Analysis of Brexit's Asymmetric Effects on Stock Returns

Yue Qi
Advisor: Dr. Mario J. Crucini
Second Reader: Dr. David Parsley

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1 Introduction

Taken at face value, the slim majority vote by Brits to leave the EU on June 24, 2016 was itself an indication that some viewed the split as having net negative effects on them and others as net positive. While views may be misinformed or potentially misguided, it is important to understand the sources. While individual surveys may provide evidence on the nature of a voters' views, the stock market reactions provide a more tangible economic metric.

Events such as referendums are a great source for economic studies because of the uncertainty around them and the complex channels they can affect the stock market and the real economy. For example, Beaulieu, Cosset and Essaddam (2006) show that the uncertainty associated with the 1995 Quebec referendum had notable impacts on the stock returns of Quebec firms. There has been a number of studies on the effect that Brexit has on stock markets since the vote. Amedwu, Mensah and Alagidede find that Brexit generates uncertainties in world stock markets and that except in China, the markets responded negatively to the result on their first trading day after the event. Many analyses are conducted by focusing on firms' characteristics, such as the sectors they belong to, countries they export products to and import inputs from, and their market size. Ramiah, Pham and Moosa (2016) conduct a sector-by-sector analysis and concluded that certain sectors, such as banking and travel and leisure, are affected more negatively by Brexit as measured by abnormal returns. Milas, Worrall and Zymek (2016) find that companies that have Europe as their important overseas market are more significantly impacted by the event that those who do not.

While the Brexit decision is commonly thought to have a negative impact on the macroeconomy which is typically considered to affect the mean return, its impact on the level of stocks is clearly better understood through more detailed analyses. Similarly, the motivation of this paper is to also consider the possibility that Brexit affected the distribution of returns around this mean by conducting studies that focus on firms' characteristics. This study explores the cross-sectional and time series properties of a comprehensive database of stock returns. In particular, we focus on the effect of Brexit on the distribution of stock betas over time and the role of trade exposure on the asymmetric stock return responses in the cross-section.

2 The Data

2.1 Sources

The original data source for the return indices is Datastream. These data consist of return indices for the universe of companies listed on the UK stock exchange over the period 01/01/2008 to 07/20/2017. From this set, we removed stocks with unchanged return indexes in the last 30 days of the data. The number of trading days that results is 2493 and there are 1433 individual stock returns. The main data source is supplemented with macroeconomics data from 2014 from the UK's Office for National Statistics website, with tables of data describing the input-output relationships among sectors, the valued added by sector and the end use of output by sector (consumption, investment and exports).

2.2 Descriptive Statistics

The analysis begins with some basic definitions and descriptive statistics. The raw data come in the form of return indices computed by Datastream using the following formula:

$$RI_{it} = RI_{it-1}(\frac{P_{it} + D_{it}}{P_{it-1}}) \ , \tag{1}$$

where P_{it} is the market price of stock of company i at date t, D_{it} is the dividend company i paid on that day, which is typically 0 because dividends are paid infrequently. The return index is normalized to 100 in a base year.

As we will be working with rates of return, let us define the return as the change in the natural logarithm of the return index:

$$R_{it} = \ln RI_{it} - \ln RI_{it-1} = ln(\frac{P_{it} + D_{it}}{P_{it-1}}) \tag{2}$$

To the extent that capital gains and losses are unpredictable based on efficient markets theory, the change in the return would follow a random walk were it not for the inclusion of the dividend yield.

The Brexit decision is commonly thought to have a negative impact on the macroeconomy which is typically considered to affect the mean return. The motivation of this paper is to also consider the possibility that Brexit affected the distribution of returns around this mean. To begin to understand this distinction, the following decomposition of stock return to common and idiosyncratic parts is a useful starting point:

$$R_{it} = \mu_t + \varepsilon_{it} \ , \tag{3}$$

where μ_t is defined as the simple average return in the cross-section on each day:

$$\mu_t = \frac{1}{N} \sum_i R_{it} \ . \tag{4}$$

By construction, ε_{it} has a cross-sectional average of zero at each date and thus represents the deviation of the stock return for company i at date t from the mean of the distribution of returns (μ_t) across all companies. Unless otherwise indicated, 'all' companies will refer to a balanced panel of stocks listed on the London stock exchange. The balanced panel includes companies that we have full stock returns data of.

2.3 Common and Idiosyncratic components of returns

The symmetric macroeconomic effects of Brexit may thus be described as shifts in the time series profile of μ_t whereas the asymmetric effects in the cross-section of stock returns would be the distribution of ε_{it} around the cross-sectional mean. The asymmetries could be due to different impacts of the Brexit news on the cross-section of returns or the idiosyncratic facets of Brexit itself.

We characterize the relative importance of macroeconomic and microeconomic variation in the cross-section and how that changes in the neighborhood of the Brexit vote date.

$$\underbrace{E_i[var_t(R_{it})]}_{Total} = \underbrace{var_t(\mu_t)}_{Common} + \underbrace{E_i[var(\varepsilon_{it})]}_{Idiosyncratic} \tag{5}$$

To get a sense of the basic properties of the distribution of returns, this decomposition is computed for a two-year window from June 9, 2015 to July 7, 2017 and then for three sub-samples: June 9, 2015 - February 16, 2016 (181 trading days), February 17, 2016 - October 27, 2016 (181 trading days), and October 28, 2016 - July 7, 2017 (181 trading days). These are referred to as the pre-Brexit, Brexit and post-Brexit sub-periods, respectively, with the Brexit sub-period centered at the Brexit vote date, June 24, 2016. The variance decomposition exercise allows us to gain insight into how idiosyncratic daily returns are in each period. We use the balanced panel, which is obtained after deleting all the stocks with missing data points in this period, and we now have 1304 stocks in the sample.

Table 1. Variance Decomposition of Stock Returns

	Variance in Percent			Percent
Sample	Total	Common	Idiosyncratic	Common
Panel A: Daily Returns				
Full	14	0.271	14	1.97
Pre-Brexit	13	0.327	12	2.58
Brexit	15	0.400	14	2.69
Post-Brexit	14	0.074	14	0.53
Panel B: Weekly Returns				
Full	65	1.88	63	9.10
Pre-Brexit	60	1.90	58	4.20
Brexit	69	2.61	67	12.00
Post-Brexit	66	0.70	65	2.96
Panel C: Monthly Returns				
Full	255	9.10	246	3.56
Pre-Brexit	217	4.20	213	1.94
Brexit	277	12.00	266	4.26
Post-Brexit	252	2.96	249	1.17

Table 1 reports the findings. The upper panel reports the variances of daily returns. We see that the individual stock returns are characterized as highly variant with a daily return variance of 14%. The variance of the return of the average stock rises very modestly from 13% to 15% and then declines back to the broader two-year sample average of 14%. The increase in variance in the period surrounding the Brexit vote may reflect the general increase in uncertainty brought about by the discussion and some respite following the vote.

Since Brexit is of national scope, it is expected to alter the mean stock return. The feature focused on here, however, is the amplified role the mean return has in the overall variance of returns in a period in which such news arrives. We see that the mean return accounts for more of the variance of the typical stock, during the Brexit period, particularly for returns at the weekly and monthly frequency. At the weekly frequency, for example, the contribution of the mean return variance rises 4.2% to 12% in the move from the pre-Brexit period to the Brexit period. The other interesting feature is that the contribution of the mean return is lower post-Brexit compared to pre-Brexit. So, there also seems to be more uncertainty about individual returns (relative to the mean) after the vote.

Our conjecture is that this reflects the realization that the distributive effect of Brexit will be asymmetric across firms and there is more uncertainty about these effects than in normal times (i.e., when events of the magnitude of Brexit are not occurring). While the market may have some confidence that Brexit is on average negative for the macroeconomy and equity returns, it is an order of magnitude more challenging to figure out the distribution of effects in the cross-section of equities.

3 Variance Decomposition Using Beta-Method

To make additional progress on the heterogeneity underlying individual stock returns and their relationship to the mean return, we exploit a variance decomposition used in Crucini and Landry (2017) in accounting for real exchange rate variability. In fact, the decomposition has its origins in finance, the concept of stock-return betas. First, let us define the equally-weighted change in the market return as:

$$R_t = N^{-1} \sum_{i=1}^{N} R_{it} \ . \tag{6}$$

Now, compute the variance of the change in the market return (over time) using covariances:

$$var(R_t) = N^{-1} \sum_{i=1}^{N} cov(R_{it}, R_t) \tag{7}$$

and dividing through by the variance of the market return, which gives:

$$1 = N^{-1} \sum_{i=1}^{N} \beta_i \tag{8}$$

where

$$\beta_i \equiv \frac{cov(R_{it}, R_t)}{var(R_t)} \tag{9}$$

Our main motivation for this microeconomic variance decomposition is to try to tease on asymmetries in the sensitivity of stock returns to the Brexit vote.

3.1 Rolling Betas

In order to understand how the movements of individual stock returns contribute to the movements of the aggregate stock return, we estimate the betas over 100-day overlapping intervals, advancing the rolling window by one day for each estimation. The figure below present the first and third quartiles of the cross-sectional distribution of the betas over the period June 9, 2015 to July 7, 2017. What is stark in the figure is the compression of the inter-quartile range of betas when the day of the Brexit vote falls within the 100-day window. This behavior shows up as a sharp drop in the upper quartile and increase in the lower quartile of betas. In effect, this means that the dispersion of the betas across stocks has fallen, as measured by their inter-quartile range. This compression is consistent with the idea that the Brexit event changes the ratio of common shocks to company-specific shocks relative to "normal" times. And yet, the effect of the increased one-day co-movement of stock returns seems much more sharply identified than when we used the ratio of the common component of returns to the total variance of individual returns.

