Essays on Asset Pricing



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To my Parents,
for their endless support.

Acknowledgements

'The record shows I took the blows
And did it my way'

Frank Sinatra, *'My way'*

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Abstract

This dissertation presents the reader with three empirical analyses in the asset pricing realm. The first chapter, *Mind the (Trade) Gap! Stock market implications of barriers to trade*, looks into the impact of free trade agreements on stock prices. It quantifies the effect of the United Kingdom's departure from the European Union (the so-called *Brexit*) on European equity prices. In this chapter, I identify an overwhelmingly negative response of the cross-section of European equities to this decision and show that varying degrees of Brexit exposure explain differences in returns on European stocks over the Brexit negotiations period (between July 2016 and December 2019). Both results are more pronounced in the UK than in the EU. I go on to exploit this cross-sectional variation in equity returns to construct a Brexit mimicking portfolio tracking latent Brexit shocks over time. This portfolio explains a significant amount of time-series variation of European stock market in the post-referendum period. Finally, its correlations with the European stock market indices suggest Brexit constituted far greater and more lasting a shock to the local United Kingdom's than the European Union's economy. The second chapter, *Sources of Return Predictability*, develops an approach to determine whether known return predictors are proxies for fundamental risk in the economy or not. To this end, it builds on previous literature which has documented differences between days when important macroeconomic news is scheduled to be released onto the market and the remaining days. The chapter shows that known stock return predictors forecast returns accrued on either announcement or non-announcement days but never on both types of days. Interestingly, most known predictors forecast non-announcement day returns only. The paper further shows that the excess volatility puzzle of Shiller 1981 is predominantly a non-announcement days puzzle. Taken together, these results suggest that known return predictors forecast the excess volatility component of the stock market. This is joint work with Pavel Savor and Mungo Wilson. The third chapter, *Old wine in new bottles. Are industry risks still not understood?*, examines the relationship between Fama-French risk factors and industry-specific returns. It shows that industry indices can consistently explain large shares of risk premiums documented by Fama and French. Similarly, Fama-French univariate and multivariate sort portfolios commonly used in the literature show strikingly consistent trends with respect to co-movement with a limited set of industries. Moreover, as expected in a commercially integrated world, geographic zone factors also constitute portfolios of industry indices. Together, these results suggest that various risk premiums credited to existence of the corresponding risk factors can in fact just be combinations of industry-specific risks which nature has just been insufficiently understood up till now. Taken together, these three chapters contribute to the growing body of literature on markets' informational efficiency and the impact of information arrival on investors' beliefs.

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1 | Introduction

A pivotal concept in asset pricing is market efficiency – the idea that all information available to market participants is promptly discounted into asset prices. As market participants receive signals about the future states of the world and their probability, they adjust their demanded rates of return (discount rates) and cash flows' expectations. This in turn results in price changes that are recorded as realised rates of return.

This thesis builds on the above idea that information is quickly incorporated into asset prices in all three analyses presented. In Chapter 3, *Mind the (Trade) Gap! Stock market implications of barriers to trade*, I use an event study to analyze the effect of Free Trade Agreements on stock prices. The natural experiment of United Kingdom's departure from the European Union and the adjustment of asset prices it triggered is used to compare the impact on asset prices of the stock market of the country leaving a Free Trade Agreement and these of the countries which remained part thereof. A co-authored Chapter 4, *Sources of Return Predictability*, uses differences in the information disclosed to the market on days when important macroeconomics news is scheduled to be released to market participants and the remaining types of days in order to identify stock market return predictors which are driven by fundamentals and these that are not. Finally, Chapter 5, *Old wine in new bottles? Are industry risks (still) not understood?*, uses regressions of contemporaneous returns to risk premia and industry portfolios to show that many risk premiums can be explained away by industry-specific sources of risks.

Given the distinct nature of each analysis, I review the major findings of each paper separately.

Paper 1: Mind the (Trade) Gap! Stock market implications of barriers to trade.

This chapter studies the effects of Free Trade Agreements (FTAs) on stock prices. Historically such impact has been hard to quantify. This is due to both the length of the negotiation process when joining a free trade union and the

limited and infrequent examples of leaving one. Here, I use the natural experiment setting provided by United Kingdom's recent decision to leave the European Union in order to fill this gap.

There are two main contributions of this analysis. First, I show that there are two main drivers of the heterogeneity of stocks' responses to the *leave* vote: (i) the share of revenue derived from the other side of the newly to be erected barrier to trade and (ii) the sector in which the company is operating (i.e. whether it is a services or manufacturing one). Secondly, I show that although the withdrawal-related shocks continued to negatively affect the stock market of the leaver (i.e. United Kingdom) during the EU-withdrawal (Brexit) negotiation period, they had a positive relationship with the the stock markets of the countries which remained part of the European Union.

The empirical methodology of this paper relies on three steps. First, I use the stock market to identify a measure of individual firms' exposure to the withdrawal shock. Then, I run regressions of this measure on a range of variables capable of potentially explaining its (wide) cross-sectional heterogeneity. Finally, I use the measure in question in order to construct a portfolio which tracks the latent shocks to the withdrawal agreement negotiation process over time and their impact on equity prices in the region.

I measure individual companies' exposure to the Brexit shock using their stock market price reactions upon the release of the Brexit referendum results. The main response window considered in the analysis is between the stock market close on the day of the referendum (Thursday, 23 June 2016) and the stock market close on the day after (Friday, 24 June 2016). Such an identification strategy is possible since the decision to leave the European Union was exogenous and unexpected by the general public and financial markets alike. In particular, on the day of the referendum (23 June 2016) the financial markets were believed to have priced in a *remain* vote. In order to account for changes in the common risk factor returns, I use stocks' abnormal returns on June 24, 2016. All results remain both qualitatively and quantitatively robust to using raw returns and shorter (overnight) and longer (Friday and Monday after the referendum) response windows. First pass analysis of such constructed exposure measure shows that the response to the Brexit shock was much stronger in the leaver's cross-section and rather limited in the rest of the FTA block. The median CAPM-adjusted return on Friday after the referendum was -9% in the UK but only around -1% in the rest of the block. This discrepancy is even more pronounced when one extends the response window to include Friday

and Monday after the referendum with the cumulative abnormal return of -13% and -1% for the UK and the European Union cross-sections, respectively.

I use data on geographic attribution of firms' revenue to explain the cross-sectional heterogeneity in the exposure measure identified as outlined above. For the firms in the UK cross-section, it is the share of revenue derived from the European Union that is the strongest driver of the magnitude of the negative response to the referendum. Moreover, this effect is fully concentrated in the services sector firms. This is in line with the *no-deal* for services outcome eventually reached by negotiators in December 2020 (remarkable four and a half years *after* the vote itself). For the companies in the European Union cross-section, the magnitude of the negative response is increasing in the share of firm's revenue derived from the United Kingdom. However, both the magnitude and statistical significance of this relationship are weaker than these of the corresponding relationship identified in the UK cross-section of companies. Finally, while deriving revenue from the rest of the world has an attenuating effect on the responses of companies in European Union, it does not act as a similar hedge for firms listed in the United Kingdom. This is indicative of investors' expectations that by leaving the EU the United Kingdom would lose access to EU-negotiated free trade agreements with third countries and/or will struggle to replace them with commensurate agreements of their own.

In the final part of the paper, I show that the exposure to the Brexit shock not only mattered immediately after the referendum but also continued to have a differential impact on stocks' performance in the two regions throughout the withdrawal negotiations which have followed the vote itself. To this end, I construct a so-called Brexit-mimicking portfolio which tracks the latent Brexit shocks over time. This feature of the portfolio is particularly important for the analysis that follows because no single asset exists that would allow me to cleanly identify such shocks otherwise. In order to quantify the contribution of these latent shocks to the aggregate European stock market, I regress the returns to various European indices on this synthetic Brexit mimicking portfolio. I find that it has explanatory power for *all* European indices considered. The uncovered relationships are, however, different for the UK and the EU indices. While all the analysed EU indices exhibit a significantly positive relationships with the Brexit mimicking portfolio, the corresponding relationship for the UK ones is significantly negative. Moreover, the magnitude of the negative relationship in the UK is about six times larger for the FTSE 250 index than it is for the FTSE 100 one. Since the former comprises stocks with more of a local UK economy than international focus, the results seem

to suggest that the withdrawal from a Free Trade Agreement had more of a negative impact on the UK equity prices than these of the EU.

Paper 2: Sources of Return Predictability.

The second chapter, *Sources of Return Predictability*, develops an approach to determine whether return predictors commonly documented in the literature are proxies for fundamental risk or not. This is a co-authored chapter with Mungo Wilson and Pavel Savor. In the analysis we build on the well-established literature documenting differences between stock market's behaviour on days when important macroeconomic news is scheduled to be released onto the market and the remaining days. We show that stock return predictors forecast returns accrued on either announcement (A-) or non-announcement (N-) days but never on both types of days. In particular, empirically discovered return predictors forecast non-announcement day returns only. On the other hand, theory-backed predictors for which research has historically failed to document an empirically robust relationship with stock market returns forecast announcement day returns only. The paper further shows that the Shiller's excess volatility puzzle is predominantly a non-announcement day puzzle. Taken together, these results suggest that known return predictors forecast the excess volatility component of stock market returns.

Our identification strategy builds from the intuitive assumption that in order for the predictors to be fundamentals-related they have to forecast the share of returns accrued on days when information about these future fundamentals (inflation, unemployment, and Federal Open Market Committee (FOMC) interest rate decisions) is released onto the market. These days, we hypothesise, coincide with the so-called announcement days (i.e. days when macroeconomic news is scheduled to be released).

Using regressions of quarterly returns (aggregated separately for A- and N-days) on return predictors, we find that widely-used return predictors such as log price/dividend ratio, treasury bill yield, investment-to-capital ratio, equity issuance, term spread, default return spread, and consumption-to-wealth ratio forecast future returns accrued on N-days but not on A-days. On the other hand, the lower bound on equity premium and stock return variance predict returns accrued on A-days but lack the predictive power for the N-days component.

The predictability dichotomy discovered indicates that: (i) the announcement and non-announcement days are indeed different with respect to their information content and (ii) the predictors can be easily grouped into these linked to economic news and these that are not. All in all, these results indicate that the sources of predictability do indeed differ between predictors.

We build on the above results while revisiting the 1980s excess volatility puzzle. This well-documented phenomenon posits that observed price movements cannot be justified by changes in subsequent fundamentals. In particular they cannot be justified by the changes in the present value of subsequent dividends. Our analysis shows that this statement, while true for changes in prices realized on non-announcement days, is not correct for changes in prices realized on announcement days. Multivariate regressions of quarterly changes in fundamental value (present value of future discounted dividends) on quarterly returns accrued on announcement and non-announcement days show that the excess volatility puzzle is overwhelmingly a non-announcement day puzzle.

All in all, the results indicate crucial differences between announcement and non-announcement days. While returns accrued on announcement days are fundamentals-driven, explained by the amount of physical risk in the economy, and justified by subsequent changes in fundamental value (discounted stream of dividends), the ones accrued on non-announcement days are not. The fact that the latter are forecast by a wide range of predictors suggested in the literature indicates that these predictors do in fact forecast the excess volatility component of stock market's movements.

Paper 3: Old wine in new bottles? Are industry risks (still) not understood?.

The third chapter, *Old wine in new bottles? Are industry risks (still) not understood?*, shows that industry indices globally are capable of consistently explaining away large shares of international factor and geographic risk premiums. This in turn indicates that these various risk premiums credited to the existence of corresponding risk factors are in fact just combinations of at present poorly understood industry-specific sources of risk. This paper outlines that this indeed is the case on the example of international Fama-French factors, dividend strategies recently discovered in the literature, and geographic zone risk factors.

Many risk factors capable of delivering excess returns over the market rate have been discovered by the empirical asset pricing literature since the 1990s and fueled the growth of corresponding literature focused on differentiating between the "true" and the redundant sources of risk. This paper aims to connect these various factor risk premiums with industry-specific sources of risk using the industry composition channel. I argue that under- and over-representation in the market return, front dividend strip, and certain characteristic-sort portfolios interplay to give rise to what econometrics later on identifies as characteristics-related and dividend risk premiums. If, for example, certain industries are consistently of smaller/larger firm's market capitalization, their industry-specific risks will drive

the returns to portfolios built subject to the size sort. Same argument can apply to other sort portfolios and risk premiums.

I show that dividend strip strategies, commonly used size and value premiums, and geographic zone factors premiums are, to non-trivial extent, driven by industry-specific sources of risk. This is as industry indices are able to consistently explain away large shares of variation in these risk premiums.

The remainder of the thesis is organised as follows. Chapter 2 summarizes the various strands of literature on which this thesis builds. Chapter 3, Chapter 4, and Chapter 5 correspond to my first (*Mind the (Trade) Gap! Stock Market Implications of Barriers to Trade*), second (*Sources of Return Predictability*), and third (*Old wine in new bottles? Are industry risks (still) not understood?*) papers. Chapter 6 concludes by outlining the implications of this work and suggesting directions for future research.

2 | Literature Review

This thesis builds on the market efficiency literature started by Fama (1970). It argues that information revealed to market participants is timely discounted into asset prices. I use this hypothesis to address three distinct problems in the empirical asset pricing literature: impact of Free Trade Agreements on stock prices (Chapter 3), sources of return predictability (Chapter 4), and time-series variation of risk premiums (Chapter 5). In what follows, I review the literature relevant from the perspective of each of the chapters and how the chapter contributes to that literature realm.

Paper 1: Mind the (Trade) Gap! Stock market implications of barriers to trade.
This chapter contributes to three strands of literature: (i) the impact of economic and financial integration, (ii) policy and political uncertainty, and (iii) economic tracking portfolios literature.

First and foremost the chapter focuses on the impact of Free Trade Agreements on asset prices. Until recently this strand of literature has focused on the positive impact of financial and economic integration (Bekaert et al., 2013). Recent developments and crises have allowed for more analyses from the disintegration point of view (Kremens, 2018). This chapter focuses on the impact of the departure of United Kingdom from the European Union on stock prices in the two regions. A lot of theoretical insights on the matter have been generated immediately after the referendum (Sampson (2017), Dhingra et al. (2017)). This chapter lays out empirical evidence on the impact the referendum vote and the withdrawal negotiations that have followed have had on asset prices in both regions.

Second of all, the chapter contributes to literature on the impact of political and policy uncertainty on asset prices. Theoretical frameworks underpinning the importance of such relationships have been on the rise following the Great Recession (Pástor and Veronesi (2012), Pástor and Veronesi (2013)). Studies looked into the impact of election outcome uncertainty (Julio and Yook (2012), Jens (2017)) and

various other one-off events of political relevance (Liu et al. (2017) and Wagner et al. (2018)). This chapter studies the impact of trade policy uncertainty on individual companies and geographic risks.

Finally, the chapter adds to the economic tracking portfolios literature initiated by Breeden et al. (1989). Throughout the years (Lamont (2001), Back et al. (2013)) this strand of literature aimed to connect assets' performance with various economic variables and measure the risk premiums associated with the variation in these variables. This chapter shows that the methodology can be used to measure the extent to which political uncertainty is embedded in asset prices. In particular, it can be used to construct measures of single-event political uncertainty and trace their relevance for assets' return over time. This is what this chapter does.

Paper 2: Sources of Return Predictability.

This paper builds on and contributes to two main strands of empirical asset pricing literature: (i) stock market predictability and (ii) differences in stock market behaviour on days when macroeconomic news is scheduled to be released to the market (announcement (A-) days and remaining days (non-announcement (N-) days).

Stock market predictability literature has been growing over the past decades with many variables found to be able to predict future stock market returns (Campbell (1996), Cochrane (1991), Baker and Wurgler (2000), and Lettau and Ludvigson (2001) among others). At the same time, variables which according to theoretical asset pricing models should be capable of forecasting future returns fail to do so (Savor and Wilson (2014), Guo (2006)). This paper develops an approach to determine sources of this return predictability i.e. whether these particularly successful return predictors represent proxies for fundamental risk or not.

The above approach to determine the sources of return predictability builds on the literature which revisits differences in the behaviour of asset prices on A-days and N-days. Existent literature shows that Capital Asset Pricing Model holds on the former but not on the latter type of days (Savor and Wilson, 2014). The same applies to the expectations hypothesis (Brooks et al., 2018). This chapter shows that this is as the returns on A-days (but not N-days) are in fact driven by future fundamentals. It then goes on to use this crucial difference between returns on these two types of days to determine sources of return predictability.

Paper 3: Old wine in new bottles? Are industry risks (still) not understood?.

The third chapter builds on the extensive literature on international and geographic risk premiums and the drivers thereof.

Starting with size and value premiums (Fama and French, 1992) empirical asset pricing has delivered prolific evidence of risk factors driving assets' excess returns. The continued growth of this literature has led to the coining of the "factor zoo" term (Cochrane, 2011) and triggered interest in determining which ones were "true" and which ones redundant. Similarly, exposure to certain geographic zones has been considered more risky than exposure to others (Dumas et al., 2020). Finally, dividend strip strategies (strategies build in order to hold the risk of exposure to the stream of dividends paid by the market index over a certain period of time (Binsbergen et al., 2012)) have also been found to deliver superior excess returns which can not be explained away by their exposure to systematic (market) risk.

The way this chapter contributes to this realm of literature is by showing that the existence of many international, geographic, and dividend risk premiums may in fact be driven by and related to the interplay between various industry-specific risks which the empirical asset pricing field has struggled to properly understand till date.

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3 | Mind the (Trade) Gap! Stock Market Implications of Barriers to Trade

*

The Brexit referendum disrupted global trade: the UK's exchange with the EU and numerous third countries would suffer. Relative stock prices reacted accordingly with the damage greater and longer-lasting for the UK than the EU. UK-focused manufacturing fared worst in both regions. The UK's EU-exposed services firms were also impacted – the market correctly expected December 2020 "no-deal" outcome for that sector. Third-country exposure attenuated the shock's impact on EU but not UK companies. Consequently, the UK zone factor underperformed the old-EU one by 20 pp between 2016 and 2019. Brexit exposure high-low portfolio explains 70% of the time-series variation in this underperformance. Overall, the results showcase the impact of leaving a free trade agreement on firm and country business risk.

1 Introduction

'Maybe we're going to lose some Prosecco; you're going to lose some fish and chips exports. The difference is I'm going to lose [exports] to one country, you toward 27.'

Carlo Calenda, Italy's economic minister describing a talk with Boris Johnson on the preferred Brexit outcome, Bloomberg TV, November 2016

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Rare political events and policy shifts have the potential to disrupt financial markets and to significantly change international economic equilibria. While the latter respond slowly, the response of the former is remarkably swift and sensitive to the arrival of new information. As a result, the stock market response to these events can shed light on their expected economic impact, particularly when the event is unexpected. This type of rare and unexpected event occurred in June 2016 when the United Kingdom (UK) public voted in a referendum[1] to leave the European Union (EU). The UK's "leave vote" and the protracted negotiations that followed offer a unique setting to analyze the impact of the detachment of the second largest EU (and fifth globally) economy from the world's largest trading block and second largest territory by GDP.

Historical research on the benefits of joining trade unions has been troubled with endogeneity concerns. This is because the emergence of trading blocks and accession to existing ones is likely to be driven by geographic proximity and trade gravity. For example, central European countries joining the European Union had pre-existing trading relationships with the block – a fact, which could potentially lead to underestimating the benefits of accession. On the other hand, countries which severed trading ties with trading unions they partook in have in the past century overwhelmingly done so on the wave of de-colonization. This could likely lead to overestimating the benefits of participation as the estimate could confound the impact of other concerns related to de-colonization. Analysing the cost of leaving a trading union using the example of Britain's departure from the European Union offers the opportunity to avoid both of those issues.

This paper studies the impact of the UK's decision to leave the EU on stock prices in the EU-15[2] region. Britain's decision to leave was popularly referred to as "Brexit". It was unprecedented and yields a unique opportunity to study the

[1]United Kingdom European Union membership referendum.

[2]EU-15 area countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom.

relative winners and losers from such an outcome. Furthermore, it was completely unanticipated on the day of the referendum by betting and financial markets alike.[3] I take advantage of these characteristics of the Brexit referendum to: (i) investigate the impact of potential economic disintegration on European companies and (ii) show how financial market data can be used to identify in real-time the importance of single-source political uncertainty for asset prices.

I explore the cross-sectional heterogeneity in performance of EU-15 stocks both in the short (the week following the referendum) and in the long (July 2016 – December 2019) run. My analysis yields two important results. First, I show that the consequences of the "leave" vote weighted most profoundly on stock returns in the UK and somewhat strongly on those of its neighbouring countries (in particular Ireland and the Netherlands). At the same time, despite numerous projections to the contrary, it did not have a significantly negative impact on other EU economies. In Germany and France – the two largest economies of the post-Brexit EU – the response of the equity market is not significantly negative when adjusted for common risk factors. Secondly, I show that Brexit-related shocks keep on affecting most negatively mainly the UK geographic risk in the post-referendum period. A Brexit-mimicking portfolio – a portfolio that tracks unobservable Brexit shocks over time – correlates positively with EU-14[4] aggregate stock market returns, while its relationship with the aggregate UK stock market is significantly negative. Geographic factors constructed using GeoRev revenue data of companies further corroborate these result. A Brexit mimicking portfolio explains up to 70% of the under-performance of the UK factor with respect to that of the EU-14 region between July 2016 and December 2019. Both of the results above suggest that the stock market expected the harm to be larger for the leaver's economy than

[3]The *Remain* odds were estimated at between 76% and 84% on June 23, 2016 according to the *Financial Times*.

[4]EU-14 area countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, and Sweden.

for the other economies of the free-trade block.

The announcement of the Brexit referendum result triggered a strong negative response in the cross-section of European stock returns. On the day when results were announced after the referendum, the UK and the EU-14 stock markets lost 13.5% (350 billion USD) and 8.0% (500 billion USD) of their value, respectively. This was a profoundly negative shock to the European stock market: June 24, 2016 was the third lowest (-8.8%) daily return on the European Fama-French market factor since July 1990 when the records of returns to European factors began.[5] This is in line with theories of political uncertainty that foresee a negative stock market reaction to potential policy shifts (Pástor and Veronesi, 2012). The negative response is pervasive across all EU-14 and UK industries but is strongest for UK services. This is consistent with projections by Sampson (2017) and Dhingra et al. (2017), who point out that none of the arrangements the EU had with third countries historically would allow for cross-border provision of services with such ease as membership in the single market had done. Overall, the UK services sector lost 16.6% of its value on June 24^{th} compared to a loss of "only" 8.0% by the manufacturing sector. I find no such discrepancy for EU-14 countries, where the services and manufacturing sectors lost 9.3% and 6.8%, respectively. Geographic factor returns further confirm the different impact of the Brexit shock on the leaver and the rest of the block. The UK zone factor recorded a one-day loss of 21% on Friday after the referendum and a cumulative loss of 35% till Monday after. The losses for the EU-15 factor over the same period were 7% and 14%, respectively.

To account for the changes in common risk factor returns, I measure each individual stock's exposure to Brexit by its abnormal return on June 24, 2016, when the results of the Brexit referendum were announced in the early hours of the morning. The analysis of these abnormal returns shows that the response was strongest in the UK and surprisingly limited in the rest of Europe. The median

[5]Lowest one was March 12, 2020: -12%, and the second lowest: October 6, 2008: -8.98%.

CAPM-adjusted return on the day was -8.7% for the UK cross-section and -0.6% for the EU-14 one. I use data on geographic attribution of firms' revenue to explain these abnormal returns patterns. The share of revenue derived from the EU is the strongest driver of UK firms' negative response to the referendum result. Furthermore, this effect is fully concentrated in the services sector in line with the "no-deal for services" outcome eventually reached by negotiators in December 2020. In the EU, the negative response is increasing in the share of revenue derived from the UK but the strength of this relationship is weaker than in the UK. Finally, while deriving revenue from the rest of the world had an attenuating effect in the EU cross-section, it did not act as a similar hedge in the UK one.

The discrepancy between the responses of the two cross-sections is even more pronounced when I consider the cumulative abnormal return on both Friday (June 24th) and Monday (June 27th) following the referendum, with CAPM-adjusted cumulative returns of -12.8% and -1.0% for the UK and the EU-14, respectively. This shows that the consequences of the referendum result were not priced immediately: the market appeared to need time to process the expected impact of Brexit on European stocks, perhaps because market participants had little immediate understanding of the way in which the UK could disentangle itself from the EU and the alternative trading arrangements that it could adopt. It also suggests that it would be useful to look into long-term implications of the varying degrees of exposure to Brexit for European stock returns.

To see if Brexit exposure matters for stock returns in the *three and a half years post referendum*, I sort individual stocks into quantile portfolios based on their CAPM-adjusted return on June 24, 2016. I then construct a strategy that is long the relative Brexit winners portfolio and short the relative Brexit losers one. Using risk neutral probabilities sampled from GBP option prices, I identify two different regimes and show that such constructed strategy has different risk premium in each of these. The two regimes are defined subject to the daily change in the risk

neutral probability of no-deal Brexit (Δp), which in turn is approximated by the amount of risk-neutral probability assigned by the options market to a depreciation of the British Pound below 1.3 USD three months from a given date. On days when this probability is substantially increasing (*High* Δp regime, which identifies top quarter of all daily changes over the three and a half years) the strategy has a positive return of approximately 48 bps when constructed using stocks in the UK cross-section and 13 bps when constructed using those in the EU-14. Both of these are statistically significant. Conversely, on days when the risk-neutral probability of no-deal Brexit is substantially decreasing (*Low* Δp regime; bottom quarter of daily changes) the strategy has a significant negative return of 38 bps in the UK; in this case, the return in the EU-14 cross-section is not statistically different from zero.

The above results suggest that Brexit exposure is a material driver of European stocks throughout the post-referendum period. The relative Brexit winners (losers) consistently over-perform relative Brexit losers (winners) when the risk neutral probability of no-deal Brexit increases (decreases). This trend is more pronounced in the UK than it is in the EU-14. Furthermore, performance attribution of the long-short portfolio to the three standard Fama-Frech factors reveals that while the returns to this strategy are subsumed by the exposure to the three commonly used factors in the EU-14, the same is not the case in the UK, and the strategy constructed using UK stocks earns a premium conditional on the change in the risk neutral probability of no-deal Brexit that the three factors can not explain.

Having confirmed that Brexit exposure has been a driver of the European cross-section of stock returns in the post-referendum period, I examine the expected return to holding a unit of such exposure. I show that, as expected from the above analysis, its value is conditional on the changes in no-deal Brexit probability. While positive when the probability of Brexit is increasing, it switches to negative when this probability is decreasing. This is confirmed by both regular second-stage Fama-MacBeth and pooled OLS regressions across various European cross-sections.

Irrespective of the method, the magnitude of the relationship in the UK is double that in the EU-14. While absent in some European economies (Germany and Italy, for instance), it is present in those with closer geographic ties to the UK (the Netherlands, Ireland, Denmark, and France).

Finally, to quantify the contribution of the Brexit premium to the aggregate European stock market, I regress the returns to various European indices on that of the Brexit mimicking portfolio. This portfolio is a synthetic asset, which tracks the sequence of unobservable Brexit-related shocks over time and is a characteristics pure play portfolio in the sense of Back et al. (2013). In a nutshell, the portfolio goes long (short) relative Brexit winners (losers) while keeping a zero average exposure to other commonly used risk factors. Such a portfolio is particularly useful because no single asset exists that would allow me to cleanly identify these shocks otherwise. I find that throughout the post-referendum period the Brexit mimicking portfolio has explanatory power for all European aggregate indices considered. This relationship is, however, visibly different for the UK than it is for the EU-14. EU-14 assets (both on the whole and in the individual national cross-sections) show a significantly positive relationship with the Brexit premium. The corresponding relationship for the UK ones is significantly negative. Furthermore, the magnitude of the negative relationship in the UK is six times larger for the FTSE 250 than it is for the FTSE 100. Since the former index comprises companies with a primarily UK focus, while the latter is more international exposure heavy, the results seem to suggest that Brexit is more of a hit to the local UK than the EU economy. Revenue-based geographical zone factors corroborate these findings. Approximately 70% of the under-performance of the UK factor compared to the EU-14 one between July 2016 and December 2019 can be explained by the Brexit premium alone.

The rest of the paper is organized as follows. After the literature review, Section 2 provides a brief background of the Brexit referendum and its consequences. Then, Section 2 presents the data used in the analysis. In Section 4, I discuss the empirical

results for the immediate response of the European stock market to the Brexit shock. In Section 5, I turn to long-run implications of Brexit exposure for stock returns. Finally, Section 5 concludes.

Literature Review

This paper contributes to three strands of literature. First, it relates to vast number of studies of *the impact of economic and financial integration*. Given the lack of disintegration impulses, until recently this field has been dominated by literature on the consequences of integration. Bekaert et al. (2013) show that EU (but not eurozone) membership has facilitated integration between 1990 and 2007, significantly lowering cross-country discount rate and expected earnings growth differentials. With recent political developments comes the opportunity to investigate the impact of (potential) disintegration. Kremens (2018) studies the impact of possible eurozone exit by France or Italy on European sovereign yields and the risk of eurozone breakup and shows that while an exit by Italy would be isolated, one by France would trigger a eurozone dissolution. Meanwhile, the Brexit vote creates a novel opportunity to look into the impact of erecting fresh barriers to trade. Sampson (2017) offers a clear-cut overview of the political and social dynamics behind the referendum itself and the ultimate *Leave* outcome. He also outlines the possible post-Brexit arrangements available to the UK and their impact on GDP per capita for various EU economies. Referred in Sampson (2017), the study by Dhingra et al. (2017) deserves particular attention. Using a computational general equilibrium trade model, its authors show that UK's fiscal savings will not make up for the efficiency losses UK will suffer as a result of higher trading barriers neither in the optimistic (when UK remains in the Single Market) nor the pessimistic (with trade conducted under the World Trade Organisation terms) scenario. Given these estimates Brexit should have repercussions for firms globally. Using survey data, Bloom et al. (2019) show that the reduction in investment and decrease in productivity of UK companies starts long before the actual exit from the

EU. Hassan et al. (2020) document the influence of Brexit uncertainty on US firms and show that these more exposed to Brexit experienced substantial drops in market value and scaled back both hiring and investment. Davies and Studnicka (2018) and Breeden et al. (1989) study the heterogeneity of Brexit's impact on UK firms' prices to infer the consequences of the Brexit vote on investors' expectations. The former paper shows that the stock market has swiftly incorporated Brexit's impact on supply chains of FTSE 350 firms. The latter work shows the stock market reaction was driven by the expectations of an economic slowdown in the UK. I contribute to this strand of literature by exploring further drivers of the heterogeneity of stock responses to the Brexit shock in the UK and the EU. Furthermore, I document the differential impact of this shock on the leaver and the rest of the block and on the services and manufacturing firms in both regions.

Secondly, this study relates to literature connecting *policy and political uncertainty* with asset pricing and real economy outcomes. The relevance of those relationships has attracted significant attention in the aftermath of the Great Recession and multiple attempts have been made at quantifying both the amount of such uncertainty present in the economy and its consequences. Pástor and Veronesi (2012) use general equilibrium framework to show that stock prices experience a significant drop in value following announcements of potential policy changes by the government. They also show that the channel through which political uncertainty attracts a risk premium is the decrease in the value of the "implicit put" protection the government provides to the market (Pástor and Veronesi, 2013). Kelly et al. (2016) empirically corroborate those findings using equity option markets. Additional research throughout the years showed that policy uncertainty affects inter alia: merges and acquisitions at both macro and firm levels (Bonaime et al., 2018), firm-level capital investment (Gulen and Ion, 2015), and credit spreads and borrowing costs (Kaviani et al., 2020). Uncertainty about election outcomes has also been found to matter for firms' decisions. Using international cross-section,

Julio and Yook (2012) show firms reduce investment in election years as they wait for the electoral outcome uncertainty to be resolved. Jens (2017) shows that gubernatorial elections have similar impact on US firms and that the companies delay both equity and debt issuance before such elections take place. One-off events that heighten political uncertainty have also been found to be reflected in the cross-section of stocks valuations [Liu et al. (2017) and Wagner et al. (2018)]. This paper contributes to this literature by studying the impact of trade policy uncertainty on individual companies and geographic risks.

Finally, the paper adds to the *economic tracking portfolios literature*[6] [Breeden et al. (1989), Lamont (2001), and Back et al. (2013)]. This strand of literature connects assets performance with various economic variables and is commonly used to identify and measure risk premiums associated with various factors. However, regardless of whether they have statistically significant non-zero returns (premia), these portfolios can still serve two important goals: to hedge particular sources of risk and to track daily market's expectations of economic variables (Lamont, 2001). Some notable applications of this methodology include: Gilje and Roussanov (2016) using it to track latent technological innovation shocks and Engle et al. (2020) constructing portfolios hedging climate change risk. This paper contributes to this strand of literature by showing that the methodology can be used in the political uncertainty realm to construct measures of single-event political uncertainty and trace its importance for asset pricing relationships over time.

[6]Known also as *characteristics pure-play* or *factor mimicking* portfolios.

2 Institutional setting and hypothesis development

In 2013 the then UK prime minister David Cameron promised he would put the UK's membership in the European Union to a referendum by the end of 2017. This promise has been made in the face of rising support for the UK's Independence Party among historically Conservatives-voting electorate. Such a political sympathies' shift had the potential to threaten Conservatives' 2015 re-election in the first past the post electoral system of the United Kingdom. The referendum took place on June 23, 2016. A wafer-thin margin was expected. That it would be for the "leave" vote was not. By December 2019 the UK would have seen early elections, two new prime ministers, and numerous extensions to the final departure date.

The future shape of the UK-EU relationship was unclear when the referendum result was announced. It was, however, expected that once out of the EU, the UK would face increased barriers to trade with the EU and numerous territories covered by EU's free trade agreements. In an optimistic scenario UK would swiftly replace the latter by its own, a task with questionable feasibility given it has not negotiated one as a stand-alone entity for decades.[7] Furthermore, free trade agreements with third countries would weight onto the type of relationship UK could develop with the EU. Such considerations highlight the importance of striking the right balance between global openness and maintaining an efficient trade relationship with the geographically closest partner.

In the light of the above, the decision to leave the EU constituted a significant policy shift with regards to free exchange of goods, services, capital, and labour between world's fifth largest economy (UK) and largest trading block (EU). Such a policy shift would trigger a negative reaction of financial markets as investors

[7] O. Letwin, *The UK has no trade negotiators, says former Brexit minister*, 15 July 2016.

would require to be remunerated for holding the related policy uncertainty risk (Pástor and Veronesi (2012), Pástor and Veronesi (2013)). Hence:

Hypothesis 1: *Announcement of the referendum result triggers a decline in EU15 stock prices.*

Sampson (2017) provides a thorough summary of the alternative arrangements available to the UK after withdrawing from the EU and a detailed description of border and behind-border barriers to trade in each scenario. Here, I briefly outline the options available:

- *European Economic Area* (EEA) membership – an option opted for by Norway, Iceland and Lichtenstein – would allow free trade in goods and services between the UK and the EU. It would also permit the UK to sign free trade agreements with third parties (as EEA membership does not require partaking in EU's customs union). It would, however, demand contributions to the EU budget and erect some barriers to trade compared to EU membership. Furthermore, it would require free movement of capital and persons to remain in place.

- Turkey-style *customs union* would eradicate tariffs and some barriers to trade. It would, however, preclude the UK from signing free trade agreements with other countries and do nothing to allow free provision of services.

- *Free trade agreement* could allow for a more tailor-made solution. EU's existing ones, however, fall short of the Single Market access both in terms of economic regulation alignment and services provision. Switzerland is the most integrated with the EU non-EEA country and does effectively belong to the Single Market as far as goods exchange but not services provision is considered. This does, however, come at the cost of contributing to the EU budget and accepting free movement of labour.

- Without a new arrangement like the ones described above, UK-EU exchange

would take place on the so-called *World Trade Organisation (WTO) terms*. This would make UK goods exported to the EU subject to most-favoured nation tariffs and non-tariff barriers to trade. After years of advances in global goods trade liberalisation these terms would not be excessively detrimental to manufactured goods. Provision of services, however, would be subject to numerous barriers. Overall, WTO would be the most costly option for future trade relationship between UK and EU.

Regardless of which option from the above would be chosen as the basis for future relationship between EU and UK, it would likely lead to increased costs and (at least) some barriers to trade compared to full EU membership. The importance of curtailing immigration in the UK's political discourse and the desire for striking new trade deals with third nations would likely lead to these barriers and costs being on the higher end of the spectrum, especially with regards to services provision. In fact, for the latter Single Market access would be highly unlikely unless a tailor-made solution was agreed with UK in mind. In the light of the above:

Hypothesis 2: *In the UK (EU), the negative impact of the Brexit shock is increasing in the share of revenue the firm derives from the EU (UK). This effect is stronger for services firms than manufacturing firms.*

In 2015 UK exported (imported) 44% (53%) of its goods and services to (from) the EU.[8] As Sampson (2017) points out, in that year, the total value of goods and services exchanged between the two sides amounted to 12% and 4% of the GDP of UK and EU, respectively and UK's trade with the US – its second largest trading partner – was 3.2 times smaller than that with the EU. Consequently, the author argues, the UK-EU trade is more important to the UK than it is to the EU. General equilibrium trade simulations corroborate this thesis. Dhingra et al. (2017) show that Brexit would result in consumption per capita dropping by between

[8]UK Perspectives 2016: Trade with the EU and beyond; Office for National Statistics, 25 May 2016.

1.3 and 2.7 percent in the UK and between 0.14 and 0.35 percent in the EU in the long run. These numbers, according to the authors themselves, are likely an underestimate given the limitations of the trade models. For example: the UK would not partake in EU's future technological and productivity improvements. The above informs the final hypothesis:

Hypothesis 3: *Overall, the negative impact of the Brexit shock is stronger and longer-lasting for the UK than the EU.*

3 Data

At the core of the analysis lies a European cross-section of individual companies' stock returns. The sample covers common stocks with at least one common shares issue listed in an EU 15 country. I exclude penny stocks with a dollar price below 5 USD on the 23rd of June 2016 and stocks that could not be assigned to any industry according to either NAICS or SIC classification. I carry out the analysis using USD prices. This is to isolate the impact Brexit may have on firm price through the GBP depreciation channel. The results are robust to carrying out the analysis using local currency prices. Data on individual stock performance, country of exchange, and industry assignment comes from Thomson Reuters. Risk-free rate and the returns to the Fama-French three factors portfolios come from Professor Kenneth French's website.

Data on geographical attribution of firms' revenue between 2015 and 2019 comes from FactSet's Geographic Revenue Exposure ("GeoRev") dataset. The data is collected in March 2021[9] and the geographical attribution of the revenue is estimated by Factset. For each covered firm the dataset reports its revenue composition specifying the start and the end of the period to which such composition pertains,

[9]The collection date matters for the coverage as the author has only the subscription to the contemporary (but not historical) mappings of Factset's security IDs (*fsym_id*) to more commonly used ISINs. Given the proximity of the time period analysed in this paper this is unlikely to be an issue in this analysis.

the estimated percentage share of the revenue from each relevant country in the total firm's revenue for that period, and the confidence score for that estimate. A summary of the relevant variables from the Factset universe and an example output with comments are provided in Table 1.

