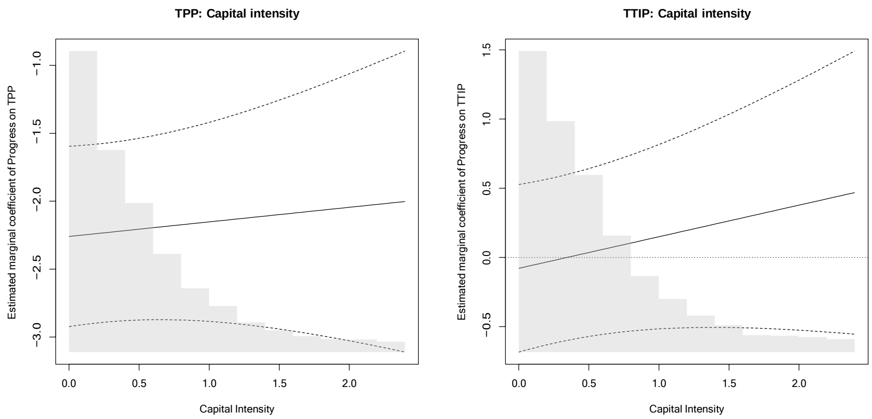
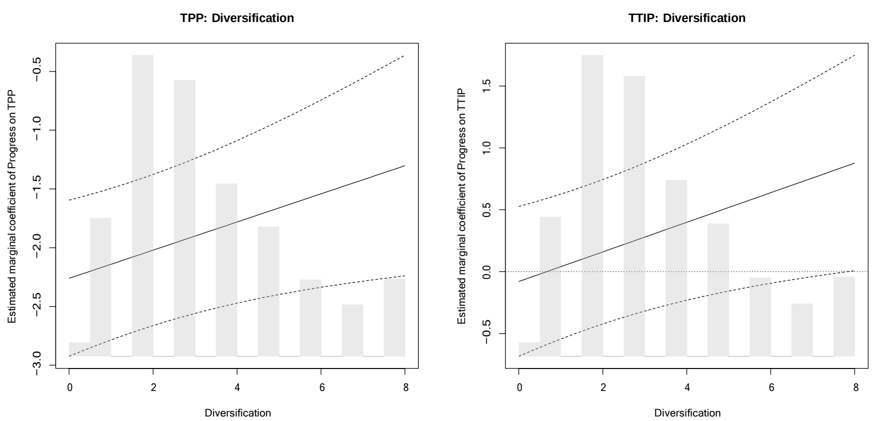
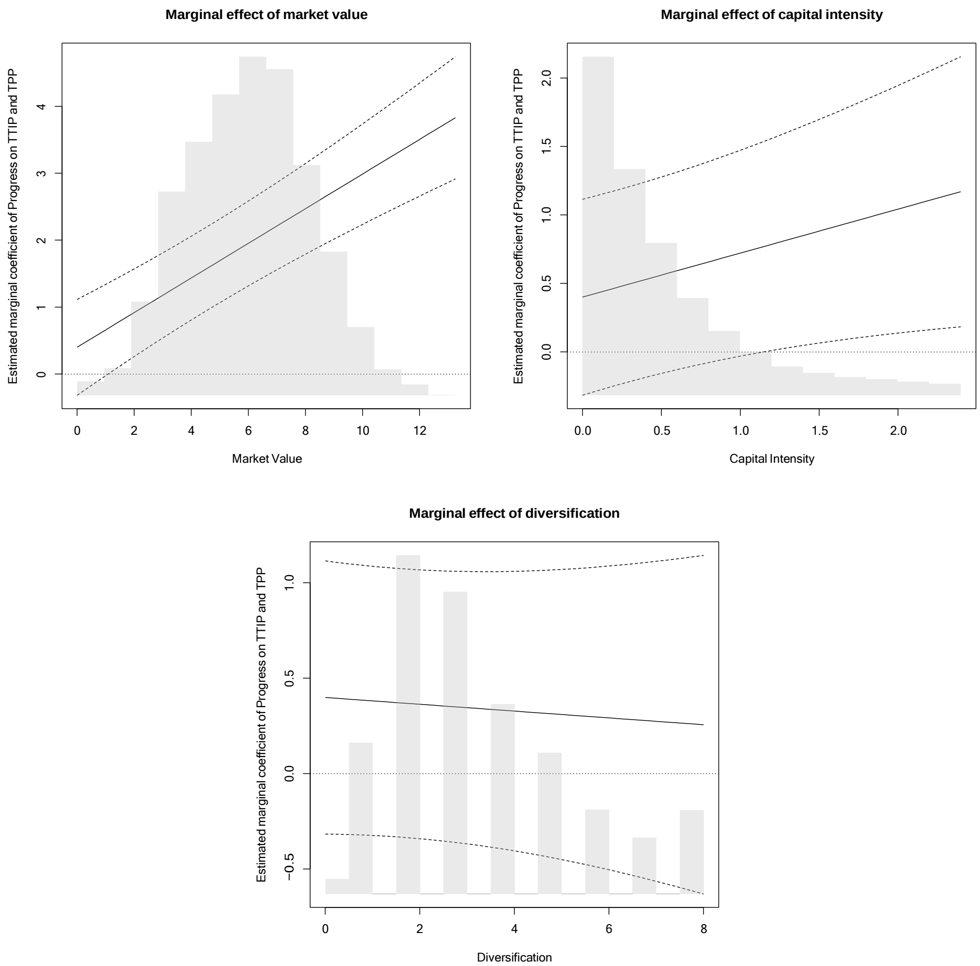


Figure AB.23: The interaction between *Progress* and *Diversification* (TPP on the left and TTIP on the right)



B.6 Placebo test

Figure AB.24: Placebo Test



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