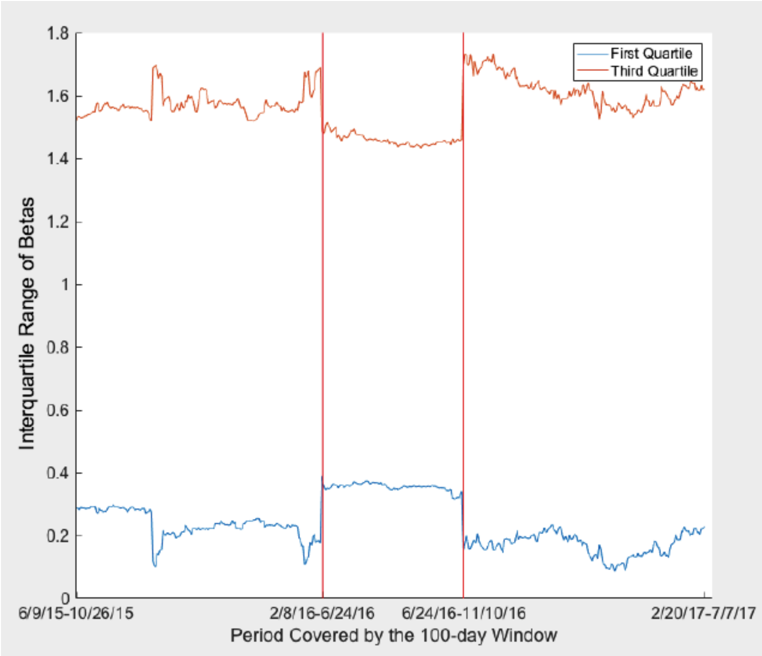


Figure 1: Compression of Stock Betas on the Brexit Vote Date

3.2 Events Identified as Relevant to the Distribution of Stock Market Returns

The same methodology also identifies key events of relevance to stock returns. This is important in demonstrating the methodology is of general use (or robust) when applied to types of news in other time periods. The same sharp contractions of the inter-quartile range of betas is evident in this broader stock history. Figure 3 is used to identify 6 major compressions in the inter-quartile range of betas, which are linked to news events thought to shift market expectations. The algorithm used to choose the dates of major shift in the interquartile range is described in the appendix.

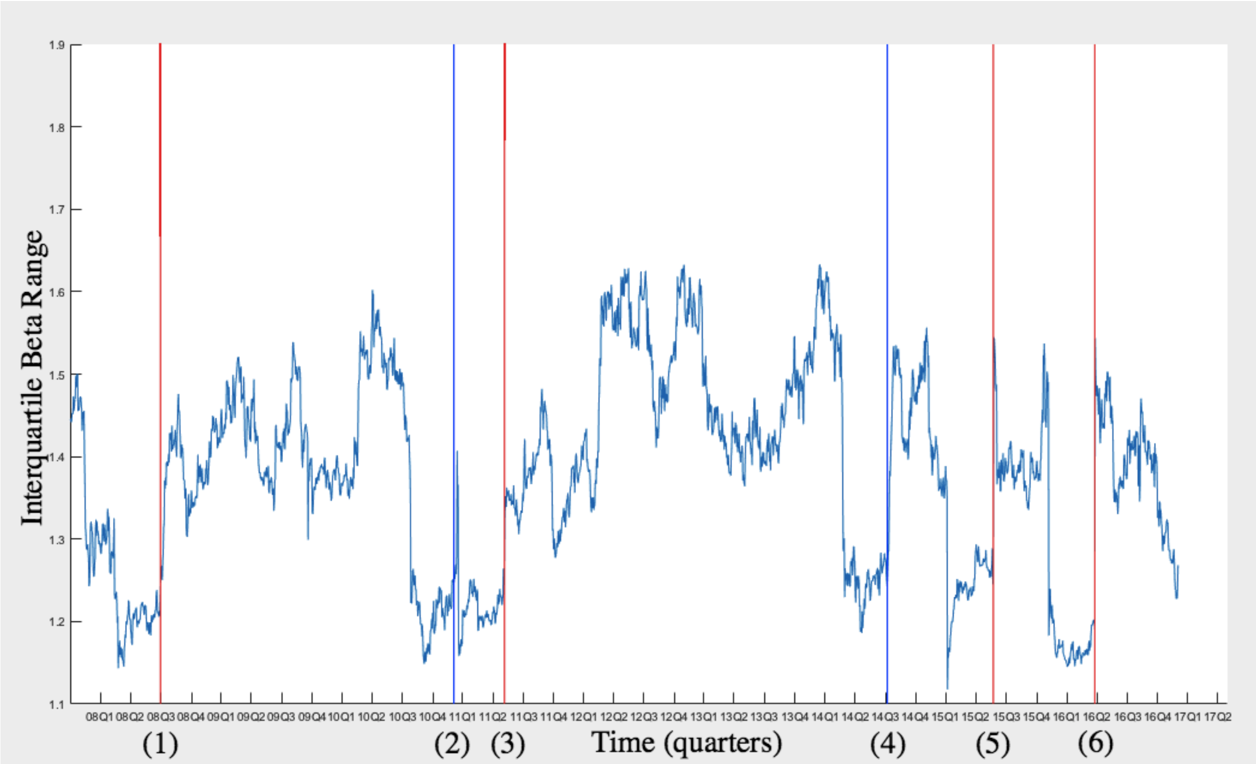


Figure 2: Identification of Events with Notable Compression of Stock Betas

We matched each date with events that significantly impacted the U.K. stock market by searching for news articles on the dates identified about the stock market, and we summarized the information in Table 2. The sources of the news articles are provided in the appendix.

Event 1. On September 29, 2008, the Dow Jones Industrial Average "fell 777.68 points intra-day trading, the largest point drop in history". Earlier on September 14, 2008, Lehman Brothers announced that it would file for liquidation. The crash had been building for a long time, and the plummet is due to "the rejection of the bank bailout bill by Congress".

Event 2. Around the beginning of March 2011, "Japanese earthquake shocked markets and global economic fears and political concerns in Saudi Arabia weighted heavily on investor sentiment". The Dow Jones industrial average (INDU) tumbled 228 points, or 1.9%.

Event 3. The 'August 2011 Stock Market Fall' happened on August 5, 2011, when there was the sharp drop in stock prices across the United States, Europe, Asia and the Middle East as investors dumped stocks. The reason of the turmoil includes that "several credit agencies downgraded their credit ratings of the U.S. federal government, with Standard & Poor's (S&P) which reduced U.S.'s rating from AAA to AA+". In addition, there

Table 2. Information on Events Identified by the Beta Method

Event Number	Date	Event
1	9/29/08	The U.S. stock market crash due to the rejection of the bank bailout bill by Congress
2	3/4/11*	Global economic fears and political concerns weighted heavily on investor sentiment; Japanese earthquake shocked markets
3	8/5/11	Global stock market fall due to concerns over the downgrading of the U.S.'s credit rating and slow global economic growth
4	10/6/14*	Global fears of economic slowdown, tensions in the Middle East and the spread of the Ebola virus
5	8/24/15	Global stock markets tumbled due to fear about China's economic slowdown
6	6/24/16	Brexit vote result

*The algorithm does not identify a particular event on a single day (such as the downgrading of the U.S.'s credit rating) but a period of volatility and turmoil in the stock market. The last data point idenfitied is chosen as the date presented.

are "fears of contagion of the European sovereign debt crisis, concerns over France's current AAA rating, and concerns over the slow global economic growth". The Dow Jones Industrial Average dropped 634.76 points (5.6%) and the FTSE 100 Index fell to under 4,800 on 9 August, its lowest level since July 2010.

Event 4. Around October 6, 2014, there was extreme turbulence in stock markets worldwide. Reasons include"fears of a global economic slowdown, growing increasingly nervous about the fate of the European and Chinese economies, tensions in the Middle East and the spread of the Ebola virus". The Dow plunged 335 points on October 9, 2014, its "worst day of the entire year on a point basis". The FTSE 100 slumped to its worst level in a year.

Event 5. On August 24, 2015, global stock markets tumbled. The FTSE 100 had more than £60bn wiped off the index of leading UK shares, "the first time the index had dropped below the 6,000 mark since early 2013".

It was the ‘Black Monday’ in China - Chinese shares had their worst day since 2007. The Dow had “an unprecedented 1,000-point decline, the worst since August 2011”.

Event 6. Brexit referendum result: London’s main FTSE 100 index plunged by nearly 9% but “recovered and closed with a loss of 3.2%”. But the FTSE 250 index closed with a loss of 7.2%. The pound quickly dropped to “its lowest level in more than 30 years against the U.S. dollar”. Other European markets also plunged following the surprise result. US stocks dropped 3.6%.

The Brexit news event is listed as number 6 in Table 2. Note that events outside the UK are more common than domestic events. This perhaps points to the inherent macroeconomic stability of the U.K. itself and its financial markets which are accessed by many countries for both equity claims and banking services. The Brexit vote result is the only one identified by the algorithm that is originated in the UK, indicating the particularity and the notable betas-compression effect of the event. It should be kept in mind that there are no guarantees that this method identifies all the significant events within the data period.