The no-deal risk neutral probability proxy is calculated using GBP/USD options data with 3 months maturity. All the relevant option pricing data comes from Thomson Reuters' Eikon. FX options trading conventions differ from the ones observed in the stock market and finance textbooks. First of all, currency options' prices are customarily quoted in terms of implied volatility units (*vols*). Secondly, instead of quoting the price for different strike levels, FX options traders quote the price (in *vols*) for various levels of (usually forward) moneyness (delta). Finally, FX options don't expire on fixed dates in the month (f.ex 3rd Friday of the month for equity options). Instead, every day quotes for options with fixed-length (i.e. 2 weeks, 1 month, 3 months etc. from the given day) expiry dates are available. Thomson Reuters reports prices of GBP/USD call options (with deltas[10] 10, 15, 20, 25, 30, 35, 40, 45), put options (with deltas 10, 15, 20, 25, 30, 35, 40, 45), and for the ATM option (with delta 50). I use daily prices calculated by Thomson Reuters using quotes provided by its contributors. Domestic interest rate benchmark (USD Ice Libor) and foreign interest rate benchmark (GBP Ice Libor) also come from Thomson Reuters.

3.1 Summary statistics

Table 2 provides summary statistics for the cross-section of individual firms' common shares issues quoted in one of the EU-15 countries. I report the number of stocks in each cross-section, the quartiles, the minimum and maximum, and the average market capitalization of the issuances on three days: that of the referendum itself (Thursday, 23/06/2016) and the two trading days that followed (Friday and Monday, 24/06/2016 and 27/06/2019). Friday market capitalization data for Finland and

[10]FX options deltas are *forward* deltas.

Sweden is missing due to public holiday (Midsummer). Since the sample includes any primary common share issue quoted on one of the EU15 exchanges, the same company may show up in more than one cross-section. For example, Royal Dutch Shell PLC has two common shares issues with primary listings in the EU-15 – one of them quoted in Amsterdam (RDSa) and the other quoted in London (RDSb). The sample will consider the former to be part of the Dutch and the latter to be part of the British cross-section. Dual listing of either issue are not counted as part of any cross-section to prevent double-counting. Day-to-day drops in the values of the average and all quartiles of the national-level market capitalization are first-pass evidence of the impact the leave vote in the Brexit referendum has had on the stock market.

Figure 1 shows the implied volatility for the GBP/USD 3 months maturity ATM option and the delta-10 call and put options between January 2015 and December 2019. I observe pronounced spikes in the implied volatility around the Brexit referendum (June 2016), difficulties in ratifying the Withdrawal Agreement by the UK parliament (December 2018), and in the run-up to Prime Minister Boris Johnson's *do-or-die* first ultimate Brexit deadline of October 2019 – all of which introduced profound uncertainty about the future relationship between United Kingdom and the European Union including but not limited to the threat of no-deal Brexit.

4 Empirical results – the immediate response

4.1 Impact of the Brexit policy uncertainty shock

The Brexit referendum outcome has had an overwhelmingly negative impact on all EU-15 markets as shown in Figure 2. The exact impact varied depending on the length of the event window considered. Overnight[11], Greece and UK were most

[11]From Thursday close to Friday open.

impacted (experiencing losses of -19.5% and -19.3% of market capitalization on value-weighted basis, respectively), while Belgium and Luxembourg stock markets responded the least (-8.9% and -3.9%). Greece and UK are also the biggest losers (with -15.5% and -13.5%) when I consider the medium-length response window of Friday, 24th of June. During that window Denmark and Luxembourg were least affected (-5.6% and -5.9%). Finally, when the longest Friday through Monday event window (24th – 27th June) is considered, Ireland and the UK loose over a fifth of their market capitalization (-23% and -21.5%), while Belgium and Denmark loose the least (-9.8% in both cases). Overall, the negative reaction is between 13.5% and 21.5% for the UK and between 8% and 13% for the rest of EU-15 depending on the response window considered. Finally, (except for Portugal) the response has been stronger for larger stocks in each cross-section as evidenced by more negative value-weighted than equal-weighted returns. [***H1, H3***].

Figure 3 and Figure 4 zoom in on the relative response of manufacturing and services industries in the UK and the rest of the EU-15 region during the medium-length response window of the 24th of June. I present value-weighted returns for all industries that had at least 5 companies in the given region. The profound negative impact on the UK service industries is immediately evident. Out of the 30 UK service industries 13 record drops in value stronger than that of the entire UK market on the day (13.5%). This is compared to only 2 out of the 13 UK manufacturing industries. There is no similar discrepancy for the rest of the EU-15 region (EU15exUK), where 7 (6) out of the 37 (19) service (manufacturing) industries have experienced decrease in value stronger that that of the aggregate market of that cross-section (8%). The stronger impact of the referendum outcome is confirmed by the fact that on a value-weighted basis UK service industries lost 16.6% on the 24th of June compared to 8% loss of manufacturing industries. What makes this response even more important is the fact that the service industries' stocks account for 64% of the aggregate UK market capitalisation. The above

dichotomy is far less pronounced for EU-15 excluding UK stocks with services and manufacturing industries losing 9.3% and 6.8%, respectively with the market split approximately equally between the two (manufacturing makes up 51.8% while services make up 48.2% of the region's market cap). [***H2***].

Response of the geographic factors (constructed in line with Appendix A) zooms onto the impact of Brexit referendum on these regions' business risks. Table 3 summarizes the cumulative returns to these factors between 24/06/2016 and 01/07/2016. The results confirm far greater a shock to the risks of operating in the UK than in the EU. UK factor looses 20% on Friday after the vote with further sell-offs on Monday leading to 35% drop versus market-close on the day of the referendum. None of the two European Union factors shows similarly strong reaction. The EU14 (older members of the block) zone factor responds stronger than the EU13[12] (the more recent members) one in the Friday – Monday window with -14% and -8%, respectively. The other geographic factors record much less negative reactions. All factors recover over the course of the week that follows the referendum. The negative response of the UK factor, however, remains over 4 times stronger that that of European Union ones even in that longest response window [**H3**].

The results described in this section are consistent with all three hypotheses outlined in Section 2. In line with ***H1***, heightened policy uncertainty triggered by the Brexit vote resulted in an ubiquitous slump in the prices of EU-15 equities. This is true regardless of the length of the response window. Introduction of Brexit uncertainty has had an overwhelmingly negative impact on the region's cross-section of stock returns and it has been present across all countries, all industries and for vast majority of stocks. The negative response of geographic factors to the *leave* vote, indicating increased business risk of operating in Europe after Brexit, further corroborates *H1*. In line with ***H2***, the difference in the response between

[12]Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

service and manufacturing stocks in the UK seems to suggest that the former have been more affected by the vote. This is consistent with the claim that while manufactured goods may still make it relatively easily onto the Single Market under alternative arrangements, the same is unlikely as far as the provision of services onto that market by firms operating from the UK is concerned. In line with ***H3***, the loss suffered by the UK stock market is stronger than that of the EU-15 region. The loss for the former (latter) amounts to 13.5% (8%) on value-weighted basis on Friday after the referendum alone – an equivalent of 350 (500) billion USD of market capitalization wiped out in one day.[13] Geographic factors' reaction in the week after the referendum further confirms the more negative hit to the UK with the UK factor losing between 25% and 35% of its value and the European Union ones much less impacted on average.

4.2 Abnormal returns upon Brexit referendum

To remove the impact of overall risk aversion (transmitted through the market return) and in order to follow the consensus in the event study literature, I now turn to analysing the impact of the Brexit referendum on the cross-section of stock returns using the abnormal returns methodology [Campbell et al. (1997) and Brown and Warner (1985)]. Since the stock market needs time to process all the available information and its implications for the various industries and individual stocks alike, I analyze two types of abnormal returns: abnormal return on the Friday following the referendum (i.e. from the market close on June 23^{rd} to the market close on June 24^{th}), and the cumulative abnormal return on Friday and Monday following the referendum (i.e. from the market close on June 23^{rd} to the market close on June 27^{th}).

To ensure robustness of the results to popular factors, I construct the abnormal

[13]The nominal value of the loss for the EU15 excluding UK region may be higher that that for the UK, but we have to bear in mind the former applies to 14 equity markets while the latter is suffered by the UK on its own.

returns with respect to two models: (1) the CAPM (market) model, and (2) the Fama-French three-factor (FF3) model. In order to calculate the *CAPM-adjusted* returns, I compute the market beta (β_i) of each stock using an ordinary least squares (OLS) regression of its daily stock returns in excess of the risk-free rate ($R^e_{i,t}$) on the excess return to the European stock market ($R^e_{m,t}$, as provided by Professor Kenneth French on his website) during the estimation window of the 52 weeks up to but not including the week of the referendum itself (i.e. between 22/06/2015 and 17/06/2016). I then compute the abnormal returns over the event window ($\tau = -3, -2, -1, 0, 1, 2$, where $\tau = 0$ is the Referendum day and non-trading days are excluded from the event window i.e. $\tau = 2$ is the following Monday). *CAPM-adjusted* abnormal returns are equal to the difference between the daily excess return on a given stock minus its market model beta times the market excess return:

$$AR^{CAPM}_{i,\tau} = R^e_{i,\tau} - (\hat{\alpha}_i + \hat{\beta}_i R^e_{m,\tau}).$$

To compute the *FF3-adjusted* returns, I compute each stock's factor betas using OLS regressions of its daily excess stock returns on the European market, size, and value factors over the estimation window specified above. I then obtain the *FF3-adjusted* abnormal returns as a difference between the daily excess return on a given stock minus the sum of its FF3 model betas times the corresponding factor returns:

$$AR^{FF3}_{i,\tau} = R^e_{i,\tau} - (\hat{\alpha}_i + \hat{\beta}^{CAPM}_i R^e_{M,\tau} + \hat{\beta}^{SML}_i R_{SMB,\tau} + \hat{\beta}^{HML}_i R_{HML,\tau}).$$

The two abnormal returns for the Friday following the referendum are denoted as $AR^{CAPM}_{i,1}$ and $AR^{FF3}_{i,1}$ for the market and the three-factor model, respectively. The cumulative abnormal returns for Friday and Monday following the referendum are defined as $CAR^{CAPM}_{i,1:2} = AR^{CAPM}_{i,1} + AR^{CAPM}_{i,2}$ and $CAR^{FF3}_{i,1:2} = AR^{FF3}_{i,1} + AR^{FF3}_{i,2}$.

Figures 5a and 5b plot some quantiles of the distributions of CAPM- and FF3-

adjusted returns in the 4 biggest EU-15 stock markets, the EU-15 stock market as a whole, and the EU-15 cross-section excluding UK (EU15exUK). Three things are immediately visible. First, the Brexit referendum shock has the strongest magnitude in the UK cross-section with vast majority of stocks experiencing negative abnormal returns for all four measures considered [***H3***]. Secondly, in the EU15exUK, French, German and Italian cross-sections the mean and median returns are higher for three-factor adjusted returns than they are for CAPM-adjusted returns. This suggests that the exposures to the SMB and HML factors play a role in explaining stocks' response to the leave vote with the corresponding factor returns of 1.8% and -2.06% on the 24^{th} June. Finally, the spreads of the abnormal returns increase greatly following the referendum and remain elevated for the whole week that follows. This indicates that the response of the cross-section was not immediate and the stock market needed some time to accurately process the Brexit vote and the relevant information released by the UK government that followed. In the next sections, I will show that the exposure to the Brexit shock (measured as the abnormal return upon the release of the information) was not only a material driver of returns in that following week, but also in the three and a half year period that followed.

Finally, I also assess the statistical significance of the abnormal return responses in the regional cross-sections. For each of the (cumulative) abnormal returns computed, I construct a t-statistic for the test that it is significantly different than zero. The computation of the relevant standard errors differs slightly depending on the length of the event window considered. For one-day abnormal returns $(AR^m_{i,1}, m = CAPM, FF3)$, I calculate the standard deviation in line with Brown and Warner (1985) as the standard deviation of the model-m adjusted returns over the estimation period. This is denoted as $std(AR^m)$ and the corresponding t-statistic is calculated as $t(AR^m_{i,1}) = AR^m_{i,1}/std(AR^m)$. For the cumulative abnormal returns $(CAR^m_{i,1:2}, m = CAPM, FF3)$, I compute the corresponding standard deviation $std(CAR^m)$ as $\sqrt{2} \times std(AR^m)$.

Figure 6 reports the share of statistically significant positive and negative abnormal returns under each of the two models for the two event window lengths considered. Under each abnormal return specification, UK and Ireland are the cross-sections showing the highest share of statistically significant negative returns with between 76% and 85% UK and 53% and 87% Irish returns significantly negative depending on the measure chosen. Greece follows closely after with between 53% and 60% of abnormal returns negative under the one-day event window specification. In turn, countries such as Belgium, Denmark, Germany, Netherlands, and Portugal exhibit high share of statistically significant positive abnormal returns especially when adjusted for the three-factor model. Particularly in the case of two-day CAR, the share of positive returns far outstrips that of the negative returns in these five regions. None of the countries, however, has a share of significantly negative abnormal returns as high as that of the United Kingdom's cross-section [***H3***].

Figure 7 compares abnormal returns and their significance for United Kingdom's manufacturing and services firms. Figure 7a reports average and quantiles of the distribution of abnormal returns for UK firms in these two sectors using both CAPM- and FF3-adjusted returns. Abnormal returns on both Friday and Monday following the referendum are lower for the services firms' cross-section then they are for the manufacturing firms one. The differences are, however, not immediately visible to the naked eye. In Figure 7b, I compare the statistical significance of the abnormal returns in these cross-sections. Here, surprisingly, the results show that the share of significantly negative abnormal returns is higher for the manufacturing firms than it is for the firms in the services sector [***H2***].

The analysis of abnormal returns corroborates hypothesis ***H3***: negative impact of the Brexit shock was stronger for the UK-listed stocks than it was for those listed elsewhere in the EU15 block. As far as hypothesis ***H2*** is concerned, the insight from abnormal returns analysis is inconclusive. Abnormal returns are indeed lower for the cross-section of services firms on Friday and Monday after the referendum.

It is, however, the manufacturing firms' cross-section that has a higher share of significantly negative abnormal returns.

4.3 Explaining the abnormal returns patterns

This section examines the impact of firms' geographic revenue composition on their abnormal returns in the wake of the Brexit referendum. Table 4 presents the results from regression of individual firms' abnormal (CAPM-adjusted) stock returns on Friday following the referendum on combinations of the following variables: the GeoRev-reported source of firm's revenue derived from the UK (rev_{UK}), the (full) EU (rev_{EU}), and the rest of the world (rev_{ROW}) in 2016; a dummy variable identifying firms classified as providing services under the NAICS classification (I_S); the interaction between this dummy and source of revenue variables. Control variables are the sensitivity of the firm's return to the changes in the value of the local currency versus the dollar (β_{FX}) and company's size (lnMktCap). Industry fixed effects present in some regressions are constructed in line with the GICS Industry Group Name classification (24 Industry FEs). Panel A and Panel B report the results for stocks with their primary listing in the United Kingdom and the EU14, respectively.

In the UK, firms experience an abnormal stock return of -8.45% on average (unreported regression on a constant alone). Deriving revenue from the EU has a negative impact on abnormal stock returns with the latter dropping between 37 and 48 bps when the share of EU revenue increases by 10 percentage points (Models 2 and 4) while keeping UK revenue share fixed i.e this increase in EU revenue share happens at the expense of the share of revenue derived from the rest of the world. This negative impact of EU revenue share is fully concentrated in the services sector (Models 5 through 8). While manufacturing firms' abnormal returns are not impacted by increases in the share of revenue from the EU, the services firms abnormal return decreases by 54 to 63 bps when this share increases

by 10 percentage points. Deriving more revenue from the UK also decreases UK companies' abnormal returns with 10 percentage points increase in the share of UK revenue (while keeping EU revenue share constant) leading to a drop of around 51 to 54 percentage points in abnormal return. This impact, however, is fully concentrated in UK's manufacturing firms (Models 5 through 8). Finally, both the aforementioned effects may interact with each other. Such is the case when an increase of the firm's share of EU revenue happens at the expense of its UK share. This change leads to 51 bps $[10 * 0 - 10 * (-0.051)]$ and up to 3 bps $[10 * (0 - 0.054) - 10 * (0 - 0.051)]$ increase in abnormal return for manufacturing and services firms, respectively. All results are present in specifications with and without controlling for the influence of companies FX-beta and size, both of which by themselves are positive and statistically significant. In the interest of space, industry dummies are not shown here but the only significant one is a -7.5 coefficient on Consumer Durables and Apparel one (t-Stat of -2.29).

Stocks listed in the EU14 experience an abnormal return of -0.41% on average. Companies with higher share of revenue derived from the EU record lower abnormal returns. A 10 percentage points increase in the share of revenue from the EU (while keeping that of the UK constant) leads to approximately 30 bps decrease in abnormal return (Models 1 through 4) with the effect fully concentrated among manufacturing firms (Models 5 through 8). Deriving more revenue from the UK also decreases EU14 firms' abnormal returns by 100 bps for a 10 percentage points increase in the share of revenue derived from the UK (keeping the EU share fixed). This effect is stronger for manufacturing firms at around -160 bps than for services ones at -85 bps. Finally, if the increase in the share of the EU revenue happens at the expense of its UK revenue, the effects described above should be considered jointly. Such a change leads to a 139 bps $[10 * (-0.021) - 10 * (-0.160)]$ and 64 bps $[10*(-0.021+0)-10*(-0.160+0.074)]$ increase in abnormal return for manufacturing and services firms, respectively. As in the UK case the results hold in the presence

of FX-beta as a control. Unlike in the UK, many industry FEs are negative.[14]

All in all, abnormal returns indicate that the negative impact of Brexit-induced severance of economic ties is much stronger for the UK- than the EU14-listed companies [**H3**]. A hypothetical 1bln USD market cap UK (EU14) manufacturing company with $\beta_{FX} = 0$ would record an abnormal return of -6.3% (-1.1%), -11.7% (-15.1%), and -5.6% (0.7%) if it derived all of its revenue from EU, UK, and the rest of the world, respectively. In the last case, the difference between UK and EU14 values shows that while exposure to the rest of the world acted as a hedge for the Brexit shock in the EU, it did not have a similarly attenuating effect on UK companies. This is intuitively straightforward if one realizes that upon exiting the EU, UK would lose access to the block's free trade agreements and would need to (swiftly) negotiate new ones. Furthermore, in line with Dhingra et al. (2017) and Sampson (2017), the impact of the policy shift is felt more negatively by UK services firms deriving revenue from the EU [**H2**]. Interestingly, for UK manufacturing firms deriving revenue from the EU Brexit is less negative a hit. This suggests that the market either expected an agreement between UK and EU to be feasible in this respect or the worst-case-scenario WTO trading terms not to be as detrimental to manufactured goods trading.

5 Empirical results – the 3.5 years that followed

The analysis presented so far has shown that the Brexit policy uncertainty shock has triggered a profound negative response across the EU-15 cross-section of stock returns as a whole and in the individual regional cross-sections. In what follows, I show that the exposure to the Brexit shock not only mattered immediately after

[14]These include Consumer Services (-4.5), Banks (-4.2), Commercial and Professional Services (-3.5), Insurance (-3.3), Real Estate (-2.5), Transportation (-2.4), Health Care Equipment and Services (-2.1), Media and Entertainment (-2.1), Consumer Durables and Apparel (-2.0), Diversified Financials (-1.9), Software and Services (-1.9), Retailing (-1.8), Capital Goods (-1.8), and Food, Beverage and Tobacco (-1.5).

the Brexit referendum, but was also a significant driver of the returns to the EU-15 stocks in a longer post-referendum period between July 2016 and December 2019.

5.1 Time-varying risk neutral probability of no-deal Brexit

Before proceeding to the usual analysis of the impact of exposure to a given source of risk and assets performance, one needs to realize that the probability of leaving the EU without an alternative agreement has been fluctuating significantly throughout the time period considered. As a result, at any point in time the return on a test asset is driven by the interaction of three variables: the change in the probability of a hard (no-deal) Brexit, asset's Brexit exposure, and the reward per union of exposure to the risk (the Brexit premium).

In order to trace the Brexit premium and its implications for asset prices over time, I therefore need a proxy for the changes in the no-deal Brexit probability. This is where the derivatives markets are useful since they allow one to make inferences about market expectations of future realizations of assets' prices and the probability assigned to the various outcomes by market participants. To this end, option prices are particularly handy since at any point in time a cross-section of options with various strikes can be observed for a fixed expiry date.

At a given point in time t, the price of an European call option is the risk-neutral expectation of its pay-off at expiry (T) discounted back to time t. This can be mathematically expressed as:

$$c(t,K,T) = e^{-r_{t,\tau}\tau} E_t^*[S_T - K]^+ = e^{-r_{t,\tau}\tau} \int_K^\infty (S_T - K) f^*(S_T) dS_T, \qquad (1)$$

where K is the strike of the option, $r_{t,\tau}$ is the risk free rate at time t for investment between time t and $T = t+\tau$, and $f^*(S_T)$ is the risk neutral density of the final pay-off.

The above suggests that one can extract the expected risk-neutral probability distribution of the price of the underlying asset at expiry time T from a cross-section

of call option prices. In fact, Breeden and Litzenberger (1978) show that:

$$\frac{\partial^2 c\,(t, K, T)}{\partial K^2} = e^{-r_{t,\tau}\tau} f^*(S_T) \tag{2}$$

i.e. the second derivative of the call option price with respect to its strike equals the discounted risk-neutral density function of the underlying asset's price. The derivation is the more accurate, the more closely spaced the strikes available. As any density function, the risk neutral probability distribution can be used to calculate the cumulative probability of the price of the underlying asset falling below a certain threshold. These can be used to approximate the market-implied probabilities of various events.

The exact steps that need to be followed in order to infer the risk neutral density using FX option prices are summarized in Appendix B. I implement these steps using 3-months-expiry daily GBP/USD option prices data between January 2015 and December 2019. The daily frequency comes here particularly handy as it allows me to trace the market response to various Brexit-related political developments reported in the news. Appendix C summarizes the behaviour of the risk neutral densities over the post-referendum period. It also reports the behaviour of the no-deal probability as approximated using the options market and shows how timely it incorporated the consequences of various events throughout the Brexit negotiations.

5.2 Brexit exposure: Brexit portfolios and Excess Returns

5.2.1 Univariate sorts: long - short portfolios

In order to investigate the importance of Brexit exposure for stock returns across the EU-15 region in the post-referendum period, I construct five Brexit portfolios in each regional cross-section. In these cross-sections, I assign each stock to one of the five porfolios depending on its CAPM-adjusted return on the 24th of June 2016. I

then obtain daily value-weighted returns for each of the portfolios between June 27, 2016 and December 31, 2019 using the USD issue capitalization on June 23, 2016 as weights. Table 5 reports the value-weighted excess returns to each of the portfolios for the 6 regions with at least 90 individual stocks in the given cross-section. P1 (P5) stands for the portfolio with the highest (lowest) exposure to the Brexit risk i.e. lowest (highest) abnormal return upon the referendum results' announcement. P5-P1 refers to the strategy that is long the lowest-exposure stocks and short the highest-exposure stock. Since, as mentioned before, not all days over the analyzed time period are equal with respect to the change in the probability in no-deal Brexit, I analyze the performance of the Brexit portfolios in each region conditional on the daily change in the probability of no-deal Brexit as implied by the FX options and calculated above. To this end, I split the entire time period between June 27, 2016 and December 31, 2019 into three regimes depending on the daily change in the NDP on that day. Low (High) refers to days, when the daily change in NDP was in the bottom (top) 1/4 of all daily changes in NDP in that period i.e. the probability of no-deal Brexit decreased (increased) the most. Medium refers to the remaining days.

The results show that Brexit exposure remains a material driver of European stock market returns in the post-referendum period. This relationship is particularly strong in the UK, where stocks with strong exposure to Brexit underperform (overperform) these with low exposure thereto by around 0.38% (0.48%) per day on days when the probability of Brexit increased (decreased) most - high (low) Δp regime. The magnitude of these two spreads is both economically meaningful and, as evidenced by the standard test for the difference in means, statistically significant. The impact of Brexit exposure is not limited solely to the UK, but also present (though to a lesser extent) in the rest of the EU-15 cross-sections. In the EU-14 one in particular, stocks with higher exposure to Brexit do overperfom these with lower exposure by approximately 0.13% in the low Δp regime. This spread is over 3 times lower than that for the UK cross-section. The magnitude of the

corresponding spread under the high Δp regime is 8 times lower and not statistically significant. This shows that while decreases in the probability of no-deal Brexit generated positive returns to European stocks and they did more so for stocks heavily exposed to Brexit, corresponding increases in the no-deal probability where not as profoundly reflected in the rest of Europe as they were in UK.

Bottom section of Table 5 shows, that although exposure to Brexit might not have mattered for EU-14 region as a whole, it still did constitute a relevant consideration for some national cross-sections. Here, the French one is particularly striking. Similarly to the UK, French P1 (P5) stocks overperform P5 (P1) stocks when the probability of no-deal Brexit is particularly decreasing (increasing). The magnitude of this relationship is economically meaningful though approximately three times lower than for corresponding UK portfolios. One sees that similar relationship is absent from the German cross-section and only present in the Italian one with respect to days with particularly strong decreases in the no-deal Brexit probability. Unreported results for the remaining cross-sections of at least 50 stocks suggest, the relationships in other regions mirror those of Germany (for Austria, Denmark, Spain) and Italy (for Belgium, Netherlands) rather than those of France.

5.2.2 Performance attribution

To test whether the P5-P1 spreads reflect different exposures to the known risk factors, as opposed to the differential impact of Brexit shocks, I carry out performance attribution of the Brexit portfolios in all regions to those factors using linear factor regression models. Table 6 reports the results of time-series regressions of the five Brexit portfolios and the P5-P1 one in each cross-section on the three-factor Fama-French model. I allow the alpha coefficients in these regressions to vary depending on the regime (with respect to the change in the probability of no-deal

Brexit, Δp) in which the given day falls. All in all, I am estimating the following:

$$r^e_{i,t} = \alpha + \alpha' I_{LOW} + \alpha'' I_{HIGH} + \beta_M r^e_{M,t} + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{SMB,t},$$

where $r^e_{i,t}$ is the excess return on a given Brexit portfolio ($i = P1, ..., P5, P5 - P1$), I_{LOW} (I_{HIGH}) is an indicator variable equal to 1 when the given day is in the bottom (top) 1/4 of all days in the post-referendum period with respect to the change in probability of no-deal Brexit (Δp); and $r^e_{M,t}$, $r_{SMB,t}$, and $r_{SMB,t}$ are the returns to the three Fama-French factors constructed using European stocks. Results are reported in Table 6.

For the UK cross-section, even after controlling for the three factors, there exists economically and statistically significant positive (negative) alpha for the individual (P1 through P5) Brexit portfolios under the low (high) Δp regime. Moreover the conditional alphas of the P5-P1 portfolio are also statistically significant and have the expected sign. Thus, the three factors of Fama-French do not subsume the importance of the Brexit exposure for the UK cross-section. The same is not true for the remaining cross-sections. In EU-14 as a whole, some of the α' (and erratically one α'') are significant, though their values are not monotonous. Furthermore, neither α' nor α'' are statistically different from zero for the P5-P1 portfolio. Among the remaining (unreported) cross-sections with at least 50 stocks, the Brexit spread P5-P1 is not subsumed by the three factors only in Italy and the Netherlands. Even there, only α' of the P5-P1 spread is statistically significant; α'' is not.

The above results show, that while the Brexit shock has had impact on the post-referendum performance of all European stocks, it has been far greater for the UK than for the EU-14. The impact it had on the EU-14 region firms is fully subsumed by the portfolios exposure to commonly used risk factors. The impact it had on the UK ones is not. Even though it is true that for the UK cross-section the magnitude of the conditional alpha coefficients is lower once controlled for the

factors compared to the univariate sorts, it is still economically and statistically significant. This shows that the impact of Brexit on the UK cross-section went beyond what can be explained by the exposure to commonly used factors [**H3**].

5.2.3 Manufacturing vs Services - differences?

In Section 4, I have addressed the fact that UK services industries were visibly more impacted by the announcements of the Brexit referendum results than UK manufacturing industries and both services and manufacturing industries in the EU-14 region. Given these different initial reactions, here I look into whether they had implications for the performance of stocks in these two sectors of the economy throughout the rest of the post-referendum period. To this end, I split the UK and EU-14 cross-sections of stocks into manufacturing and services and then conditionally on this assignment sort the stocks again into five Brexit portfolios as discussed above. Table 7 shows the returns to univariate sorts portfolios in both regions and sectors, while Table 8 presents the results of linear regressions of all these Brexit portfolios on the Fama-French three factor model.

As in the wider cross-section of UK stocks analyzed above, the results highlight strong relationship between Brexit exposure and return in the post-referendum period for UK firms in both services and manufacturing sectors. In both of them, the return is decreasing (increasing) in Brexit exposure on low (high) Δp days. While the magnitudes of the services and manufacturing P5-P1 spreads under both low-Δp and high-Δp regimes are lower compared to the wider cross-section of all stocks, they are broadly similar across the two groups. Portfolio attribution sheds more light onto the potential differences in post-referendum performance of services and manufacturing Brexit portfolios. Table 8 shows that the magnitudes of all but two α_0' and α_0'' coefficients are larger for services firms portfolios (including the P5-P1) than they are for the manufacturing firms ones. This suggests that the performance of firms in the UK services sector was more driven by Brexit shocks

over time than was the performance of firms in the manufacturing sector [**H2**].

The results for the EU-14 manufacturing and services firms cross-sections are similarly in line with those of the wider cross-section of all EU-14 stocks. While for both manufacturing and services firms the returns are decreasing (increasing) in Brexit exposure on low (high) Δp days, the P5-P1 spread is only statistically significant under the low Δp regime. Although its magnitude is larger for the services firms than for the manufacturing ones, it is only marginally so. The attribution exercise of the EU-14 Brexit portfolio returns confirms that the difference in the returns between high and low Brexit exposure EU-14 firms is subsumed by the commonly used Fama-French three factors model. Even in case of Brexit portfolios constructed using manufacturing companies stocks, for which α_0' coefficients of the P1 through P5 portfolios are statistically significant, the α_0' of the P5-P1 spread is not.

All in all, the results indicate that the UK services and manufacturing firms were differentially impacted by the Brexit shocks not only immediately after the referendum, but also throughout the longer post-referendum period. This is in line with **H2** as outlined in Section 2.

5.3 Brexit premium – time series

The results reported so far confirm the relationship between Brexit exposure and assets returns both immediately after the referendum and over the post-referendum period. Here, I want to understand to which extent the time series of Brexit-related shocks have driven the European stock markets in the post-referendum period. To this end, I rely on the Fama-MacBeth procedure commonly applied in empirical asset pricing literature. In each cross-section considered, I regress the daily returns to individual stocks on their four characteristics: Brexit exposure, market beta, SMB beta, and HML beta. The Brexit exposure is measured as the CAPM-adjusted (abnormal) return of a given stock on June 24, 2016. Stocks' betas with respect to

the three-factor model are computed using daily returns between June 2015 and May 2016. Contemporaneous market betas are not included in the regressions to account for the fact that the change in beta before and after the referendum can be driven by the very latent Brexit news impact I am interested in identifying.

As mentioned before, the probability of no-deal (hard) Brexit is varying over time in the sample considered. As a result, I adopt the Fama-MacBeth procedure and compute the λ coefficients separately for days of low, medium, and high daily change in the risk-neutral probability of hard Brexit (Δp_t). As before, a daily change is considered high (low) if it is in the top (bottom) 1/4 of the daily changes in no-deal probability between June 27, 2016 and December 31, 2019. With that in mind, I estimate the following cross-sectional regressions for each region:

$$r_t^j - r_{f,t} = \lambda_0 + \lambda_1 \overline{r}^j_{BREXIT} + \lambda_2 \beta^j_{MKT} + \lambda_3 \beta^j_{SMB} + \lambda_4 \beta^j_{HML} + \epsilon^j_t, \tag{3}$$

where at time t: r_t^j is the return on stock j, $r_{f,t}$ is the risk-free rate, $\overline{r}^j_{BREXIT}$ is the exposure to Brexit; and $\beta^j_{MKT}, \beta^j_{SMB}, \beta^j_{HML}$ are stock's exposure to the market, size, and value factors. For each of the three regimes considered, I calculate the sample coefficient estimates as the time series averages of the cross-sectional estimates, and the respective standard errors as the time series standard deviations of the cross-sectional estimates divided by the square root of the respective sample lengths. This allows me to test whether the difference in the various estimates is statistically significant by applying the basic t-test for the difference in means.

In addition to the classic second-stage Fama-MacBeth regressions ran separately for the three regimes as described above, I estimate two pooled OLS specifications that allow for directly testing whether the lambda coefficients (implied risk premiums) are different in periods when the risk-neutral probability of no-deal Brexit is increasing and in periods when this probability is decreasing. Specifically,

I estimate the following panel regressions:

$$\begin{aligned}\tilde{r}_t^j = \lambda_0 &+ \lambda_1 \overline{r}_B^j &+ \lambda_2 \beta_{MKT}^j &+ \lambda_3 \beta_{SMB}^j &+ \lambda_4 \beta_{HML}^j \\ &+ \lambda_0' I_L &+ \lambda_1' \overline{r}_B^j I_L &+ \lambda_2' \beta_{MKT}^j I_L &+ \lambda_3' \beta_{SMB}^j I_L &+ \lambda_4' \beta_{HML}^j I_L \\ &+ \lambda_0'' I_H &+ \lambda_1'' \overline{r}_B^j I_H &+ \lambda_2'' \beta_{MKT}^j I_H &+ \lambda_3'' \beta_{SMB}^j I_H &+ \lambda_4'' \beta_{HML}^j I_H + \epsilon_t^j, \quad (4)\end{aligned}$$

and

$$\begin{aligned}\tilde{r}_t^j = \lambda_0 &+ \lambda_1 \overline{r}_B^j &+ \lambda_2 \beta_{MKT}^j &+ \lambda_3 \beta_{SMB}^j &+ \lambda_4 \beta_{HML}^j \\ &+ \lambda_0' \Delta p &+ \lambda_1' \overline{r}_B^j \Delta p &+ \lambda_2' \beta_{MKT}^j \Delta p &+ \lambda_3' \beta_{SMB}^j \Delta p &+ \lambda_4' \beta_{HML}^j \Delta p + \epsilon_t^j, \quad (5)\end{aligned}$$

where $\tilde{r}_t^j$ is the excess return on stock j, I_L (I_H) is a deterministic indicator variable that equals one if day t is in the bottom (top) 1/4 of all the days between June 27, 2016 and December 31, 2019 with respect to its daily change in the risk-neutral probability of no-deal Brexit, and Δp_t is the weekly change in the risk-neutral probability of no-deal Brexit. Standard errors are clustered by time (day) to account for the cross-sectional correlation of residuals.

5.3.1 Brexit exposure and conditional premiums in cross-section

Results from estimating second-stage Fama-MacBeth regressions in line with Equation (3) for the EU-15, UK, EU-14, French, German, and Italian cross-sections are reported in Table 9. In the interest of space, I focus here mainly on the relationship between Brexit exposure and stock performance.

We see that Brexit exposure and return are significantly positively (negatively) related in the EU-15, UK, and the EU-14 cross-sections under the *High* (*Low*) Δp_t regime. The magnitude of this relationship is largest in EU-15 and smallest in EU-14, with its UK value falling in the middle. An increase of one percentage point in CAPM-adjusted return on June 24, 2016 (Brexit exposure) leads to approximately

0.7 bps higher (1 bp lower) daily return on *High* (*Low*) Δp_t days in the UK cross-section. Similarly, an equivalent increase in Brexit exposure leads to approximately 0.4 bps higher (0.5 bps lower) daily return on *High* (*Low*) Δp_t days in the EU-14 cross-section. A test for differences between the *High* and *Low* regimes, a standard t-test for the difference in means, implies that there are significant differences in the values of all λ-coefficients in EU-14, UK, and EU-15 cross-sections. In particular, the daily return to holding a unit of Brexit exposure when Δp_t is high compared to when it is low is 2 bps higher in the UK and 1 bps higher in EU-14. These numbers may not come across as particularly high per unit of Brexit exposure (abnormal return on June 24, 2016). They are, however, substantial when one recalls (see: Figure 5) that the median and the quartile spread of such measured exposure were approximately 8% and 7% in UK and the 0.5% and 5% in EU-14, respectively.

Bottom row of Table 9 zooms in on the relationship between Brexit exposure and return in the largest economies of EU-14. One sees that the importance of this relationship differs across these. In France, Brexit exposure matters in the *High* Δp_t regime with stocks earning an extra 0.6 bps daily. In Germany, on the other hand, it is the *Low* Δp_t regime that leads to a statistically significant relationship between the two with a 1 percentage point higher abnormal return on June 24, 2016 leading to 0.8 bps lower daily return. In Italy, a statistically significant relationship is non-existent regardless of Δp_t. A test for difference in means between the *High* and *Low* regimes further highlights the differences. It's results confirm the statistically significant difference for the French cross-section but not for the remaining two. The unreported results for most of the remaining national cross-sections (Austria, Belgium, Spain, Portugal, and Luxembourg) mirror those of Italy. Those for the Netherlands and Ireland are in line with UK ones with the relationship significant under both *High* and *Low* regimes and an extra unit of Brexit exposure attracting 2.7 bps higher return when Δp_t is high compared to when it is low.

The above results confirm that exposure to Brexit drives performance of both UK

and EU-14 stocks in the post-referendum period. The magnitude of this relationship in the UK is approximately double that in the EU-14 (2 bps vs. 0.9 bps). EU-14, however, exhibits substantial regional differences in the strength and significance of this relationship. Whilst non-existent or weak in majority of national cross-sections, it is of importance similar to that in the UK in the Netherlands, Ireland, Denmark, and France. This is in line with gravity theories of trade that point to importance of geographical proximity for the development of trade ties.

5.3.2 Pooled OLS regressions

In Table 10, I apply the pooled OLS methodology to directly estimate the difference in the intercept and slope coefficients across the three regimes in a single regression using all weeks of my post-referendum sample. The regression specification is given by Equation (4) and the relevant t-statistics (in brackets) are computed using standard errors clustered by day to account for the cross-sectional correlation of residuals.

We see immediately, that on an average (with regards to Δp_t) day the analyzed coefficients are overwhelmingly not statistically different than zero. Accounting for changes in the risk-neutral probability of no-deal Brexit does, however, reveal statistically significant relationships across all cross-sections. On days of *low* (*high*) Δp_t the intercept is higher (lower) than on an average day as indicated by positive (negative) value of the λ_0' (λ_0'') coefficient. This relationship is consistently reflected in all cross-sections and statistically significant in all but the Portuguese one. In the cross-section of all EU-15 stocks I observe that exposures to Brexit and the remaining three factors attract statistically significant premiums on both *high* and *low* Δp_t days. The national cross-sections show far more differences and asymmetry in this respect. In particular, weeks of *low* Δp_t see the premium to holding a unit of Brexit exposure decrease significantly by 2.4 bps in EU-15, 2 bps in Germany, 1.7 bps in the Netherlands, 1.4 bps in the UK, and 0.7 bps in EU-14. A corresponding relationship is not observed for weeks of *high* Δp_t. Although weeks of *high* Δp_t see

the premium to holding a unit of Brexit exposure increase significantly by 1.7 bps in EU-15 and in Ireland, the same is not the case in the remaining regions.

Table 11 reports results of pooled OLS specification with a continuous Δp_t variable rather than indicator variables for its low and high values. The regression specification is given by Equation (5). The relevant t-statistics (in brackets) are again computed using standard errors clustered by day. The computed estimates confirm that the return to a unit of Brexit exposure is increasing in Δp_t. Although it is not priced during weeks with limited change in p_t, it becomes a significant driver of firms' stock performance when Δp_t deviates from zero. Similarly, the intercept and the market and size risk premiums tend to change value subject to changes in Δp_t with the former decreasing and the latter increasing as Δp_t increases.

The pooled OLS estimates confirm that Brexit exposure is a significant driver of both the UK and EU-14 cross-sections. Moreover, the return to a unit of that exposure varies in the changes in the risk-neutral probability of hard Brexit as evidenced by the significance of the interaction terms analyzed. Geographical proximity to the UK seems to determine how strong the impact on the national cross-sections is. These results motivate my attempt to identify the return to a unit of Brexit exposure - the return to the Brexit pure play portfolio - that follows.

5.4 Brexit premium and assets returns

The results so far are consistently pointing towards a relationship between Brexit exposure and stocks performance in both UK and EU-14 regions throughout the post-referendum period. The goal now is thus to identify the return to holding a unit of Brexit exposure (the Brexit risk premium), its behaviour over the post-referendum period, and its ability to explain other assets' returns during that time.

This is where the cross-sectional analysis of the previous sections comes particularly handy as it can be used to extract information about the time-series

of relevant risk premiums. Such information is contained in the time-series of slopes from the second-stage Fama-MacBeth regressions. As Back et al. (2013) and (Fama, 1976) show, these individual slope values can be interpreted as returns to portfolios with distinct characteristics.

Let's look back at Equation (3) – the cross-sectional Fama-MacBeth regression:

$$r_t^j - r_{f,t} = \lambda_0 + \lambda_1 \overline{r}^j_{BREXIT} + \lambda_2 \beta^j_{MKT} + \lambda_3 \beta^j_{SMB} + \lambda_4 \beta^j_{HML} + \epsilon^j_t.$$

We can observe that in each period the slope of that regression is given by

$$\boldsymbol{\lambda_t} = [\lambda_t^0 \quad \lambda_t^1 \quad \lambda_t^2 \quad \lambda_t^3 \quad \lambda_t^4]' = (X'X)^{-1}X'R_{t+1},$$

where:

$$X = \left[\mathbf{1} \ \overline{\boldsymbol{r}}^{\boldsymbol{j}}_{\boldsymbol{BREXIT}} \ \boldsymbol{\beta}^{\boldsymbol{j}}_{\boldsymbol{MKT}} \ \boldsymbol{\beta}^{\boldsymbol{j}}_{\boldsymbol{SMB}} \ \boldsymbol{\beta}^{\boldsymbol{j}}_{\boldsymbol{HML}}\right] = \begin{bmatrix} 1 & ... & \beta^1_{HML} \\ 1 & ... & \beta^2_{HML} \\ 1 & ... & \beta^J_{HML} \\ ... & ... & ... \\ 1 & ... & \beta^N_{HML} \end{bmatrix} \text{ and } R^k_{t+1} = \begin{bmatrix} r^1_{t+1} \\ r^2_{t+1} \\ r^j_{t+1} \\ .. \\ r^N_{t+1} \end{bmatrix}.$$

As a result, at any point in time t, the slope $\boldsymbol{\lambda_t}$ can be interpreted as time-t returns to five portfolios. Each of these portfolios is a linear combination of the N assets (individual stocks in the given regional cross-section) with a set of weights

$$W^k = [\overline{w}_I \quad \overline{w}_{BREXIT} \quad \overline{w}_{MKT} \quad \overline{w}_{SMB} \quad \overline{w}_{HML}]' = (X'X)^{-1}X'.$$

Because of that, each of the portfolios has an appealing interpretation. The first set of weights ($\overline{w}_I$) delivers a unit-investment portfolio. The remaining ones correspond to zero-investment portfolios with a weighted average exposure of one to the given

characteristic and zero to the others. Such portfolios are referred to in the literature as so-called "characteristic pure play" (Back et al., 2013) portfolios since they allow for isolating the impact of the given characteristic on the cross-section of assets. They are useful to track down the time-series behaviour of risk premiums earned for holding a unit of a particular source of risk.

Because of the above relationships, I can use time series of λ^1 computed using data from each regional cross-section to infer the period-by-period premium for holding a unit of Brexit exposure and thus track the behaviour of Brexit shocks over time. Positive values of λ^1 characterise periods during which, as on June 24, 2016, high-$\overline{r}_{Brexit}$ (low-exposure) assets relatively out-perform low-$\overline{r}_{Brexit}$ (high exposure) ones. Similarly, time series of λ^2, λ^3, and λ^4 track the premiums for holding a unit of market, size, and value exposure. Figure 8 plots the cumulative returns to pure play portfolios mimicking the three Fama-French factors (λ^2, λ^3, and λ^4) in EU15, UK, and EU14 regions and compares them to the cumulative returns of the corresponding European factors as provided by Professor Kenneth French. Figure 9 plots the cumulative returns to the Brexit mimicking portfolios constructed using the same three regional cross-sections. Since, as evidenced by the regression results presented before, the behaviour of these time series fits the changes in Brexit uncertainty over time, in what follows I use them as a proxy for the time-varying Brexit risk premium.

I now test whether and to which extent the identified characteristic pure play portfolios can explain the variation of the return on various test assets (aggregate market indices and returns to geographic factors a la Dumas et al. (2020)) in the post-referendum period. To answer this question, I regress the returns on these test assets on the returns to the factor mimicking portfolios:

$$R_t^j = \gamma_0^j + \gamma_{Brexit}^j R_t^{Brexit} + \gamma_{MKT}^j R_t^{MKT} + \gamma_{SMB}^j R_t^{SMB} + \gamma_{HML}^j R_t^{HML} + \epsilon_t^j, \quad (6)$$

where R_t^j is the return on the relevant test asset j, and R_t^{Brexit}, R_t^{MKT}, R_t^{SMB}, and R_t^{HML} are the returns to the relevant characteristic pure play portfolios identified in line with Equation (3) using the EU-15 cross-section.

5.4.1 European market indices

I provide a brief summary of the European aggregate stock market indices in Table 12. Table 13 summarizes the results of running the regressions described in Equation (6) for these indices.

The first 7 columns (FTEU3 through N150) of Table 13 report results for the European aggregate stock market indices of various regional coverage. One can see that regardless of the specific national markets covered by these, the relationship between the Brexit mimicking portfolio return and the index return is positive for all of them. This is the case both when only Brexit and market factor mimicking portfolios are used as aggressors (*Panel A2*) and when Brexit pure play portfolio is considered together with the mimicking portfolios of the three Fama-French factors (*Panel B2*). Interestingly, the relationship is weakest for the three indices that do include stocks listed in United Kingdom: FTEU3, STOXX, and STOXX50. The results indicate that as the Brexit risk premium increases in the European cross-section, so does the return to aggregate European stock market indices. Heightened considerations with respect to hard Brexit are contemporaneously positively related with returns on European indices.

I find the same positive relationship between Brexit mimicking portfolio and aggregate stock market return for the vast majority of the national EU-14 aggregate indices. The only exceptions are Greece, Ireland, and Spain. The magnitude of this relationship is largest in Germany, followed by Luxembourg, Austria, and France. Both in Germany and France the magnitude of the relationship between Brexit premium and aggregate stock market return is larger for the mid and small cap stocks included in the SDAX and the CAC MID 60, respectively than it is for the

blue-chip indices of these markets (FCHI and GDAXI).

In the light of the above relationships, the UK is a substantial outlier. Here, the relationship between Brexit mimicking portfolio return and the return to either of the two market indices is negative. FTSE100 and FTSE250 are value-weighted indices of the first 100 and the next 250 (101st through 350th) largest companies quoted on the London Stock Exchange. While FTSE100 comprises companies with international exposure, FTSE250 comprises those with more focus on the local economy. The magnitude of the negative relationship between the Brexit premium and the UK stock market return is almost six times larger for the FSTE250 (FTMC) than it is for the FTSE100 (FTSE). This indicates that the Brexit risk premium is increasing in periods when the aggregate UK stock market indices are losing value. The relationship is both economically meaningful and statistically significant and much stronger for the companies with less international revenue. This, together with a positive relationship between Brexit premium and return on the EU-14 market indices, is indicative of the Brexit risk being a greater and more lasting negative shock to the local UK than to the EU economy.

5.4.2 Geographic factors

Further analysis using geographic zone factors constructed in line with Dumas et al. (2020) methodology confirms the above. Figure 10 shows the behaviour of the European Union zone factors prior to the Brexit vote. In 2015 the cumulative return to the EU14 and the UK one are at similar levels with the latter often above the former. This starts to shift beginning of 2016 as Brexit referendum is approaching and the relative underperformance of the UK factor vs the EU14 one does not reverse till December 2019. Table 14 reports the results of Regression (6) for geographic zone factors as the dependent variable. The relationship between the Brexit mimicking portfolio (in the presence of the market or Fama-French three factors) is positive for the EU14 zone factor but negative for the United Kingdom one. The Brexit

mimicking portfolio explains approximately 12% (5%) of the UK (EU-14) geographic factor's performance between June 2016 and December 2019. As evident from Figure 10, the Brexit announcement drives a material wedge between cumulative returns to UK and EU14 zone factors with the underperformance of the former vs the latter amounting to approximately 30 percentage points by the end of December 2019. The Brexit-mimicking portfolio explains 70% of this underperformance on a stand-alone basis and up to 45% in the presence of the remaining factors. This corroborates the exceptionally strong negative pressure faced by UK stock market and wider economy as a result of the Brexit vote and departure negotiations.

6 Conclusion

This paper uses the lens of the stock market to investigate costs of erecting barriers to trade in developed economies. United Kingdom's decision to leave the European Union constitutes a unique setting to examine this question. This is as to date exits from and accessions to trade unions have been endogenous i.e. determined by pre-existing trade flows and political considerations. I show that the costs of Brexit are higher for the leaver than they are for the rest of the block. The strength of economic ties (revenue share derived from a location) and the difference in the expected arrangements for manufacturing and services trade explain these results. Brexit uncertainty remains a driver of European geographic risks throughout the lengthy negotiations period leading to 20 percentage points under-performance of the UK factor compared to the EU14 one between July 2016 and December 2019. A Brexit-mimicking portfolio explains up to 70% of this under-performance.

Table 1: FactSet's data – variables summary and excerpt

This table provides the explanation of selected variables from the FacSet GeoRev and Symbology universes (Panel A) and a short excerpt of the content used (Panel B).

Panel A

Variable	Variable's description
factset_entity_id	Unique identifier FactSet assigns to an entity
entity_proper_name	Name the entity is commonly referred to
entity_country	Two-letter ISO country code representing the country of the company's domicile/headquaters.
security_isin	ISIN assifned to the security
sec_type	Code denoting the security type
period_end_date	The date on which the geographic revenue report period completed. Usually but not always the end of a fiscal period.
revenue_country	ISO country code that corresponds to the country for which the geographic revenue data is reported.
country_name	Name of the country for which the geographic revenue data is reported.
est_pct	The estimated percentage of revenue derived from the associated country.
est_conf	Confidence score for the value in the est_pct field

Panel B

factset_entity_id	entity_proper_name	entity_country	security_isin	sec_type	period_end_date	revenue_country	country_name	est_pct	est_conf
000BDX-E	1st Source Corp.	US	US3369011032	SHARE	2015-12-31	US	United States	100	1
000BDX-E	1st Source Corp.	US	US3369011032	SHARE	2016-12-31	US	United States	100	1
000BDX-E	1st Source Corp.	US	US3369011032	SHARE	2017-12-31	US	United States	100	1
000BDX-E	1st Source Corp.	US	US3369011032	SHARE	2018-12-31	US	United States	100	1
000BDX-E	1st Source Corp.	US	US3369011032	SHARE	2019-12-31	US	United States	100	1
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	ZM	Zambia	0.01276	0.986108
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	ZA	South Africa	0.189055	0.981582
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	YE	Yemen	0.022666	0.992312
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	VN	Vietnam	0.114904	0.983942
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	VE	Venezuela	0.156232	0.990933
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	UZ	Uzbekistan	0.039287	0.996314
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	UY	Uruguay	0.031901	0.993575
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	US	United States	66.348868	1
000BFS-E	AAR Corp.	US	US0003611052	SHARE	2015-05-31	...	...	...	...
...	...	...	...	...	...	...	...	...	...

Table 2: Summary statistics for the EU-15 cross-section of common stock issuance

This table provides summary statistics for the cross-section of individual companies' common shares issues quoted in one of the EU-15 countries. I report the number of stocks in each cross-section, the quartiles, the minimum and maximum, and the average market capitalization of the issuances on three days: that of the referendum itself (Thursday, 23/06/2016) and the two trading days that followed (Friday and Monday, 24/06/2016 and 27/06/2019). Friday market capitalization data for Finland and Sweden is missing due to public holiday (Midsummer).

		Market Cap 23/06/2016 (million USD)						Market Cap 24/06/2016 (million USD)				Market Cap 27/06/2016 (million USD)			
Country	N	min	Q1	Q2	Q3	max	average	Q1	Q2	Q3	average	Q1	Q2	Q3	average
Austria	52	5.1	126.4	790.3	2,274.4	11,058.8	1,636.1	123.4	739.8	2,127.2	1,510.3	122.9	710.5	2,024.9	1,445.2
Belgium	107	2.8	79.8	431.2	1,532.6	208,914.9	3,650.9	76.6	411.4	1,443.5	3,424.1	72.7	385.5	1,387.0	3,317.1
Denmark	96	6.4	50.2	311.5	2,280.2	107,178.3	3,748.6	48.1	298.6	2,131.2	3,545.0	47.2	277.8	2,055.1	3,403.0
Finland	84	3.4	90.0	316.9	1,678.8	33,451.3	2,263.7					87.0	298.6	1,483.6	2,019.6
France	469	0.1	49.5	247.8	1,406.9	124,508.1	3,969.7	47.7	238.8	1,328.7	3,602.9	47.9	230.3	1,266.7	3,457.6
Germany	423	0.1	59.7	254.3	1,835.9	99,458.0	3,801.3	57.9	244.9	1,727.1	3,507.7	57.6	235.5	1,642.6	3,368.4
Greece	20	2.9	202.2	395.9	1,360.4	4,854.9	932.2	191.1	373.2	1,198.7	812.3	188.9	364.3	1,159.2	793.7
Ireland; Republic of	15	64.5	343.1	1,012.4	9,072.7	19,744.7	5,748.4	322.3	841.9	7,196.0	5,071.4	299.0	776.4	5,821.4	4,581.2
Italy	94	2.3	161.1	878.9	3,178.7	60,325.0	3,356.0	157.3	823.0	2,676.6	2,948.0	156.0	771.5	2,340.0	2,799.6
Luxembourg	14	4.1	60.2	359.0	930.8	14,064.5	1,653.0	58.8	348.5	901.9	1,560.2	58.3	347.6	867.2	1,493.9
Netherlands	68	7.8	205.0	1,483.4	5,627.2	117,939.1	8,447.8	190.8	1,409.8	5,291.8	7,846.5	188.6	1,363.9	5,058.2	7,582.9
Portugal	11	31.8	176.7	1,116.6	5,898.8	10,865.0	3,207.8	171.3	1,037.2	5,698.8	2,994.9	167.5	1,024.8	5,415.0	2,892.7
Spain	69	0.7	219.3	1,838.9	4,572.1	110,032.9	7,169.7	204.3	1,635.5	4,139.2	6,349.4	202.1	1,565.4	3,986.8	6,214.4
Sweden	235	1.6	162.6	522.1	2,007.8	45,984.1	2,491.7					146.4	481.1	1,777.2	2,186.9
United Kingdom	1079	0.5	31.3	155.5	974.8	133,960.1	2,649.6	27.4	137.6	841.7	2,323.8	25.9	127.5	719.6	2,157.2
EU15exUK	1757	0.1	76.7	376.9	2,166.5	208,914.9	3,772.9	66.5	337.7	2,107.6	3,723.7	73.3	347.7	1,890.7	3,319.1
EU15	2836	0.1	53.8	271.3	1,635.5	208,914.9	3,345.5	46.0	233.9	1,422.2	3,123.6	48.6	243.4	1,341.1	2,877.1

Table 3: Cumulative returns to geographical factors following the Brexit referendum

This table reports cumulative returns between 24/06/2016 and 01/07/2016 (the week after the Brexit referendum) to 13 geographical factors constructed in line with Dumas et al. (2020) methodology using Factset GeoRev data.

	24-Jun-16	**26-Jun-16**	**27-Jun-16**	**28-Jun-16**	**29-Jun-16**	**30-Jun-16**	**01-Jul-16**
				Panel A: Europe			
United Kingdom	-20.80	-20.78	-35.12	-30.56	-26.57	-26.84	-25.92
EU14	-7.04	-7.03	-13.94	-11.43	-8.67	-7.75	-6.02
EU13	-6.81	-6.81	-8.49	-6.77	-5.68	-4.89	-4.71
				Panel B: Other countries			
Australia	-4.86	-4.82	-6.60	-6.92	-4.99	-3.16	-2.43
Brazil	-3.39	-3.37	-4.89	-1.05	2.98	4.43	4.15
Canada	-3.59	-3.61	-5.43	-4.04	-2.40	-2.57	-2.52
China	-3.10	-3.03	-2.86	-2.71	-2.08	-0.76	-0.55
India	-1.80	-1.78	0.23	1.32	3.06	3.91	5.00
Japan	-3.42	-3.38	0.81	-0.88	0.54	-0.78	1.30
Malaysia	-2.03	-2.01	-2.56	-1.57	-0.23	0.27	1.02
Singapore	-2.11	-2.10	-2.73	-1.53	-0.70	-0.24	0.16
United States	-3.52	-3.53	-6.16	-4.53	-2.50	-0.26	-0.16
RestOfWorld	-3.85	-4.12	-4.85	-3.43	-1.81	-1.31	-0.81

Table 4: Explaining abnormal returns

This table presents results from OLS regressions of individual abnormal stock returns on Friday following the Brexit referendum on the following variables: the GeoRev-reported source of firm's revenue derived from UK, EU, and the rest of the world (ROW); a dummy variable identifying firms classified as providing services under the NAICS classification; the interaction between this dummy and source of revenue variables; and the sensitivity of the firm's return to the local currency value changes. Industry fixed effects are constructed in line with the GICS classification. Panel A reports the results for stocks with their primary listing in the United Kingdom, while Panel B reports the results for those with primary listing elsewhere in the EU15 block.

Panel A: United Kingdom

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	***-10.987***	***-9.524***	***-11.156***	***-9.859***	***-12.610***	***-10.812***	***-12.411***	***-10.813***	***-17.825***	***-15.887***	***-11.362***	***-10.557***
	-6.236	***-2.700***	***-6.473***	***-2.859***	***-6.535***	***-2.995***	***-6.569***	***-3.062***	***-9.992***	***-4.579***	***-4.411***	***-2.748***
β_{FX}			***1.990***	***1.968***			***1.957***	***1.948***	***1.957***	***1.948***	***1.957***	***1.948***
			6.535	***6.569***			***6.419***	***6.490***	***6.419***	***6.490***	***6.419***	***6.490***
I_S					***1.944***	1.246	1.459	0.765	0.262	0.636	***-5.971***	***-4.599***
					1.969	1.189	1.505	0.744	0.302	0.658	***-2.677***	***-2.045***
lnMktCap	***0.350***	***0.412***	***0.241***	***0.306***	***0.356***	***0.413***	***0.248***	***0.306***	***0.248***	***0.306***	***0.248***	***0.306***
	3.925	***4.400***	***2.721***	***3.301***	***3.983***	***4.397***	***2.788***	***3.278***	***2.788***	***3.278***	***2.788***	***3.278***
rev_{EU}	***-0.056***	***-0.048***	***-0.045***	***-0.037***	0.006	-0.001	0.010	0.003	***0.065***	***0.053***		
	-4.583	***-3.926***	***-3.693***	***-3.097***	0.264	-0.025	0.436	0.107	***2.919***	***2.438***		
$rev_{EU} : I_S$					***-0.084***	***-0.063***	***-0.074***	*-0.054*	***-0.062***	***-0.052***		
					-2.947	***-2.230***	***-2.672***	*-1.925*	***-2.452***	***-2.088***		
rev_{UK}	***-0.066***	***-0.054***	***-0.063***	***-0.051***	***-0.054***	***-0.050***	***-0.054***	***-0.051***			***-0.065***	***-0.053***
	-11.639	***-8.541***	***-11.416***	***-8.249***	***-4.425***	***-4.027***	***-4.568***	***-4.191***			***-2.919***	***-2.438***
$rev_{UK} : I_S$					-0.016	-0.006	-0.012	-0.001			***0.062***	***0.052***
					-1.188	-0.453	-0.887	-0.092			***2.452***	***2.088***
$rev_{notEUnotUK}$									***0.054***	***0.051***	-0.010	-0.003
									4.568	***4.191***	-0.436	-0.107
$rev_{notEUnotUK} : I_S$									0.012	0.001	***0.074***	*0.054*
									0.887	0.092	***2.672***	*1.925*
N	933	933	933	933	933	933	933	933	933	933	933	933
R^2(%)	13.86	17.97	17.56	21.62	14.38	18.18	17.95	21.74	17.95	21.74	17.95	21.74
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: EU14

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	***-2.509***	***-3.382***	***-2.727***	***-3.568***	*-2.504*	*-3.166*	***-2.741***	***-3.375***	***-20.108***	***-19.423***	***-5.601***	***-5.445***
	-1.978	***-2.148***	***-2.164***	***-2.288***	*-1.809*	*-1.887*	***-1.993***	***-2.031***	***-5.303***	***-5.047***	***-4.955***	***-3.851***
β_{FX}			***0.181***	***0.211***			***0.183***	***0.212***	***0.183***	***0.212***	***0.183***	***0.212***
			4.185	***4.910***			***4.240***	***4.920***	***4.240***	***4.920***	***4.240***	***4.920***
I_S					-0.886	0.035	-0.895	0.076	*7.581*	*7.513*	***-1.088***	-0.121
					-1.280	0.048	-1.304	0.104	*1.883*	*1.877*	***-2.290***	-0.213
lnMktCap	***0.239***	***0.303***	***0.248***	***0.312***	***0.251***	***0.304***	***0.261***	***0.314***	***0.261***	***0.314***	***0.261***	***0.314***
	4.236	***5.011***	***4.420***	***5.211***	***4.371***	***4.955***	***4.565***	***5.161***	***4.565***	***5.161***	***4.565***	***5.161***
rev_{EU}	***-0.035***	***-0.021***	***-0.036***	***-0.022***	***-0.028***	***-0.020***	***-0.029***	***-0.021***	***0.145***	***0.140***		
	-8.080	***-4.243***	***-8.348***	***-4.461***	***-3.560***	***-2.496***	***-3.674***	***-2.605***	***3.863***	***3.760***		
$rev_{EU} : I_S$					-0.002	-0.002	-0.002	-0.002	***-0.087***	*-0.076*		
					-0.185	-0.159	-0.203	-0.201	***-2.053***	*-1.825*		
rev_{UK}	***-0.107***	***-0.102***	***-0.108***	***-0.102***	***-0.173***	***-0.160***	***-0.174***	***-0.160***			***-0.145***	***-0.140***
	-5.906	***-5.608***	***-5.988***	***-5.682***	***-4.635***	***-4.304***	***-4.682***	***-4.352***			***-3.863***	***-3.760***
$rev_{UK} : I_S$					***0.085***	*0.075*	***0.085***	*0.074*			***0.087***	*0.076*
					1.983	*1.749*	***1.988***	*1.757*			***2.053***	*1.825*
$rev_{notEUnotUK}$									***0.174***	***0.160***	***0.029***	***0.021***
									4.682	***4.352***	***3.674***	***2.605***
$rev_{notEUnotUK} : I_S$									***-0.085***	*-0.074*	0.002	0.002
									-1.988	*-1.757*	0.203	0.201
N	1179	1179	1179	1179	1179	1179	1179	1179	1179	1179	1179	1179
R^2(%)	9.08	12.86	10.34	14.58	9.56	12.93	10.85	14.65	10.85	14.65	10.85	14.65
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Brexit exposure – univariate sorts portfolios

This table reports mean excess daily returns to Brexit exposure portfolios conditional on the change in the market-implied probability of no-deal Brexit. P1 (P5) refers to a portfolio with largest (smallest) exposure to the Brexit shock i.e. lowest (highest) CAPM-adjusted return on June 24, 2016 in the given region. These are the relative Brexit losers (winners). P5-P1 stands for an investment strategy that is long the portfolio of firms with the smallest exposure to the Brexit shock and short the portfolio of firms with largest exposure to the Brexit shock. Given the variation in the probability of no-deal Brexit over time, I asses both economical and statistical significance of the returns to the various portfolios conditional on the daily change in that probability (Δp). Low (High) regime indicates these days in the post-referendum period, for which the daily change in no-deal Brexit probability has been in the bottom (top) 1/4 of all days throughout that period. For each regime, the first row reports average daily returns and the second one the values of the t-Statistics of a test for either a difference from zero (P1 through P5) or for difference in two means (P5-P1 strategy). Returns are reported in %.

	EU15					
	P1	P2	P3	P4	P5	P5-P1
Low	0.802685	0.510914	0.423216	0.361348	0.327291	-0.47539
	9.6***	8.74***	7.62***	7.08***	5.98***	-6.16***
Med	-0.02633	0.006518	0.030181	0.012561	0.029455	0.055782
	-0.64463	0.189129	0.799523	0.365562	0.823274	1.85*
High	-0.704	-0.44148	-0.36206	-0.33235	-0.30683	0.397165
	-8.87***	-8.05***	-6.55***	-6.86***	-6.12***	6.47***
High - Low	-1.50668	-0.9524	-0.78527	-0.6937	-0.63412	
	-13.1***	-11.9***	-10***	-9.86***	-8.54***	

	UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Low	0.903965	0.750978	0.706869	0.623935	0.428687	-0.47528
	9.24***	9.62***	10.6***	9.61***	7.82***	-5.32***
Med	-0.00582	-0.09865	-0.01707	0.005469	0.00711	0.012932
	-0.1287	-2.27**	-0.53235	0.141237	0.203924	0.350122
High	-0.78931	-0.67913	-0.64259	-0.56888	-0.41319	0.376126
	-8.59***	-9.44***	-11.1***	-9.01***	-8.35***	5.06***
High - Low	-1.69328	-1.43011	-1.34946	-1.19281	-0.84187	
	-12.6***	-13.5***	-15.3***	-13.2***	-11.4***	

	EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Low	0.409713	0.368302	0.321428	0.339453	0.28042	-0.12929
	6.32***	6.66***	6.15***	5.74***	4.96***	-2.97***
Med	0.031381	0.048598	0.01625	0.037398	0.027487	-0.00389
	0.734631	1.279815	0.437134	0.961613	0.733366	-0.14906
High	-0.32405	-0.31488	-0.3078	-0.29117	-0.26682	0.057231
	-4.97***	-5.78***	-5.85***	-5.24***	-5.31***	1.502257
High - Low	-0.73376	-0.68318	-0.62922	-0.63062	-0.54724	
	-7.98***	-8.8***	-8.48***	-7.77***	-7.23***	

	France					
	P1	P2	P3	P4	P5	P5-P1
Low	0.455853	0.377612	0.312621	0.305162	0.306472	-0.14938
	5.15***	5.01***	5.03***	5.09***	4.86***	-1.88*
Med	0.029829	0.059089	0.013014	0.049862	0.064096	0.034267
	0.537569	1.209324	0.329355	1.293092	1.595415	0.824592
High	-0.33811	-0.30154	-0.33092	-0.28533	-0.22625	0.111864
	-3.97***	-4.28***	-6.09***	-5.22***	-4.17***	1.84*
High - Low	-0.79397	-0.67916	-0.64354	-0.59049	-0.53272	
	-6.47***	-6.59***	-7.79***	-7.28***	-6.41***	

	Germany					
	P1	P2	P3	P4	P5	P5-P1
Low	0.340119	0.353556	0.359543	0.346932	0.296719	-0.0434
	5.86***	5.84***	5.34***	4.84***	5.31***	-0.97422
Med	0.041836	-0.01353	0.022221	0.014108	0.017035	-0.0248
	1.044141	-0.31476	0.476707	0.288221	0.451256	-0.87744
High	-0.21837	-0.39445	-0.27187	-0.36026	-0.2722	-0.05384
	-3.67***	-6.68***	-4.02***	-5.4***	-5.3***	-1.42441
High - Low	-0.55849	-0.74801	-0.63141	-0.70719	-0.56892	
	-6.72***	-8.84***	-6.62***	-7.23***	-7.49***	

	Italy					
	P1	P2	P3	P4	P5	P5-P1
Low	0.565936	0.425922	0.339416	0.377157	0.361723	-0.20421
	6.08***	5.51***	5.5***	5.01***	4***	-2.5**
Med	0.064919	0.061561	0.045776	0.024163	0.11218	0.047261
	1.061193	1.131147	0.995647	0.489249	1.74*	0.863082
High	-0.43232	-0.36565	-0.25354	-0.40484	-0.36365	0.068661
	-4.06***	-4.64***	-3.57***	-5.13***	-3.91***	0.852679
High - Low	-0.99825	-0.79157	-0.59296	-0.782	-0.72538	
	-7.06***	-7.17***	-6.31***	-7.17***	-5.59***	

Table 6: Univariate sorts portfolios - attribution

This table reports the results of regressing Brexit exposure portfolios on the three factors proposed by Fama and French. P1 (P5) refers to a portfolio with largest (smallest) exposure to the Brexit shock i.e. lowest (highest) CAPM-adjusted return on June 24, 2016 in the given region. P5-P1 stands for an investment strategy that is long the portfolio of firms with the smallest exposure to the Brexit shock and short the portfolio of firms with largest exposure to the Brexit shock. Given the variation in the probability of no-deal Brexit over time, I allow the constant term in the regressions to differ across the three regimes constructed subject to the daily change in that probability (Δp). I report results of the following linear regressions:

$$r^e_{i,t} = \alpha + \alpha' I_{LOW} + \alpha'' I_{HIGH} + \beta_M r^e_{M,t} + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{SMB,t},$$

where $r^e_{i,t}$ is the excess return on a given Brexit portfolio ($i = P1, ..., P5, P5 - P1$), I_{LOW} (I_{HIGH}) is an indicator variable equal to 1 when the given day is in the bottom (top) 1/4 of all days in the post-referendum period with respect to the change in probability of no-deal Brexit (Δp); and $r^e_{M,t}$, $r_{SMB,t}$, and $r_{SMB,t}$ are the returns to the three Fama-French factors constructed using European stocks.

	EU15					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.07066	-0.03727	-0.02043	-0.03162	-0.01205	0.058609
	-2.08**	-1.98**	-1.38115	-2.37**	-0.86174	1.616904
MKT Beta	1.094153	0.981329	1.093166	0.989426	0.980153	-0.114
	26.7***	43.2***	61.3***	61.4***	58.1***	-2.61***
SMB Beta	0.690645	0.311638	0.218027	0.094285	-0.17262	-0.86327
	7.73***	6.29***	5.61***	2.69***	-4.7***	-9.07***
HML Beta	0.581713	0.407752	0.286884	-0.02176	-0.07137	-0.65308
	8.99***	11.4***	10.2***	-0.85614	-2.68***	-9.47***
Alpha (%) * low	0.38643	0.136708	0.002709	0.016244	-0.01482	-0.40125
	6.21***	3.97***	0.100185	0.664903	-0.57968	-6.06***
Alpha (%) * high	-0.2483	-0.08351	0.001591	-0.0059	-0.02247	0.225836
	-3.98***	-2.42**	0.058656	-0.24062	-0.87608	3.4***
R2 (%)	60.9266	77.4482	86.1309	86.0155	85.6398	26.1753

	UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.04775	-0.13164	-0.05034	-0.03463	-0.01824	0.029516
	-1.1241	-3.48***	-1.8*	-1.32302	-0.88501	0.686525
MKT Beta	1.141223	0.940081	0.85451	1.045049	0.804851	-0.33637
	22.3***	20.6***	25.4***	33.1***	32.4***	-6.49***
SMB Beta	0.828075	0.665644	0.697833	0.452657	-0.28721	-1.11529
	7.42***	6.69***	9.51***	6.58***	-5.31***	-9.87***
HML Beta	0.590473	0.099693	-0.00685	-0.05026	-0.06857	-0.65904
	7.31***	1.384887	-0.12892	-1.00945	-1.75*	-8.06***
Alpha (%) * low	0.438238	0.482782	0.393703	0.24077	0.165513	-0.27272
	5.64***	6.98***	7.71***	5.03***	4.39***	-3.47***
Alpha (%) * high	-0.33309	-0.22416	-0.29503	-0.19949	-0.18161	0.151479
	-4.28***	-3.23***	-5.76***	-4.16***	-4.81***	1.92*
R2 (%)	53.1399	48.1957	58.9433	66.57	69.5682	22.9739

	EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.02258	-0.00812	-0.03331	-0.016	-0.0171	0.005481
	-1.09548	-0.48651	-2.05**	-1.01538	-1.05907	0.259255
MKT Beta	1.10877	1.077866	1.044684	1.116427	1.006847	-0.10192
	44.6***	53.6***	53.3***	58.8***	51.7***	-4***
SMB Beta	0.126354	0.242356	0.184812	0.039265	-0.11877	-0.24513
	2.33**	5.53***	4.33***	0.948763	-2.8***	-4.41***
HML Beta	0.748937	0.277035	0.082593	-0.00325	-0.14693	-0.89587
	19.1***	8.73***	2.67***	-0.10847	-4.78***	-22.3***
Alpha (%) * low	-0.03539	-0.05967	-0.05424	-0.06677	-0.06563	-0.03024
	-0.93909	-1.96*	-1.83*	-2.32**	-2.22**	-0.78251
Alpha (%) * high	0.054389	0.033343	0.045945	0.053576	0.031737	-0.02265
	1.43887	1.089365	1.541778	1.85*	1.071836	-0.58434
R2 (%)	79.0993	82.0238	81.4944	84.6418	81.7199	39.0136

	France					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.0308	-0.00507	-0.03346	-0.0011	0.014217	0.045012
	-0.9237	-0.20007	-1.48557	-0.05766	0.7294	1.312073
MKT Beta	1.246667	1.33601	1.062183	1.045725	1.022444	-0.22422
	31***	43.8***	39.1***	45.4***	43.5***	-5.42***
SMB Beta	0.228948	0.307196	0.267669	-0.01924	-0.27783	-0.50678
	2.61***	4.62***	4.52***	-0.3832	-5.43***	-5.62***
HML Beta	1.287973	0.349426	0.061061	-0.11956	-0.25579	-1.54376
	20.3***	7.25***	1.425612	-3.29***	-6.9***	-23.7***
Alpha (%) * low	-0.07001	-0.15862	-0.07329	-0.07914	-0.06087	0.009142
	-1.14874	-3.42***	-1.78*	-2.26**	-1.71*	0.145772
Alpha (%) * high	0.112597	0.125736	0.033085	0.016252	0.031265	-0.08133
	1.84*	2.71***	0.801198	0.463755	0.874793	-1.29298
R2 (%)	67.7528	74.5302	69.7987	76.9199	77.0611	42.1899

	Germany					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.00217	-0.06863	-0.03293	-0.04013	-0.02362	-0.02145
	-0.08522	-2.79***	-1.28313	-1.55524	-1.15976	-0.7946
MKT Beta	0.938272	1.049636	1.197551	1.244515	0.988479	0.050207
	30.6***	35.4***	38.7***	40***	40.3***	1.542799
SMB Beta	0.024699	0.540843	0.011181	0.009168	0.124484	0.099785
	0.369836	8.36***	0.16585	0.135253	2.33**	1.406711
HML Beta	0.311416	0.659242	-0.01573	0.204725	-0.09125	-0.40266
	6.44***	14.1***	-0.32232	4.17***	-2.36**	-7.84***
Alpha (%) * low	-0.03003	-0.04332	-0.05784	-0.09342	-0.05388	-0.02385
	-0.64627	-0.96232	-1.23311	-1.98**	-1.44713	-0.48315
Alpha (%) * high	0.069284	0.038353	0.111195	0.050437	0.04589	-0.02339
	1.486463	0.849493	2.36**	1.06617	1.228828	-0.47252
R2 (%)	61.5282	68.1374	70.4392	72.4782	71.4163	6.8625

	Italy					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.01947	-0.01691	-0.01203	-0.02862	0.045388	0.064854
	-0.44772	-0.44864	-0.34934	-0.89214	1.149614	1.227797
MKT Beta	1.283124	1.223045	0.956617	1.124392	1.496136	0.213011
	24.5***	26.9***	23.1***	29.1***	31.4***	3.35***
SMB Beta	0.208664	0.127288	0.05079	0.042317	0.174633	-0.03403
	1.83*	1.285411	0.561594	0.502127	1.68*	-0.24523
HML Beta	1.378788	0.302164	-0.17405	0.824562	0.654317	-0.72447
	16.7***	4.22***	-2.66***	13.5***	8.71***	-7.21***
Alpha (%) * low	0.01106	-0.04233	-0.00157	-0.06701	-0.2946	-0.30566
	0.139154	-0.61427	-0.02498	-1.14269	-4.08***	-3.17***
Alpha (%) * high	0.01915	0.02668	0.036032	-0.01921	0.060346	0.041196
	0.240211	0.386032	0.57085	-0.32665	0.833608	0.425347
R2 (%)	58.1827	54.4559	45.8947	62.9411	62.1049	7.539

Table 7: Services vs manufacturing Brexit exposure - univariate sorts portfolios

This table investigates differences in the returns to Brexit exposure univariate sort portfolios constructed using firms from manufacturing and services sectors in the UK and in the EU-14 region. I report mean excess daily returns to Brexit exposure portfolios conditional on the change in the market-implied probability of no-deal Brexit. P1 (P5) refers to a portfolio with largest (smallest) exposure to the Brexit shock i.e. lowest (highest) CAPM-adjusted return on June 24, 2016 in the given region. These are the relative Brexit losers (winners). P5-P1 stands for an investment strategy that is long the portfolio of firms with the smallest exposure to the Brexit shock and short the portfolio of firms with largest exposure to the Brexit shock. Given the variation in the probability of no-deal Brexit over time, I asses both economical and statistical significance of the returns to the various portfolios conditional on the daily change in that probability (Δp). Low (High) regime indicates these days in the post-referendum period, for which the daily change in no-deal Brexit probability has been in the bottom (top) 1/4 of all days throughout that period. For each regime, the first row reports average daily returns and the second one the values of the t-Statistics of a test for either a difference from zero (P1 through P5) or for difference in two means (P5-P1 strategy). Returns are reported in %.