We identified the periods with significant jumps of the Economic Policy Uncertainty Index using the technique in Bloom’s 2009 paper and matched the periods with political and economic events. The table, which includes the “jump factor” we calculated and the details of selected events, is presented in the appendix. It is clear that Brexit, including both the referendum and the political events associated with it afterward, causes a significant increase in the jump factor. We see that the high political uncertainty associated with Brexit has a notable effect on the financial side of the UK economy.

4 Understanding Asymmetries in the Cross-section of Returns

That stocks are affected asymmetrically in a period of major macroeconomic news was evident in the rolling beta analysis. This suggests an asymmetric information story motivated by the asymmetric effect of Brexit on individuals and firms that led to the ambiguous vote on the exit at the outset. To move beyond a pure variance story, we need to put some additional structure on the analysis in the sense of figuring out which firms are more or less affected by a piece of macroeconomic news (like Brexit) and what direction (i.e., sign) that impact takes. This is not an easy task given the very large number of firms listed on the U.K. stock exchange (recall, our balance panel has 1,304 firms).

Two approaches are pursued with this aim in mind. The first approach uses the nominal exchange rate return as an 'instrument' in an attempt to identify winners and losers from Brexit. It is conceivable that the (presumed symmetric) distribution of returns would "cleave" into two groups, one with higher returns and one with lower returns after the Brexit vote. While a full information model would say these differences in mean returns are fully capitalized on the announcement data (relative appreciation of winners and relative depreciation of losers), the uncertainty surrounding the impact of Brexit surely clouds even that simple story. It could also be that there are three groups or some more continuous index along with the gauge the size and/or sign of the effect. The second approach is more structural and uses macroeconomic data on input-output relationships, value-added and end-uses of industry output (i.e., use in consumption, investment and exports of an industry/firm's output). This approach, while much more empirically demanding, allows a clearer separation of the impact of potential cost increases of inputs arising from Brexit in comparison to shifts in demand for final products by home and foreign purchasers.

4.1 A Two Factor Model of Stock Market Betas

We attempt to use the change in the nominal exchange rate to identify winners and losers, which is presumably asymmetric across sectors on the two sides of the trade balance. The motivation comes from the remarkably high exchange rate volatility during dates and periods associated with Brexit events (see Appendix 3). We are interested in how unexpected changes in the nominal exchange rate affect the distribution of returns. We use the GBP/EUR exchange rate, so an increase represents an appreciation of the Pound against the Euro. The regression equation is

$$R_{it} = \phi_i R_t + \gamma_i R_t^s + \varepsilon_{it} \tag{10}$$

where $R_t^s = lnS_t - lnS_{t-1}$ is the nominal exchange rate 'return'. The equation can be written as

$$\frac{cov(R_{it}, R_t)}{var(R_t)} = \phi_i + \gamma_i \frac{cov(R_t^s, R_t)}{var(R_t)} \tag{11}$$

Hence the equation for individual stock beta is

$$\beta_i = \phi_i + \gamma_i \beta_S \tag{12}$$

where

$$\beta_S \equiv \frac{cov(R_S, R_t)}{var(R_t)} \tag{13}$$

The idea is to examine the distribution of the β_i with a focus on the second factor, the covariance of the aggregate return and the nominal exchange rate interacting with the stock-specific loading, which perhaps captures the asymmetric effect of nominal exchange rate movements over the Brexit period.

From (12) we know that

$$var(\beta_i) = var(\phi_i) + \beta_S^2 var(\gamma_i) + 2\beta_S cov(\phi_i, \gamma_i) \tag{14}$$

We run the regression (12) for both the 01/01/08-07/20/17 and the 06/09/15-07/07/17 periods using balanced panels with 973 and 1,304 stocks, respectively. The sensitivity of changes in exchange rate return to changes in market return is captured by β_S, whose values in the two periods are presented below:

Table 3. Values β_S and its Components: Full vs. Brexit

Data Period	β_S	$cov(R_S, R_t)$	$var(R_t)$
1/1/08 - 7/20/17	0.076	0.0297	0.391%
6/9/15 - 7/7/2017	0.4673	0.1271	0.270%

β_S is significantly - more than six times - larger in the period associated with Brexit than in the full data period, and this significant increase can mostly be attributed to the higher covariance between the exchange rate "return" and the market return, which corresponds to the macroeconomic phenomena during this period: the stock market experienced a significant fall while the Pound also depreciated to the lowest level in recent years against the Euro. The high covariance represents the more systematically related movements in the stock market returns and the exchange rate returns, illustrating the significance of the macroeconomic impact of Brexit.

The following results help gauge the effects that each part on the right-hand side of (14) has on the variance of the β_i values:

Table 4. Variance of β_i and its Components: Full vs. Brexit

Period	Var(β_i)	Var(ϕ_i)	Var(γ_i)	β_S^2	$2\beta_S cov(\phi_i, \gamma_i)$
1/1/08 - 7/20/17	0.4407	0.4422	0.0313	0.005	-0.0017
6/9/15 - 7/7/17	0.5543	0.5128	0.1034	0.2184	0.0189
% Increase	25.78	15.97	230.35	4268	1212

We see that $Var(\beta_i)$ in the Brexit period is greater than that in the full data period. This is mainly due to the increase in the second part in equation (14), with β^2 being remarkably 4,000% more impactful (0.005 versus 0.2184) and $Var(\gamma_i)$ increasing by 230%. This illustrates the increased heterogeneity of the sensitivity of individual stock returns to the nominal exchange rate. The third term, $2\beta_S cov(\phi_i, \gamma_i)$, also increases significantly (1212%).

Next, we conduct the variance decomposition exercise for the three sub-periods of 06/09/2015 - 07/20/2017 to see if the pattern discerned above is similarly applied to the sub-periods. The regression results are presented in the following table.

Table 5. Variance of β_i and its Components: Pre-Brexit, Brexit & Post-Brexit

Period	$var(\beta_i)$	$var(\phi_i)$	$var(\gamma_i)$	β_S^2	$2\beta_S cov(\phi_i, \gamma_i)$
Pre-Brexit	0.793	0.789	0.225	0.147	-0.029
Brexit	0.912	0.816	0.237	0.454	-0.0108
Post-Brexit	1.530	1.567	0.302	0.024	-0.044

We see that $var(\beta_i)$ increases substantially in the Post-Brexit period, which is primarily due to the increase of $var(\phi_i)$, the variance of individual stock returns' correlation with the market return. Variance of γ_i's also increases, but not as significantly.

This general analysis shows that although the higher variance of stock betas in the Brexit-related period is primarily due to the increasingly more dispersed stock-specific response to changes in the exchange rate return, when we decompose the period into three sub-periods the result does not hold. The high variance of stock betas in the Post-Brexit is mainly attributed to the variance in individual stocks' response to changes in market return. The reason for this could be that the majority of the companies in the dataset are likely to have operations and sales predominantly in the U.K., so the exchange rate component, which emphasizes trade exposure, cannot pick up and explain the variations in their stock returns. Davies and Studnicka (2017) found that diverse characteristics of firms such as their global value chain and market size all contribute to the heterogeneity in the relative changes of their stocks, which reveals the complicated channels that can influence the variance of stock betas.

We computed γ_i values for a few of the UK's top exporting companies listed on the World's Top Exports website in order to gauge the effectiveness of the regression method on companies with sufficient trade exposure. These companies consist of:

- Anglo American plc: a multinational mining company based in Johannesburg, South Africa and London.
- Astrazeneca plc: a multinational pharmaceutical and biopharmaceutical company. It has headquarters in Cambridge (U.K.) and concentrated R&D sites in Cambridge (U.K.), Gaithersburg (Sweden), Maryland (U.S.), and Mlndal (Sweden).
- BP plc: formerly British Petroleum, a British multinational oil and gas company.
- British American Tobacco plc: a British multinational tobacco company and the largest publicly traded tobacco company in the world.
- Diageo plc: a British multinational alcoholic beverages company, the world's largest distiller until 2017.
- GlaxoSmithKline plc: a British pharmaceutical company and had the fourth largest market capitalization on the London Stock Exchange as of August 2016.
- Rio Tinto: an Australian-British multinational and one of the world's largest metals and mining corporations.

Table 6. Largest U.K. Exporters and Their γ_i Values

Company	γ_i
Anglo American	-0.24
Astrazeneca	-0.33
BP	-0.32
British American Tobacco	-0.14
Diageo	-0.16
GlaxoSmithKline	-0.14
Rio Tinto	-0.33

Because these companies are the biggest exporting companies in the UK, we expected them to have negative γ_i values, i.e. when the Pound appreciates, the stock returns of large exporting companies are negatively affected, and the result here corresponds with our expectation. Although the value of γ_i is influenced by other factors, such as the amount of the companies' import, the result supports our discussion above. Therefore, we shift the focus to a small set of firms for which the method would be more promising to unveil the influence of trade exposure. We do so by classifying companies by their ϕ_i's and γ_i's and investigate the effect of trade exposure on the heterogeneous impact of Brexit. We found that for companies with γ_i values in the lower and upper quartiles (hence with notable trade exposure by assumption), their γ_i's become more dispersed during the Brexit window, indicating a magnified effect of stock returns' response to nominal exchange rate return. The results are included in Appendix 5.