	Services - UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Low	0.910351	0.757778	0.703655	0.640327	0.510138	-0.40021
	9.18***	9.51***	10.5***	9.29***	8.62***	-5.04***
Med	-0.00613	-0.09988	-0.02045	0.009377	0.001197	0.007323
	-0.13294	-2.2**	-0.62243	0.233557	0.031193	0.209408
High	-0.79313	-0.68436	-0.64234	-0.56859	-0.48603	0.307108
	-8.48***	-9.25***	-10.9***	-8.29***	-8.82***	4.4***
High - Low	-1.70349	-1.44214	-1.34599	-1.20892	-0.99616	
	-12.5***	-13.3***	-15.1***	-12.4***	-12.3***	

	Services - EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Low	0.426889	0.365557	0.355002	0.316661	0.306637	-0.12025
	6.13***	6.61***	7.1***	5.7***	5.57***	-2.46**
Med	0.025695	0.048428	0.014841	0.031679	0.01921	-0.00648
	0.56569	1.231824	0.403103	0.820681	0.527158	-0.22592
High	-0.34797	-0.27442	-0.34693	-0.26991	-0.29167	0.056298
	-4.99***	-4.88***	-6.66***	-4.99***	-5.73***	1.285543
High - Low	-0.77485	-0.63998	-0.70194	-0.58657	-0.5983	
	-7.86***	-8.12***	-9.73***	-7.56***	-7.98***	

	Manufacturing - UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Low	0.754402	0.702709	0.706861	0.57893	0.357601	-0.3968
	8.86***	8.56***	9.3***	8.93***	6.11***	-4.52***
Med	0.003828	-0.06218	-0.07673	0.02249	0.012064	0.008237
	0.098423	-1.3961	-1.36151	0.502086	0.330054	0.190867
High	-0.69399	-0.60556	-0.61597	-0.57957	-0.35076	0.34323
	-10.1***	-8.26***	-9.09***	-9.11***	-6.7***	4.95***
High - Low	-1.44839	-1.30826	-1.32283	-1.1585	-0.70836	
	-13.2***	-11.9***	-13***	-12.8***	-9.02***	

	Manufacturing - EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Low	0.370403	0.332917	0.313784	0.331228	0.266237	-0.10417
	5.5***	4.93***	5.4***	5.13***	4.58***	-2.38**
Med	0.06642	0.002738	0.036292	0.043218	0.023604	-0.04282
	1.551486	0.063854	0.935598	1.049952	0.604151	-1.59961
High	-0.32758	-0.31072	-0.28995	-0.28296	-0.26512	0.062462
	-4.99***	-4.94***	-5.41***	-4.77***	-5.05***	1.345837
High - Low	-0.69798	-0.64364	-0.60374	-0.61419	-0.53135	
	-7.41***	-6.97***	-7.64***	-7.01***	-6.78***	

Table 8: Services vs manufacturing univariate sorts portfolios attribution

This table investigates the differences in the ability of the three-factor Fama-French model to explain Brexit exposure portfolios constructed using firms from manufacturing and services sectors. P1 (P5) refers to a portfolio with largest (smallest) exposure to the Brexit shock i.e. lowest (highest) CAPM-adjusted return on June 24, 2016 in the given region. P5-P1 stands for an investment strategy that is long the portfolio of firms with the smallest exposure and short the portfolio of firms with the largest exposure to the Brexit shock. I allow the constant term in the regressions to differ across three regimes constructed subject to the daily change in the market-implied no-deal Brexit probability (Δp):

$$r^e_{i,t} = \alpha + \alpha' I_{LOW} + \alpha'' I_{HIGH} + \beta_M r^e_{M,t} + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{SMB,t},$$

where $r^e_{i,t}$ is the excess return on a given Brexit portfolio ($i = P1, ..., P5, P5-P1$), I_{LOW} (I_{HIGH}) is an indicator variable equal to 1 when the given day is in the bottom (top) 1/4 of all days in the post-referendum period with respect to Δp; and $r^e_{M,t}$, $r_{SMB,t}$, and $r_{SMB,t}$ are the returns to the three Fama-French factors constructed using European stocks.

	Service - UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.04801	-0.13284	-0.05289	-0.03092	-0.02839	0.019621
	-1.10968	-3.36***	-1.8*	-1.08064	-1.23476	0.476078
MKT Beta	1.151566	0.944832	0.826683	1.075169	0.932404	-0.21916
	22.1***	19.8***	23.3***	31.2***	33.6***	-4.41***
SMB Beta	0.818104	0.624291	0.698634	0.470004	0.003375	-0.81473
	7.2***	6.01***	9.03***	6.25***	0.055867	-7.52***
HML Beta	0.613722	0.098598	-0.02224	0.072212	0.18149	-0.43223
	7.46***	1.310767	-0.39702	1.32709	4.15***	-5.51***
Alpha (%) * low	0.440268	0.491563	0.404343	0.23405	0.177154	-0.26311
	5.57***	6.8***	7.51***	4.47***	4.21***	-3.49***
Alpha (%) * high	-0.33359	-0.22967	-0.30077	-0.18913	-0.17936	0.154231
	-4.2***	-3.17***	-5.57***	-3.61***	-4.25***	2.04**
R2 (%)	52.7448	46.4125	55.4131	63.7465	69.2909	15.1944

	Service - EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.02914	-0.00675	-0.03568	-0.02102	-0.02496	0.004182
	-1.24232	-0.3587	-1.99**	-1.13814	-1.29627	0.176993
MKT Beta	1.119578	1.04228	1.00235	1.04863	0.986295	-0.13328
	39.6***	45.9***	46.4***	47.1***	42.5***	-4.68***
SMB Beta	0.094246	0.088763	0.384982	0.086718	0.168666	0.07442
	1.529527	1.8*	8.18***	1.79*	3.33***	1.198899
HML Beta	0.903283	0.328638	0.314518	-0.12996	-0.07349	-0.97678
	20.3***	9.18***	9.23***	-3.7***	-2.01**	-21.7***
Alpha (%) * low	-0.02261	-0.04402	-0.02782	-0.05466	-0.04551	-0.0229
	-0.52735	-1.27932	-0.84959	-1.61915	-1.2931	-0.53013
Alpha (%) * high	0.04278	0.053125	0.017724	0.059367	0.030702	-0.01208
	0.994759	1.539363	0.539706	1.75*	0.869764	-0.27877
R2 (%)	76.2338	77.958	77.2905	77.5547	73.493	39.5116

	Manufacturing - UnitedKingdom					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	-0.03884	-0.09678	-0.11384	-0.01688	-0.00954	0.029306
	-1.02597	-2.37**	-2.71***	-0.50817	-0.38093	0.679789
MKT Beta	0.891681	0.898637	1.044323	0.934651	0.691574	-0.20011
	19.5***	18.3***	20.6***	23.3***	22.9***	-3.85***
SMB Beta	1.037157	0.982285	0.684455	0.431927	-0.54012	-1.57728
	10.4***	9.17***	6.21***	4.95***	-8.21***	-13.9***
HML Beta	0.05112	0.044712	-0.09002	-0.33669	-0.28671	-0.33783
	0.709965	0.576652	-1.12758	-5.33***	-6.02***	-4.12***
Alpha (%) * low	0.391812	0.399137	0.391359	0.237203	0.156206	-0.23561
	5.66***	5.36***	5.1***	3.91***	3.41***	-2.99***
Alpha (%) * high	-0.32202	-0.17758	-0.15295	-0.27051	-0.18508	0.136944
	-4.64***	-2.38**	-1.99**	-4.44***	-4.03***	1.73*
R2 (%)	46.6889	41.0117	44.5352	51.2808	57.4769	24.672

	Manufacturing - EU15exUK					
	P1	P2	P3	P4	P5	P5-P1
Alpha (%)	0.013056	-0.04893	-0.01304	-0.00968	-0.01984	-0.0329
	0.54688	-2.02**	-0.71524	-0.53776	-1.03047	-1.21331
MKT Beta	1.206307	1.19387	1.059078	1.129365	1.001336	-0.20497
	41.9***	40.8***	48.2***	52.1***	43.1***	-6.27***
SMB Beta	0.37622	0.38935	0.030011	-0.17626	-0.14278	-0.519
	6***	6.11***	0.626598	-3.73***	-2.82***	-7.29***
HML Beta	0.187104	0.066765	-0.13983	-0.00581	-0.11499	-0.30209
	4.12***	1.446347	-4.03***	-0.16972	-3.14***	-5.86***
Alpha (%) * low	-0.13006	-0.09479	-0.06543	-0.07293	-0.07537	0.054688
	-2.98***	-2.14**	-1.96**	-2.22**	-2.14**	1.103266
Alpha (%) * high	0.043368	0.115739	0.030205	0.044407	0.033916	-0.00945
	0.99071	2.6***	0.9036	1.345555	0.960578	-0.19012
R2 (%)	72.384	70.6626	78.7178	82.2144	75.7786	10.7106

Table 9: Cross-sectional evidence: second-stage Fama-MacBeth regressions

This table reports estimates from the second-stage Fama-MacBeth regressions of the cross-section of daily excess stock returns on four characteristics: Brexit exposure, market beta, SMB beta, and HML beta. Following regression is estimated separately for each regional cross-section:

$$r_t^j - r_{f,t} = \lambda_0 + \lambda_1 \overline{r}^j_{BREXIT} + \lambda_2 \beta^j_{MKT} + \lambda_3 \beta^j_{SMB} + \lambda_4 \beta^j_{HML} + \epsilon^j_t,$$

where at time t: r_t^j is the return on stock j, $r_{f,t}$ is the risk free rate (for a USD investment), $\overline{r}^{j,k}_{BREXIT}$ is stock's Brexit exposure measured as its CAPM-adjusted return on June 24, 2016; and β^j_{MKT}, β^j_{SMB}, and β^j_{HML} are its exposures to European market, size, and value factors calculated using daily data between June 2015 and June 2016. Estimates are computed separately for days during which the daily change in the probability of hard Brexit was high, medium, and low. Last column reports the difference between the estimates in the *high* and *low* regimes. The sample covers a period between July 2016 and December 2019. t-statistics are reported in parentheses using the standard deviation of the time series of coefficient estimates under the given regime. For the individual regimes these are the t-statistics for a test that the corresponding coefficient is different than zero. For the *high-low* column, it is a t-statistics for the standard difference in means test.

	EU15				**UnitedKingdom**				**EU14**			
	Low	**Med**	**High**	**High - Low**	**Low**	**Med**	**High**	**High - Low**	**Low**	**Med**	**High**	**High - Low**
λ_0	0.316	0.002	-0.332	-0.648	0.458	-0.049	-0.556	-1.014	0.307	0.025	-0.280	-0.587
$t(\lambda_0)$	9.57***	0.083	-10.5***	-14.2***	11.6***	-2.2**	-15.7***	-19.1***	8.2***	1.102	-7.6***	-11.2***
λ_1	-0.021	0.002	0.021	0.042	-0.013	-0.001	0.008	0.020	-0.004	0.000	0.005	0.009
$t(\lambda_1)$	-7.75***	1.369	6.98***	10.4***	-5.36***	-0.541	2.79***	5.61***	-1.92*	0.230	2.02**	2.79***
λ_2	0.164	0.011	-0.150	-0.314	0.136	0.042	-0.086	-0.222	0.085	0.003	-0.087	-0.172
$t(\lambda_2)$	3.82***	0.449	-3.16***	-4.91***	2.55**	1.460	-1.615	-2.95***	1.95*	0.116	-1.85*	-2.68***
λ_3	-0.090	-0.006	0.071	0.160	-0.033	-0.020	0.004	0.037	-0.066	-0.010	0.038	0.104
$t(\lambda_3)$	-4.91***	-0.547	3.33***	5.73***	-1.276	-1.290	0.164	1.038	-3.44***	-0.735	1.500	3.27***
λ_4	0.043	0.004	-0.037	-0.080	0.031	0.005	-0.003	-0.034	0.025	0.010	-0.034	-0.059
$t(\lambda_4)$	4.1***	0.518	-2.76***	-4.71***	2.97***	0.693	-0.267	-2.23**	1.588	0.760	-1.378	-2.01**
N	204	409	204		204	409	204		204	409	204	
R^2	1.76%	1.11%	1.60%		1.16%	0.86%	1.09%		2.02%	1.73%	2.00%	

	France				**Germany**				**Italy**			
	Low	**Med**	**High**	**High - Low**	**Low**	**Med**	**High**	**High - Low**	**Low**	**Med**	**High**	**High - Low**
λ_0	0.331	0.030	-0.250	-0.581	0.302	0.051	-0.374	-0.676	0.389	-0.033	-0.274	-0.663
$t(\lambda_0)$	7.39***	1.053	-6.45***	-9.81***	6.38***	1.623	-5.83***	-8.48***	5.65***	-0.888	-5.06***	-7.57***
λ_1	-0.002	-0.002	0.007	0.008	-0.009	0.010	-0.004	0.005	-0.006	-0.006	0.008	0.014
$t(\lambda_1)$	-0.647	-0.752	2.28**	2.13**	-1.95*	1.68*	-0.342	0.464	-0.889	-1.474	1.341	1.570
λ_2	0.062	0.006	-0.102	-0.164	0.115	-0.050	0.000	-0.114	0.047	0.048	-0.108	-0.155
$t(\lambda_2)$	1.549	0.242	-2.58***	-2.92***	1.88*	-1.110	0.005	-1.209	0.738	1.220	-1.75*	-1.75*
λ_3	-0.077	-0.031	0.022	0.099	-0.084	0.010	0.031	0.115	-0.025	0.010	0.030	0.055
$t(\lambda_3)$	-3.57***	-2.18**	0.942	3.09***	-2.95***	0.481	0.671	2.13**	-0.768	0.454	0.883	1.170
λ_4	0.028	0.011	-0.028	-0.056	0.030	0.024	-0.029	-0.059	0.014	-0.028	-0.092	-0.106
$t(\lambda_4)$	1.532	0.936	-1.65*	-2.25**	1.136	0.795	-0.521	-0.958	0.449	-1.430	-2.89***	-2.39**
N	204	409	204		204	409	204		204	409	204	
R^2	1.90%	1.81%	2.15%		2.99%	2.74%	3.14%		6.02%	5.27%	5.81%	

Table 10: Cross-sectional evidence: pooled OLS with indicator variables

This table reports estimates from pooled OLS regressions of the cross-section of daily excess stock returns on four characteristics – Brexit exposure, market beta, SMB beta, and HML beta – in the presence of indicator variables for *high* and *low* daily change in no-deal Brexit probability and the interaction terms between these dummies and the characteristics:

$$\begin{aligned}\tilde{r}_t^j = \lambda_0 &+ \lambda_1 \overline{r}_B^j &+ \lambda_2 \beta_{MKT}^j &+ \lambda_3 \beta_{SMB}^j &+ \lambda_4 \beta_{HML}^j \\ &+ \lambda_0' I_L &+ \lambda_1' \overline{r}_B^j I_L &+ \lambda_2' \beta_{MKT}^j I_L &+ \lambda_3' \beta_{SMB}^j I_L &+ \lambda_4' \beta_{HML}^j I_L \\ &+ \lambda_0'' I_H &+ \lambda_1'' \overline{r}_B^j I_H &+ \lambda_2'' \beta_{MKT}^j I_H &+ \lambda_3'' \beta_{SMB}^j I_H &+ \lambda_4'' \beta_{HML}^j I_H + \epsilon_t^j.\end{aligned}$$

I_{LOW} (I_{HIGH}) is a deterministic indicator variable equal to one if day t is in the bottom (top) 1/4 of all trading days between July 2016 and December 2019 with respect to the daily change in the probability of no-deal Brexit and zero otherwise. t-statistics are reported in parentheses using standard errors clustered by time to account for cross-sectional correlation of residuals. ** and *** correspond to 5% and 1% statistical significance, respectively.

EU15

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	λ_0''	λ_1''	λ_2''	λ_3''	λ_4''	R2 (%)
-0.00554	0.003555	-0.01088	0.002237	-0.00025	0.321873	-0.02448	0.174727	-0.09176	0.043591	-0.32618	0.01722	-0.13935	0.068315	-0.03659	1.102424
[-0.29]	[1.4]	[-0.34]	[0.16]	[-0.033]	[8.4]***	[-6.6]***	[3.3]***	[-4]***	[3.3]***	[-8.8]***	[4.4]***	[-2.4]**	[2.7]***	[-2.4]**	

UnitedKingdom

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	λ_0''	λ_1''	λ_2''	λ_3''	λ_4''	R2 (%)
-0.04659	0.001648	0.018555	-0.0113	0.002041	0.504112	-0.01436	0.117221	-0.02146	0.028571	-0.50973	0.006079	-0.10438	0.015286	-0.00496	1.979525
[-2.2]**	[0.64]	[0.53]	[-0.68]	[0.26]	[11]***	[-4.1]***	[1.8]*	[-0.7]	[2.2]**	[-12]***	[1.6]	[-1.6]*	[0.52]	[-0.37]	

EU14

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	λ_0''	λ_1''	λ_2''	λ_3''	λ_4''	R2 (%)
0.014769	0.003275	-0.02325	0.002964	0.00302	0.292132	-0.00771	0.108043	-0.06902	0.021516	-0.29475	0.001599	-0.06386	0.035154	-0.03743	0.481984
[0.67]	[1.1]	[-0.67]	[0.2]	[0.23]	[6.7]***	[-2.1]**	[1.9]*	[-2.8]***	[1.1]	[-6.9]***	[0.42]	[-1.1]	[1.2]	[-1.3]	

Spain

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	λ_0''	λ_1''	λ_2''	λ_3''	λ_4''	R2 (%)
0.053276	0.006777	-0.05503	0.024568	-0.01494	0.246751	-0.00839	0.098762	-0.04344	-0.00355	-0.2258	-0.00352	-0.08811	0.030659	-0.03623	1.10926
[1.2]	[1.8]*	[-1.1]	[1]	[-0.4]	[3.3]***	[-1.3]	[1.2]	[-1.1]	[-0.065]	[-3.2]***	[-0.52]	[-1.1]	[0.73]	[-0.69]	

Italy

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	λ_0''	λ_1''	λ_2''	λ_3''	λ_4''	R2 (%)
-0.04663	-0.0019	0.0141	0.018244	-0.03443	0.43576	-0.00394	0.032584	-0.04295	0.0482	-0.22696	0.010362	-0.12193	0.0122	-0.0575	1.664163
[-1.3]	[-0.43]	[0.32]	[0.78]	[-1.8]*	[5.6]***	[-0.5]	[0.43]	[-1.1]	[1.3]	[-3.5]***	[1.3]	[-1.6]	[0.29]	[-1.6]	

Table 10: Continued

France

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.01537	0.001289	-0.01975	-0.0132	0.004645	0.315551	-0.00297	0.081635	-0.06337	0.022978	-0.26523	0.005246	-0.08222	0.035698	-0.03256	0.995531
[0.56]	[0.4]	[-0.6]	[-0.81]	[0.39]	[6]***	[-0.71]	[1.6]	[-2.4]**	[1.1]	[-5.6]***	[1.2]	[-1.6]	[1.2]	[-1.6]	

Germany

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.039246	0.011736	-0.06753	0.01826	0.015429	0.262782	-0.02072	0.182142	-0.10276	0.01462	-0.41309	-0.01536	0.06791	0.012536	-0.04453	0.22531
[1.3]	[1.9]*	[-1.4]	[0.81]	[0.53]	[4.7]***	[-2.7]***	[2.3]**	[-2.8]***	[0.37]	[-5.8]***	[-1.3]	[0.78]	[0.25]	[-0.71]	

Denmark

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
-0.00414	0.002012	-0.00834	0.018903	0.004731	0.199139	-0.01366	0.203676	-0.09456	0.064876	-0.20779	0.005406	-0.10446	0.008649	-0.05225	1.100175
[-0.12]	[0.37]	[-0.14]	[0.77]	[0.23]	[3.3]***	[-1.5]	[1.9]*	[-2]**	[1.6]	[-3.5]***	[0.61]	[-1]	[0.2]	[-1.4]	

Netherlands

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.00442	0.004381	0.003337	-0.01578	-0.00348	0.238103	-0.01779	0.129695	-0.03733	0.031056	-0.24849	0.009676	-0.09411	0.052362	-0.03987	1.350283
[0.13]	[1]	[0.066]	[-0.68]	[-0.21]	[3.8]***	[-2.4]**	[1.5]	[-1]	[1.1]	[-3.7]***	[1.3]	[-1]	[1.3]	[-1.4]	

Austria

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
-0.01696	-0.00608	-0.01495	0.02048	0.034179	0.275101	0.003976	0.158866	-0.09517	-0.01462	-0.20461	0.002357	-0.21545	0.117313	0.038139	1.689688
[-0.48]	[-1]	[-0.29]	[0.54]	[1.2]	[4.3]***	[0.38]	[1.7]*	[-1.4]	[-0.3]	[-3.3]***	[0.22]	[-2.4]**	[1.8]*	[0.76]	

Luxembourg

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
-0.07643	-0.01717	0.045815	0.043905	0.041352	0.501666	0.034141	-0.13603	-0.07984	-0.08392	-0.19204	0.052217	-0.32309	0.07013	0.004288	1.528708
[-0.71]	[-1]	[0.3]	[0.4]	[0.49]	[2.5]**	[1]	[-0.45]	[-0.42]	[-0.54]	[-0.86]	[1.6]	[-1.1]	[0.36]	[0.029]	

Table 10: Continued

Belgium

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.04905	0.008083	-0.03468	-0.03462	-0.00188	0.247076	-0.00625	0.089846	-0.00172	0.010739	-0.2078	-0.0015	-0.20427	0.082389	-0.06759	1.282785
[1.5]	[1.4]	[-0.7]	[-1.2]	[-0.071]	[3.8]***	[-0.6]	[0.96]	[-0.031]	[0.2]	[-3.3]***	[-0.16]	[-2.1]**	[1.6]	[-1.2]	

Portugal

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.105635	0.011678	-0.17937	0.166014	0.005594	0.159795	0.005605	0.142581	-0.07095	-0.02842	-0.26903	0.008123	-0.08524	-0.03825	-0.02103	2.189585
[0.94]	[1.2]	[-1.4]	[0.99]	[0.13]	[0.87]	[0.3]	[0.59]	[-0.23]	[-0.34]	[-1.6]	[0.47]	[-0.38]	[-0.14]	[-0.27]	

IrelandRepublicof

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
-0.112	-0.00256	-0.00596	0.066963	-0.07021	0.319546	-0.00953	0.257952	-0.23215	0.099574	0.095382	0.017148	-0.31259	0.018201	0.021302	1.500332
[-1.7]*	[-0.47]	[-0.093]	[1.3]	[-1.9]*	[2.8]***	[-0.98]	[1.9]*	[-2.3]**	[1.4]	[0.87]	[2]**	[-2.3]**	[0.18]	[0.33]	

Greece

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	λ''_0	λ''_1	λ''_2	λ''_3	λ''_4	R2 (%)
0.086915	0.010453	-0.20415	0.169808	-0.05098	0.272778	-0.00848	0.183932	-0.12651	0.087745	-0.08683	0.014378	-0.12657	0.079618	-0.03884	0.910918
[1.3]	[1.2]	[-1.8]*	[1.8]*	[-1.1]	[2]**	[-0.54]	[0.99]	[-0.79]	[1]	[-0.78]	[1]	[-0.69]	[0.49]	[-0.47]	

Table 11: Cross-sectional evidence

This table reports estimates from pooled OLS regressions of the cross-section of daily excess stock returns on four characteristics – Brexit risk exposure, market beta, SMB beta, and HML beta – in the presence of a time-varying variable capturing the daily change in the probability of no-deal Brexit (Δp_t) and the interaction terms between this variable and the stock characteristics:

$$\begin{aligned} \tilde{r}_t^j = \lambda_0 &+ \lambda_1 \bar{r}_B^j &+ \lambda_2 \beta_{MKT}^j &+ \lambda_3 \beta_{SMB}^j &+ \lambda_4 \beta_{HML}^j \\ + \lambda_0' \Delta p &+ \lambda_1' \bar{r}_B^j \Delta p &+ \lambda_2' \beta_{MKT}^j \Delta p &+ \lambda_3' \beta_{SMB}^j \Delta p &+ \lambda_4' \beta_{HML}^j \Delta p + \epsilon_t^j. \end{aligned}$$

t-statistics are reported in parentheses using standard errors clustered by time to account for cross-sectional correlation of residuals. ** and *** correspond to 5% and 1% statistical significance, respectively.

EU15

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
-0.0032	0.000797	0.008903	-0.00788	0.003549	-5.7845	0.492952	-3.56818	1.643346	-0.60702	1.608745
[-0.21]	[0.76]	[0.45]	[-0.88]	[0.62]	[-13]***	[9.8]***	[-4.3]***	[5.2]***	[-4.5]***	

UnitedKingdom

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
-0.04954	-0.00158	0.033493	-0.01724	0.009593	-9.84261	0.260686	-2.64194	0.315108	-0.1715	3.099114
[-3.2]***	[-1.5]	[1.4]	[-1.5]	[1.8]*	[-21]***	[5.1]***	[-2.7]***	[0.82]	[-1.3]	

EU15exUK

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
0.019149	0.000323	0.001021	-0.01182	0.002626	-5.15641	0.105722	-1.79883	0.927729	-0.24538	0.582643
[1.1]	[0.26]	[0.048]	[-1.1]	[0.26]	[-11]***	[3]***	[-2.5]**	[2.9]***	[-1.2]	

Spain

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
0.058386	0.002163	-0.03686	0.017313	-0.02133	-3.6368	0.094056	-2.13571	0.586467	-0.16468	1.312889
[1.9]*	[0.88]	[-1.2]	[1]	[-0.89]	[-4.7]***	[1.3]	[-2.3]**	[1.5]	[-0.35]	

Italy

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
0.01206	-0.00222	0.008587	0.006632	-0.03342	-4.74715	0.206344	-2.04636	0.142105	-0.45304	1.986759
[0.41]	[-0.74]	[0.29]	[0.4]	[-2.3]**	[-5.2]***	[2.2]**	[-2.1]**	[0.3]	[-1]	

France

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
0.035055	0.000334	-0.00688	-0.02892	0.005397	-4.9813	0.108	-1.73756	0.840441	-0.29546	1.213038
[1.7]*	[0.22]	[-0.36]	[-2.7]***	[0.63]	[-9.4]***	[2.5]**	[-2.7]***	[2.6]***	[-1.5]	

Germany

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
0.00755	0.001947	0.003709	-0.00816	0.012443	-6.06233	0.060086	-1.32052	1.140187	-0.17411	0.268885
[0.3]	[0.46]	[0.11]	[-0.47]	[0.57]	[-9.2]***	[0.81]	[-1.4]	[2.6]**	[-0.48]	

Denmark

λ_0	λ_1	λ_2	λ_3	λ_4	λ_0'	λ_1'	λ_2'	λ_3'	λ_4'	R2(%)
-0.00584	-0.00137	0.030782	-0.00621	0.010507	-3.31999	0.145368	-3.7227	1.210566	-0.85567	1.507586
[-0.24]	[-0.38]	[0.73]	[-0.34]	[0.67]	[-5.5]***	[1.5]	[-2.9]***	[2.3]**	[-2.1]**	

Table 11: Continued

Netherlands

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
0.002089	0.000751	0.02959	-0.01915	-0.0033	-4.00717	0.261989	-2.57259	0.792959	-0.31303	1.703764
[0.079]	[0.26]	[0.84]	[-1.2]	[-0.27]	[-6.2]***	[2.8]***	[-2.4]**	[1.9]*	[-1]	

Austria

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
0.003549	-0.00614	-0.01518	0.019784	0.043264	-3.51927	0.120535	-3.66114	1.290379	0.173289	2.149782
[0.13]	[-1.5]	[-0.43]	[0.72]	[2.1]**	[-5.2]***	[1.1]	[-3.1]***	[1.8]*	[0.36]	

Luxembourg

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
3.58E-05	0.003304	-0.05245	0.041935	0.017513	-5.90506	0.104652	-2.24794	1.674324	0.783926	1.531795
[0.00042]	[0.25]	[-0.44]	[0.52]	[0.28]	[-2.5]**	[0.29]	[-0.7]	[0.8]	[0.49]	

Belgium

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
0.064301	0.004465	-0.05167	-0.02052	-0.0142	-3.75742	0.037615	-2.94388	0.520038	-0.83407	1.589537
[2.5]**	[1.1]	[-1.4]	[-0.96]	[-0.66]	[-5.3]***	[0.37]	[-2.5]**	[0.88]	[-1.3]	

Portugal

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
0.119832	0.014899	-0.14888	0.092139	-0.0165	-4.24033	0.007972	-0.2033	-1.97781	-0.34857	2.758382
[1.6]	[2]**	[-1.6]	[0.78]	[-0.51]	[-2.6]***	[0.051]	[-0.091]	[-0.76]	[-0.44]	

IrelandRepublicof

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
-0.01073	-0.00241	-0.01118	0.015397	-0.03723	-3.55142	0.294395	-5.68308	2.976643	-0.72213	2.852278
[-0.23]	[-0.66]	[-0.21]	[0.38]	[-1.3]	[-2.9]***	[3.8]***	[-3]***	[2.2]**	[-0.85]	

Greece

λ_0	λ_1	λ_2	λ_3	λ_4	λ'_0	λ'_1	λ'_2	λ'_3	λ'_4	R2(%)
0.143267	0.011828	-0.17552	0.145234	-0.03641	-2.04271	0.337857	-3.19873	2.66706	-1.63124	0.710128
[2.9]***	[2]**	[-2.4]**	[2.2]**	[-1]	[-1.4]	[1.9]*	[-1.8]*	[1.7]*	[-1.8]*	

Table 12: Stock market indices used

This table provides additional details on the stock market indices used in Table 13. For each stock market index, I report the region it covers and the full name.

Region	RIC	Full name
Europe	.FTEU3	FTSEUROFIRST 300 INDEX
Europe	.STOXX	STOXX EUROPE 600 EUR PRICE
Europe	.STOXXE	EURO STOXX INDEX
Europe	.STOXX50	STOXX EUROPE 50 EUR PRICE
Europe	.STOXX50E	EURO STOXX 50 EUR PRICE..
Europe	.N100	EURONEXT 100 INDEX
Europe	.N150	EURONEXT NEXT 150 INDEX
Austria	.ATX	AUSTRIAN TRADED INDEX
Belgium	.BFX	BEL 20 INDEX.
Denmark	.OMXC20	OMX COPENHAGEN 20 INDEX
France	.FCHI	CAC 40 INDEX
France	.CN20	CAC NEXT20 INDEX
France	.CACMD	CAC MID 60 INDEX
Germany	.GDAXI	DEUTSCHE BOERSE DAX
Germany	.MDAXI	MDAX PERFORMANCE INDEX
Germany	.SDAXI	SDAX SHARE INDEX
Greece	.ATG	ATHEX COMPOSITE SHARE PRICE
Ireland	.ISEQ	SEQ OVERALL PRICE INDEX
Italy	.FTMIB	FTSE MIB INDEX
Luxembourg	.LUXX	LUXEMBOURG SE LUXX INDEX
Netherlands	.AEX	AMSTERDAM EXCHANGES INDEX
Portugal	.PSI20	EURONEXT LISBON PSI 20.
Spain	.IBEX	IBEX 35 INDEX
UK	.FTSE	FTSE 100 INDEX
UK	.FTMC	FTSE MID 250 INDEX

Table 13: Explaining market return

This table presents the results of the regression of various USD-denominated market index returns of the EU-15 region on the returns to four characteristic pure play portfolios:

$$R_t^j = \gamma_{Brexit}^j R_t^{Brexit} + \gamma_{MKT}^j R_t^{MKT} + \gamma_{SMB}^j R_t^{SMB} + \gamma_{HML}^j R_t^{HML} + \epsilon_t^j,$$

where R_t^j is the return on the relevant test index j, and R_t^{Brexit}, R_t^{MKT}, R_t^{SMB}, and R_t^{HML} are the returns to the relevant characteristic pure play (factor mimicking) portfolios computed in line with Equation (3) using the EU-15 cross-section of individual stock returns. A brief summary of the indices used is provided in Table 12.

	FTEU3	**STOXX**	**STOXXE**	**STOXX50**	**STOXX50E**	**N100**	**N150**	**ATX**	**BFX**	**OMXC20**	**FCHI**	**CN20**	**CACMD**	**GDAXI**	**MDAXI**	**SDAXI**	**ATG**	**ISEQ**	**FTMIB**	**LUXX**	**AEX**	**PSI20**	**IBEX**	**FTSE**	**FTMC**
Panel A1: CAPM																									
γ_{MKT}	0.92	0.95	1.01	0.86	1.03	0.92	0.96	1.03	0.94	0.62	1.01	0.93	0.94	1.02	0.93	0.92	0.96	1.11	1.33	1.06	0.88	0.80	1.10	1.05	1.33
	32.49	33.80	32.40	28.64	31.27	29.25	29.53	24.03	27.62	13.70	30.05	27.01	27.24	29.18	26.29	23.92	14.89	28.20	29.28	18.25	28.06	20.42	27.49	35.23	38.45
R^2	55.69	57.64	55.55	49.41	53.80	50.55	51.02	41.77	47.68	18.76	51.90	46.57	46.99	50.75	45.55	40.92	21.57	49.01	50.86	28.43	48.47	33.23	47.44	60.31	64.42
Panel B1: Fama-French three-factor model																									
γ_{MKT}	0.92	0.98	1.03	0.83	0.99	0.94	1.27	1.14	1.01	0.88	0.98	1.10	1.23	0.99	1.08	1.31	1.49	1.28	1.36	1.11	0.88	0.89	1.14	0.92	1.42
	15.42	16.59	15.70	13.15	14.32	14.16	18.76	12.47	14.18	9.11	13.83	15.27	17.36	13.40	14.61	16.43	11.01	15.41	13.98	8.98	13.43	10.72	13.43	14.44	19.31
γ_{SMB}	-0.11	-0.04	-0.07	-0.16	-0.20	-0.10	0.65	0.37	0.05	0.44	-0.19	0.26	0.57	-0.22	0.18	0.82	1.42	0.27	0.09	0.22	-0.10	0.22	0.08	-0.37	0.12
	-0.76	-0.29	-0.47	-1.09	-1.26	-0.66	4.15	1.73	0.28	1.95	-1.17	1.53	3.48	-1.27	1.02	4.41	4.48	1.42	0.40	0.76	-0.63	1.13	0.40	-2.48	0.70
γ_{HML}	-0.44	-0.49	-0.51	-0.38	-0.46	-0.59	-0.60	0.35	-0.60	-0.93	-0.48	-0.74	-0.82	-0.57	-0.86	-0.80	0.07	-0.69	0.10	0.38	-0.49	-0.09	-0.14	-0.08	-0.46
	-3.61	-4.09	-3.85	-2.98	-3.28	-4.40	-4.39	1.88	-4.17	-4.82	-3.36	-5.07	-5.65	-3.80	-5.78	-4.97	0.26	-3.96	0.53	1.50	-3.64	-0.56	-0.81	-0.61	-3.10
R^2	56.27	58.37	56.23	49.85	54.31	51.56	53.29	42.03	48.68	21.53	52.46	48.35	49.90	51.52	47.76	44.25	23.31	50.08	50.77	28.48	49.16	33.22	47.37	60.51	64.80
Panel A2: Brexit & CAPM																									
γ_{Brexit}	3.54	3.13	4.70	3.17	4.22	4.83	5.97	4.79	4.30	4.29	4.76	4.37	5.43	6.10	6.89	8.02	-0.23	1.02	3.70	4.95	4.67	3.39	0.97	-1.19	-7.06
	7.36	6.53	9.05	6.20	7.59	9.14	11.18	6.54	7.46	5.45	8.44	7.42	9.47	10.56	12.00	12.97	-0.21	1.48	4.70	4.93	8.93	4.98	1.39	-2.27	-12.60
γ_{MKT}	1.09	1.10	1.24	1.01	1.23	1.16	1.26	1.27	1.15	0.84	1.24	1.15	1.20	1.32	1.27	1.32	0.95	1.16	1.51	1.30	1.10	0.97	1.15	0.99	0.99
	30.23	30.55	31.65	26.27	29.47	29.21	31.29	22.88	26.48	14.08	29.23	25.98	27.89	30.39	29.37	28.32	11.07	22.34	25.49	17.25	28.08	18.96	21.76	25.17	23.45
R^2	58.34	59.64	59.46	51.58	56.72	54.99	57.36	44.64	50.90	21.55	55.63	49.82	52.07	56.58	53.60	50.89	21.48	49.09	52.09	30.38	52.91	35.09	47.50	60.51	70.19
Panel B2: Brexit & Fama-French three-factor model																									
γ_{Brexit}	3.32	2.87	4.47	2.99	4.02	4.54	5.70	5.29	3.98	3.73	4.55	3.94	4.99	5.87	6.46	7.67	-0.23	0.54	3.90	5.40	4.46	3.43	0.90	-1.29	-7.63
	6.82	5.90	8.48	5.76	7.11	8.48	10.70	7.12	6.83	4.72	7.95	6.66	8.72	10.02	11.19	12.49	-0.20	0.78	4.88	5.30	8.40	4.96	1.26	-2.43	-13.67
γ_{MKT}	1.08	1.12	1.24	0.97	1.18	1.15	1.54	1.40	1.20	1.06	1.19	1.29	1.47	1.27	1.39	1.68	1.48	1.31	1.54	1.36	1.09	1.06	1.19	0.85	1.06
	17.23	17.91	18.32	14.58	16.32	16.84	22.53	14.59	16.05	10.32	16.25	17.01	20.07	16.90	18.72	21.28	10.14	14.61	14.97	10.43	16.08	11.93	12.96	12.53	14.76
γ_{SMB}	-0.09	-0.02	-0.04	-0.14	-0.18	-0.07	0.69	0.42	0.07	0.47	-0.17	0.28	0.61	-0.18	0.22	0.87	1.42	0.28	0.12	0.25	-0.07	0.24	0.08	-0.38	0.06
	-0.63	-0.17	-0.30	-0.99	-1.15	-0.51	4.66	2.00	0.44	2.12	-1.04	1.72	3.82	-1.09	1.37	5.12	4.47	1.43	0.53	0.89	-0.48	1.25	0.42	-2.56	0.41
γ_{HML}	-0.29	-0.36	-0.31	-0.25	-0.28	-0.39	-0.35	0.62	-0.43	-0.76	-0.28	-0.57	-0.59	-0.31	-0.57	-0.46	0.06	-0.66	0.28	0.62	-0.29	0.06	-0.10	-0.13	-0.79
	-2.41	-3.04	-2.41	-1.95	-2.03	-2.97	-2.66	3.34	-2.97	-3.94	-1.98	-3.91	-4.22	-2.13	-4.06	-3.05	0.22	-3.75	1.42	2.46	-2.20	0.34	-0.57	-1.03	-5.79
R^2	58.53	59.99	59.65	51.71	56.87	55.36	58.89	45.41	51.34	23.55	55.76	50.91	54.04	56.75	54.62	53.10	23.22	50.05	52.09	30.74	53.07	35.06	47.41	60.75	71.35

Table 14: Explaining geographic zone factors

This table presents the results of the regression of five European geographic zone factors and one spread constructed using two of these factors on the returns to four characteristic pure play portfolios:

$$R_t^j = \gamma_{Brexit}^j R_t^{Brexit} + \gamma_{MKT}^j R_t^{MKT} + \gamma_{SMB}^j R_t^{SMB} + \gamma_{HML}^j R_t^{HML} + \epsilon_t^j,$$

where R_t^j is the return on the relevant geographic zone factor or spread j, and R_t^{Brexit}, R_t^{MKT}, R_t^{SMB}, and R_t^{HML} are the returns to the relevant characteristic pure play (factor mimicking) portfolios computed in line with Equation (3) using the EU-15 cross-section of individual stock returns.

	UK	**EU14**	**EU14 − UK**
		Panel A: Brexit	
γ_{Brexit}	-20.14	-4.52	15.62
	-33.96	-7.63	43.63
N	840	840	840
R^2(%)	57.86	6.38	69.40
		Panel B: CAPM	
γ_{MKT}	1.53	0.89	-0.64
	34.79	26.01	-14.71
N	840	840	840
R^2(%)	59.04	44.61	20.43
		Panel C: Fama French 3 factors	
γ_{HML}	-0.71	-0.69	0.01
	-3.75	-4.77	0.07
γ_{MKT}	1.64	1.12	-0.52
	17.71	15.67	-5.66
γ_{SMB}	0.12	0.42	0.31
	0.54	2.56	1.44
N	840	840	840
R^2(%)	59.68	46.61	20.44
		Panel D: Brexit & CAPM	
γ_{Brexit}	-11.97	5.53	17.50
	-18.42	9.73	37.97
γ_{MKT}	0.94	1.16	0.22
	19.32	27.16	6.28
N	840	840	840
R^2(%)	70.82	50.17	70.74
		Panel E: Brexit & Fama-French 3 factors	
γ_{Brexit}	-12.91	5.19	18.10
	-20.31	9.08	39.92
γ_{HML}	-1.28	-0.46	0.82
	-8.18	-3.27	7.34
γ_{MKT}	1.03	1.36	0.33
	12.69	18.59	5.64
γ_{SMB}	0.04	0.46	0.42
	0.22	2.87	3.31
N	840	840	840
R^2(%)	72.98	51.34	72.61

Figure 1: Implied volatilities over time

This figure plots the implied volatility for the GBP/USD 3 months maturity ATM and the delta-10 call and put options between January 2015 and December 2019.