4.2 Stuctural Model

4.2.1 Revenue and Cost Exposure to Trade

The limitations of analysis on an individual company basis by trade exposure given our data and the more promising results of analysis on a group basis are discussed in the above section. This gives us the motivation to classify the stocks by industry and use national trade statistics on the industry level to further conduct our study. The idea here is to build a profit function for a firm and consider the sensitivity of profits to Brexit based on changes in sales and in costs. We conduct the analysis on the industry level. Consider a firm with revenue from domestic and foreign sales:

$$R_t = P_{h,t}Q_{h,t} + S_tP_{f,t}Q_{f,t} \tag{15}$$

where, R_t is nominal revenue in British Pounds, $P_{h,t}$ and $Q_{h,t}$ are the nominal UK price and quantity of domestic sales, and $S_tP_{f,t}$ and $Q_{f,t}$ are the nominal UK price of foreign sales (the foreign price multiplied by the foreign currency value in units of pounds) and the quantity of foreign sales.

The firm also uses both domestic and foreign inputs to produce its goods or services:

$$C_t = P_{h,t}C_{h,t} + S_tP_{f,t}C_{f,t} \tag{16}$$

where, C_t is the nominal production cost in UK pounds, $P_{h,t}$ and $C_{h,t}$ are the nominal UK price and quantity of production inputs that are sourced domestically, and $S_tP_{f,t}$ and $C_{f,t}$ are the nominal UK price of production inputs purchase from abroad (the foreign price multiplied by the foreign currency value in units of pounds) and the quantity of inputs purchased. It is natural to think of labor and capital as domestic inputs and materials as both home and foreign sourced:

$$C_t = W_{h,t}N_{h,t} + R_{h,t}K_{h,t} + P_{h,t}M_{h,t} + S_tP_{f,t}M_{f,t} \tag{17}$$

This example assumes a single foreign market for exports and a single foreign output, but one could think of the second terms as an aggregate of foreign sales across a vector of countries and constructing a less aggregated version.

If the Law of One Price held, revenue variance would be simply depending on the variance-covariance matrix of the two quantities purchased. However, in the short-run and particularly in the period surrounding Brexit and other financial crises, the presumption is that the nominal exchange rate dominates the variance and a depreciation of the British Pound brings about a windfall gain on exports and an increase in the cost of foreign inputs. If the focus is the variance of revenue, the same logic would say that volatile periods in exchange rate markets would introduce volatility in revenue which is rising in the share of foreign sales and falling share of foreign input costs.

Since foreign exchange rate effect enters the revenue side positively and the cost side negatively, changes in the nominal exchange rate have offsetting effects. Therefore, we would want to focus on the revenue share of foreign sales, $\frac{S_tP_{f,t}Q_{f,t}}{R_t}$, in relation to the cost share of foreign inputs, $\frac{S_tP_{f,t}M_{f,t}}{C_t}$.

4.2.2 Data

We use our stock returns dataset and classify the stocks using FTSE Russell's Industry Classification Benchmark (ICB), which groups companies into ten industries.

Table 7. Classification ot Stocks by Industry

Code	Industry	Number of Stocks
0001	Oil and Gas	70
1000	Basic Materials	103
2000	Industrials	224
3000	Consumer Goods	70
4000	Health Care	58
5000	Consumer Services	134
6000	Telecommunications	11
7000	Utilities	12
8000	Financials	184
9000	Technology	85
		952

This analysis uses the UK input-output analytical tables and Supply and Use Tables for 2014 from the UK's Office for National Statistics website. We grouped the 97 categories of products in the datasets into 11 industries, of which 10 correspond to the ICB industries and one is labeled as "others", which includes public goods and services such as libraries and education. We calculate the shares of exports and foreign inputs using the demand and supply data. The data includes an additional term in the costs component of each industry,"taxes less subsidies", which we subtract from total costs, and we calculate the proportions of costs based on the number after the deduction. This does not affect the analysis because the share of this component is very small (between 0.02% to 2%) for all industries. The tables we constructed are included in the appendix.

4.2.3 Results

The share of exports as a proportion of final demand and the share of imported intermediate inputs as a proportion of total costs are presented in the following table, and we rank the industries based on the differences between the two shares. The larger this difference is, the higher is the proportion of the industry's exports compared to its proportion of foreign inputs.

Table 8. Rank of Industries by Trade Exposure

Rank by Difference in Shares	Industry	Share of Exports	Share of Foreign Inputs	Difference in Shares
1	Basic Materials	0.475	0.216	0.259
2	Oil and Gas	0.503	0.246	0.257
3	Industrials	0.330	0.099	0.230
4	Technology	0.367	0.143	0.224
5	Healthcare	0.242	0.104	0.138
6	Financials	0.178	0.043	0.135
7	Telecommunications	0.242	0.154	0.088
8	Consumer Goods	0.175	0.107	0.068
9	Consumer Services	0.117	0.073	0.044
10	Utilities	0.006	0.138	-0.132

We see that Oil and Gas, Basic Materials, and Technology all have very high trade exposure, and Consumer goods, Consumer services, and Financials have very low trade exposure, both in terms of exports and imported intermediate imports. The other industries have moderate trade exposure. The ranking by the difference in exports and foreign inputs share is roughly the same as the ranking if we were to rank them by the raw values of the two shares from the largest to the smallest.

We conduct the rolling betas and variance decompositions exercises for each industry, and we expect the results to be highly dependent on the difference between the two shares. Because of the small sample size (around 10 stocks) of the telecommunications and utilites industries in our data, we leave them out of the following discussion.

a. Rolling Betas by Industry

In the figure below, we see that on June 24, 2016, the day of the Brexit vote, companies in industries that are ranked 1-5 in the table (Basic Materials, Oil and Gas, Industrials, Technology and Healthcare) experienced a compression of their inter-quartile beta range. This is similar, at least qualitatively, to the compression of the beta distribution for the entire cross-section of stock betas. However, for industries that are ranked near the bottom of the list (Financials, Consumer Goods and Consumer Services), there is no apparent compression effect. This result suggests that trade exposure tends to magnify the effect of Brexit on stock betas.

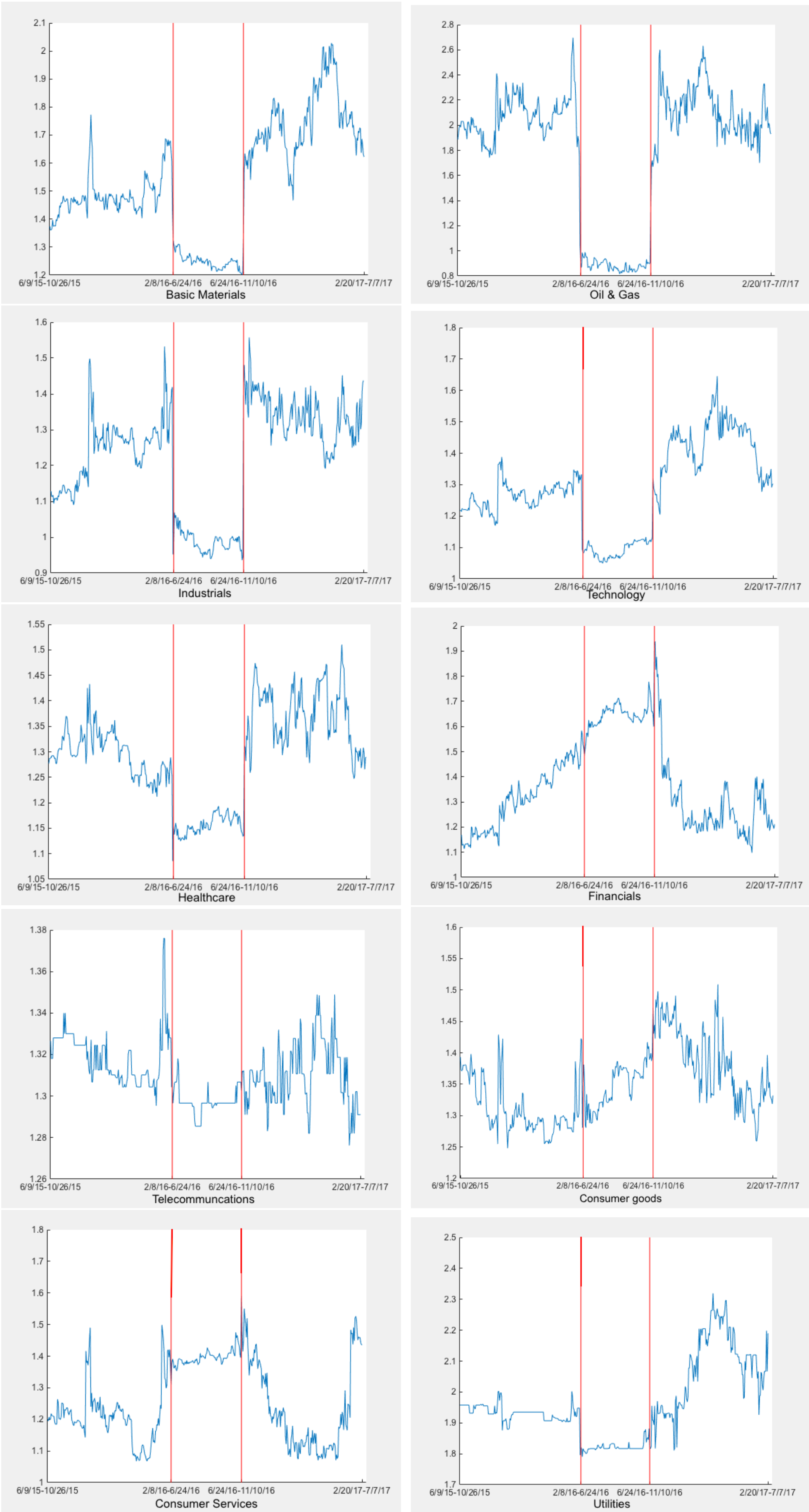


Figure 3: Rolling Interquartile Range of Betas by Industry

Another interesting idiosyncrasy of the Brexit vote event is apparent when we look at the rolling interquartile range of betas of the full data period by industry. The graphs for three industries are presented below:

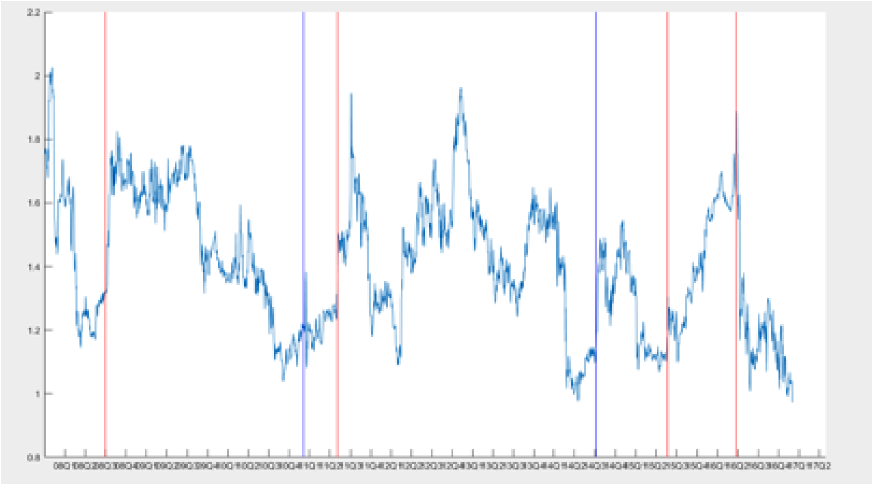


Figure 4: Rolling Interquartile Range of Betas: Financials Companies

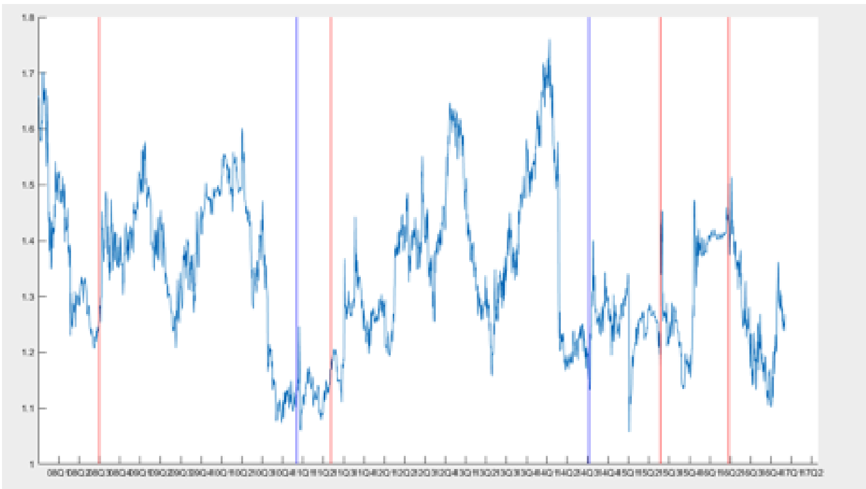


Figure 5: Rolling Interquartile Range of Betas: Consumer Services Companies

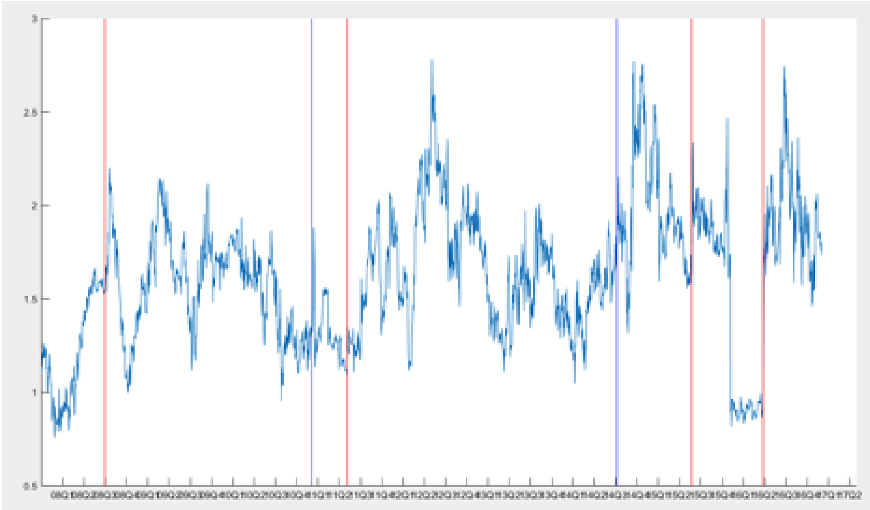


Figure 6: Rolling Interquartile Range of Betas: Oil and Gas Companies

The vertical lines are the dates of significant events that we identified in the rolling exercise for the whole market. For the Financials Industry, except for the Brexit vote event, the movement of the financials interquartile beta range corresponds to the movement of the market (a sudden compression of individual stock betas) at the dates of the events (all associated with global markets' turmoil or a gloom global economic outlook), which is very reasonable considering that financial companies should be very sensitive to the events that impact the whole market. But for the Brexit vote event this is not the case, suggesting some fundamentally different structures in the way the Brexit vote impacts the market. We see that this is also true for the Consumer Services Industry in the second figure. For Oil and Gas industry, we see that the industry does not always have a compression of its interquartile beta range on the dates but has a very significant compression on the Brexit vote day. The graphs suggest that Brexit, which although has a notable impact on the U.K. stock market and an overall negative macroeconomic effect on the level of the market indices just as the other significant economic and financial events do, is distinct in the way it affects stock betas when a more detailed industry analysis is conducted.

b. Variance Decomposition by Industry

To see if the difference between the two shares values in the profit function impacts how Brexit affects the volatilities of the stocks in different industries, we should look at not only the day of the referendum but also changes over a longer period. Therefore, we conduct the variance decomposition exercise again, now for each industry. We summarize the information by industry in the following table, which includes the percentage change of the common variance component in the Brexit period from that in the Pre-Brexit period, as well as the percentage change in the Post-Brexit period from that in the Brexit period, so a positive value indicates an increase and a negative value indicates a decrease in the common variance component. We see that while some industries have an increased common variance component in the Brexit period (February 17, 2016 - October 27, 2016), just as the whole market does, other industries have more idiosyncratic-driven variances in the Brexit period.

Table 9. Variance Decomposition by Industry

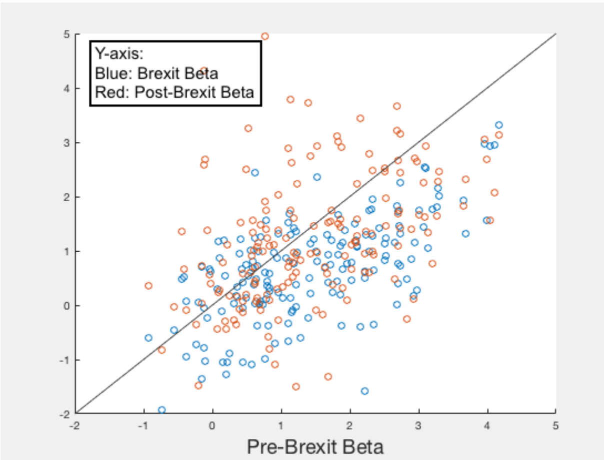
Rank by Difference in Shares	Industry	$\triangle$% of the common variance component: Brexit Period	$\triangle$% of the common variance component: Post-Brexit Period
1	Basic Materials	-23	-38
2	Oil and Gas	-61	-26
3	Industrials	21	-75
4	Technology	8	-48
5	Healthcare	-18	-34
6	Financials	90	-80
8	Consumer Goods	94	-78
9	Consumer Services	31	-69

Although the result is not as neat as it was in the previous exercise, we see that in general, industries with higher trade exposure are more likely to experience a decrease in the common component of the stock return variance while those with lower trade pressure are more likely to experience an increase. This suggests that the impact of Brexit is more heterogeneous on those industries large trade exposures while companies in the other industries are more systematically impacted by the macroeconomic shock.

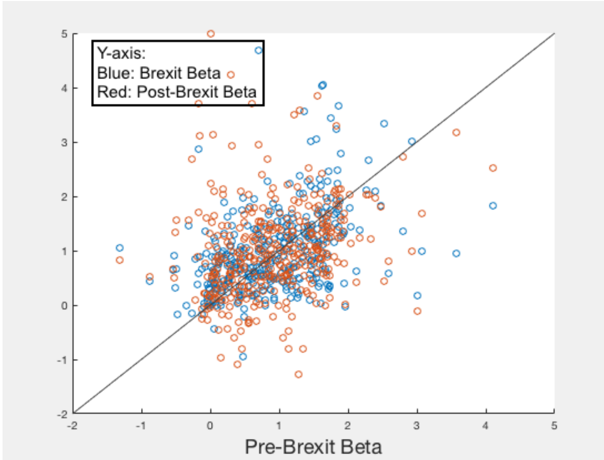
c. Changes in Betas by Industry

We plot the beta values of stocks in the Brexit and Post-Brexit periods against their values in Pre-Brexit periods to see if there are patterns of shifts in different sub-periods. We then divide the 8 industries (not including Telecommunications and Utilities) into three categories:

- 'Large' (189 stocks), the group of industries with large differences in the exports and imported inputs shares, or group of industries with large trade exposures, which includes Basic Materials and Oil and Gas.



(a) Large differences group (189 stocks)



(b) Medium differences group (367 stocks)

(c) Small differences group (389 stocks)

Figure 7: Graphs of Stock Betas Across Sub-Periods, Classified by Trade Exposure

- 'Medium' (367 stocks), the group industries with medium differences in the exports and imported inputs shares, or group of industries with medium trade exposures, which includes Industrials, Technology and Healthcare.

- 'Small' (389 stocks), the group industries with small differences in the exports and imported inputs shares, or group of industries with small trade exposures, which includes Financials, Consumer Goods and Consumer Services.

There seems to be a strong positive correlation of an individual stock's beta in one period with its beta in another (most points cluster around the 45-degree line), which is a reassuring feature as that it suggests that a stock's beta is a robust feature of that stock when the industry is the mode of classification.

We consider the betas in the pre-Brexit period the benchmark of the normal-time betas of the stocks. We see several features of the movement of stock betas across periods in the figure. The stocks with moderate exchange rate exposure seem to not have the distribution of the betas shifted across periods. The large exposure sectors have particularly large increases in their betas in the post-Brexit period relative to the Brexit or pre-Brexit period. The small exposure sectors that are mostly insulated from direct international competition or cost shocks appear to have an increase in betas for a large subset of firms in the Brexit period, which could be due to the pure uncertainty of domestic demand during the Brexit discussion and vote.

The structural analysis of the heterogeneous effect in this section presents us with promising results on the correlation between trade exposure and the impact of the Brexit result on stock returns. The comprehensive tables that we constructed with the dollar values and proportions of supply and demand by industry are included in the appendix and can be used for further analyses.

5 Conclusion

We have found that on the day of the Brexit vote, there was a systematic response across the market to the shock in that on average stock returns become more correlated with the market return. This is indicated by a notable compression of individual stock betas toward to direction of $\beta = 1$. The rolling betas method we use is robust in identifying events that significantly impact the stock market, and these events are associated with the similar compression of betas. Nevertheless, the betas quickly adjust after the day of the vote, which possibly indicates internationalization at the firm-level and efficiency of the U.K. stock market. We see that the 181-days interval with the vote date at its center has an increased common component of the stock returns variance while the 181-days interval that follows from it has a significantly decreased common component. These results suggest that Brexit impacts firms' stock returns in a heterogeneous fashion, and we find that the impact is affected by trade exposure, or the difference in shares of exports and shares of imported inputs, at least on the industry level. Those industries with larger trade exposure or larger difference responded with a compression of their stock betas on the day of the referendum, but over the longer 181-days period the variance of their stock returns tend to be driven more by the idiosyncratic component. Further studies on the asymmetric effect of Brexit on the distribution of stock returns around the mean, stock betas, and volatilities on the aggregate industry level can be conducted using the input-ouput tables we constructed and more comprehensive data that include detailed characteristics of the firms. Techniques such as the rolling betas method can also be used for other event studies. Belke, Dubova and Osowski (2018) conclude that Brexit-induced policy uncertainty can potentially do harm to the U.K. and other European countries' real economy by continuing to cause instability in the world's key financial markets, and understanding of the channels that Brexit affects different stock market indicators and characteristics is essential for future policy-making and analyses.

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Appendix

Appendix 1. Method of Identifying Dates of Major Shifts in the Interquartile Range

We identify all the dates whose interquartile range of the stock betas are less than 1.25, a value we chose after examining the long-run trend of the interquartile range value. Four clusters of the dates identified are exactly 100-days groups, which indicates that on the last dates of the 100-days clusters identified, there were events that significantly impacted the U.K. stock market (the betas immediately compress as soon as the date enters the rolling calculation window and immediately return to the higher level when the date leaves the calculation window). Two clusters of the dates identified also have approximately 100 days (93 days and 104 days), indicating that around the dates of the clusters there were turmoil and volatility in the U.K stock market. We report the last date in each cluster in the table. We then match the 6 dates identified with notable events that impacted the stock market, and all events identified are associated with global stock markets fall or gloom economic outlook except for the Brexit referendum result.

Appendix 2. Links of News Articles Used in the Event Identification Exercise

- Event 1:
  $https://www.thebalance.com/stock-market-crash-of-2008-3305535$
- Event 2:
  $http://money.cnn.com/2011/03/10/markets/markets_newyork/index.html$
- Event 3:
  $https://www.telegraph.co.uk/finance/financialcrisis/8688049/Debt-crisis-as-it-happened-August-5-2011.html$
  $https://www.washingtonpost.com/business/economy/sandp-considering-first-downgrade-of-us-credit-rating/2011/08/05/gIQAqKeIxI_story.html?noredirect=on$
- Event 4:
  $http://money.cnn.com/2014/10/09/investing/stocks-markets-$

wall − street − selloff/index.html
https : //www.theguardian.com/business/2014/oct/10/world − markets − slide − bad − news − slowdown − ebola − eurozone

- Event 5:
  https : //www.theguardian.com/business/2015/aug/24/black − monday − chinese − stock − market − loses − all − gains − since − start − of − year
  http : //money.cnn.com/2015/08/24/investing/stocks − markets − selloff − china − crash − dow/index.html

- Event 6:
  http : //money.cnn.com/2016/06/24/investing/brexit − london − stocks − crashing/index.html
  https : //www.ft.com/content/50436fde − 39bb − 11e6 − 9a05 − 82a9b15a8ee7

Appendix 3. Identifying Significant Jumps in the Economic Policy Uncertainty Index

Table 10. Events With The EPU Index Above 1 SD (=79.54) Of The HP Detrended Mean

Event Description	Max Volatility Date	Max Value of Computed Factor	Duration
Iraq War	Feb 2003	145.66	Jan-Mar 2003
	Oct 2010	86.86	Oct 2010
	Oct 2011	110.07	Oct 2011
	Nov 2012	127.16	Oct 2012-Jan 2013
Scottish Independent Referendum	Sep 2014	85.45	Sept 2014
Immediate reactions to the Brexit Referedum	Jul 2016	676.97	June-July 2016
The High Court rules that the U.K. must hold a vote in Parliament before starting Brexit process	Nov 2016	320.96	Nov 2016

Appendix 4. Identifying Significant Jumps in Exchange Rate Volatility

We try to measure the extent of exchange rate volatility caused by Brexit by using the testing for jumps method (Bloom 2009). The data we use come from the CBOE/CME FX British Pound Volatility (BPVIX) index and covers the period from June 10, 2013 to June 30, 2017 ($https://www.investing.com/indices/fx-british-pound-volatility-historical-data$). The algorithm identifies dates with exchange rate volatility above 1.65 standard deviation (=2.1556) of the HP detrended mean (we choose λ=43,200). We associate selected dates with notable economic events happened during the period of high volatility.

Table 11. Events With Exchange Rate Volatility Is Above 1 SD (=2.16) Of The HP Detrended Mean

Event Description	Max Volatility Date	Max Value of Computed Factor	Duration
	9/10/14	4.69	9/8/14-9/18/14
	4/1/15	2.66	3/31/15-4/2/15
	5/4/15	2.18	5/4/15
	2/24/16	2.37	2/24/16
Anticipation of Brexit referedum result	6/14/16	10.00	6/1/16-6/22/16
Negotiations took place to determine whether the Prime Minister could trigger Article 50 without parliamentary approval	10/11/16	3.51	1/11/16-10/17/16
Speculation surrounding Theresa May's headline approach to Brexit and the expectation that she would announce that Britain will be leaving the EU single market	1/13/17	2.6192	1/11/17-1/13/17

Note the surge in exchange rate volatility during the immediate period before the Brexit referendum date, manifested by both the extremely high computed volatility factor (10.00) and the long duration (22 days). Furthermore, we see that after the referendum, the exchange rate became more volatile when there were significant political events associated with the Brexit, indicating the event's impact on the volatility of the British Pound.