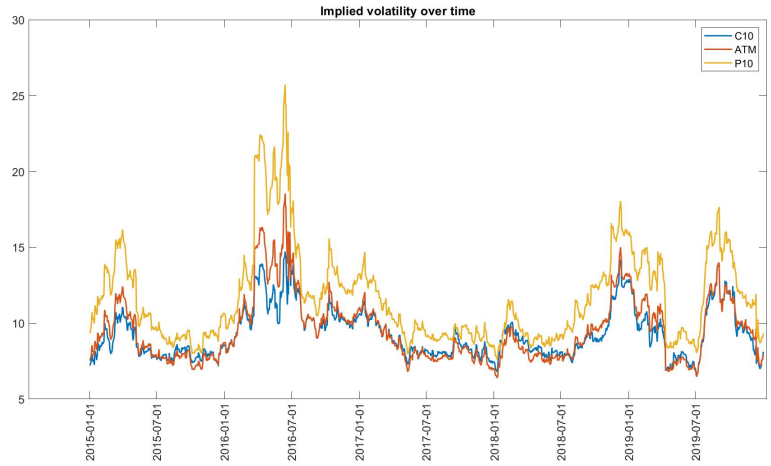


Figure 2: Brexit impact by country

This figure plots the response of the various cross-sections of stock returns in the EU-15 region upon the announcement of the Brexit referendum outcome. Three lengths of response window are considered: overnight, Friday following the referendum (24th June 2016), and Friday and Monday following the referendum (24th - 27th June 2016). Both value-weighted (top panel) and equal-weighted (bottom panel) returns are reported. Finnish and Swedish stock exchanges were closed on Friday the 24th June due to national holiday.

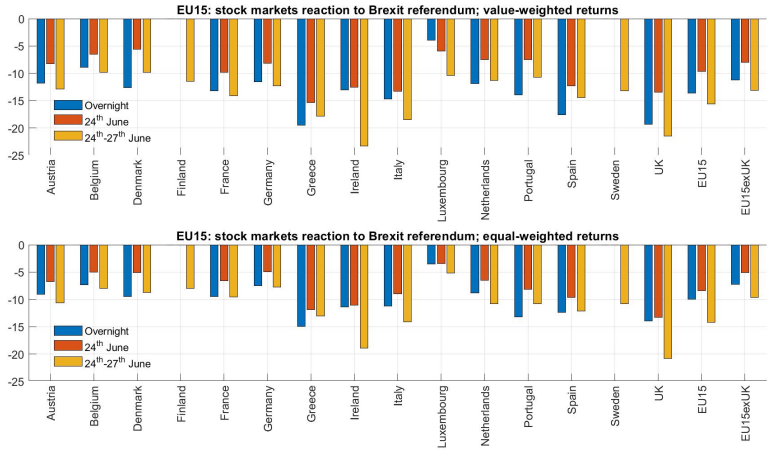
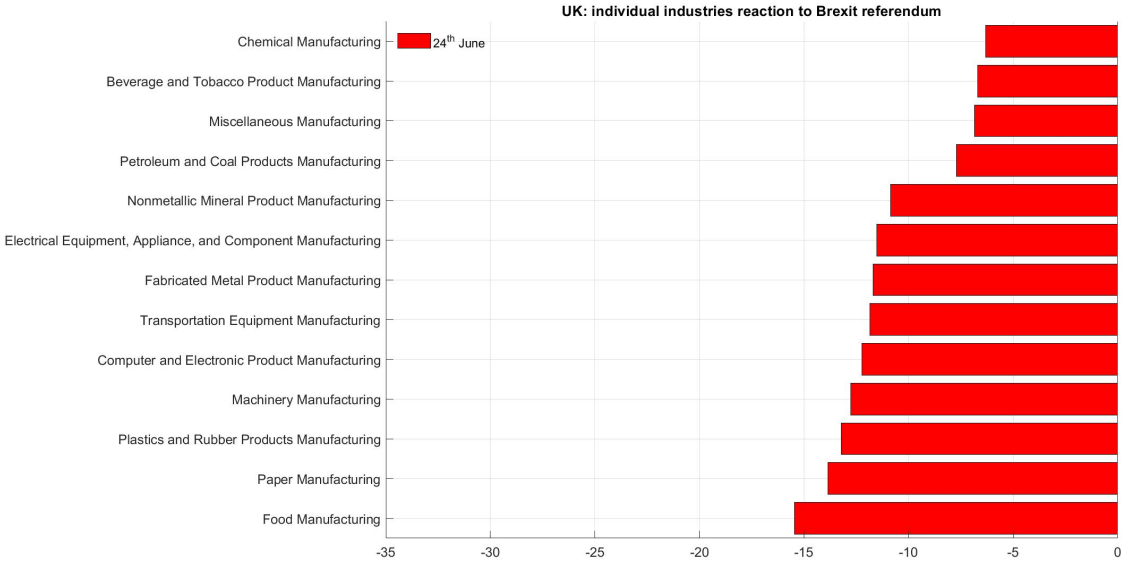
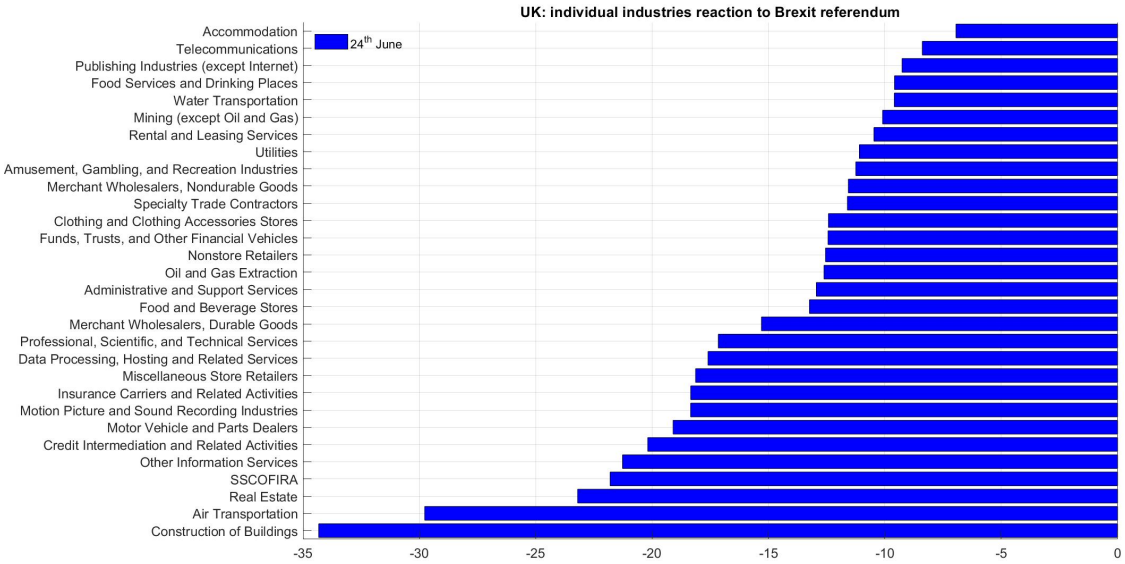


Figure 3: Brexit impact – UK industries

This figure plots the response of UK manufacturing and service industries to the Brexit referendum outcome using value-weighted return over the medium-length response window of Friday, 24th June 2016. I consider industries for which at least 5 individual stocks existed. Figure a plots the returns to manufacturing industries. Figure b plots the returns to service industries.



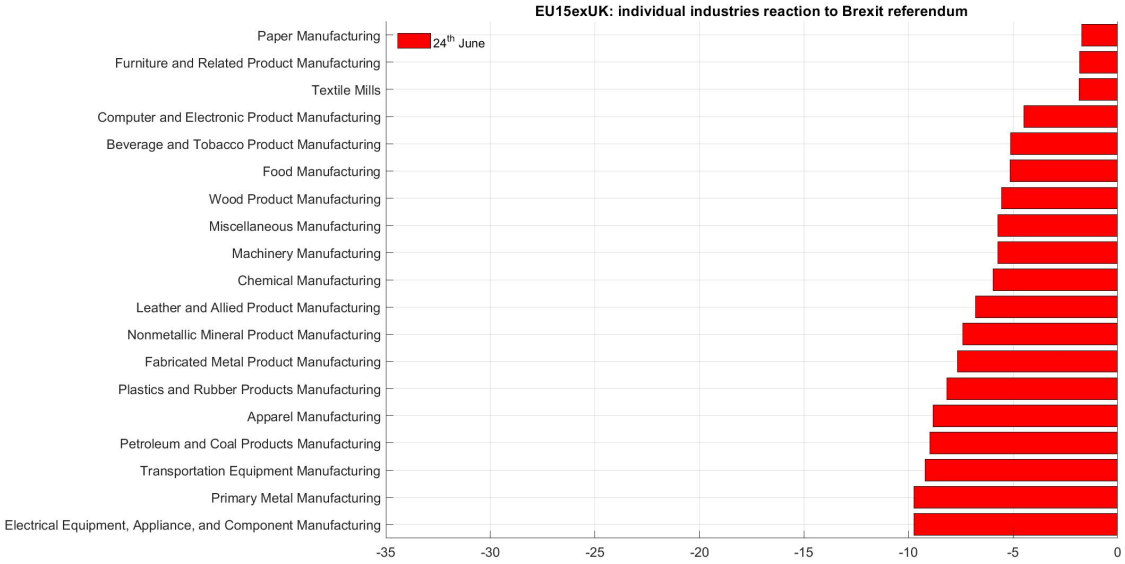
Manufacturing industries



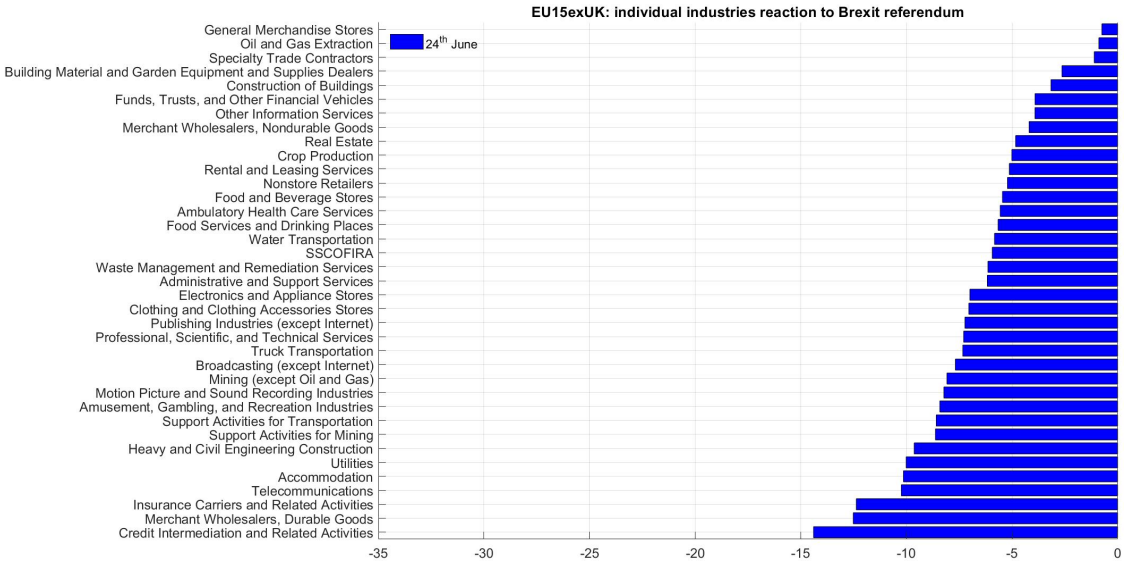
Service industries

Figure 4: Brexit impact – EU-15 excluding UK industries

This figure plots the response of EU-15 excluding UK manufacturing and service industries to the Brexit referendum outcome using value-weighted return over the medium-length response window of Friday, 24th June 2016. I consider industries for which at least 5 individual stocks existed. Figure a plots the returns to manufacturing industries. Figure b plots the returns to service industries.



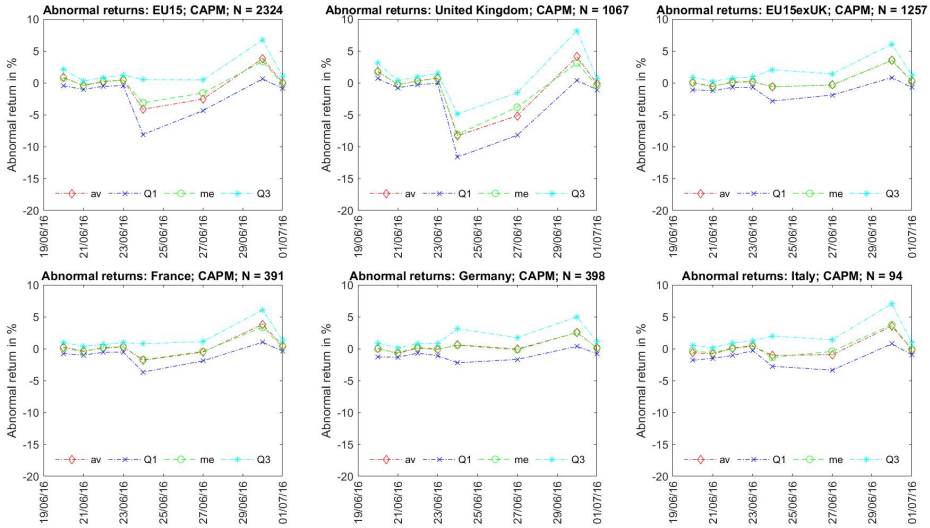
Manufacturing industries



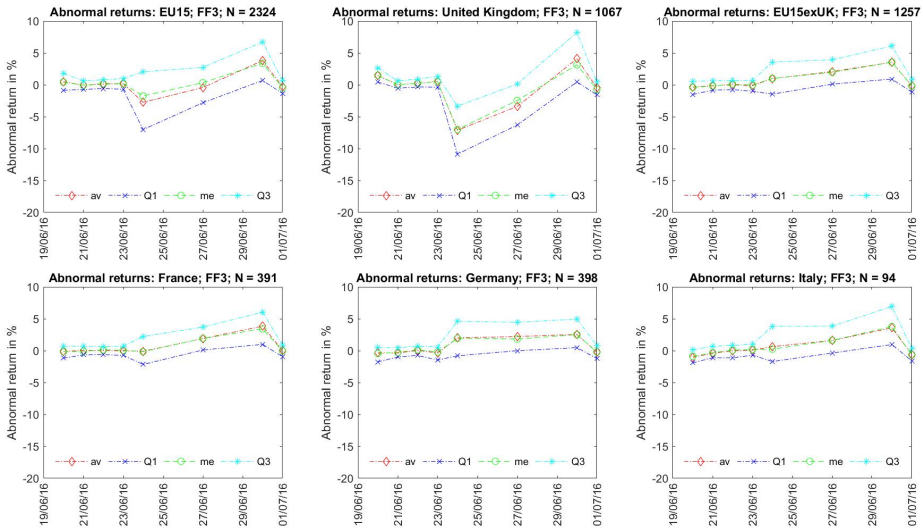
Service industries

Figure 5: Abnormal stock returns around the Brexit Referendum of June 26, 2016

This figure shows the equally-weighted average and quartiles of abnormal returns in the week of and the week following the Brexit referendum (June 20, 2016 through July 1, 2016; the event window). The returns are adjusted either in line with the CAPM (a) or the Fama-French three-factor model (b). I report the results for the 4 largest national cross-sections, the EU-15 stock market as a whole, and the EU-15 excluding UK cross-section. The relevant betas necessary to calculate the abnormal returns are estimated using daily data between June 22, 2015 and June 17, 2016 (the estimation period).



CAPM-adjusted returns



Fama-French three-factor adjusted returns

Figure 6: Statistical significance of abnormal returns upon the Brexit Referendum

This figure reports the share of statistically positive and negative abnormal returns in each cross-section following the Brexit referendum. Two event windows are considered: the one of the Friday following the referendum ($AR^m_{i,1}$) and the one of the Friday and Monday following the referendum ($CAR^m_{i,1:2}$). Abnormal returns are calculated by adjusting for either the market (CAPM) or Fama-French three-factor model m.

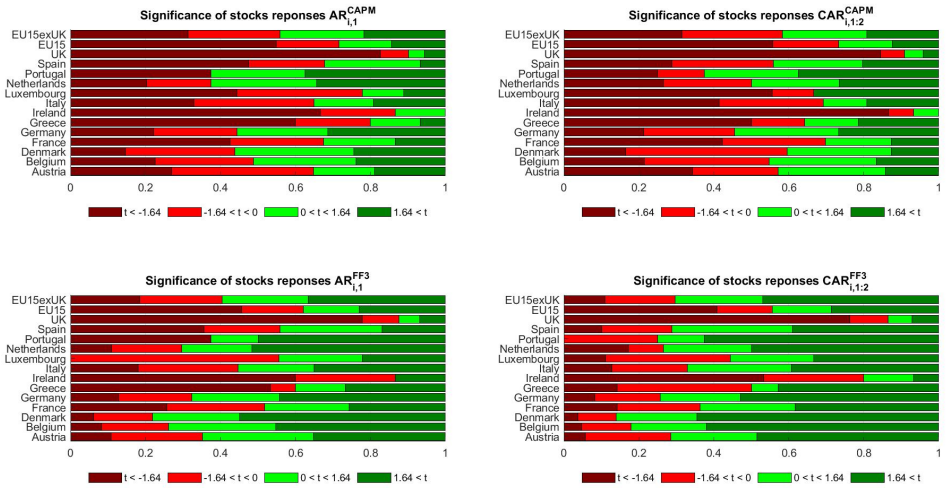
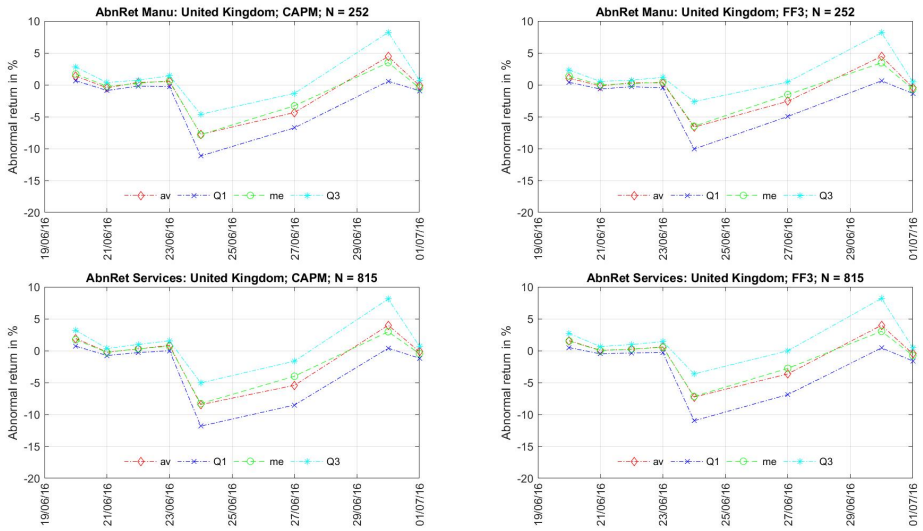
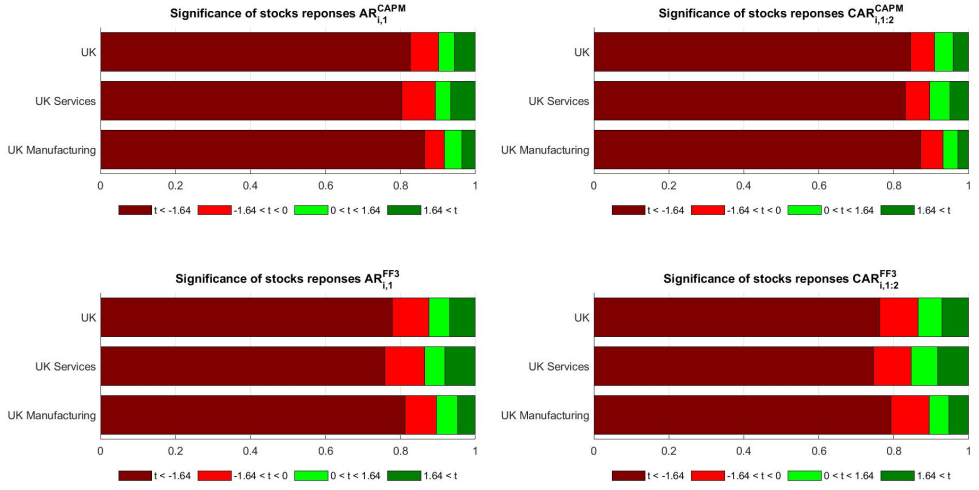


Figure 7: UK's manufacturing and services stocks: abnormal returns

This figure compares abnormal returns for UK's manufacturing and services firms. Figure a reports the equally-weighted average and quartiles of abnormal returns in the week of and the week following the Brexit referendum. The returns are adjusted either in line with the CAPM or the Fama-French three-factor model. Figure b reports the share of statistically positive and negative abnormal returns following the Brexit referendum. Two event windows are considered: the one of the Friday following the referendum ($AR^m_{i,1}$) and the one of the Friday and Monday following the referendum ($CAR^m_{i,1:2}$). Abnormal returns are calculated by adjusting for either the market (CAPM) or Fama-French three-factor model m.



Abnormal returns



Abnormal returns' significance

Figure 8: Cumulative return to the three Fama-French factor mimicking portfolios

This figure plots cumulative returns to the three Fama-French factor mimicking portfolios constructed using cross-sections of individual stocks in EU15, UK, and EU14 regions and compares them to the cumulative returns to the corresponding European factors provided by Professor Kenneth French. Time series of daily returns to the factor mimicking portfolios are the time series of λ_2, λ_3, and λ_4 estimated in each of the three regional cross-sections using the following regression:

$$r_t^j - r_{f,t} = \lambda_0 + \lambda_1 \overline{r}_{BREXIT}^j + \lambda_2 \beta_{MKT}^j + \lambda_3 \beta_{SMB}^j + \lambda_4 \beta_{HML}^j + \epsilon_t^j,$$

where at time t: r_t^j is the return on stock j, $r_{f,t}$ is the risk free rate (for a USD investment), $\overline{r}_{BREXIT}^{j,k}$ is stock's Brexit exposure measured as its CAPM-adjusted return on June 24, 2016; and β_{MKT}^j, β_{SMB}^j, and β_{HML}^j are its exposures to European market, size, and value factors calculated using daily data between June 2015 and June 2016. Time period of the analysis is between June 27, 2016 and December 31, 2019.



Figure 9: Cumulative return to the Brexit characteristic portfolio (λ_1)

This figure plots cumulative returns to the Brexit pure play portfolios constructed using cross-sections of individual stocks in EU15, UK, and EU14 regions. Time series of daily returns to the factor mimicking portfolios are the time series of λ_1 estimated in each of the three regional cross-sections using the following regression:

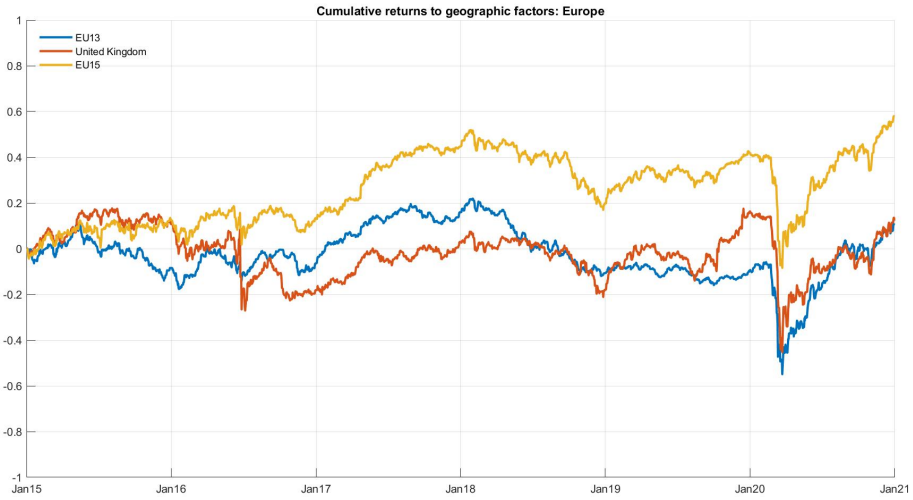
$$r_t^j - r_{f,t} = \lambda_0 + \lambda_1 \overline{r}_{BREXIT}^j + \lambda_2 \beta_{MKT}^j + \lambda_3 \beta_{SMB}^j + \lambda_4 \beta_{HML}^j + \epsilon_t^j,$$

where at time t: r_t^j is the return on stock j, $r_{f,t}$ is the risk free rate (for a USD investment), $\overline{r}_{BREXIT}^{j,k}$ is stock's Brexit exposure measured as its CAPM-adjusted return on June 24, 2016; and β_{MKT}^j, β_{SMB}^j, and β_{HML}^j are its exposures to European market, size, and value factors calculated using daily data between June 2015 and June 2016. Time period of the analysis is between June 27, 2016 and December 31, 2019.



Figure 10: Cumulative returns the European geographic factors

This figure plots cumulative returns to the European geographic factors computed in line with Dumas et al. (2020) methodology between January 2015 and December 2019.



Appendix

A Geographic factors

In an open economy, individual firm's returns do not reflect solely and fully the business risks of the country of its headquarters (or listing) but rather a mixture of latent geographical factors relevant from the point of view of its operations. To make inferences about the region's risk on the basic of its stock market is, therefore, to ignore the complexity of these underlying relationships. Dumas et al. (2020) aim to overcome this problem by using revenue information about stocks listed worldwide to construct stock market indices, which would better reflect the intrinsic business risks of investing in a given country or region. These synthetic zone factors are called "geographic risks".

Dumas et al. (2020) use World Vest Base to identify thirteen geographic factors: France, Germany, Great Britain, Brazil, United States, Canada, Australia, Malaysia, Singapore, China, Japan, India, and the Rest of the World. In this paper, I use Factset GeoRev dataset to identify sixteen of them: the thirteen from the original work and three additional for Italy, EU15, and the Rest of EU15. The reason for this is that the paper discusses the response of European Union and United Kingdom to Brexit.

A.1 Data trimming

For all companies covered by the FactSet GeoRev dataset, I collect information about the share of revenue derived from various geographic locations between 2015 and 2019. Information on a total of 61,613 equity ISINs is available across these five years. These are then filtered in three steps aimed to closely mirror these of the original work (Dumas et al., 2020):

1. In the first step ISINs are dropped subject to their static properties obtained

from Thomson Reuters's Eikon. First, only stocks listed in one of the 56 countries (28 developed and 28 developing ones) are selected as indicated by the first two letters of their ISIN.[15] This leaves 54,299 ISINs. Second, I drop ISINs that are not considered ordinary shares by Eikon.[16] This leaves me with 50,502 ISINs. Finally, I delete Chinese Class A shares. This results in 46,485 ISINs. The resulting number of ISINs in each year is summarized in Table A.1 column (1).

2. In the second step ISINs are dropped for specific years depending on their properties in that year. First, I drop all ISINs for which market capitalization information is not available in the given year. This leaves the number of ISIN/year combinations in column (2a). Second, for each country of exchange, I only keep these stocks that are in the top 25th percentile of the market capitalization distribution for that country.[17] This results in the ISIN/year combinations in (2b). Finally, for each company (as identified by FactSet *entity_id*), I only keep the ISIN of the equity issue with the largest market capitalization. This leaves me with yearly ISINs as in (2c).

3. In the third and last step, ISINs are filtered based on the returns data from Eikon. First, I delete stocks for which there is no local currency returns available. Although the geographic factors are constructed using returns derived from USD prices, this step ascertains that the move in these USD prices is not solely a result of the change in the value of the local currency versus the dollar. It results in yearly counts as in (3a). Second, in a given year I only keep ISINs for which there is a whole-year history of returns in

[15]Developed countries: AU, AT, BE, CA, CY, DK, FI, FR, DE, GR, HK, IE, IL, IT, JP, LU, NL, NZ, NO, PT, SG, KR, ES, SE, CH, TW, GB, US.
Developing Countries: AR, BD, BR, BG, CL, CN, CO, CZ, EG, HU, IN, ID, KE, LT, MY, MX, MA, PK, PE, PH, PL, RO, ZA, LK, TH, TR, VE, ZW.

[16]I am keeping only shares that are flagged as *Ordinary Shares* or *Fully Paid Ordinary Shares* according to Eikon's TR.InstrumentType property.

[17]This value is higher than the 3rd percentile in (Dumas et al., 2020) and chosen to match the number of ISINs per year for USA in the original paper.

that year. This results in counts as per (3b). Finally, I eliminate thinly traded shares i.e. ones that have a zero monthly return in the given currency at least once in a given year. This leaves me with the final number of ISINs each year as given in column (3c).

Year	**(1)**	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**
2015	44209	35584	8899	8679	8448	8251	8157
2016	45047	37111	9282	8901	8618	8446	8367
2017	45163	38437	9616	9035	8739	8608	8526
2018	44709	39939	9993	9258	8987	8865	8774
2019	42723	41396	10358	9264	8970	8842	8754

Table A.1: ISINs count per year after each stage of the filtering process

As a result of the filtering process described above, no Venezuelan shares are included in the final sample despite them being initially kept as one of the 56 markets considered.

A.2 Brief summary of methodology

The latent geographic-zone factors are calculated using the following model:

$$R_t = B \times C_t + e_t,$$

where R_t is the vector of firms' returns and B is the matrix of loadings of the firms' returns on the latent zone factors C_t. For a given firm i, its loadings on all the factors are non-negative and equal to the percentage of revenues the firm derives from the given zone. Consequently, they also sum to 1.

To handle missing information about geographical segments and zero-return data points, Dumas et al. (2020) calculate the latent factors using *expectation-*

maximisation algorithm as introduced by Brooks and Del Negro (2004) on a year-by-year basis using daily frequency of returns. Because the revenue share coverage is imbalanced (many more firms sell to the United States than, for example, to Italy), I follow the authors in calculating the latent zone factors for 100 random subsamples of the dataset and calculate the final zone factors C_t as the average of these 100 estimates. The details of the expectation maximisation algorithm and the subsampling can be found in the original paper.

B FX options: from implied volatilities to RNDs

I use GBP/USD options with 3 months to expiry to extract RNDs for the future value of the GBP/USD exchange rate. Figure B.1 shows the procedure step-by-step for the 23^{rd} and the 24^{th} of June 2016. Such data choice for the example also allows me to observe the shift in market expectations of the value of the sterling as a result of the Brexit referendum.

Time t price of a European FX option according to the Black Scholes formula can be expressed as follows:

$$v_t(S_t, \tau, K, \sigma, r_{t,\tau}, r^*_{t,\tau}, \phi) = \phi e^{-r_{t,\tau}\tau}[f(t,T)N(\phi d_+) - KN(\phi d_-)] \tag{B.1}$$

$$= \phi e^{-r_{t,\tau}\tau}[S_t e^{(r_{t,\tau}-r^*_{t,\tau})\tau}N(\phi d_+) - KN(\phi d_-)] \tag{B.2}$$

$$= \phi(S_t e^{-r^*_{t,\tau}\tau}N(\phi d_+) - Ke^{r_{t,\tau}\tau}N(\phi d_-)) \tag{B.3}$$

where S_t is the time t exchange rate, τ is the time till expiry, $\phi = 1$ for a call option, $\phi = -1$ for a put option, K is the strike price, σ is the volatility, $T = t + \tau$, $r_{t,\tau}$ is the domestic interest rate, $r^*_{t,\tau}$ is the foreign currency interest rate, and N(x) indicates the cumulative normal distribution function. Moving between Equation (B.1) and (B.2) requires realising that $f(t,T) = S_t e^{(r_{t,\tau}-r^*_{t,\tau})\tau}$ (i.e the definition of the outright forward rate). Moreover,

$$d_+ = \frac{\ln(\frac{f(t,T)}{K}) + \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}} = \frac{\ln(\frac{S_t}{K}) + (r_{t,\tau} - r^*_{t,\tau} + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}} \tag{B.4}$$

$$d_- = \frac{\ln(\frac{f(t,T)}{K}) - \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}} = \frac{\ln(\frac{S_t}{K}) + (r_{t,\tau} - r^*_{t,\tau} - \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}} \tag{B.5}$$

$$d_+ = d_- + \sigma\sqrt{(\tau)} \qquad d_- = d + -\sigma\sqrt{(\tau)}. \tag{B.6}$$

Equation (B.3) is at the core of the procedure and computations that follow. First, since only prices of in-the-money options are readily available, one needs to

infer the prices of out-of-the-money call options from the prices of in-the-money put options. This is necessary to use the relationship implied by equation the Breeden and Litzenberger (1978) formula (equation (2) in the main body of the paper):

$$\frac{\partial^2 c\left(t,K,T\right)}{\partial K^2} = e^{-r_{t,\tau}\tau} f^*(S_T).$$

The *vol* in which the price of an FX option is quoted is the implied volatility for a given option i.e. the level of volatility σ that when plugged into Equation (B.3) would deliver the desired price in currency units.[18] The various levels of moneyness for which FX options prices are quoted are the values of forward delta, that can be shown (Reiswich and Wystup (2010)) to be mathematically equal to the following:

$$\Delta_f(K,\sigma,\phi) = \phi N(\phi d_+). \tag{B.7}$$

In particular:

$$\Delta_f^{call}(K,\sigma) = N(d_+), \qquad \Delta_f^{put}(K,\sigma) = -N(d_-).$$

The above allows us to construct a put-call forward-delta parity as follows:

$$\Delta_f^{call}(K,\sigma) - \Delta_f^{put}(K,\sigma) = 100.$$

This means that a 65-delta call will have the same implied volatility as a 45-delta put, which allows us to convert the in-the-money put options' *vol* price to out-of-the-money call options' *vol* price and plot the volatility smile as a function of call delta only (see: Figure B.1A, dotted points)

In practice, a continuum of strikes desired for the numerical differentiation of the Breeden and Litzenberger (1978) formula is never observed. As a result,

[18]This does not imply that the Black Scholes model is assumed to hold for FX options. It's merely a market quotation convention.

interpolation and smoothing techniques for the values between the available data points need to be applied. Figlewski (2008) shows that, because the call function is differentiated twice to derive the relevant RND, the space in which one interpolates is crucial to maintain correct properties of the derived density function. According to the author, however, this problem is solved automatically if cubic splines are applied in the delta-IV space. This is since such curves will be smooth up to 2nd order in terms of delta, and hence smooth up to 3rd order in terms of price.[19] This eliminates undesired kinks in the derived RND. I apply cubic splines to interpolate between the available data points in the delta-IV space (see: Figure B.1A, solid line).

Having smoothed in the delta-volatility space, I now use Equation (B.7) to convert levels of forward delta moneyness to their corresponding strike prices. This can be done by observing that

$$\Delta_f^{call}(K,\sigma) = N(d_+) = N\left(\frac{\ln(\frac{S_t}{K}) + (r_{t,\tau} - r^*_{t,\tau} + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}\right),$$

which can be numerically solved for the correct value of the strike price K. Figure B.1B plots the *vols* price against the corresponding strike prices. I also calculate the cash price of each option by plugging in the implied volatility (*vols* price) and the corresponding strike value into Equation (B.3). This gives me a set of call option cash prices (v_t) for various strikes K . Figure B.1C plots the cash values of the options analyzed as a function of their strike prices.

I now proceed to numerically differentiate the call value function $\hat{v}(K)$ with respect to strike price K to extract the estimate of the cumulative distribution function, denoted $\hat{\Pi}(K)$, and the probability density function, $\hat{\pi}(K)$. Malz (1997) shows that the estimated value of the cumulative distribution function at each

[19]For more information see Figlewski (2008): *Section 4: Extracting a Risk Neutral Density from Option Market Prices, in Practice.*

point can be approximated by:

$$\hat{\Pi}(K) = e^{-r_{t,\tau}\tau}\left[\frac{\hat{v}(K) - \hat{v}(K - \Delta K)}{\Delta K} + 1\right], \tag{B.8}$$

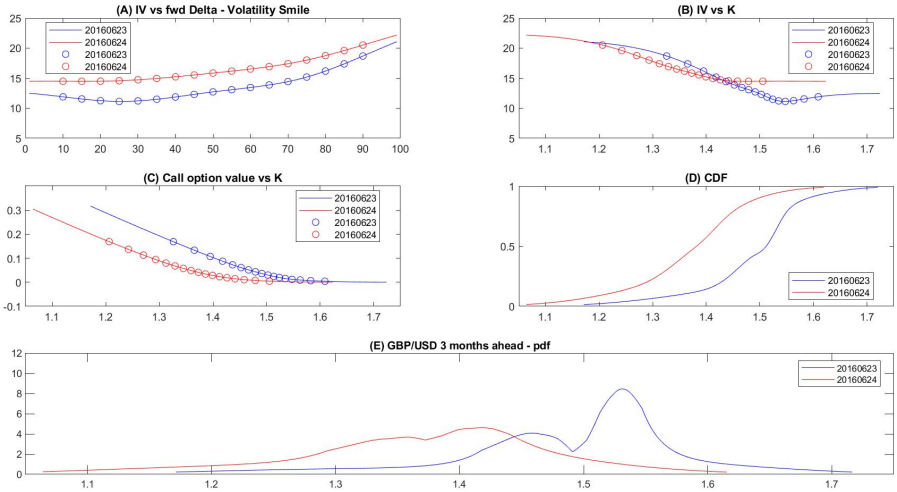
and the corresponding probability density function by:

$$\hat{\pi}(K) = \frac{\hat{\Pi}(X) - \hat{\Pi}(X - \Delta X)}{\Delta X}. \tag{B.9}$$

Figure B.1D plots the cumulative distribution functions for the values of 3-months-ahead GBP/USD exchange rate implied by the GBP/USD option prices on the 23^{rd} and the 24^{th} of June 2016. Finally, Figure B.1E reports the corresponding probability density functions on both dates.

Figure B.1: Extracting the RNDs: steps followed

This figure outlines the steps followed to convert daily cross-sections of GBP/USD option prices into the risk neutral density (RND) implied by these prices for two days: the 23rd June and the 24th June 2016 – the day of and the day after the Brexit Referendum. Options with 3 months to expiry are used. Figure A plots options' prices in *vols* against their delta-forward moneyness. Figure B plots options' prices in *vols* against their strikes K. Figure C plots options' numeraire prices against their strikes. Figure D plots the cumulative distribution function implied by the cross-section of options' prices on a given day. Figure E plots the corresponding risk neutral density on that day.



As well as aiding the understanding of the procedure just described, Figure B.1 sheds further light on the shift in the expectations of the value of the sterling

experienced by the market as a reaction to the announcement of the Brexit referendum results. The estimated CDFs (Figure B.1D) show that extremely low realizations of the 3-months-ahead GBP/USD echange rate as implied by the end-of-day options prices were considered more likely on the 24th of June (once the results of the referendum have been revealed to the market) than they were on the 23rd of June (the day of the Brexit Referendum). The implied probability of the 3-months-ahead sterling value below 1.2 USD was only 2.15% on June 23rd, but 8.82% on June 24th (a 7-fold increase). Similarly, the probability of its value below 1.3 USD was 6.56% on the 23rd, but 22.74% on the 24th (a 17-fold increase). The shift of the probability density function between June 23 and June 24 showcases the downward pressure on the value of the pound induced as a result of the Brexit referendum. Interestingly, the probability density function (Figure B.1E) has two visible humps on the 23rd of June – this is indicative of two divergent expectations of the future value of the pound in the run-up to referendum results' announcement. These two bumps are no longer present in the PDF computed for the 24th of June. This confirms the expectations computed using option prices reacted to the leave vote.

C Post-referendum RNDs and no-deal probability

The RNDs implied at the end of each quarter are shown in Figure C.1 and confirm the downward pressure exerted on the value of the sterling by the leave vote and the turbulent negotiations of an acceptable exit agreement that followed. Throughout 2015, despite the scheduled referendum, the majority of the distribution of the sterling value concentrated in the 1.4–1.6 USD region. By the end of the first quarter of 2016, the distribution widened to cover both lower and higher values as the outcome of the looming referendum was uncertain. Starting from the end of the second quarter of 2016, however, the distribution shifted to significantly lower territories with its majority concentrated in the 1.2–1.4 USD region. It remained in those territories ever since with a brief exception towards the end of the first quarter of 2018 when a short-lived glimpse of hope for a transition deal between UK and EU has sparked and temporarily shifted the implied RNDs in the 1.3–1.5 USD region.

Figure C.1: End-of-quarter RNDs implied by GBP/USD 3M options: 2015-2019

This figure plots risk neutral densities implied by cross-sections of GBP/USD option prices with 3 months to expiry at the end of each quarter between 2015 and 2019.

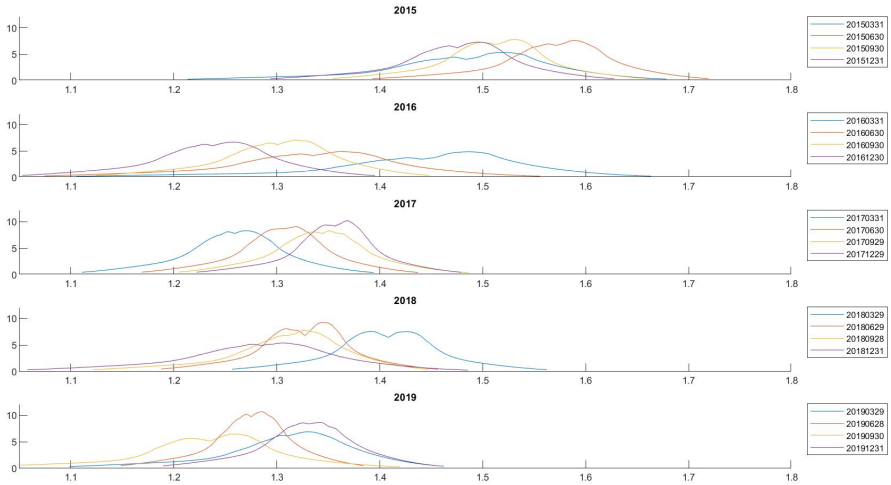


Figure C.2 summarizes the behaviour of the RNDs over the time period considered using mean, skewness, and kurtosis of the daily distributions inferred.

Once again, the mean oscillates in the 1.4 – 1.6 USD region throughout 2015. It then drops 11 cents between the end-of-day on the 23rd and the 24th of June to 1.36 USD and remains in the 1.2 – 1.4 USD region since then except for a brief period between March and May 2018 for reasons explained above. The skewness remains negative throughout the entire period indicating a longer left tail of the distribution which corresponds to sterling's depreciation. Looming Brexit referendum and the immediate considerations of the leave vote strengthen this tendency as evidenced by the skewness dropping below -0.4 between April and July 2016. The kurtosis remains relatively stable throughout the entire period oscillating in the 2.7 – 2.9 region. Once again, the exception to this tendency is the sub-period between April and July 2016, when it spikes above 2.9 reaching values as high as 3, which suggest that more probability is assigned to tail realisations. The joint evidence from the skewness and kurtosis during that 3 – 4 months period is in line with higher probability being assigned to strong depreciation of the sterling as a result of the leave vote. These summary statistics corroborate previous evidence that the leave vote and negotiations it triggered have been exerting downward pressure on the value of the pound.

I use the fact that the British pound reacts to news about hard Brexit with a strong depreciation of its value to estimate the probability assigned by the market to this event. I approximate the no-deal Brexit probability (NDP) by the risk-neutral probability mass assigned to a drop of the value of the sterling below the 1.3 USD cut-off. As a robustness check, I compute similar measures using the 1.25, 1.2, and 1.15 USD cut-offs. The amount of probability below each of those values, as implied by the RNDs computed, between January 2015 and December 2019 is shown in Figure C.3. The correlations of the measures computed for robustness purposes with that computed using 1.3 USD threshold are 0.93, 0.85, and 0.75 for the 1.25, 1.2, and 1.15 thresholds, respectively.

Figure C.2: Summary statistics for the daily distributions inferred: 2014 - 2019

This figure plots summary statistics (mean, skewness, and kurtosis) of implied daily risk neutral distributions for the 3-months-ahead GBP/USD exchange rate between 2014 and 2019.

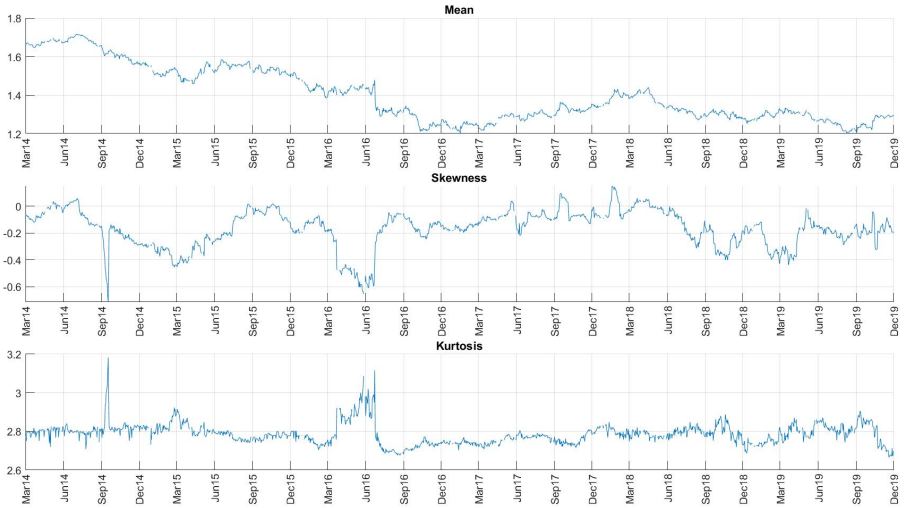


Figure C.3: No-deal Brexit probability proxies

This figure plots market-implied proxies for hard (no-deal) Brexit probability between March 2015 and December 2019. Each proxy is computed by equating the probability of no-deal Brexit on a given day to the mass of probability the risk neutral densities implied by GBP/USD options market attach to a depreciation of GBP below a certain threshold 3 months from that date. The thresholds considered are 1.3, 1.25,, 1.2, and 1.15 USD.

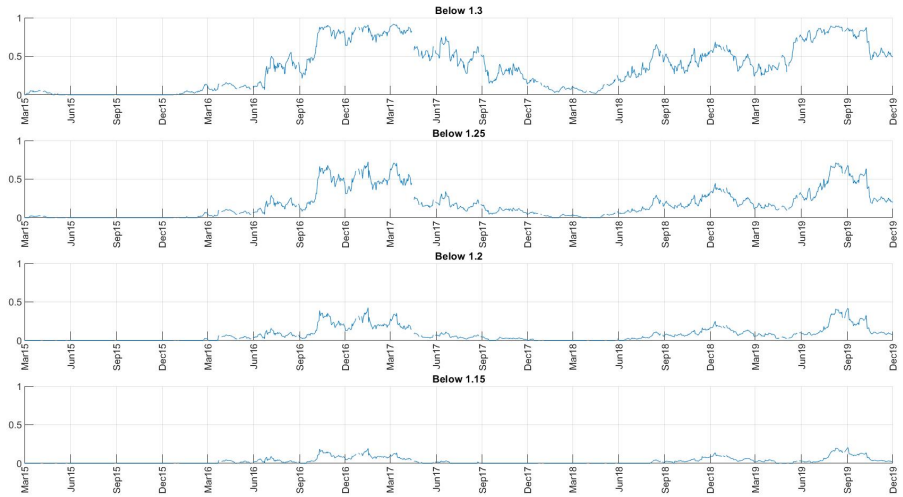


Figure C.4 zooms in on the behaviour of the main measure of the no-deal Brexit probability (the one computed using a 1.3 USD threshold) throughout the

post-referendum period. Figure C.5 reports the behaviour of the corresponding measure computed using the 1.2 threshold for comparison. Expectedly, as evidenced by the high correlation value of 0.93, the two move pretty much in sync over time and are likely driven by similar policy developments.

Figure C.4: No-deal probability proxy – 1.3 USD threshold

This figure plots the main market-implied proxy for hard (no-deal) Brexit probability between January 2015 and December 2019. This main proxy is computed by equating the probability of no-deal Brexit on each day to the mass of probability the risk neutral densities implied by GBP/USD options market attach to a depreciation of GBP below the 1.3 USD threshold 3 months from the given date.

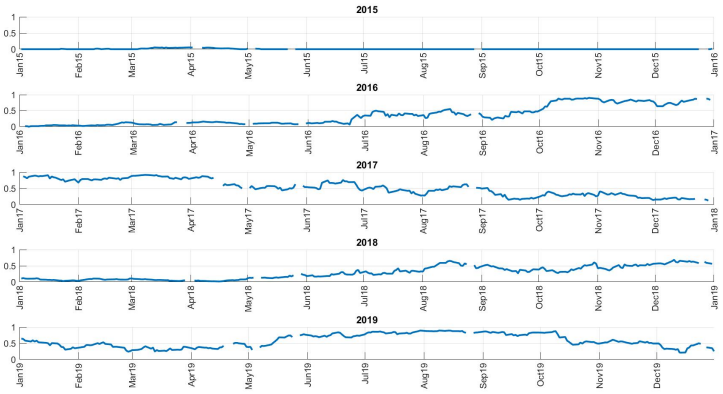
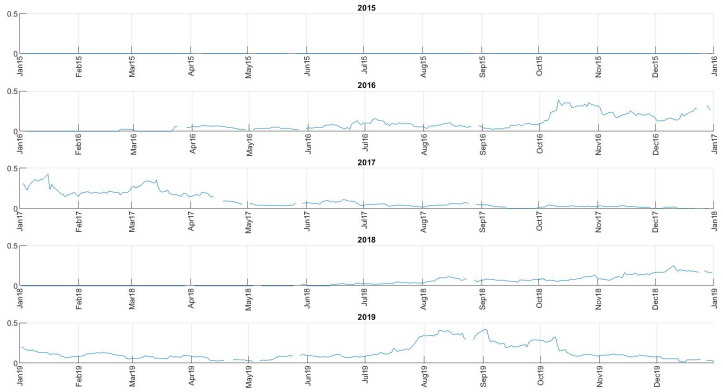


Figure C.5: No-deal probability proxy – 1.2 USD threshold

This figure plots the alternative market-implied proxy for hard (no-deal) Brexit probability between January 2015 and December 2019. This alternative proxy is computed by equating the probability of no-deal Brexit on each day to the mass of probability the risk neutral densities implied by GBP/USD options market attach to a depreciation of GBP below the 1.2 USD threshold 3 months from the given date.



Throughout 2015 the NDP (1.3 USD threshold) remains around 0% with the

exception of a brief uptick into the 5% region between mid-February and end of April as the investors price in the consequent referendum on UK membership in UK election run-up. During the first half of 2016, the NDP remains profoundly below 20%, dropping to its lowest for the year as markets close on the day of the referendum ($NDP_{23/06/2016} = 6.6\%$). The market is believed to price in a majority Remain vote as the polling stations close. As pro-Remain David Cameron steps down as UK's prime minister immediately after the vote, summer 2016 sees an internal Tory competition for who is going to replace him with the seat contested between the Remain and Leave Tory fractions. The mood sours in the beginning of July as the odds for the next PM are split almost equally between pro-Leave Andreau Leadrom and pro-Remain Theresa May ($NDP_{07/07/2016} = 50\%$). The pressure eases off briefly in the middle of July as Leadrom pulls out of the race ($NDP_{14/07/2016} = 29.6\%$) and economic data in August and early September are not as bad as expected. It returns in early October as the now-PM Theresa May sets the Brexit date for early 2019 promising to trigger the infamous Article 50 by March 2017 and hints a break from the EU single market is on the table as control of immigration is widely quoted as most pressing issue ($NDP_{27/10/2016} = 90.3\%$). Despite early December remarks from David Davis[20] about the possibility of averting hard Brexit by paying EU single market access fee ($NDP_{05/12/2016} = 64.0\%$), the NDP increases towards the end of the year ($NDP_{30/12/2016} = 84.0\%$) and remains in the 70% region till Article 50 is triggered end of March 2017.

In 2017, the NDP drastically drops following April 18^{th} announcement of a UK general election to be held on the 8^{th} June ($NDP_{18/04/2017} = 57.9\%$) as the PM wants the public to back her cabinet in the ongoing Brexit discussions thus strengthening her negotiating position against the EU. Hopes are on a Tory majority strong enough to sideline the pro-Brexit Tories and enable Theresa May to deliver a smooth Brexit without having to live up to their expectations. The NPD remains in the 43% –

[20]Secretary of State for Exiting the European Union, 2016 - 2018.

63% region till the election date. Throughout the summer of 2017 the changes in the NDP are driven by arrival of fresh economic data and the implications of the commencing Brexit negotiations in the face of a hung UK parliament. Especially in August, following reports of lack of negotiations progress particularly with regards to honouring pre-agreed budget commitments, the NDP oscillates at high levels ($NDP_{30/08/2017} = 50.0\%$). September sees the NDP decrease following conciliatory statements from the UK's Prime Minister and positive statements on the progress of the talks by EU's lead negotiator rising hopes of a post-Brexit transition deal ($NDP_{28/09/2017} = 18.42\%$). The NDP surges again in early October ($NDP_{06/10/2017} = 40\%$) as the EU excludes the possibility of commencing transition deal negotiations without an agreement on the "divorce bill" itself. The very same considerations drive NDP in November as it eventually drops following an agreement on honouring financial obligations thus opening the door for transition period negotiations ($NDP_{30/11/2017} = 13.9\%$).

Beginning of 2018 sees the NDP at below pre-referendum levels as the outlook for a post-Brexit transition period is particularly promising ($NDP_{16/04/2018} = 1.7\%$). The concerns about the lack of progress return over the summer as three consequent EU summits are focused on matters different than Brexit, newly introduced UK legislation does not exclude no-deal outcome ($NDP_{28/06/2018} = 37.4\%$), and the possibility of a further extension to the March 2019 deadline is excluded ($NDP_{19/07/2018} = 42.1\%$) by the UK Prime Minister. As the Irish backstop issue and the existence of no-deal contingency plans dominate the news, the NDP fluctuates at above 50% for the first time in a year ($NDP_{15/08/2018} = 65.4\%$). As the fears of a hard Brexit subside the NDP stays in the 30 - 50% corridor till late October. It returns to the 50+% territory as the Brexit deal turns out to lack political backing in the UK parliament and surges to above 60% as Theresa May struggles to push the Withdrawal Agreement through the House of Commons and the EU rules out its renegotiation ($NDP_{11/12/2018} = 68.7\%$).

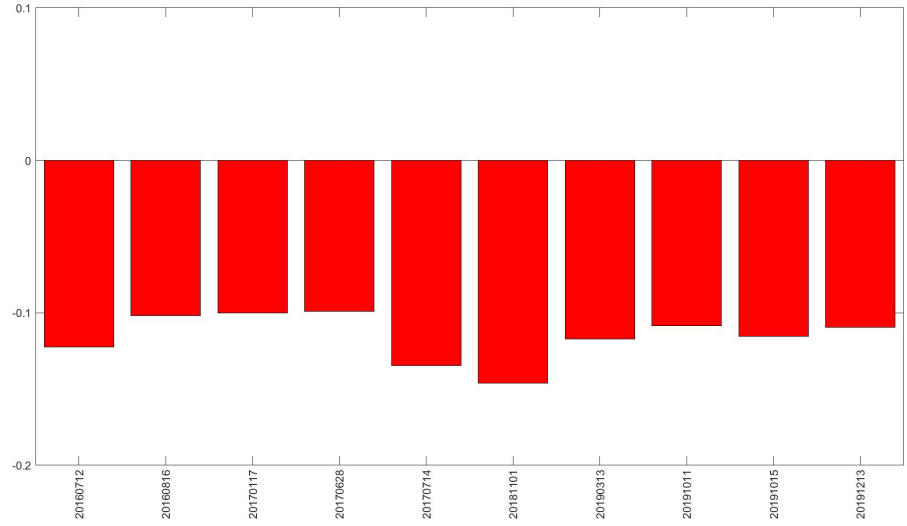
In 2019, January and February see the NDP at around 50% as the Irish backstop issue appears insurmountable with a brief drop end of January as the parliament tries to demand the PM rules out a no-deal Brexit ($NDP_{25/01/2019} = 30.31\%$). The NDP then drops end of February as the likelihood of postponing the Brexit date rises ($NDP_{27/02/2019} = 24.0\%$) and remains in the 25% – 40 % corridor as an extension to Brexit is agreed. It rallies to the 70+% territory as Labour pulls the plug on cross-party talks regarding the Withdrawal Agreement prompting Theresa May to eventually step down as prime minister ($NDP_{22/05/2019} = 73.9\%$) and as the Brexit party wins the European Parliament elections ($NDP_{30/05/2019} = 78.0\%$). The NDP further rises as Boris "come-what-may" Johnson's chances of becoming the next Prime Minister increase ($NDP_{17/06/2019} = 83.8\%$). It briefly drops middle of September as EU president Jean-Claude Juncker offers reassurance that an agreement can be reached before the then Brexit deadline of October 2019 and that he was to do his best to have a deal by that deadline to avoid the consequence of a no-deal Brexit ($NDP_{17/06/2019} = 72.3\%$). The NDP raises back to almost 90% as those prospects disappear ($NDP_{09/10/2019} = 87.35\%$) to then drop to below 50% as the UK Government is forced by its Parliament to ask for an extension of the Brexit date till 31st of January 2020. It further drops to the 20% territory following Conservatives' victory in December 2019 elections that gave Boris Johnson parliamentary majority necessary to finally remove the Brexit-related uncertainty ($NDP_{13/12/2019} = 21.09\%$). The rebound does not last long, however, and before the Holiday Season the NDP returns to the 50+% region ($NDP_{23/12/2019} = 49.74\%$) although with a slight dip towards the end of the year ($NDP_{31/12/2019} = 25.32\%$)

Table C.1 reports the exact values of the peaks and troughs of the no-deal Brexit probability proxies discussed and the mean and standard deviation of its daily values. The average NDP and its volatility significantly differ over the years analyzed. The average NDP is highest throughout 2017 (52.4% daily average) as the negotiations commence and in 2019 (58.3% daily average) as it becomes obvious

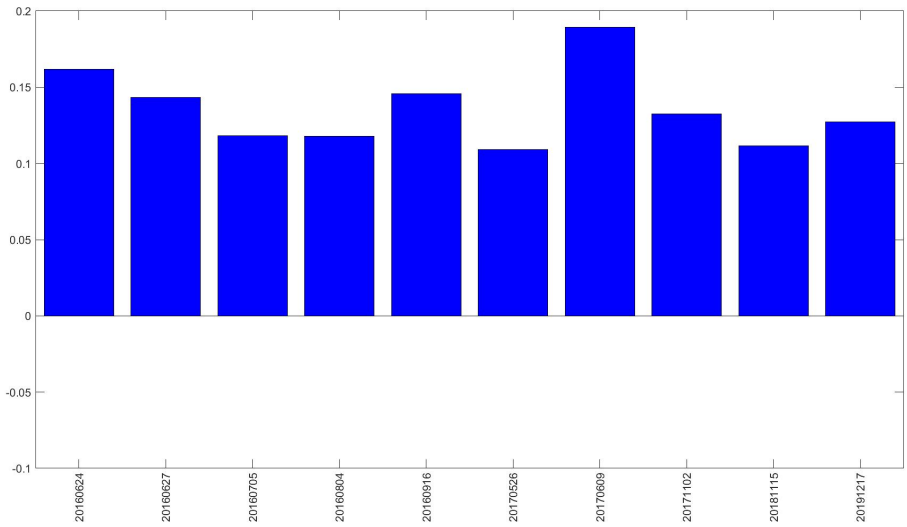
the painstakingly negotiated Withdrawal Agreement has no chances of getting approved by the hung UK parliament. The average NDP is lowest in 2018 as the Agreement is being finalized and the transition period favoured by the businesses appears to be an achievable solution. On the other hand, the volatility of the NDP drops over time as the Brexit options crystallise – it is highest in 2016 at 30% and lowest in 2018 and 2019 at 20%. The NDP is highly volatile throughout the 4 year period considered with large changes happening at daily frequencies. Figure C.6 reports the ten biggest daily drops and rises in the main no-deal Brexit probability proxy computed using the 1.3 USD threshold.

Figure C.6: Biggest daily changes in the no-deal probability proxy

This figure plots ten biggest daily drops and increases in the main no-deal Brexit probability proxy. This main proxy is computed by equating the probability of no-deal Brexit on each day to the mass of probability the risk neutral densities implied by GBP/USD options market attach to a depreciation of GBP below the 1.3 USD threshold 3 months from the given date.



Ten biggest daily drops



Ten biggest daily rises

Table C.1: Peaks and troughs of the no-deal Brexit probability proxies - 1.3 USD and 1.2 USD thresholds

This table reports the peaks and troughs of the no-deal Brexit probability proxies computed using the 1.3 USD and 1.2 USD thresholds between January 2016 and December 2019. Each no-deal probability measure is computed as the amount of probability assigned to the depreciation of the sterling below the given threshold as implied by the RNDs computed using the GBP/USD options with 3 months to maturity. The dates listed are determined using the trajectory of the main no-deal probability measure computed using the 1.3 USD threshold.

	2016			**2017**			**2018**			**2019**	
	Day	Below 1.3	Below 1.2	Day	Below 1.3	Below 1.2	Day	Below 1.3	Below 1.2	Day	Below 1.3	Below 1.2
	23-Jun-2016	0.066	0.022	01-Feb-2017	0.679	0.149	16-Apr-2018	0.017	0.000	25-Jan-2019	0.303	0.064
	07-Jul-2016	0.501	0.152	08-Mar-2017	0.917	0.338	02-May-2018	0.131	0.000	14-Feb-2019	0.532	0.138
	15-Aug-2016	0.553	0.107	18-Apr-2017	0.579	0.086	29-May-2018	0.252	0.021	27-Feb-2019	0.240	0.051
	06-Sep-2016	0.212	0.023	19-May-2017	0.438	0.032	28-Jun-2018	0.374	0.036	25-Apr-2019	0.513	0.048
	11-Oct-2016	0.879	0.389	20-Jun-2017	0.757	0.113	06-Jul-2018	0.219	0.019	03-May-2019	0.294	0.023
	27-Oct-2016	0.903	0.354	31-Jul-2017	0.277	0.021	19-Jul-2018	0.421	0.054	22-May-2019	0.739	0.093
	05-Dec-2016	0.640	0.129	24-Aug-2017	0.625	0.073	25-Jul-2018	0.285	0.032	30-May-2019	0.780	0.103
	30-Dec-2016	0.840	0.264	15-Sep-2017	0.148	0.000	15-Aug-2018	0.654	0.113	07-Jun-2019	0.688	0.073
				06-Oct-2017	0.400	0.044	20-Sep-2018	0.270	0.044	17-Jun-2019	0.838	0.109
				02-Nov-2017	0.406	0.035	03-Oct-2018	0.454	0.090	24-Jun-2019	0.679	0.074
				30-Nov-2017	0.139	0.000	11-Oct-2018	0.277	0.055	09-Jul-2019	0.865	0.132
				29-Dec-2017	0.124	0.000	30-Oct-2018	0.608	0.135	30-Jul-2019	0.894	0.335
							07-Nov-2018	0.355	0.068	19-Sep-2019	0.723	0.198
							11-Dec-2018	0.687	0.250	18-Oct-2019	0.455	0.095
										08-Nov-2019	0.611	0.113
										13-Dec-2019	0.211	0.018
										23-Dec-2019	0.497	0.044
Mean		0.348	0.092		0.524	0.092		0.281	0.048		0.583	0.133
StDev		0.297	0.095		0.240	0.096		0.198	0.059		0.205	0.098

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4 | Sources of Return Predictability

A large literature establishes a set of predictors that robustly forecast future market returns, raising questions about these predictors' origins. We develop an approach to determine whether a particular predictor represents a proxy for fundamental risk, which is based on an intuitive assumption that risk-based predictors should be linked to new information about economic conditions. We show that each predictor forecasts returns either on days with macroeconomic announcements or on other days, but never on both types of days. These results suggest that sources of return predictability differ across predictors, with some driven by economic fundamentals and others having different origins. Consistent with this interpretation, announcement-day returns are positively related to future changes in fundamental value, while there is no such relation for non-announcement-day returns.

1 Introduction

Stock returns are predictable, as shown by a large and still-growing literature.[1] While there exists little dispute about this basic result, the interpretation of many of the best-known predictors is another matter, with proposed explanations ranging from behavioral theories to various frictions to risk-based theories.

In this paper, we develop an approach for identifying predictors that represent proxies for fundamental risk, which is based on an intuitive assumption that such predictors should be linked to new information about economic fundamentals. We hypothesize that days when important macroeconomic news is scheduled to be

[1] See Cochrane (2007), Goyal and Welch (2007), Campbell and Thompson (2007), and Harvey et al. (2015), among others.

announced (announcement days) are more likely to coincide with releases of such information than other days (non-announcement days).[2] Thus, predictors whose forecasting power is concentrated on announcement (non-announcement) days are more (less) likely to represent proxies for fundamental risk.

As in Savor and Wilson (2013) and subsequent papers, we define as announcement days those trading days when news about inflation, unemployment, or Federal Open Market Committee (FOMC) interest rate decisions is scheduled to be released (A-days) and all other trading days as non-announcement days (N-days). Using quarterly returns (aggregated separately for A- and N-days), we find that many of the widely used stock market predictors forecast returns only on non-announcement days. For example, the log price/dividend ratio (pd_t, Campbell (1996), Litzenberger and Ramaswamy (1979)), Treasury bill yield (tbl), investment-to-capital ratio (i/k, Cochrane (1991)), and equity issuance ($eqisBW$, Baker and Wurgler (2000)) forecast future returns accrued on N-days with a negative sign, while the term spread (tms, Fama and French (1989); Campbell (1987)), default return spread (dfr, Fama and French (1989)), and consumption-to-wealth ratio ($cayLL$, Lettau and Ludvigson (2001)) forecast future N-day returns with a positive sign. There are no comparable results for A-day returns, and most of the time the point estimates have opposite signs (none are statistically significant). By contrast, the lower bound on the equity premium ($epbound3M$, Martin (2016)) and the stock return variance (sum of squared daily returns on the S&P 500, $svar$, Guo (2006)) both forecast with a positive sign stock returns accrued on A-days but do not work on N-days.

This evidence shows that a clear dichotomy exists between days with important macroeconomic announcements and the remaining ones on which no such news is scheduled for release with respect to their return predictors. Strikingly, the predictors we study forecast returns either only on announcement days or only on

[2]Previous literature finds that announcement days are indeed special, both in terms of time-series (Savor and Wilson, 2013) and cross-sectional (Savor and Wilson, 2014) return patterns.

non-announcement days, which supports the hypothesis underlying our approach that the two sets of days are different. Furthermore, it means that we can easily group predictors into those that are linked to economic news and those that are not. The predictors that are based on direct measures of the amount of risk in the economy, which according to asset pricing theory should forecast returns (but fail to do so in reality), forecast quarterly returns accrued on A-days (but not on N-days). For the predictors historically documented to forecast future stock returns, we show that while they forecast N-day returns, they do not exhibit explanatory power for A-day returns. Overall, these findings are consistent with the hypothesis that sources of return predictability differ across predictors, with direct risk-based measures driven by economic fundamentals and most of the others having different origins.

We build on the above predictability results to revisit the 1980s excess volatility puzzle which claims that the observed price movements cannot be justified by subsequent events (Shiller, 1981). In particular, they cannot be explained by the stream of subsequent dividends since the realized prices move too much compared to the time-series of ex-post rational price (fundamental value) realizations. Our tests show that the excess volatility puzzle defined in this way is very strong on N-days and moderate on A-days. We use multivariate regressions ($Y_{t+1} = \beta_0 + \beta_1 r_t^A + \beta_2 r_t^N$) of future log changes in ex-post rational price (Y_{t+1}) on past returns accrued on both A-days (r_t^A) and N-days (r_t^N). The results highlight, once again, a clear difference between these two types of days. Quarterly and annual returns accrued on A-days are positively related to future changes in fundamental value (with $\beta_1 = 0.02$ and $\beta_1 = 0.04$) in regressions using quarterly and annual frequency data, respectively. This relation does not hold for their N-day counterparts with β_2 not significantly different from zero at any frequency. Hence, although it may be true that the price movements on N-days are too big to be justified by subsequent dividends, this is not the case for price movements experienced on A-days.

Finally, we ask whether this superior fundamental-value-predictive power of

A-day returns is the result of their better informational content with respect to discount-rate news or dividend-growth news. To accurately pin down those two alternative channels, we build on the predictors suggested by Li and Wang (2018). The authors use relative prices of long-term and short-term dividends to identify drivers of future returns and dividend growth. Given the lack of CRSP options and futures contracts and acknowledging the limited time coverage of the S&P 500 ones, we construct the predictive variables of Li and Wang (2018) using historical CRSP equity yield data for various maturities. This data is made available by Giglio et al. (2020). We confirm it allows us to replicate the original result. Using such constructed Li and Wang (2018) predictors, we show that while discount-rate news forecasts N-day returns, the same is not true for A-day returns, which are more related to dividend-growth predictors.

The combined evidence presented above reconfirms that A-day returns are in fact crucially different from N-day returns. The returns accrued on A-days are more fundamentals-driven, explained by the amount of physical risk in the economy, and justified by subsequent changes in fundamental value. The same is not true for returns accrued on N-days, which are forecast by a wide range of predictors suggested in the literature. This may suggest that these predictors do in fact forecast the excess volatility component of the stock market movement.

Related literature. This paper relates to a strain of literature documenting the differential behavior of asset returns on A-days and N-days and the potential explanations for these findings. Savor and Wilson (2014) show that stock returns on said A-days are significantly higher and their patterns easier to reconcile with known asset pricing theories than their N-day counterparts. In particular, they show that while the CAPM holds on A-days, it fails to hold on N-days. Similarly Brooks et al. (2018) show that while the expectations hypothesis holds on A-days, it fails thereafter and this failure increases in the length of the window considered. Attempts have been made to reconcile these differences within standard asset pricing

models (Savor and Wilson, 2014) and to find the drivers behind the phenomenon pointing to increases in the price of risk as opposed to the quantity of risk on A-days (Savor et al., 2015). Meanwhile, other authors argued this differential behavior of A-day returns is only a by-product of high ex-post returns on those days rather than evidence of them being in any way special (Ernst et al., 2019). The paper also relates to the wider literature on returns predictability.

2 Data and summary statistics

The macroeconomic announcements considered are in line with those used by Savor and Wilson (2013) and Savor and Wilson (2014). As in these papers, inflation and unemployment announcement dates come form the US Bureau of Labor Statistics (`https://www.bls.gov/`) with the available time series staring in 1958. We follow the authors in using consumer price index (CPI) announcements up to and including February 1972. Producer price index (PPI) announcements are used between March 1972 and January 2018 (inclusive). This is because in that time period PPI numbers are reported a few days prior to the CPI ones thus diminishing the informational content of the CPI numbers. Between February 2018 and December 2019, for some months CPI is again released before PPI. In our analysis we use the date of the earlier of these two announcements. FOMC interest rate announcement days come from the Federal Reserve website and are available from 1978 onwards. Unscheduled FOMC meetings are excluded from the sample.

Data on stock market returns comes from Center for Research in Security Prices (CRSP). Data on risk-free interest rate comes from Professor Kenneth French's website. Our main stock market proxy is the CRSP NYSE, Amex, and Nasdaq value-weighted index of all listed shares. We collect daily values of this index between January 1953 and December 2019. We use those valuations and the daily risk free rate to construct log daily excess returns over this time period. These

are then aggregated on a quarterly basis for all trading days in the given quarter ($r_t^{A\&N}$), all A-days in a given quarter (r_t^A), and all N-days in a given quarter (r_t^N). Panel A of Table 3 presents the summary statistics for these returns. We see that the average quarterly return on A-days (0.5%) and all days (0.7%) are almost equal despite the former constituting a much smaller part of the sample period. Compared to N-day quarterly returns, A-day returns are higher (0.5% vs. 0.2%), less volatile (0.03 vs. 0.08), exhibit no autocorrelation (0.001 vs. 0.113), and are less negatively skewed (-0.65 vs. -0.96).

Synthetic equity strip yield data (Giglio et al., 2020) for the value-weighted CRSP NYSE, Amex, and Nasdaq index for maturities between 1 and 100 years between August 1975 and November 2016 come from Professor Serhiy Kozak website.

We use a wide range of variables historically documented to be predictors of stock returns. Table 2 provides a summary of those, their abbreviations used throughout the paper, references to papers that introduced them to the literature, and the source of the time-series used. Panel B and Panel C of Table 3 provide summary statistics of the variables that are subsequently found to be predictors of A-day and N-day returns, respectively.

3 Evidence A: predictive regressions

In this section we analyse the ability of the various predictors considered to forecast future aggregate quarterly stock market returns, their part accrued on A-days, and their part accrued on N-days. The predictive variables (Table 2) can be divided into two groups. The *first group* comprises variables which constitute measures of or proxies for the amount of physical risk on the market. These are the lower bound on the 3-months-ahead equity premium ($epbound3M$) derived by Martin (2016) and the stock market variance ($svar$) i.e. the sum of squared daily returns on the S&P 500. These variables should be able to explain future stock returns since

according to fundamental asset pricing theories the amount of physical risk should be the driving factor behind stock market returns. The *second group* includes the remaining variables that are not such proxies for the physical amount of risk but have nonetheless been historically found to predict returns.

We start our analysis using the univariate linear regression framework. We regress the relevant quarterly returns on the various predictors considered lagged by one quarter. The regression can be summarized as follows:

$$r^{i}_{t+1} = \alpha + \beta x_t, \quad i = (A\&N, A, N).$$

In the above regression $r^{A\&N}_{t+1}$, r^{A}_{t+1}, and r^{N}_{t+1} are the aggregate quarterly return, quarterly return accrued on A-days in a given quarter, and quarterly returns accrued on N-days in a given quarter, respectively. x_t is one of the predictors considered.

Panel A of Table 4 shows, that for quarterly returns accrued on all days in the quarter, *epbound* and *svar* are not statistically significant explanatory variables. This means that measures of physical variance do not drive aggregate quarterly returns in general. On the other hand, the majority of the remaining predictors (except for default yield spread *dfy* and the log price dividend ratio *logPD*) are statistically significant drivers of quarterly returns at at least 10% confidence level. Treasury bill rate (*tbl*), investment to capital ratio (*ik*), and percent equity issuing (*equisBW*) are negatively related with future returns. A percentage point *increase* in the treasury bill rate leads to a *decrease* in aggregate quarterly return of approximately 36 basis points. Similarly, a percentage point *increase* in the investment to capital ratio and percent equity issuing lead to 433 and 16 basis points *decrease* in aggregate quarterly return, respectively. The relationship between the remaining predictors and future quarterly returns is positive. An *increase* of one percentage point in term spread (*tms*), default return spread (*dfr*), and consumption to wealth ratio (*cayLL*) lead to a 71, 36, and 45 basis points *increases* in next quarter's return, respectively.

Panel B shows that these relationships reverse when we only consider as the independent variable the part of quarterly returns accrued on A-days. The results indicate that only proxies of physical risk (lower bound on equity premium, *epbound3M* and stock variance, *svar*) are statistically significant predictors of returns accrued on A-days in a given quarter at 5% significance level. A one percentage point increase in lower bound on the 3-months-ahead equity premium (*epbound3M*) and stock variance (*svar*) lead to respectively 42 and 58 basis points increases in returns accrued on A-days over the next quarter. The default yield spread (*dfy*) is a significant predictor of quarterly A-day returns at a 10% confidence level. A one percentage point increase in the default yield spread leads to 71 basis points increase in next quarter's cumulative A-day returns. None of the remaining variables are statistically significant.

Panel C shows that the estimates computed when the part of quarterly returns accrued on N-days is considered as the independent variable are in line with those reported in Panel A. This is not surprising since N-days make the overwhelming majority of any given period. Here, again, we observe that physical risk proxies (*epbound3M*, *svar*) and default yield (*dfy*) are not statistically significant drivers of N-day returns, while the remaining variables are. The magnitudes of the estimated coefficients are also in line with those estimated in Panel A. An *increase* of one in the log price-dividend ratio *decreases* next quarter's cumulative N-days return by 2 basis points. *Increases* of one percentage point in the treasury-bill rate (*tbl*), investment to capital ratio (*i/k*), and percent equity issuing (*equisBW*) lead to *decreases* in next quarter's cumulative N-days return of 34, 455, and 16 basis points, respectively. On the other hand, *increases* of one percentage point in term spread (*tms*), default return spread (*dfr*), and the consumption to wealth ratio (*cayLL*) lead to 60, 33, and 33 basis points increases in next quarter's cumulative N-days returns. Here, it is important to note that the relationship between the consumption to wealth ratio as provided by its original authors (Lettau and Ludvigson, 2001)

and returns accrued on N-days is not statistically significant in the time period considered. The relationship between its Goyal and Welch (2007) counterpart and these returns, however, is. An increase of one percentage point the latter leads to 39 basis points increase in next quarter's cumulative N-day return. This relationship is significant at 10% confidence level.

Those results highlight a startling dichotomy between the predictors of returns accrued on A-days and those accrued on N-days. We observe that predictors typically assumed to be able to forecast future returns, are both economically and statistically significant in explaining the future behaviour of aggregate quarterly returns and their part accrued on non-announcement days. By contrast, they are not statistically significant predictors of returns accrued on announcement days. On the contrary, variables that have roots in fundamental asset pricing theories and are proxies for physical risk, such as lower bound on equity premium and stock variance, are both economically and statistically significant predictors of future returns accrued on announcement days but not their non-announcement days counterpart or the quarterly returns in general.

These results are highly suggestive and intriguing. They seem to indicate that great many of well-known stock returns predictors suggested in the literature are not related to new information about fundamentals being revealed to the market (A-days) but seem to be predicting something different instead. In order to investigate the matter further, we proceed to concentrate on analysing the relationship between the changes in prices on those two days and the changes in ex-post rational prices (fundamental value) as calculated by Shiller (1981).

4 Evidence B: Shiller's fundamental value

Shiller (1981) shows that the realized stock prices move too much to be justified by the subsequent changes in dividends. In this section we revisit the relationship

between these price changes and the subsequent dividends independently for A-days and N-days. We show that quarterly (annual) returns accrued on A-days forecast changes in next quarter (year) ex-post rational price (*fundamental value*). The same is not true for quarterly (annual) returns accrued on N-days. In regressions of fundamental value changes on lagged returns accrued on these two types of days, the coefficient for returns accrued on A-days is positive and significantly higher than that for returns accrued on N-days.

We follow Shiller (1981) methodology very closely to calculate the real values of prices and dividends, and their de-trended counterparts. The only difference compared to the original paper is that we sample prices at the end of each period while the original paper records them for its beginning. Since this slightly alters the formulas and as we acknowledge the time that has passed since the original work, in what follows we briefly summarize the main idea behind the original excess volatility puzzle and the steps taken to arrive at it.