Appendix 5. Analysis using ϕ_i and γ_i

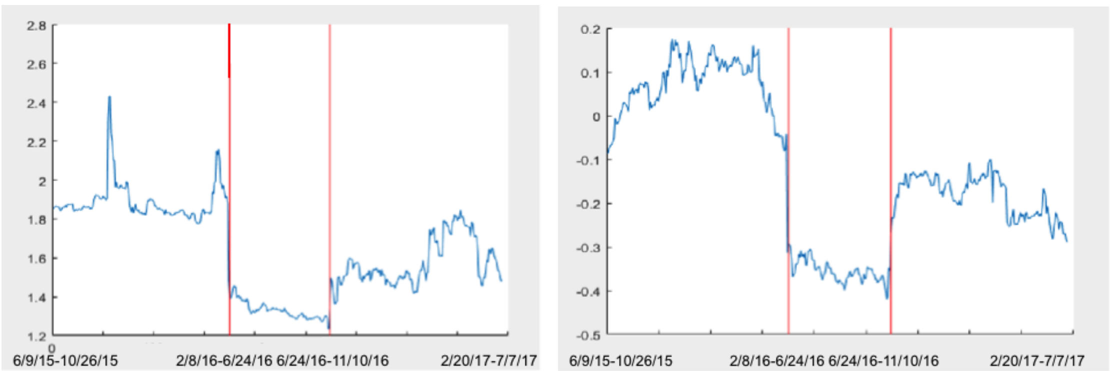
We first run regression (10) for all 952 stocks and obtain their respective ϕ_i and γ_i values and then divide both parameters into three categories: the lower quartile (< 0.25), the middle two quartiles (0.25-0.75) and the upper quartile (> 0.75). The joint and marginal distributions are as follows:

Table 12. Classification By ϕ_i and γ_i Values

		ϕ_i			
		< 0.25	0.25-0.75	> 0.75	Sum
	< 0.25	32	130	76	238
γ_i	0.25-0.75	154	229	93	476
	> 0.75	52	117	69	238
	Sum	238	476	238	952

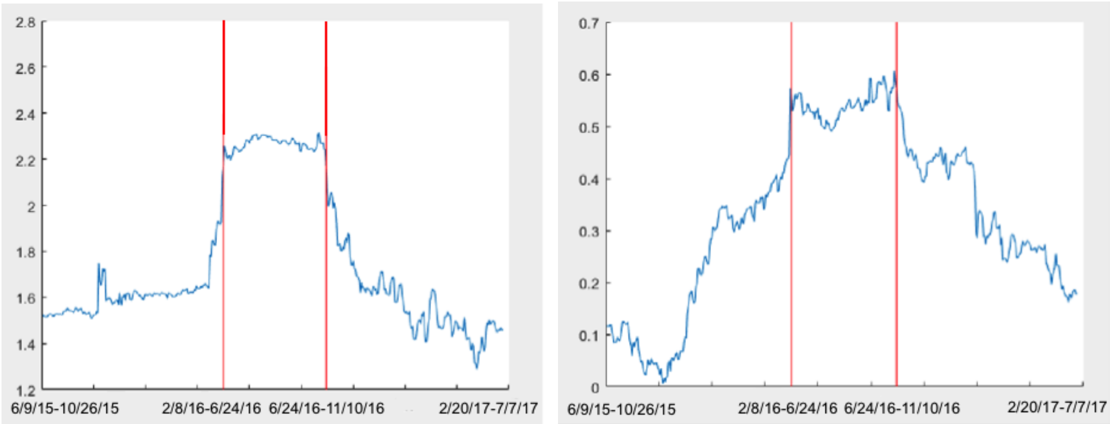
We now conduct separate rolling exercises for companies in the four corner cells. These four cells include companies with tail values of ϕ_i and γ_i, and in particular are in the lower and upper quartiles of γ_i, which indicates that they are likely to have large trade exposure. For each group of companies, we present their rolling mean of ϕ_i and γ_i values.

Figure 8: Group I: Companies with $\phi_{>0.75}$ and $\gamma_{<0.25}$ (sample: 76)



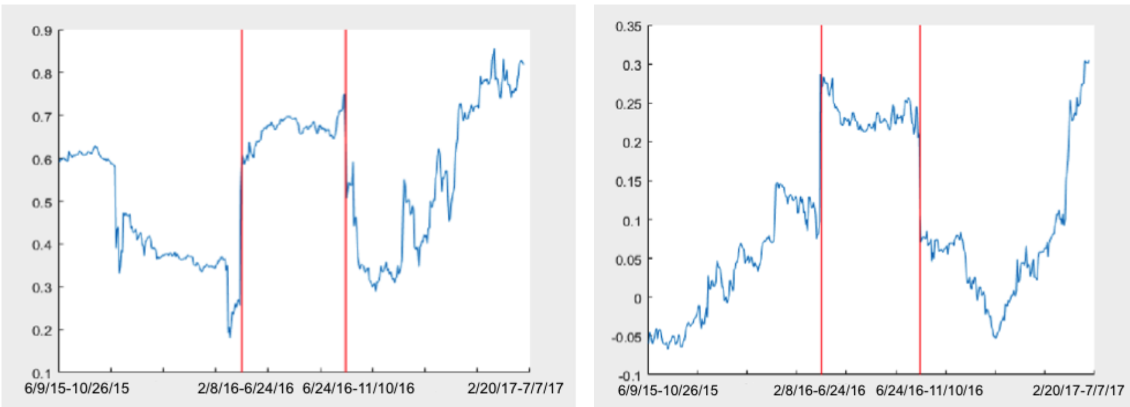
(a) $\overline{\phi}(\phi_{>0.75}, \gamma_{<0.25})$ (b) $\overline{\gamma}(\phi_{>0.75}, \gamma_{<0.25})$

Figure 9: Group II: Companies with $\phi_{>0.75}$ and $\gamma_{>0.75}$ (sample: 69)



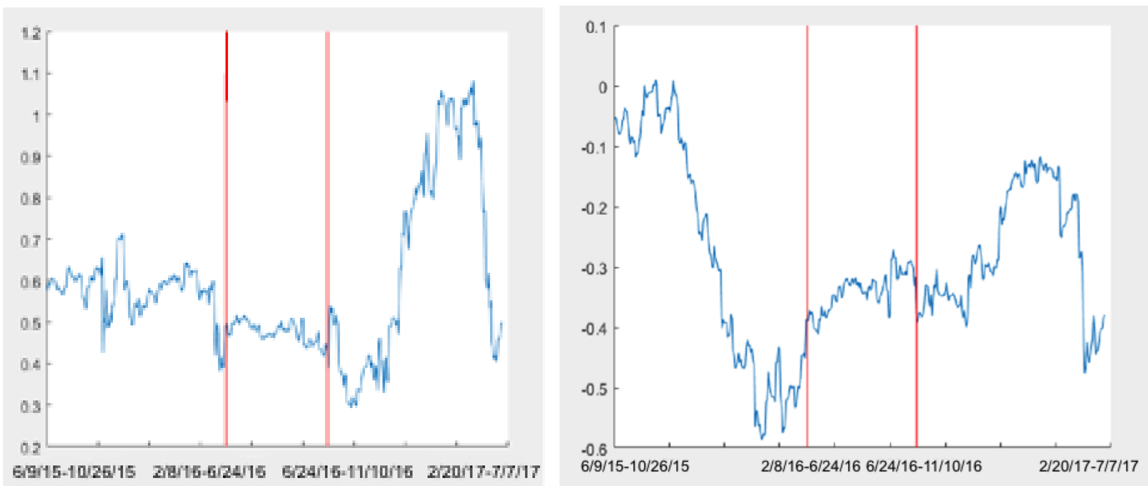
(a) $\overline{\phi}(\phi_{>0.75}, \gamma_{>0.75})$ (b) $\overline{\gamma}(\phi_{>0.75}, \gamma_{>0.75})$

Figure 10: Group III: Companies with $\phi_{<0.25}$ and $\gamma_{>0.75}$ (sample: 52)



(a) $\overline{\phi}(\phi_{<0.25}, \gamma_{>0.75})$ (b) $\overline{\gamma}(\phi_{<0.25}, \gamma_{>0.75})$

Figure 11: Group IV: Companies with $\phi_{<0.25}$ and $\gamma_{<0.25}$ (sample: 32)



(a) $\overline{\phi}(\phi_{<0.25}, \gamma_{<0.25})$ (b) $\overline{\gamma}(\phi_{<0.25}, \gamma_{0.25})$

The $\overline{\gamma}$ and $\overline{\phi}$ values of Group I, II, and III exhibit notable patterns in the Brexit rolling window, while the values of Group IV do not. We compare two pairs of company groups in order to examine the details:

(1) Group I and II:

Both groups have members with the largest ϕ_i values (above the third quartile), but the patterns of both $\overline{\phi}$ and $\overline{\gamma}$ are opposite for the two groups. Therefore, for the same level of ϕ_i, when we vary γ_i's we obtain opposite effects of the rolling means' response to the Brexit vote result. In addition, the companies with the smallest γ_i's have even smaller values and those with the largest γ_i's have even large values, indicating a wider dispersion of individual stock returns' response to the exchange rate returns (which is the hypothesis that we expect to see but did not quite obtain in the previous variance decomposition exercise).

(2) Group II and III:

Both groups have members with the largest γ_i values (in the third quartile), and the patterns of both $\overline{\phi}$ and $\overline{\gamma}$ are the same for the two groups (significant jump and then decline in the 100-day windows that incorporates the Brexit vote result). Therefore, according to the analysis, for the same level of γ_i, when we vary ϕ_i's we obtain similar effects of the rolling means' response to the Brexit result.

The two comparisons suggest that γ_i, i.e. how a company's stock return varies with exchange rate return, contributes more to the average response of the stock returns of groups of companies to the brexit vote result, in terms of both the correlation with market return and the correlation with nominal exchange rate return. In the Brexit window, the γ_i values seem to experience a magnified dispersion effect, with increased upper quartile mean and decreased lower quartile mean.