Shiller 1981 approach. For the simple efficient markets model to be correct the real price P_t at the end of time period t should be equal to:

$$P_t = \sum_{k=1}^{\infty} \gamma^k E_t D_{t+k}, \text{[3]} \tag{1}$$

where the D_t is the real dividend paid at time t and γ is a constant real discount factor. As in the original work, we assume all dividends D_t occur at the end of the relevant time period t. The constant real interest rate r is defined such that $\gamma = 1/(1+r)$ and has the property that $r = E_t(H_t)$, where H_t is the holding period return $H_t \equiv (\Delta P_{t+1} + D_{t+1})/P_t$.[4]

It is possible to restate the relationship in Equation (1) using detrended prices and dividends. Such detrending is done by restating those time series as a proportion

[3] $P_t = \sum_{k=0}^{\infty} \gamma^{k+1} E_t D_{t+k}$ in Shiller (1981).
[4] $H_t \equiv (\Delta P_{t+1} + D_t)/P_t$ in Shiller (1981).

of the long-run growth factor: $p_t = P_t/\lambda^{t-T}$, $d_t = D_t/\lambda^{t-T}$,[5] where T is the last period for which we have observations (the base period) and λ^{t-T} is the growth factor. The growth factor is calibrated by estimating a long-run exponential growth path for the time series of real prices. To this end, we regress $ln\,(P_t)$ on a constant and time and set $\lambda = e^b$, where b is the coefficient on time in $ln\,(P_t) = a + b * t$. It can be shown that the following holds for such detrended time series:

$$p_t = \sum_{k=1}^{\infty} \overline{\gamma}^k E_t d_{t+k},^{6} \tag{2}$$

where $\overline{\gamma} \equiv \lambda\gamma$ is the constant discount factor appropriate for the detrended time series of p_t and d_t. The corresponding discount rate $\overline{r}$, $\overline{\gamma} = 1/(1+\overline{r})$, can be shown to be equal to the mean detrended dividend divided by the mean detrended price: $\overline{r} = E\,(d)\,/E\,(p)$.[7]

The above relationship (2) can be re-written in terms of *ex-post* rational price series p_t^*. Such *ex-post* rational price is the present value of actual subsequent dividends:

$$p_t^* = \sum_{k=1}^{\infty} \overline{\gamma}^k d_{t+k}.^{8} \tag{3}$$

As pointed out in the original paper, although the summation extends to infinity, with long enough time series we can observe a reasonably accurate approximation of p_t^*. Subject to the choice of terminal (base year) value of the *ex-post* rational price, p_T^*, the entire time series can be determined recursively by

$$p_t^* = \overline{\gamma}\left(p_{t+1}^* + d_{t+1}^*\right)^{9}$$

[5] $d_t = D_t/\lambda^{t+1-T}$ in Shiller (1981).

[6] $p_t = \sum_{k=0}^{\infty} \overline{\gamma}^{k+1} E_t d_{t+k}$ in Shiller (1981).

[7] This follows from taking unconditional expectation of both sides of equation (2) and solving for $\overline{r}$. Compare: footnote 7, page 424 in (Shiller, 1981).

[8] $p_t^* = \sum_{k=0}^{\infty} \overline{\gamma}^{k+1} d_{t+k}$ in Shiller (1981).

[9] $p_t^* = \overline{\gamma}\left(p_{t+1}^* + d_t^*\right)$ in Shiller (1981).

working backwards from the base year.

Calibration. We follow the above process for the CRSP NYSE, Amex, Nasdaq value-weighgted index of all common shares. Prices (p_t) are assumed to be the time series of CRSP index level excluding dividends. We calculate dividends (d_t) at monthly intervals between January 1950 and December 2019. Both prices and dividends are deflated using the CPI values provided by Professor Shiller on his website. We estimate the long-run exponential growth path using daily frequency data in line with $ln\,(P_t) = a + bt$ and set λ as e^b. $\overline{r}$ is estimated using monthly frequency data as the mean of the detrended dividend divided by the mean of the detrended price. For the purpose of calculating p_t^*, the terminal value p_T^* is set as the average of the detrended real price over the sample. For the purpose of calculating P_t^*, the terminal value P_T^* is set to the terminal value of the real price process: P_T.

Excess volatility. Figure (1) shows the behaviour of detrended real prices (p_t) and detrended ex-post rational prices (p_t^*) of the CRSP NYSE, Amex, Nasdaq value-weighgted index between 1950 and 2020. This figure corresponds to Figures (1) and (2) in Shiller (1981). As in the original work, also here we observe that the realized prices seem too volatile for their movements to be driven by new information about the stream of subsequent dividends (i.e. for the efficient markets model as proposed by Equation (1) to accurately describe the price process).

Forecasting fundamental value changes. Having computed the fundamental value (*ex-post* rational price) time series we are now in a position to test whether there is a difference in the informational content of changes in prices on A-days and N-days. In particular, we can now test which of them is better able to forecast future changes in fundamental value.

Let $\widetilde{P}_{t+1}^* = log(P_{t+1}^*) - log(P_t^*)$ and $\widetilde{p}_{t+1}^* = log(p_{t+1}^*) - log(p_t^*)$. These are the log change in the real ex-post rational price and the log change in the detrended real ex-post rational price, respectively. Setting Y_{t+1} to either $\widetilde{P}_{t+1}^*$ or $\widetilde{p}_{t+1}^*$, we can run the following regression to predict these changes at monthly, quarterly,

and annual frequencies:

$$Y_{t+1} = \beta_0 + \beta_1 r_t^A + \beta_2 r_t^N, \tag{4}$$

where r_t^A and r_t^N are the part of the lagged return of the relevant frequency accrued on A-days and N-days, respectively. Since we are not only interested in the economic and statistical significance of β_1 and β_2, but also in formally testing whether $\beta_1 > \beta_2$, we turn to the following regression:

$$Y_{t+1} = \delta_0 + \delta_1(r_t^A + r_t^N) + \delta_2(r_t^A - r_t^N). \tag{5}$$

In the above, we observe that: $\beta_1 = \delta_1 + \delta_2$ and $\beta_2 = \delta_1 - \delta_2$. As a result, the following is true:

1. if $\beta_1 > \beta_2$, then $\delta_1 + \delta_2 > \delta_1 - \delta_2$, and so $\delta_2 > 0$

2. since $\delta_1 = 0.5(\beta_1 + \beta_2)$ and $\delta_2 = 0.5(\beta_1 + \beta_2)$, $\delta_2 > 0$ implies $\beta_1 > \beta_2$.

Hence, $\delta_2 > 0$ if and only if $\beta_1 > \beta_2$.

We estimate the relationships in Equation 4 and 5 at monthly, quarterly, and annual frequencies for two time periods: 1953 – 2019 and 1953 – 2012. This is to account for the fact that starting from January 2013 the terminal values of p_T^* and P_T^* become non-negligible share of p_t^* and P_t^*. Table 5 summarizes the results for $Y_{t+1} = \widetilde{P}_{t+1}^*$ i.e. the real ex-post rational price. Table 6 summarizes the results for $Y_{t+1} = \widetilde{p}_{t+1}^*$ i.e the *detrended* real ex-post rational price.

At *monthly frequency*, we observe that although the relationship between the returns and the future fundamental value changes is positive for the share of monthly returns accrued on A-days (β_1 equal to 0.003 when $Y_{t+1} = p_t^*$; β_1 equal to 0.004 when $Y_{t+1} = P_t^*$) and negative for the share of monthly returns accrued on N-days (β_2 equal to -0.002 when $Y_{t+1} = p_t^*$; β_2 between -0.003 and -0.002 when $Y_{t+1} = P_t^*$),

neither relationship is statistically significant ($t(\beta_1)$ equal to 0.8; $t(\beta_2)$ between –1.4 and –1.3 depending on specification). Similarly, although positive (0.003 across all specifications), δ_2 is not statistically significant ($t(\delta_2)$ between 1.2 and 1.3). There is no evidence that cumulative monthly A-day returns forecast future one-month-ahead changes of fundamental value better than their N-day counterparts. The same is, however, no longer true at quarterly and annual frequencies.

Quarterly frequency data shows that cumulative A-day returns forecast next quarter's log change of fundamental value with a positive sign. In the shorter time period (1953 – 2012) β_1 is equal to 0.010 and 0.015 when $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$, respectively. This means that a one percentage point increase in the cumulative A-day return in a given quarter leads to a 1.5 basis points (1 basis point) increase in the next quarter's log change in (detrended) real ex-post rational price P_t^* (p_t^*), while the average of such log changes in the analysed time period is 86 (-6) basis points. This relationship is statistically significant at 10% confidence level ($t(\beta_1)$ equal to 1.7 and 1.8 when $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$, respectively). A corresponding relationship in the longer time period (1953 – 2019) is of a similar magnitude but no longer statistically significant ($t(\beta_1)$ equal to 1.4 and 1.3 when $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$, respectively). The relationship between N-day returns and future fundamental value changes is negative but not statistically significantly so ($t(\beta_2)$ between –0.5 and –0.1 depending on specification). Estimates of equation (5) indicate that $\beta_1 > \beta_2$ at quarterly frequency: δ_2 is positive in all specifications although only statistically significant at 10% level in the shorter time period ($t(\delta_2) = 1.7$ using p_t^*; $t(\delta_2) = 1.8$ using P_t^*).

We find similar, though statistically weaker, results for *annual frequency* data. Cumulative A-day returns at this frequency forecast next year's changes in fundamental value with a positive sign in all four specifications considered. In the shorter time period β_1 is equal to 0.028 and 0.043 for $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$, respectively. As such, a one percentage point increase in the cumulative A-day return in a given year leads to a 4.3 (2.8) basis points increase in next year's log

change in (detrended) real ex-post rational price P_t^* (p_t^*), while the average of such log changes in that time period is 345 (-28) basis points. Unlike its quarterly counterpart, this relationship is not statistically significant ($t(\beta_1)$ equal to 1.4) A corresponding relationship in the longer time period is weaker and also not statistically significant ($t(\beta_1)$ between 1.2 and 1.3). As in the quarterly returns case, the relationship between cumulative annual N-day returns and next year's fundamental value changes is negative but not statistically significantly so ($t(\beta_2)$ between –1.1 and –0.8). Finally, estimates of equation (5) indicate that $\beta_1 > \beta_2$ at annual frequency: δ_2 is positive in all specifications and statistically significant at 10% level in the shorter time period with $t(\delta_2)$ equal to 1.7.

These results are of crucial importance for the excess volatility puzzle (Shiller, 1981). Though it is true that price movements in general are too big to be attributed to new information about actual subsequent events, a clear dichotomy exists in this respect for aggregate movements on A-days and N-days. We show that, although the aggregate returns accrued on N-days can not be justified by subsequent changes in fundamental value, the same is not true for aggregate returns accrued on A-days. Quarterly returns accrued on A-days forecast future changes in ex-post rational price (detrended or not) with a positive sign. Furthermore, at both quarterly and annual frequency the ability to forecast such future changes in fundamental value is superior for A-day compared to N-day returns. This suggests that the movements in prices on A-days are not "too big relative to actual subsequent dividends" (Shiller, 1981).

Despite the fact that Shiller's fundamental value calculations do not allow for time-varying discount rates, the above suggests A-day returns poses superior ability to forecast future dividend streams. In the next section we confirm that is indeed the case using predictors suggested by Li and Wang (2018).

5 Discount rate or dividend news?

We use the dataset of equity yields provided by Giglio et al. (2020) to construct the *price ratio* – a new return predictor proposed by Li and Wang (2018) – for the CRSP value-weighted index. We show that while discount rate news drives N-day returns it is insignificant a predictor of A-day returns, which are in turn driven by information about dividends.

New predictors. Li and Wang (2018) revisit returns predictability by introducing *price ratio* (pr_t) i.e. the ratio of long- to short-term dividend prices. They show that this ratio predicts annual market returns and subsumes the predictive power of price-dividend ratio (pd_t) in such tests. They also show that the residuals from projecting the price-dividend ratio on the price ratio predict dividend growth. These two results are crucial as we use them to trace down the informational content of A-day and N-day returns. In what follows, we briefly summarize the construction of the price ratio and show the modification we adopt to cover the wider aggregate CRSP market (the authors use SP500 price ratio) for a longer period of time than in the original paper. Four main predictors considered in the original paper are summarized in Table 1.

Price ratio. Li and Wang (2018) define the *price ratio* as the relative price of long-term and short-term dividends. It is possible to show, that under no-arbitrage condition, the ex-dividend market value S_t is the expected sum of discounted future dividends.

$$S_t = \sum_{\tau=1}^{\infty} E_t^Q \left[e^{-\int_t^{t+\tau} r_s ds} D_{t+\tau} \right] \tag{1}$$

$$= \sum_{\tau=1}^{T} E_t^Q \left[e^{-\int_t^{t+\tau} r_s ds} D_{t+\tau} \right] + \sum_{\tau=T+1}^{\infty} E_t^Q \left[e^{-\int_t^{t+\tau} r_s ds} D_{t+\tau} \right] \tag{2}$$

$$= P_t^{T^-} + P_t^{T^+}, \tag{3}$$

where $P_t^{T^-} = \sum_{\tau=1}^{T} E_t^Q \left[e^{-\int_t^{t+\tau} r_s ds} D_{t+\tau} \right]$ and $P_t^{T^+} = \sum_{\tau=T+1}^{\infty} E_t^Q \left[e^{-\int_t^{t+\tau} r_s ds} D_{t+\tau} \right]$ are the prices of short-term and long-term dividends, respectively.

The authors then proceed to decompose the price dividend ratio as follows:

$$\frac{S_t}{D_t} = \frac{P^{T^-}}{D_t} + \frac{P^{T^+}}{D_t}. \tag{4}$$

The price-dividend ratio is the sum of the two valuation ratios. Li and Wang (2018) construct their *price ratio* (pr_t) as their log difference:

$$pr_t = ln\left(\frac{P^{T^+}}{D_t}\right) - ln\left(\frac{P^{T^-}}{D_t}\right) = ln\left(\frac{P^{T^+}}{P^{T^-}}\right). \tag{5}$$

Computing the above ratio requires data on index futures or option prices. While available for the S&P 500, these are not available for the wider CRSP universe aggregate index. Moreover, these contracts only started trading at the end of the last century and hence do not allow for computing time series long enough for the purpose of our analysis. We therefore turn to Giglio et al. (2020) who extend the term structure of equity yields back to 1970s for the wider universe of CRSP and Compustat stocks covering all NYSE, Amex, and Nasdaq firms. The authors graciously make their preliminary estimates of these equity yields available on-line. These cover maturities between 1 and 100 years between August 1975 and November 2016.

To calculate the price ratio, we recall the definition of equity yield (Binsbergen et al., 2013):

$$e_{t,n} = \frac{1}{n} ln\left(\frac{D_t}{P_{t,n}}\right), \tag{6}$$

where $P_{t,n}$ is the price at time t of the stochastic dividend paid out in n years from time t. Thus, this price can be restated as $P_{t,n} = D_t e^{-n e_{t,n}}$.

The above allows us to rearrange the ex-dividend price equation as

$$S_t = \sum_{\tau=1}^{\infty} P_{t,\tau} = \sum_{\tau=1}^{\infty} D_t e^{-\tau e_{t,\tau}} \tag{7}$$

$$= \sum_{\tau=1}^{T} D_t e^{-\tau e_{t,\tau}} + \sum_{\tau=T+1}^{\infty} D_t e^{-\tau e_{t,\tau}} \tag{8}$$

$$= P_t^{T^-} + P_t^{T^+}, \tag{9}$$

and restate the *price ratio*, pr_t, as:

$$pr_t = ln\left(\frac{P^{T^+}}{D_t}\right) - ln\left(\frac{P^{T^-}}{D_t}\right) = ln\left(\frac{P^{T^+}}{P^{T^-}}\right) \tag{10}$$

$$= ln\left[\frac{\sum_{\tau=T+1}^{\infty} D_t e^{-\tau e_{t,\tau}}}{\sum_{\tau=1}^{T} D_t e^{-\tau e_{t,\tau}}}\right] = ln\left[\frac{\sum_{\tau=T+1}^{\infty} e^{-\tau e_{t,\tau}}}{\sum_{\tau=1}^{T} e^{-\tau e_{t,\tau}}}\right]. \tag{11}$$

In particular for T = 1 (as in Li and Wang (2018)) using the maturities coverage provided by Giglio et al. (2020) data:

$$pr_t = ln\left[\frac{\sum_{\tau=2}^{\infty} e^{-\tau e_{t,\tau}}}{e^{-e_{t,1}}}\right] \tag{12}$$

$$= ln\left[\frac{e^{-2e_{t,2}} + e^{-3e_{t,3}} + e^{-4e_{t,4}} + e^{-5e_{t,5}} + ... + e^{-100e_{t,100}}}{e^{-e_{t,1}}}\right]. \tag{13}$$

Appendix A reports the behaviour of the price ratio constructed using Giglio et al. (2020) equity yields over time and shows that it replicates the two main results of Li and Wang (2018): (a) the price ratio (pr_t) predicts one-year returns and (b) the residual from regressing the price-dividend ratio on the price ratio (e_t^{pd}) predicts log dividend growth over the next year. The reasoning behind both results is intuitively explained in the Li and Wang (2018) paper. First, long-term dividends are more sensitive to discount rate movements than short-term dividends. As a result, the ratio of the two – the price ratio – increases (decreases) when the discount rates decrease (increase). This drives result (a). Secondly, since the price-dividend ratio is driven by both the information about discount rates and the

information about dividend growth, the residual from projecting it on the price ratio forecasts dividend growth. This explains result (b).

A-day & N-day returns. Knowing the informational content of the variables proposed by Li and Wang (2018), we now proceed to use them as predictors of A-day and N-day returns at various frequencies. To this end, we estimate regressions of the following type:

$$r^i_{t,t+m} = \alpha + \beta x_t + \epsilon_{t,t+12} \qquad i = \{A, N, A\&N\}, \tag{14}$$

where $r^i_{t,t+m}$ is the cumulative return over m months using returns accrued on days of type i, and x_t is one of the four predictors summarized in Table 1. $m = 3, 6,$ and 12 for quarterly, bi-annual, and annual data, respectively. Table 7 reports the results. Since the returns are overlapping in this part of the estimation, we use Newey-West t-statistics with 18, 9, and 4 lags for annual, bi-annual, and quarterly data, respectively.

Once again, the results reported highlight a clear dichotomy between A-day and N-day returns. This time it is with regard to their relative informational content about future discount rates and dividends. The price ratio and the price-dividend ratio – both discount-rate news predictors – consistently forecast returns accrued on N-day across all frequencies considered and this relationship is significant at any commonly adopted significance level. Neither of the two is statistically significant a predictor of returns accrued on A-days at any of the frequencies. Returns accrued on A-days are in turn forecast with a *positive* sign by the residual ϵ^{pr}_t across all frequencies. Furthermore, returns accrued on A-days at bi-annual and quarterly frequency are also forecast with a *negative* sign by the dividend-news heavy residual ϵ^{pd} of projecting the price-dividend ratio onto the price ratio.

The negative relationship between ϵ^{pd} and the part of returns accrued on announcement days indicates the existence of a strong negative contemporaneous

correlation between A-day returns and dividend growth. This is because high levels of ϵ^{pd} are found to be predictors of high dividend growth and low A-day returns over the one-year ahead horizon. We confirm that to be the case. Annual dividend growth has significantly positive correlation with annual returns and annual N-day returns: $\rho(r^{A\&N}_{t,t+12}, log(\Delta D_{t,t+12})) = 0.1564$, $\rho(r^{N}_{t,t+12}, log(\Delta D_{t,t+12})) = 0.2246$. Annual A-day returns, on the other hand have a significant negative correlation with contemporaneous dividend growth: $\rho(r^{A}_{t,t+12}, log(\Delta D_{t,t+12})) = -0.1105$.

6 Conclusion

In this paper, we develop an approach to determine whether a particular predictor represents a proxy for fundamental risk. Our methodology is based on an intuitive assumption that risk-based predictors should be linked to new information about economic conditions. As our measure of such new information, we use days when important macroeconomic announcements are released. We study a wide range of well-known predictors and find that each predictor forecasts returns either on days with macroeconomic announcements or on other days, but never on both types of days. These results support the hypothesis underlying our approach that the two sets of days are different, and means that we can group predictors into those that are linked to economic news and those that are not.

More specifically, those predictors that are based on direct measures of the amount of risk in the economy, which according to asset pricing theory should forecast returns, forecast quarterly returns accrued on A-days but not on N-days. The opposite holds for most of the predictors historically documented to forecast future stock returns. Together, these results suggest that sources of return predictability differ across predictors, with direct risk-based measures driven by economic fundamentals and many of the others having different origins. In support of this hypothesis, we show that A-day returns are positively related to future

changes in fundamental value, while there is no such relation for N-day returns. Our methodology and results can be used to evaluate other predictors of asset returns.

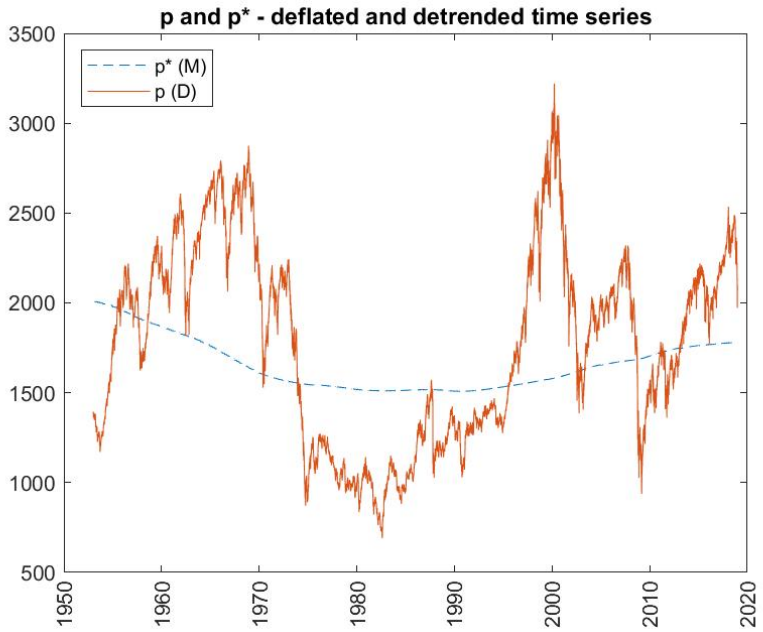


Figure 1: Deflated and de-trended market price (p) and fundamental value (p*)

This figure shows the behaviour of detrended real prices (p_t) and corresponding ex-post rational prices (p_t^*) for the CRSP NYSE, Amex, Nasdaq value-weighted index between 1950 and 2020. It corresponds to Figure (1) and Figure (2) in Shiller (1981).

Table 1: Summary of the predictors introduced by Li and Wang (2018)

This table summarizes the predictors introduced by Li and Wang (2018)

Predictor	Explanation
pr	price ratio: the ratio of long-term to short-term dividend prices
pd	price dividend ratio: the ratio of price to current dividends
ϵ^{pd}	residual from projecting the price-dividend ratio onto the price ratio
ϵ^{pr}	residual from projecting the price ratio onto the price-dividend ratio

Table 2: Stock market returns' predictors – variables definition

This table presents definitions of variables used to forecast stock market returns on A-days and N-days and the source of the data used.

Variable	Name	Description	Reference	Source
cayGW	Consumption to wealth ratio	Consumption, wealth, income ratio calculated using only prevailing data to eliminate the look-ahead bias inherent in the original variable suggested by Lettau and Ludvigson (2001)	Lettau and Ludvigson (2001) Goyal and Welch (2007)	Amit Goyal's website
cayLL	Consumption to wealth ratio	Consumption, wealth, income ratio calculated using look-ahead (in-sample) estimation. The original variable suggested by Lettau and Ludvigson (2001)	Lettau and Ludvigson (2001)	Martin Lettau's website
dfr	Default Return Spread	Difference between long-term corporate bond and long-term government bond returns	Fama and French (1989)	Amit Goyal's website
dfy	Default Yield Spread	Difference between BAA and AAA rated corporate bond yields	Fama and French (1989)	Amit Goyal's website
epbound3M	Lower bound on equity premium	Expected return on the S&P 500 over the next 3 months	Martin (2016)	Ian Martin's website
equisBW	Percent Equity Issuing	Ratio of equity issuing activity as a fraction of total issuing activity	Baker and Wurgler (2000)	Amit Goyal's website
ik	Investment to capital ratio	Ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy	Cochrane (1991)	Amit Goyal's website
logPD	Log price dividend ratio	Logarithm of the price to dividend ratio	Litzenberger and Ramaswamy (1979) Campbell (1996)	CRSP data
svar	Stock Variance	Sum of squared daily returns on the S&P 500	Guo (2006) Goyal and Welch (2007)	Amit Goyal's website
tbl	Treasury-bill rate	The 3-month treasury bill: secondary market rate as reported by the Federal Reserve Bank at St. Louis economic research data base	Goyal and Welch (2007)	Amit Goyal's website
tms	Term spread	Difference between the long term yield on government bonds and the treasury bill	Fama and French (1989)	Amit Goyal's website

Table 3: Summary statistics

The table reports summary statistics of variables analysed. Panel A provides summary statistics of quarterly returns, quarterly returns accrued on A-days, and quarterly returns accrued on N-days. Panel B reports summary statistics of variables that have been found to be A-day returns' predictors in univariate linear regressions using quarterly data. Panel C reports summary statistics of variables that have been found to be N-day returns' predictors in univariate linear regressions using quarterly data. For each of the time-series we report its length and the first and last quarter for which the data is available. We then report the summary statistics of the relevant time-series. Mean, standard deviation, minimum value, maximum value, first order autocorrelation, and skewness are reported.

	N	Start	End	Mean	SD	Min	Max	Autocorr	skew
Panel A: Returns									
r	268	19530331	20191231	0.007	0.083	-0.315	0.194	0.070	-0.940
rA	268	19530331	20191231	0.005	0.029	-0.184	0.127	0.001	-0.650
rNA	268	19530331	20191231	0.002	0.075	-0.299	0.165	0.113	-0.957
Panel B: A-day return predictors									
epbound3M	64	19960329	20111230	0.050	0.032	0.015	0.164	0.529	1.611
dfy	268	19530331	20191231	0.010	0.004	0.003	0.034	0.871	1.859
svar	268	19530331	20191231	0.006	0.010	0.000	0.114	0.414	7.524
Panel C: N-day return predictors									
logPD	267	19530630	20191231	4.947	0.383	4.085	5.946	0.937	0.287
cayGW	268	19530331	20191231	0.000	0.023	-0.049	0.040	0.960	-0.219
tbl	268	19530331	20191231	0.043	0.031	0.000	0.155	0.950	0.892
tms	264	19530331	20181231	0.017	0.014	-0.035	0.045	0.837	-0.214
dfr	268	19530331	20191231	0.001	0.024	-0.118	0.163	-0.083	0.242
ik	268	19530331	20191231	0.036	0.003	0.029	0.044	0.969	0.376
cayLL	267	19530331	20190930	0.000	0.019	-0.049	0.038	0.911	-0.385
eqisBW	241	19581231	20181231	0.173	0.084	0.045	0.430	0.960	0.848

Table 4: Univariate regressions

This table reports the results of univariate regressions of quarterly returns on selected predictor variables that have been found statistically and economically significant in predicting A-day or N-day returns. All regressions are of the following type:

$$r^i_{t+1} = \alpha + \beta x_t, \quad i = (A\&N, A, N),$$

where r^i_{t+1} is the quarterly return, quarterly return accrued on A-days, and quarterly return accrued on N-days in Panel A, Panel B, and Panel C, respectively. Column header is the name of the variable x_t used in the respective regression. Variables are summarized in Table 2. Values marked in bold signify statistical significance at 10% level.

Panel A: Quarterly returns

	logPD	epbound3M	cayGW	tbl	tms	dfy	svar	dfr	ik	cayLL	eqisBW
α	0.105	-0.025	0.007	0.023	-0.005	-0.001	0.006	0.007	0.163	0.008	0.033
$t(\alpha)$	1.592	-1.085	1.471	2.669	-0.605	-0.057	0.997	1.436	3.016	1.515	2.696
β	-0.020	0.606	**0.461**	**-0.362**	**0.712**	0.846	0.275	**0.363**	**-4.328**	**0.445**	**-0.163**
$t(\beta)$	-1.478	1.598	**2.061**	**-2.211**	**1.949**	0.725	0.527	**1.688**	**-2.889**	**1.676**	**-2.519**
R^2	0.4%	2.4%	1.2%	1.4%	1.1%	-0.2%	-0.3%	0.7%	2.7%	0.7%	2.2%
N	266	64	267	267	264	267	267	267	267	267	241

Panel B: Quarterly returns accrued on announcement days

	logPD	epbound3M	cayGW	tbl	tms	dfy	svar	dfr	ik	cayLL	eqisBW
α	-0.008	-0.009	0.005	0.007	0.004	-0.001	0.002	0.005	-0.003	0.005	0.006
$t(\alpha)$	-0.351	-0.905	3.025	2.143	1.237	-0.339	0.984	3.017	-0.146	3.056	1.355
β	0.003	**0.423**	0.076	-0.027	0.110	**0.708**	**0.579**	0.031	0.230	0.114	-0.002
$t(\beta)$	0.587	**2.581**	0.960	-0.465	0.852	**1.734**	**3.215**	0.407	0.430	1.211	-0.094
R^2	-0.2%	8.2%	0.0%	-0.3%	-0.1%	0.7%	3.4%	-0.3%	-0.3%	0.2%	-0.4%
N	266	64	267	267	264	267	267	267	267	267	241

Panel C: Quarterly returns accrued on non-announcement days

	logPD	epbound3M	cayGW	tbl	tms	dfy	svar	dfr	ik	cayLL	eqisBW
α	0.112	-0.015	0.002	0.017	-0.008	0.001	0.004	0.002	0.165	0.002	0.028
$t(\alpha)$	1.896	-0.747	0.445	2.130	-1.160	0.082	0.738	0.412	3.427	0.485	2.474
β	**-0.022**	0.180	**0.386**	**-0.335**	**0.602**	0.123	-0.309	**0.328**	**-4.545**	0.334	**-0.162**
$t(\beta)$	**-1.863**	0.518	**1.919**	**-2.285**	**1.832**	0.117	-0.660	**1.700**	**-3.398**	1.395	**-2.790**
R^2	0.9%	-1.2%	1.0%	1.6%	0.9%	-0.4%	-0.2%	0.7%	3.8%	0.4%	2.7%
N	266	64	267	267	264	267	267	267	267	267	241

Table 5: Forecasting changes in fundamental value using real ex-post rational price P^*_{t+1} as its proxy

This table reports the results of regressing the change in real ex-post rational price $\widetilde{P}^*_{t+1}$ on lagged returns accrued on A-days and N-days at various frequencies. The left-hand side of the table presents results of estimating equation (4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$. The right-hand side of the table presents results of estimating equation (5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$. In both cases $Y_{t+1} = \widetilde{P}^*_{t+1}$. For each of the equations two time periods are considered: 1953 – 2019 and 1953 – 2012. This is to account for the fact that starting from January 2013 the terminal value of P^*_T is becoming non-negligible share of P^*_t. t-statistics are reported in the second row below each coefficient value. Since Y_{t+1} are constructed using non-overlapping windows, standard unadjusted t-statistics are reported. Values marked in bold signify statistical significance at 10% level.

Eq.(4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$					Eq.(5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$				
β_0	β_1	β_2	$Adj.R^2$	N	δ_0	δ_1	δ_2	$Adj.R^2$	N
Panel A: Monthly data 1953 – 2019					Panel A: Monthly data 1953 – 2019				
0.003	0.004	- 0.002	0.02%	803	**0.003**	0.001	0.003	0.02%	803
39.350	0.796	- 1.272			**39.350**	0.231	1.220		
Panel B: Monthly data 1953 – 2012					Panel B: Monthly data 1953 – 2012				
0.003	0.004	- 0.003	0.07%	719	**0.003**	0.001	0.003	0.07%	719
34.281	0.834	- 1.361			**34.281**	0.238	1.289		
Panel C: Quarterly data 1953 – 2019					Panel C: Quarterly data 1953 – 2019				
0.009	0.010	- 0.001	-0.10%	267	**0.009**	0.005	0.005	-0.10%	267
38.497	1.318	- 0.169			**38.497**	1.206	1.244		
Panel D: Quarterly data 1953 – 2012					Panel D: Quarterly data 1953 – 2012				
0.008	**0.015**	- 0.002	0.57%	239	**0.008**	0.007	**0.008**	0.57%	239
35.050	**1.809**	- 0.501			**35.050**	1.571	**1.808**		
Panel E: Annual data 1953 – 2019					Panel E: Annual data 1953 – 2019				
0.036	0.035	- 0.009	-0.15%	66	**0.036**	0.013	0.022	-0.15%	66
17.708	1.163	- 0.781			**17.708**	0.813	1.350		
Panel F: Annual data 1953 – 2012					Panel F: Annual data 1953 – 2012				
0.034	0.043	- 0.011	1.57%	59	**0.034**	0.016	**0.027**	1.57%	59
16.205	1.409	- 0.985			**16.205**	0.971	**1.660**		

Table 6: Forecasting changes in fundamental value using *detrended* real ex-post rational price p^*_{t+1} as its proxy

This table reports the results of regressing the change in *detrended* real ex-post rational price $\widetilde{p}^*_{t+1}$ on lagged returns on A-days and N-days at various frequencies. The left-hand side of the table presents results of estimating equation (4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$. The right-hand side of the table presents results of estimating equation (5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$. In both cases $Y_{t+1} = \widetilde{p}^*_{t+1}$. For each equation two time periods are considered: 1953 – 2019 and 1953 – 2012. This is to account for the fact that starting from January 2013 the terminal value of p^*_T is becoming non-negligible share of p^*_t. t-statistics are reported in the second row below each coefficient value. Since Y_{t+1} are calculated using non-rolling windows, standard unadjusted t-statistics are reported. Values marked in bold signify statistical significance at 10% level.

Eq.(4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$					Eq.(5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$				
β_0	β_1	β_2	$Adj.R^2$	N	δ_0	δ_1	δ_2	$Adj.R^2$	N
Panel A: Monthly data 1953 – 2019					Panel A: Monthly data 1953 – 2019				
- 0.000	0.003	- 0.002	0.08%	803	**- 0.000**	0.000	0.003	0.08%	803
- 2.501	0.843	- 1.423			**- 2.501**	0.214	1.322		
Panel B: Monthly data 1953 – 2012					Panel B: Monthly data 1953 – 2012				
- 0.000	0.003	- 0.002	0.06%	719	**- 0.000**	0.000	0.003	0.06%	719
- 3.261	0.771	- 1.363			**- 3.261**	0.179	1.232		
Panel C: Quarterly data 1953 – 2019					Panel C: Quarterly data 1953 – 2019				
- 0.000	0.007	- 0.000	0.01%	267	**- 0.000**	0.003	0.004	0.01%	267
- 3.189	1.421	- 0.138			**- 3.189**	1.317	1.326		
Panel D: Quarterly data 1953 – 2012					Panel D: Quarterly data 1953 – 2012				
- 0.001	**0.010**	- 0.001	0.45%	239	**- 0.001**	0.004	**0.005**	0.45%	239
- 4.207	**1.746**	- 0.361			**- 4.207**	1.561	**1.704**		
Panel E: Annual data 1953 – 2019					Panel E: Annual data 1953 – 2019				
- 0.002	0.026	- 0.007	1.04%	66	- 0.002	0.009	0.016	1.04%	66
- 1.597	1.342	- 0.987			- 1.597	0.908	1.589		
Panel F: Annual data 1953 – 2012					Panel F: Annual data 1953 – 2012				
- 0.003	0.028	- 0.008	1.87%	59	**- 0.003**	0.010	**0.018**	1.87%	59
- 2.096	1.405	- 1.080			**- 2.096**	0.934	**1.690**		

Table 7: Discovering the informational content of A-day and N-day returns

This table reports the results of regressing cumulative returns over various time horizons on the predictor variables suggested by Li and Wang (2018). Here, these predictors are calculated using Giglio et al. (2020) equity yields data which are available between 1975/08 and 2016/11. The regressions are of the following type:

$$r^{i}_{t,t+m} = \alpha + \beta x_t + \epsilon_{t,t+12} \qquad i = \{A, N, A\&N\},$$

where m is the length of the time horizon in months and i is the type of days on which the returns have been accrued (A-days, N-days, and both A- and N-days). Predictor variables (x_t) are as follows: the price ratio (pr), the price-dividend ratio (pd), the residual from projecting the price-dividend ratio onto the price ratio (ϵ^{pd}_t), and the residual from projecting the price ratio onto the price-dividend ratio (ϵ^{pr}). Newey-West t-statistics are reported below each of the β-coefficient estimates. The lags are 18, 9, and 4 for annual, bi-annual, and quarterly data, respectively. Values marked in bold signify statistical significance at 10% level.

Annual returns, m = 12

	i = A & N					i = A					i = N			
	pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}
β	**-0.101**	**-0.097**	-0.110	0.010	β	0.011	0.002	-0.148	**0.167**	β	**-0.112**	**-0.099**	0.038	-0.157
t	**-1.761**	**-1.879**	-0.548	0.046	t	0.301	0.055	-1.536	**1.755**	t	**-2.602**	**-2.890**	0.185	-0.665
R^2	6.0%	6.4%	0.5%	0.0%	R^2	0.3%	0.0%	3.7%	4.1%	R^2	8.6%	7.7%	0.1%	0.9%

Bi-annual returns, m = 6

	i = A & N					i = A					i = N			
	pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}
β	-0.046	**-0.052**	-0.178	0.138	β	0.007	0.000	**-0.112**	**0.124**	β	**-0.053**	**-0.051**	-0.066	0.014
t	-1.504	**-1.918**	-1.332	0.921	t	0.370	-0.008	**-2.149**	**2.389**	t	**-2.076**	**-2.432**	-0.491	0.093
R^2	2.5%	3.6%	2.3%	1.2%	R^2	0.3%	0.0%	5.0%	5.4%	R^2	3.7%	4.0%	0.4%	0.0%

Quarterly returns, m = 3

	i = A & N					i = A					i = N			
	pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}		pr	pd	ϵ^{pd}	ϵ^{pr}
β	-0.018	**-0.026**	**-0.179**	**0.169**	β	0.004	-0.001	**-0.082**	**0.091**	β	**-0.022**	**-0.025**	-0.097	0.078
t	-1.200	**-1.931**	**-2.307**	**1.997**	t	0.477	-0.104	**-3.021**	**3.262**	t	**-1.690**	**-2.162**	-1.183	0.898
R^2	0.8%	1.9%	4.8%	3.7%	R^2	0.2%	0.0%	5.7%	5.9%	R^2	1.4%	2.1%	1.7%	0.9%

Appendices

A Price ratio

The figure below shows the behaviour of the price ratio proposed by Li and Wang (2018) but computed using Giglio et al. (2020) equity yields data for the wider CRSP index between August 1975 and November 2016. Table A.1 and Table A.2 below show that such constructed price ratio replicates the two main results from Li and Wang (2018) paper.