Appendix 6. Variance Decomposition By Industry

Table 13. Variance Decomposition: Basic Materials

Sample	Variance in Percent Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	1.9	98.1	
Pre-Brexit	100	2.5	97.5	
Brexit	100	1.9	98.1	-23.1
Post-Brexit	100	1.2	98.8	-38.1

Table 14. Variance Decomposition: Oil and Gas

Sample	Variance in Percent Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	3.3	96.7	
Pre-Brexit	100	5.8	74.2	
Brexit	100	2.3	97.7	-60.8
Post-Brexit	100	1.7	98.3	-26.4

Table 15. Variance Decomposition: Industrials

Sample	Variance in Percent Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	3.8	96.2	
Pre-Brexit	100	4.5	95.5	
Brexit	100	5.5	94.5	-20.1
Post-Brexit	100	1.4	98.6	-74.5

Table 16. Variance Decomposition: Technology

Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
	Variance in Percent			
Full	100	2.2	97.8	
Pre-Brexit	100	2.5	97.5	
Brexit	100	2.7	97.3	8.4
Post-Brexit	100	1.4	98.6	-47.7

Table 17. Variance Decomposition: Healthcare

Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
	Variance in Percent			
Full	100	3.0	97.0	
Pre-Brexit	100	3.7	96.3	
Brexit	100	3.0	97.0	-18.0
Post-Brexit	100	2.0	98.0	-33.5

Table 18. Variance Decomposition: Financials

Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
	Variance in Percent			
Full	100	3.7	96.3	
Pre-Brexit	100	3.1	96.9	
Brexit	100	5.9	94.1	89.6
Post-Brexit	100	1.2	98.8	-80.4

Table 19. Variance Decomposition: Telecommunications

	Variance in Percent			
Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	6.9	93.1	
Pre-Brexit	100	9.3	90.7	
Brexit	100	6.4	93.6	-31.2
Post-Brexit	100	5.3	94.7	-16.8

Table 20. Variance Decomposition: Consumer Goods

	Variance in Percent			
Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	4.6	95.4	
Pre-Brexit	100	4.2	95.8	
Brexit	100	8.1	91.9	93.6
Post-Brexit	100	1.8	98.2	-78.2

Table 21. Variance Decomposition: Consumer Services

	Variance in Percent			
Sample	Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	4.7	95.3	
Pre-Brexit	100	5.0	95.0	
Brexit	100	6.5	93.5	30.8
Post-Brexit	100	2.0	98.0	-69.5

Table 22. Variance Decomposition: Utilites

Sample	Variance in Percent: Total	Common	Idiosyncratic	Percentage Change in Common Component
Full	100	7.8	92.2	
Pre-Brexit	100	8.0	92.0	
Brexit	100	9.2	90.8	15.6
Post-Brexit	100	6.2	93.8	-32.6

Appendix 7. Tables

Table 23. 2014 U.K. Input-Output Table

	Oil&Gas	Basic Materials	Industrials	Consumer Goods	Health Care	Consumer Services	Telecommu nication	Utilities	Financials	Technology	Others
Oil&Gas	20822	6390	12318	1591	378	7340	570	25071	1610	551	2841
Basic Materials	5223	56138	60027	25488	2633	8774	1306	1465	1828	5108	3401
Industrials	4036	16142	305254	15969	16682	93466	5389	6014	83529	18648	44000
Consumer Goods	119	3896	5945	29844	1590	34553	238	188	1177	306	7892
Health Care	27	307	217	767	14792	537	5	32	424	9	810
Consumer Services	374	1105	13083	2360	2045	24418	982	623	17549	1118	15018
Telecommunication	31	474	4522	1538	970	4503	5128	257	9360	419	2618
Utilities	1340	6585	8514	3784	2484	4647	403	50492	2840	919	3695
Financials	3063	6628	42114	4583	6171	29224	1672	2978	75707	4696	13215
Technology	657	1912	25760	1425	9294	9602	7658	3022	12958	13384	16409
Others	74	419	11381	1884	2309	5503	450	206	7850	468	29508
Tax less subsidies	170	-1326	6571	65	163	12218	435	2300	3411	579	755
Compensation of employees	5913	35048	246783	31460	71564	160488	14651	11106	95104	39728	190449
Gross operating surplus and mixed income	14801	21354	150196	22442	29849	93542	14926	22541	285160	11532	44744
Imports	18428	42978	96934	17204	18710	37298	9680	19806	26869	16125	21789
Total	75078	198050	989619	160404	179634	526113	63493	146101	625376	113590	397144

Table 24. 2014 U.K. Final Demand Table

Industry	Intermediate Demand	Household Consumption	Government	Investment	Exports	Total final demand	Total demand for products
Oil&Gas	79482	35059	0	1368	36879	73306	152788
Basic Materials	171391	48744	0	3858	47644	100246	271637
Industrials	609129	172208	11178	234725	206028	624139	1233268
Consumer Goods	85748	223107	2761	11900	50416	288184	373932
Health Care	17927	24682	133929	138	22118	180867	198794
Consumer Services	78675	170661	6345	2854	23905	203765	282440
Telecommu nication	29820	19323	0	692	6392	26407	56227
Utilities	85703	39443	0	-12	221	39652	125355
Financials	190051	340599	338	11973	76555	429465	619516
Technology	102081	29175	0	43261	41985	114421	216502
Others	60052	40918	261088	3578	6782	312366	372418
Total	1510059	1143919	415639	314335	518925	2392818	3902877

Table 25. Components of Industries' Cost Functions, Presented as Proportions

Industry	Oil&Gas		Basic Materials		Industrials		Consumer Goods		Health care		Consumer Services		Telecom municatio ns		Utilities		Financials		Technolo gy	
	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import	Domestic	Import
Oil&Gas	0.2773	0.2240	0.0323	0.0174	0.0124	0.0052	0.0099	0.0028	0.0021	0.0005	0.0140	0.0054	0.0090	0.0025	0.1716	0.1143	0.0026	0.0011	0.0049	0.0014
Basic Materials	0.0696	0.0087	0.2835	0.1631	0.0607	0.0203	0.1589	0.0337	0.0147	0.0042	0.0167	0.0073	0.0206	0.0040	0.0100	0.0031	0.0029	0.0011	0.0450	0.0203
Industrials	0.0538	0.0083	0.0815	0.0241	0.3085	0.0573	0.0996	0.0173	0.0929	0.0072	0.1777	0.0193	0.0849	0.0120	0.0412	0.0052	0.1336	0.0116	0.1642	0.0447
Consumer Goods	0.0016	0.0005	0.0197	0.0030	0.0060	0.0021	0.1861	0.0396	0.0089	0.0019	0.0657	0.0183	0.0037	0.0009	0.0013	0.0001	0.0019	0.0007	0.0027	0.0004
Health Care	0.0004	0.0001	0.0016	0.0012	0.0002	0.0001	0.0048	0.0039	0.0823	0.0641	0.0010	0.0006	0.0001	0.0000	0.0002	0.0000	0.0007	0.0000	0.0001	0.0000
Consumer Services	0.0050	0.0017	0.0056	0.0014	0.0132	0.0028	0.0147	0.0062	0.0114	0.0032	0.0464	0.0130	0.0155	0.0023	0.0043	0.0010	0.0281	0.0071	0.0098	0.0049
Telecommunication	0.0004	0.0000	0.0024	0.0002	0.0046	0.0001	0.0096	0.0001	0.0054	0.0000	0.0086	0.0001	0.0808	0.0719	0.0018	0.0000	0.0150	0.0001	0.0037	0.0001
Utilities	0.0178	0.0000	0.0332	0.0000	0.0086	0.0000	0.0236	0.0000	0.0138	0.0000	0.0088	0.0000	0.0063	0.0000	0.3456	0.0071	0.0045	0.0000	0.0081	0.0000
Financials	0.0408	0.0015	0.0335	0.0021	0.0426	0.0020	0.0286	0.0015	0.0344	0.0015	0.0555	0.0028	0.0263	0.0014	0.0204	0.0009	0.1211	0.0203	0.0413	0.0019
Technology	0.0088	0.0008	0.0097	0.0044	0.0260	0.0074	0.0089	0.0016	0.0517	0.0214	0.0183	0.0038	0.1206	0.0574	0.0207	0.0039	0.0207	0.0009	0.1178	0.0683
Others	0.0010	0.0000	0.0021	0.0001	0.0115	0.0006	0.0117	0.0005	0.0129	0.0000	0.0105	0.0003	0.0071	0.0000	0.0014	0.0000	0.0126	0.0000	0.0041	0.0001
Total (Domestic vs. Import)	0.4764	0.2455	0.5049	0.2170	0.4943	0.0980	0.5563	0.1073	0.3304	0.1042	0.4230	0.0709	0.3749	0.1525	0.6184	0.1356	0.3435	0.0430	0.4017	0.1420
Taxes less subsidies	0.0023		-0.0067		0.0066		0.0004		0.0009		0.0232		0.0069		0.0157		0.0055		0.0051	
employees	0.0788		0.1770		0.2494		0.1961		0.3984		0.3050		0.2307		0.0760		0.1521		0.3497	
Gross operating surplus and mixed income	0.1971		0.1078		0.1518		0.1399		0.1662		0.1778		0.2351		0.1543		0.4560		0.1015	
Total	1.0000		1.0000		1.0000		1.0000		1.0000		1.0000		1.0000		1.0000		1.0000		1.0000	