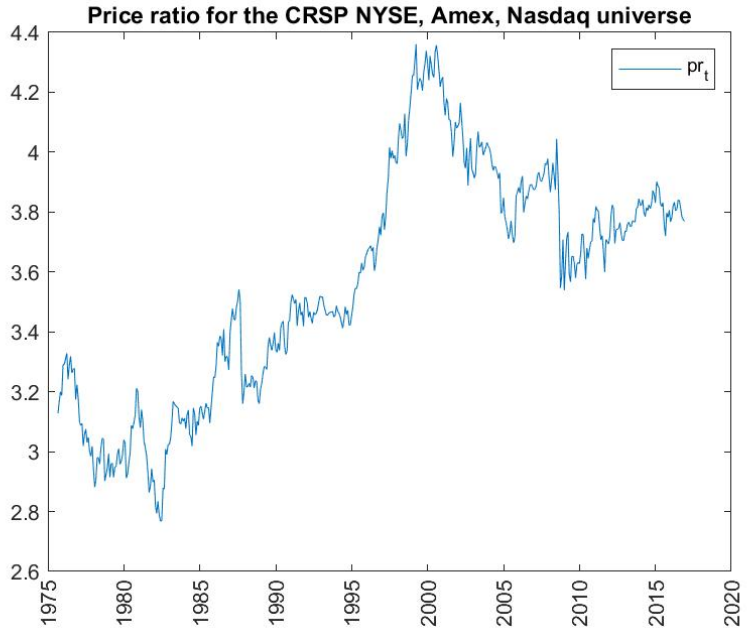


Figure A.1: Price ratio for CRSP: Aug 1975 – Nov 2016

Table A.1 presents the results of forecasting one-year ahead return on the aggregate market index by four predictors suggested by Li and Wang (2018): the price ratio (pr_t), the price-dividend ratio (pd_t),[10] residuals of pd_t after projecting on pr_t (e_t^{pd}), and the residuals of prt_t after projecting on pd_t (e_t^{pr}). We find that both the pr_t and pd_t predict future returns with a negative sign, while e_t^{pd} (i.e. the

[10]The price dividend ratio in this section is calculated by equating the current dividend to the sum of dividends paid in previous years in order to remove seasonality.

part of pd_t orthogonal to pr_t) is not statistically significant. Unlike Li and Wang (2018), we don't find the relationship between e_t^{pr} to be negative.

Table A.1: Forecasting one-year ahead aggregate market index return

This table presents the results of forecasting the one-year ahead return on the aggregate stock market index with the four predictors suggested by Li and Wang (2018): the price ratio (pr_t), the price-dividend ratio (pd_t), residuals of pd_t after projecting on pr_t (e_t^{pd}), and the residuals of prt_t after projecting on pd_t (e_t^{pr}). Newey-West t-statistics with 18 lags are reported below the estimate of the β coefficient for each predictor. Values marked in bold signify statistical significance at 10% level.

$r_{t,t+12} = \alpha + \beta x_t + \epsilon_{t,t+12}$				
x_t	prt_t	pd_t	e_t^{pd}	e_t^{pr}
β	**-0.102**	**-0.098**	-0.110	0.010
t	**-1.779**	**-1.898**	-0.554	0.047
R^2	0.061	0.065	0.005	0.000
N	485	485	485	485

Table A.2 presents the results of forecasting one-year ahead dividend growth of the aggregate market index by the four predictors described above. We find that while e_t^{pd} forecasts future dividend growth with a positive sign, the pd_t is not a statistically significant predictor thereof. Unlike Li and Wang (2018), we don't find the relationship between pr_t and dividend growth to be significantly negative. We do, however, find the residual of pr_t after projecting on pd_t (e_t^{pr}) to have a negative and statistically significant relationship with dividend growth.

Table A.2: Forecasting one-year ahead dividend growth of the aggregate market index

This table presents the results of forecasting one-year ahead dividend growth of the aggregate market index by the four predictors suggested by Li and Wang (2018): the price ratio (pr_t), the price-dividend ratio (pd_t), residuals of pd_t after projecting on pr_t (e_t^{pd}), and the residuals of prt_t after projecting on pd_t (e_t^{pr}). We measure dividend growth in line with Li and Wang (2018) as the ratio of adjacent, non-overlapping cumulative dividends,

$$\Delta D_{t,t+12} = \frac{\sum_{i=1}^{12} D_{t+i}}{\sum_{i=1}^{12} D_{t-12+i}}.$$

The left-hand side variable is the logarithm of the above ratio. Newey-West t-statistics with 18 lags are reported below the estimate of the β coefficient for each predictor. Values marked in bold signify statistical significance at 10% level.

	$log(\Delta D_{t,t+12}) = \alpha + \beta x_t + \epsilon_{t,t+12}$			
x_t	prt_t	pd_t	e_t^{pd}	e_t^{pr}
β	-0.024	-0.009	**0.227**	**-0.263**
t	-0.856	-0.321	**1.917**	**-2.165**
R^2	0.015	0.002	0.088	0.102
N	485	485	485	485

The above results prove that the price ratio we construct for the wider universe of CRSP stocks using Giglio et al. (2020) equity yields replicates the two core results of the Li and Wang (2018) paper. *The price ratio pr_t forecasts one-year ahead returns and the residual (e_t^{pd}) of the price-dividend ratio after projecting it on the price ratio forecasts future dividend growth.*

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5 | Old wine in new bottles? Are industry risks (still) not understood?

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I show that industry indices consistently explain large shares of international factor and geographic risk premia. In Europe and North America, global industry indices explain at least 50% of the value (HML) and 30% of the size (SMB) and productivity (RMW) factors, respectively. In Asia-Pacific and North America, they explain approximately 30% of the regions' investment (CMA) factors. Similarly, univariate and multivariate sort portfolios show strikingly consistent trends with respect to co-movement with the relevant industries. Finally, as expected in a commercially integrated world, geographic zone factors also constitute portfolios of these indices. Together, the results indicate that various premia credited to existence of risk factors can in fact be just combinations of at present poorly understood industry-specific risks.

1 Introduction

Empirical asset pricing documents a wide range of factors capable of delivering excess returns. The literature started in the early 1990s with the discovery of the size

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and value effects (Fama and French, 1992). It's continued growth throughout the years led to the coining of the "factor zoo" term (Cochrane, 2011) used to describe the existence of a multitude of risk factors and the steady and continued arrival of new ones. This in turn has fueled the growth of a parallel strand of literature focused on taming the factor zoo (i.e. identifying the "true" and the redundant factors and sources of risk). Till date models are being suggested to explain not only the size and value drivers but also those of the other factors suggested in the literature.

The aim of this paper is to connect the existence of various (factor) risk premiums with industry-specific sources of risk using the industry composition channel. If, for instance, certain industries are more likely than others to pay dividends *and* are underrepresented in the market portfolio, then the dividend strip risk premiums (calculated over the market return) will (1) materialize and (2) likely be driven by the combination of industry risks relevant for the industries dominating the index's dividend payouts. Similarly, if certain industries tend to be consistently composed of smaller/larger market cap firms or firms which have lower/higher book-to-market value of equity compared with the other ones, their specific risks will drive the returns to the characteristic sort portfolios and, in turn, the returns to the size and value factors. Finally, risk premiums commonly credited to various geographic regions may also be driven by these regions' differential exposures to certain industries. These are the matters this paper aims to investigate.

First, I look into the relationship between dividend strategies of Binsbergen et al. (2012) and industry returns. I use returns on 48 industry portfolios defined in line with Kenneth French's classification to construct synthetic index and front strip portfolios of the S&P 500. I then regress the returns to the dividend strategies on the returns to these synthetic portfolios and find that the returns to the dividend strip strategies are, to non-trivial extent, driven by industry-specific sources or risk.

Building on the above results, I proceed to test the hypothesis that also other commonly used risk premiums, like *size* and *value*, are combinations of industry-

specific sources of risk. When not fully grasped by industries' contributions to the market factor, their relevance may materialize as excess return unexplained by the market factor. I show that various end-of-spectrum characteristic sort portfolios constructed using US stocks tend to pick a non-trivial number of stocks assigned to such under-represented in the market factor industries. Consequently, a small number of such underrepresented industries explains a significant share of popular US factors. It takes only fourteen (thirteen) of the 48 Kenneth French industries to explain 62% (29%) of the US value (size) premium. Corresponding results are also present in international cross-sections. Univariate and bivariate sort portfolios globally show consistent trends with respect to co-movement with numerous industries. The relevant industries then go on to explain around 30% (50%) of the European and North American size (value) factors.

Finally, I show that a considerable part of variation in returns to geographic risk premiums/factors is also due to their different exposures to industry risks. This is in line with the popular in the literature (Dumas et al., 2020) argument that in a world well integrated commercially returns to geographic zone "factors" should be combinations of portfolios of industries. I show that except for Japan and Malaysia, the geographic zone factors identified using Dumas et al. (2020) methodology are highly correlated with global industry returns. Between 66% (UK) and 85% (US) of the variation in geographic zone factors can be credited to variation in industry returns between January 2009 and December 2014.

Taken together, the results indicate that industry indices are able to consistently explain away large shares of variation in international factor and geographic risk premiums and dividend strategies. This means that various risk premiums credited to cash-flows' timing, stock market characteristics, and geographic zones can in fact be just combinations of industry-specific risks which the finance literature has failed to correctly understand till date.

2 Data

Data on the daily returns to the Binsbergen et al. (2012) *long dividend* and *dividend steepener* strategies come from the authors' website.

Data on the daily returns to *Fama-French 5 factors, univariate, and bivariate sort portfolios* in the US and international cross-sections come from Kenneth French's website. Returns to factors and univariate sort portfolios are considered for the following regions: developed, developed ex US, North America, Europe, Japan, and Asia Pacific ex Japan. The summary of countries covered for each of these regions is available on Kenneth French's website. Bivariate sorts are considered only for the US cross-section.

Breakpoints used to assign individual stocks to various portfolios with respect to size, book-to-market, investment, and operating profitability come from Kennet French's website. Individual stocks' financial information necessary to calculate the value of the above characteristics come from Compustat.

Geographic factors are constructed in line with Dumas et al. (2020). I briefly summarize the methodology in Appendix A. Data on geographical attribution of firms' revenue between 2009 and 2019 comes from FactSet's Geographic Revenue Exposure (GeoRev) dataset. This data is collected in July 2021. For each firm covered, the dataset reports its revenue composition specifying the start and the end of the period to which this composition pertains, the estimated percentage share of the revenue from each relevant country for that period, and the confidence score for that estimate. All data is calculated and provided by Factset. The trimming applied to this dataset is detailed in Appendix A. Daily returns for the resulting cross-section of international stocks with revenue attribution information comes from the Thomson Reuter's EIKON database.

Daily returns to US *industry portfolios* come from Kenneth French's website. I compute international industry returns using the cross-section of stocks for which

relevant revenue attribution data was available. I assign stocks to various industries subject to their GIC Industry Group and GIC Sector classifications. Stocks are assigned to the relavant industry on the basis of their GIC code at the end of June for the given year. For such assignments, returns to the relevant industry or sector are then calculated between July and June of the following year.

3 Dividend strip premiums and industry returns

3.1 Theoretical background

Let us suppose there are three periods, 0, 1, and 2 and three assets (stocks or industries) A, B, and C. Each asset pays a dividend $D_{t=1,2}^{j=A,B,C}$ in the future. Expected returns for each stock are $R_{t=0,1}^{j=A,B,C}$ and may differ across stocks. Then, each stock's price at date zero is given by

$$P_0^{j=A,B,C} = \frac{D_1^j}{1+R_0^j} + \frac{D_2^j}{(1+R_0^j)(1+R_1^j)}$$

The value of the *index* is simply $P_0 = \Sigma_j P_0^j$. Thus, the index weights of each stock can be expressed as $w_j = P_0^j / \Sigma_j P_0^j$.

A *dividend strip*, in particular the front strip, is a claim on the total dividend paid by the index and is given by

$$V_0 = \Sigma_j V_0^j = \Sigma_j \frac{D_1^j}{1+R_0^j}.$$

The weights in this front strip are given by $v_j = V_0^j / \Sigma_j V_0^j$.

Note that an asset's market weight could be either very similar to or very different from its front strip weight. In particular, stocks like Google or Facebook which do not pay dividends but have huge market capitalizations have a high market weight but a zero front strip weight, while the tobacco and utility industries

have low market weights but high front strip weights. Other industries may have similar market and strip weights.

Binsbergen et al. (2012) show that the front strip has a market beta of about one half and a positive and significant alpha. Now, whether this result is interesting and insightful depends on which of the two examples below more closely reflects reality.

Example 1: Dividend strips are interesting and insightful

Suppose all stocks pay a similar D_1^j and a similar D_2^j. Then the finding that the front strip has a high alpha is interesting because it says that R_0^j and R_1^j are indeed different from each other for reasons solely to do with their duration. This suggests an important role for models of the term structure of equity premia and a high price of short term cash flow risk, none of which is easy to reconcile with standard models of the equity risk premium. It also says, note, that the index behaves like an individual stock.

Example 2: Dividend strips are neither interesting nor insightful. They are concentrated bets on old economy industries.

Now suppose $D_1^A = 1$, $D_1^B = D_1^C = 0$, $D_2^A = 0$, $D_2^B = D_2^C = 5$, and for some reason $R_1^A = R_2^A = 0.1$ while $R_1^{j=B,C} = R_2^{j=B,C} = 0.05$. Asset A is like a value stock, an old economy industry like tobacco and has a high current and low future dividend, and probably a high alpha and low beta. Assets B and C are high growth stocks with low risk and probably low alphas and high betas. We can rig it so that in the index the market weighted alphas sum to zero and the betas to one, as required by adding up.

In the index it is easy to show that $w_A = 9.1\%$, while $w_B = w_C = 45.5\%$: asset A has a low market weight and does not play much of a role in affecting index valuation. As of date 1 it will disappear from the market completely. However, in the front strip it has a weight of 100% while B and C have weighs of zero. A claim on the strip is a bet on industry A. Now the finding that dividend strip alphas are positive and have low betas is neither new nor surprising.

In this example the index is not like a single stock – it is 100% a bet on stock/industry A in period 1 and 100% a bet on industries A and B in period 2. This change of composition causes expected market returns to change even though individual stock expected returns are constant. The analysis that follows investigates whether scenario of *Example 1* or that of *Example 2* is more closely reflected by the data.

3.2 Empirical analysis

I construct index (w_j) and front strip (v_j) weights of 48 ($j = 1, ..., 48$) industry portfolios between 1996 and 2009. I then use these weights and the corresponding industry returns to construct synthetic index and front strip portfolios. Going forward, I denote the returns to these two synthetic portfolios with r_i and r_{fs}. Figure 1 plots the cumulative returns to the two Binsbergen et al. (2012) strategies (long dividend and dividend steepener), two synthetic portfolios constructed using weighted industry returns, and the return to the value-weighted CRSP index between January 1996 and January 2010. The time period is constrained by the Binsbergen et al. (2012) strategies' data availability.

I am interested in finding out whether the interesting properties of the returns to the long dividend and the dividend steepener strategies are in fact a result of betting on specific industries with divergent weights in the index and in the front strip. To this end, I regress both Binsbergen et al. (2012) strategies on the returns to the synthetic index and the synthetic front strip portfolios. Table 1 reports the results of the following regressions:

$$r^{BBK} = \alpha + \beta_1 r_i + \beta_2 r_{fs} + \epsilon_{BBK},$$

where r^{BBK} is the return to one of the Binsbergen et al. (2012) strategies (long dividend or dividend steepener), r_i is the return to the synthetic index portfolio

constructed using industry returns and weights w_j, and r_{fs} is the return to the synthetic front strip portfolio constructed using industry returns and weights v_j.

Panel A reports results for the long dividend strategy. In columns (1) and (2), I observe that the relationship between the return to this strategy and each of the synthetic portfolios individually is positive and statistically significant. Column (3) shows that including both synthetic portfolios as explanatory variables results in a positive relationship between the front strip portfolio and the long dividend strategy and a negative relationship between the synthetic index return and the long dividend strategy with both relationships statistically significant at common significance levels. Moreover, the magnitude of the positive relationship between synthetic front strip portfolio and long dividend strategy increases more than twofold compared to when it's a standalone explanatory variable. In this third regression, I also observe a positive and statistically significant α. The synthetic front strip alone explains 11% of the variation in the long dividend strategy. The improvement in the R^2 from adding the synthetic index return is only 1.4 percentage points.

Panel B reports the relevant results for the dividend steepener strategy. Columns (1) and (2) show that the relationship between the return to this strategy and each of the synthetic portfolios is positive and statistically significant. Column (3) shows that including both synthetic portfolios, as in the long dividend strategy case, results in more than twofold increase in the magnitude of the positive relationship between the synthetic front strip portfolio and the strategy return and a change of the sign for the relationship between the synthetic index portfolio and the strategy return to negative. Unlike in the long dividend strategy case, none of the αs is statistically significant. The synthetic front strip alone explains 8.8% of the variation in the dividend steepener strategy. The improvements in the R^2 from adding the synthetic index return is only 2.5 percentage points.

The results above suggest that the interesting and insightful behaviour of the dividend strip return strategies is, at least to some non-trivial extent, driven by

the two dividend strategies constituting claims to certain industries and behaving in line with risks relevant for these industries and reflected in these industries' returns. This is investigated further in Table 2. In this table, I report the results of regressing the two Binsbergen et al. (2012) strategies on returns to 12, 17 and 30 Fama French industries. The achieved R^2 closely resembles that from Table 1 with some industries significantly positively and negatively correlated with the long dividend and dividend steepener strategies. Further research shall investigate the dividend payouts of these industries and hence the channel through which they would be impacting the dividend strategies.

4 Common risk premiums and industry returns

I test the hypothesis that widely used (size, book-to-market, investment, and profitability) risk premiums are in fact just combinations of industry-specific risks. If such risks are not fully grasped by industries' contribution to the market factor (or in other words such industries are "under-represented" in the market factor), their relevance materializes as the part of the excess return that cannot be explained by the exposure to the market factor. Using US cross-section of stocks, I show that univariate and bivariate sorts with respect to the popular characteristics allocate non-trivial number of such under-represented industries to various end-of-spectrum portfolios. A small number of such industries then goes on to explain a significant share of returns to popular factors. This phenomenon is present in both US and interational data.

4.1 US cross-section evidence

4.1.1 US sort portfolios and industry returns

I use Kenneth French's breakpoints with respect to the four popular characteristics to allocate the universe of US CRSP-covered stocks into univariate and bivariate sort portfolios between 1970 and 2020. For univariate sort portfolios, stocks are sorted using the 30th and 70th percentile resulting in three portfolios: bottom-30, mid-40, and top-30. For bivariate sort portfolios stocks are first sorted with respect to size into below and above the median and then into three portfolios as above with respect to the second characteristic. This results in the popular 2x3 sorts.

For each of the univariate and bivariate portfolios considered, I then record the top 3 industries with respect to market capitalization (constructed in line with the 48 industries classification by Kenneth French) represented in the given portfolio between 1970 and 2020 at 5-years intervals. The share of these top industries in all stocks in a given portfolio over time are reported in Figures 2 through 5 for Univariate sorts and in Figures 6 through 8 for bivariate sort portfolios.

The industies identified to have the largest share of the market capitalization among the univariate and bivariate sort portfolios are strikingly consistent across the years. Across all cases considered, at most 11 different industries consistently rank among the top ones for each of the sort portfolios.

In the next step, I proceed to regress the weekly returns to each of the univariate and bivariate sort portfolios on the returns to these industries that have been most represented in the corresponding sort portfolio across the years. The results are summarized in Tables 3 through 6 for univariate sort portfolios and in Tables 7 through 9 for bivariate sort portfolios.

Across the *univariate* sort portfolios eight, eleven, eight, and ten industries explain 95%, 90%, 79%, and 92% of the book-to-market (BEME), investment, size,

and operating profitability bottom-30 portfolios, respectively. At the same time nine, nine, nine, and eight industries explain 89%, 94%, 95%, and 93% or the returns to the top-30 BEME, investment, size, and operating profitability portfolios, respectively. The results for the mid-40 univariate sort portfolios are of similar magnitude but since these portolios are not used to construct any of the factors, these results are not summarized here. As evidenced by the last row of the table, adding the remaining 30+ industries to the regression does not increase the R^2 for any of the univariate sort portfolios by more than 10 percentage points.

With respect to the *bivariate* sort portfolios the results are similarly robust. For the size/value sorts between six and eleven industries explain between 82% and 95% of the return to small and large bottom-30 and top-30 BEME portfolios. For the size/investment sorts between eight and eleven industries explain between 76% and 93% of the return to small and large bottom-30 and top-30 investment portfolios. Finally, for the size/operating-profitability sorts between 7 and 10 industries explain between 81% and 94% of the return to small and large bottom-30 and top-30 operating profitability portfolios. All in all, regardless of the sorts considered, a handful of industries robustly and consistently explains the returns to these sort portfolios.

4.1.2 US factors and industry returns

Building on the above, I ask the question if and to which extent do the most represented industries drive the returns to commonly used risk factors. To this end, I regress the return to each of the four popular factors on the industries I found to be most represented in the bottom-30 and top-30 univariate sort portfolios with respect to the corresponding characteristics in the previous step. Table 10 reports the results.

The return to the US value factor is best explained by the industry returns found to be most represented in the bottom 30 and top 30 *univariate* sort portfolios. Approximately 62% of the variation in the return to this factor is explained by the

variation of returns to fourteen industries. Similarly, 38% of the US investment premium and 36% of the US operating profitability premiums are explained by thirteen and fourteen industry returns, respectively. Finally, thirteen industries returns explain 29% of the US size premium.

Relying on the industries most represented in bivariate sort portfolios with respect to the various characteristics does not generate substantial improvement in the R^2 as documented in Table 11. This is despite an increase in the number of the relevant industries considered at all stages. Fifteen industries most represented in the small or large value and growth (2x3) bivariate sort portfolios explain 63% of the variation in the value premium. Similarly, 39% of the US investment premium and 33% of the US operating profitability premiums are explained by fifteen and thirteen industry returns. Finally, fifteen industries explain 29% of the US size premium. With the exception of the size premium, the improvements from using all 48 industry portfolios as explanatory variables compared to using the ones identified as relevant by bivariate sorts are small. For size premium 29 percentage points increase in R^2 is recorded from adding the remaining 33 industry returns. Improvements of 11, 4, and 3 percentage points are recorded for operating profitability, investment, and value premiums from adding the remaining 35, 33, and 33 industry returns, respectively.

The results above highlight the fact that industries identified to be most represented in the univariate sorts carry significant explanatory power for each of the four popular premiums in the developed markets. In what follows, I check whether corresponding results can be identified in international cross-sections of stocks.

4.2 International cross-sections

The results presented so far suggest that non-trivial part of variation in both Binsbergen et al. (2012) dividend risk premia and commonly used US premia is driven by exposure to various industry risks. In what follows, I try to identify whether the same is the case for commonly used risk premia in developed regions and returns to geographic risk factors globally.

4.2.1 Industry returns and international factors

In this section, I identify whether the relationship between factors and industry returns which is observed for the US risk premia has its counterpart in other developed regions globally. To this end, I regress the five risk premiums (value, size, investment, operating profitability, and momentum) for various regions as reported by Professor Kenneth French on his website on 24 equal-weighted industry indices built subject to stocks GIC Industry Group allocation collected from EIKON. This is done for the developed countries as a whole (Table 12), developed countries excluding US (Table 13), North America (Table 14), Europe (Table 15), Japan (Table 16), Asia Pacific ex Japan (Table 17).

The *value* premium's time-series variation is the best explained by the industry portfolios. In the wider cross-section of developed markets, the returns to industry portfolios explain approximately 66% of its value premium. A total of 6 industry indices[1] are positively correlated with the value premium, while 9 such indices[2] are negatively correlated. In North America (Table 14) and in Europe (Table 15), the industry portfolios explain 62% and 54% of the value premium, respectively. The relationship is weaker in Japan (Table 16) and Asia Pacific ex Japan (Table

[1]Namely: Banks, Capital Goods, Consumer Durables Apparel, Energy, Food Staples Retailing, and Insurance

[2]Namely: Commercial Professional Services, Consumer Services, Diversified Financials, Food/Beverage & Tobacco, Health Care Equipment Services, Pharmaceuticals & Biotechnology Life Sciences, Retailing, Software Services, and Technology Hardware Equipment

17) cross-sections with industry portfolios explaining approximately 26 – 27% of value premium in these cross-sections.

The *profitability* premium is the second best explained by the variation in industry portfolios with approximately 51% of its variability in the developed markets cross-section attributed to these portfolios. In developed markets in general 6 industries[3] are positively correlated with the profitability factor, while 4 others[4] are negatively correlated with the profitability factor. Smaller share of the profitability premium is explained by the industry returns outside of the US as evidenced by the R^2 of the regressions dropping to approximately 30% in the European and Japanese cross-sections and only 12% in the Asia Pacific ex Japan one.

Investment and size risk premiums in developed markets are not as well explained by industry risks as the value and profitability risk premiums described above. Approximately 34% of the *investment* premium's variation can be credited to the industry risks with 5 industries[5] showing statistically significant positive relationship with the investment premium and 6 industries[6] showing a statistically significant negative relationship. The R^2 in North American cross-sections is higher at 32% than in the European and Japanese ones at 14% and 11%, respectively. Industry risks explain 25% of the *size* premium in the developed markets with 7 industries[7] showing a significantly positive relationship and 8 industries[8] showing a statistically significant negative one. The relationship between size premium and industry risks is stronger in Europe ($R^2 = 29\%$) than in Japan ($R^2 = 20\%$) or Asia Pacific

[3]Namely: Food/Beverage & Tobacco, Household Personal Products, Retailing, Software Services, Transportation, and Utilities

[4]Namely: Banks, Diversified Financials, Energy, and Pharmaceuticals & Biotechnology Life Sciences

[5]Namely: Banks, Capital Goods, Consumer Durables Apparel, Food Staples Retailing, and Utilities

[6]Namely: Automobiles Components, Consumer Services, Diversified Financials, Materials, Semiconductors & Semiconductor Equipment, and Software Services.

[7]Namely: Capital Goods, Food Staples Retailing, Materials, Media Entertainment, Pharmaceuticals & Biotechnology Life Sciences, Real Estate, and Technology Hardware Equipment

[8]Namely: Consumer Durables Apparel, Diversified Financials, Household Personal Products, Insurance, Semiconductors Semiconductor Equipment, Software Services, Telecommunication Services, and Utilities

excluding Japan ($R^2 = 13\%$).

Finally, industry risks explain 40% of the developed market's *momentum* premium with 4 industries[9] showing a significantly positive relationship with the momentum premium and 5 industries[10] showing a significantly negative one. The relationship between the momentum premium and industry risks is fairly stable across regions with R^2 of 38% in North American and 36% in European cross-section though slightly lower in the Asian ones with 29% in the Japanese one and 22% in the Asia Pacific ex Japan one.

These results seem to suggest that there exist combinations of industry returns capable of consistently explaining away large shares of international factor risk premia. In what follows, I investigate whether the same can be said for returns to geographic (country) risk factors.

4.2.2 Industry returns and geographical zone factors

Table 18 reports the results of regressing returns to 13 geographic factors between January 2009 and December 2014 on the returns to 24 industry indices. The returns to geographic factors are constructed in line with Dumas et al. (2020) methodology using a global cross-section of individual firms' stock returns. These are then joined with information on individual companies' annual revenue attribution data supplied by Factset GeoRev dataset. Details of the procedure can be found in Appendix A. Industry indices are constructed using the GIC Industry group classification resulting in 24 allocation groups.

In a world integrated commercially, returns to such geographic zone "factors" should be a combination of portfolios of industries (Dumas et al., 2020). The results show that this is indeed the case for vast majority of geographic zone factors considered in the analysis. Except for Japan ($R^2 = 55\%$) and Malaysia ($R^2 = 57\%$),

[9]Namely: Health Care Equipment Services, Software Services, Telecommunication Services and Utilities

[10]Namely: Automobile Components, Banks, Diversified Financials, Energy, and Insurance

the geographic zone factors are highly correlated with global industry returns with the corresponding R^2 between 66% (UK) and 85% (US). The industries that are significantly related to geographic factors' returns differ between the relevant countries. Their total number also varies between 6 significant industry returns for France and 15 for Japan and China. The reported results corroborate the hypothesis that the returns to geographic zone factors are in fact combinations of returns to industry portfolios of stocks listed globally.

5 Conclusion

In this paper, I show that industry indices can consistently explain away large shares of international factor and geographic risk premiums. My results also suggest that it is the dynamics of industry returns that is responsible for non-trivial share of the variation in returns to other strategies that have gathered considerable attention in the literature – in particular the long dividend and dividend steepener strategies of Binsbergen et al. (2012).

Univariate and bivariate sort portfolios used to construct factor returns in international cross-sections tend to be heavily dominated by a small number of industries. Consequently, the returns to these sort portfolios and factors constructed using them are explained away by returns to these industries. My results show that this phenomenon is present not only in the US cross-section but also internationally. Furthermore, it is present to some extent for all factors commonly used in the literature.

Together, the results in this chapter indicate that various risk premia credited to the timing of cash-flows, stock market characteristics, and geographic zones can in fact be just combinations of industry-specific risks that are hard to understand at present. Further analysis using more advanced techniques like mean-variance spanning of risk premiums could be particularly useful to shed more light on this matter.

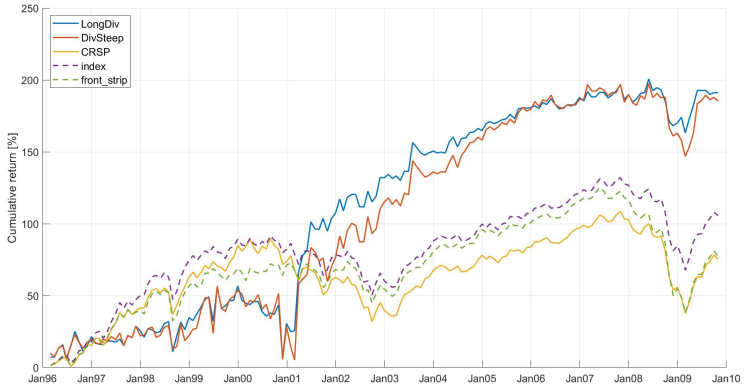


Figure 1: Cumulative returns to selected strategies

This figure plots cumulative returns to the *long dividend* and *dividend steepener* strategies of Binsbergen et al. (2012), two synthetic portfolios (index and front strip) constructed using industry returns, and the CRSP value-weighted index between March 1996 and October 2009.

Table 1: Regressions of Binsbergen et al. (2012) strategies on synthetic index and front strip portfolios

This table reports the following regressions for the long dividend and the dividend steepener strategies of Binsbergen et al. (2012):

$$r^{BBK} = \alpha + \beta_1 r_i + \beta_2 r_{fs} + \epsilon BBK.$$

where r^{BBK} are the return to the Long Dividend and the Divided Steepener strategies in Panel A and Panel B, respectively and the r_i and r_{fs} are the returns to synthetic index and front strip strategies constructed using weighted industry returns. Monthly returns bewteen March 1996 and October 2009 are used.

Panel A: Long Dividend				
	(1)	(2)	(3)	(4)
α	0.86	0.91	***1.07***	***0.98***
	1.46	1.58	***1.85***	***1.66***
r_{CRSP}				***0.45***
				3.58
r_i	***0.46***		***- 0.75***	
	3.73		***- 1.91***	
r_{fs}		***0.53***	***1.22***	
		4.60	***3.24***	
N	165	165	165	165
$R^2(\%)$	7.28	10.97	12.40	6.71

Panel B: Long Dividend				
	(1)	(2)	(3)	(4)
α	0.81	0.84	1.09	0.92
	1.10	1.17	1.52	1.26
r_{CRSP}				***0.49***
				3.10
r_i	***0.48***		***- 1.17***	
	3.12		***- 2.39***	
r_{fs}		***0.59***	***1.66***	
		4.10	***3.54***	
N	165	165	165	165
$R^2(\%)$	5.05	8.78	11.34	4.98

Table 2: Regressions of dividend strategies on Fama French industry indices

This table reports the results of regressing long dividend and dividend steepener strategies on industry indices. Industry classifications resulting in assignment groups of various size are used. Industry indices are value weighted. Monthly returns between March 1996 and October 2009 are used.

	12 Industries			17 Industries			30 Industries	
	LongDiv	DivSteep		LongDiv	DivSteep		LongDiv	DivSteep
(Intercept)	0.939	0.795	(Intercept)	0.990	0.821	(Intercept)	1.223	1.169
	1.543	1.085		1.642	1.097		***1.963***	1.543
NoDur	-0.115	0.007	Food	0.016	0.308	Food	0.059	-0.039
	-0.407	0.021		0.070	1.057		0.228	-0.124
Durbl	0.166	0.286	Mines	0.064	0.066	Beer	-0.178	-0.005
	1.093	1.568		0.666	0.555		-1.083	-0.024
Manuf	-0.221	-0.484	Oil	0.058	0.159	Smoke	-0.052	-0.090
	-0.743	-1.354		0.361	0.801		-0.561	-0.794
Enrgy	0.138	0.240	Clths	-0.067	-0.135	Games	-0.270	-0.283
	0.913	1.319		-0.318	-0.519		-1.641	-1.417
Chems	0.366	0.566	Durbl	-0.160	-0.154	Books	-0.010	-0.031
	1.437	***1.845***		-0.773	-0.603		-0.045	-0.117
BusEq	0.139	0.200	Chems	0.195	0.146	Hshld	0.188	0.282
	1.093	1.305		1.039	0.625		0.875	1.080
Telcm	0.253	0.325	Cnsum	-0.240	-0.424	Clths	0.032	0.021
	1.583	***1.688***		-1.115	-1.583		0.161	0.085
Utils	0.025	0.019	Cnstr	0.202	0.284	Hlth	-0.460	-0.676
	0.138	0.085		1.101	1.249		***-2.154***	***-2.605***
Shops	-0.160	-0.247	Steel	-0.120	-0.130	Chems	0.330	0.424
	-0.708	-0.905		-0.833	-0.726		1.410	1.493
Hlth	-0.372	-0.553	FabPr	0.365	0.268	Txtls	-0.099	-0.112
	-1.935	***-2.391***		1.501	0.887		-0.834	-0.783
Money	0.384	0.704	Machn	0.010	0.134	Cnstr	0.392	0.471
	2.012	***3.065***		0.067	0.719		***1.936***	***1.911***
Other	-0.287	-0.698	Cars	0.142	0.189	Steel	-0.048	-0.039
	-0.983	***-1.985***		0.973	1.043		-0.313	-0.211
			Trans	-0.374	-0.423	FabPr	-0.229	-0.411
				-1.639	-1.494		-0.930	-1.373
			Utils	-0.086	-0.135	ElcEq	-0.120	-0.148
				-0.472	-0.595		-0.674	-0.683
			Rtail	-0.344	-0.363	Autos	0.128	0.165
				-1.410	-1.199		0.994	1.053
			Finan	0.395	0.680	Carry	-0.163	-0.248
				2.036	***2.821***		-0.983	-1.234
			Other	0.196	-0.185	Mines	0.039	-0.016
				0.782	-0.594		0.389	-0.134
						Coal	0.014	-0.009

Continuation of Table 2

	12 Industries			17 Industries			30 Industries	
	LongDiv	DivSteep		LongDiv	DivSteep		LongDiv	DivSteep
							0.219	-0.117
						Oil	0.010	0.186
							0.058	0.851
						Util	-0.149	-0.169
							-0.756	-0.706
						Telcm	0.349	0.441
							1.997	***2.074***
						Servs	-0.077	-0.296
							-0.383	-1.218
						BusEq	0.204	0.361
							1.287	***1.870***
						Paper	0.065	-0.003
							0.256	-0.010
						Trans	-0.235	-0.116
							-1.069	-0.433
						Whlsl	0.387	0.510
							1.815	***1.969***
						Rtail	-0.354	-0.477
							-1.428	-1.583
						Meals	0.182	0.206
							0.831	0.770
						Fin	0.378	0.667
							1.786	***2.595***
						Other	-0.005	-0.209
							-0.029	-1.016
N	164	164	N	164	164	N	164	164
R^2(%)	9.33	13.90	R^2(%)	9.81	9.06	R^2(%)	10.22	13.14

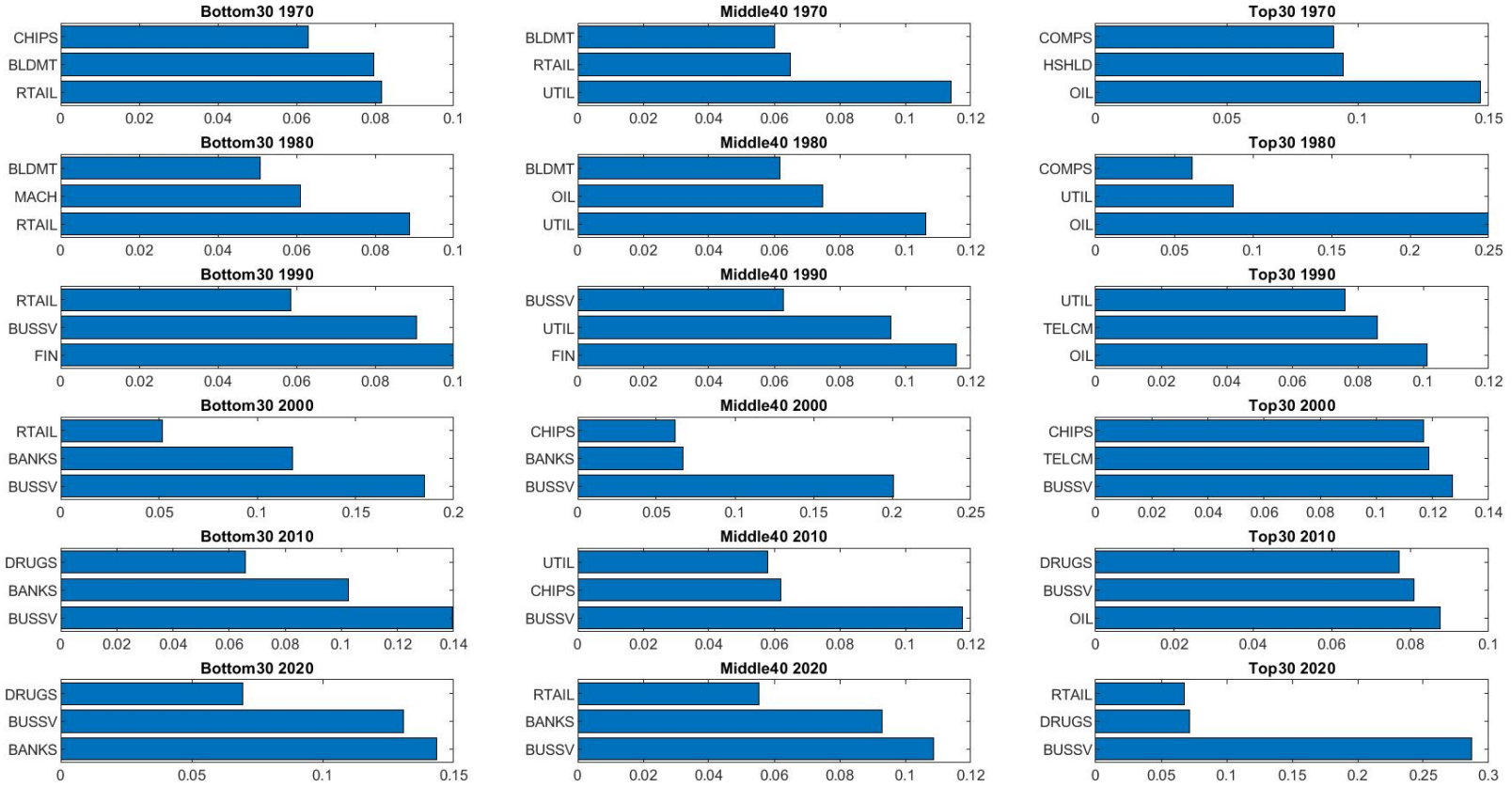
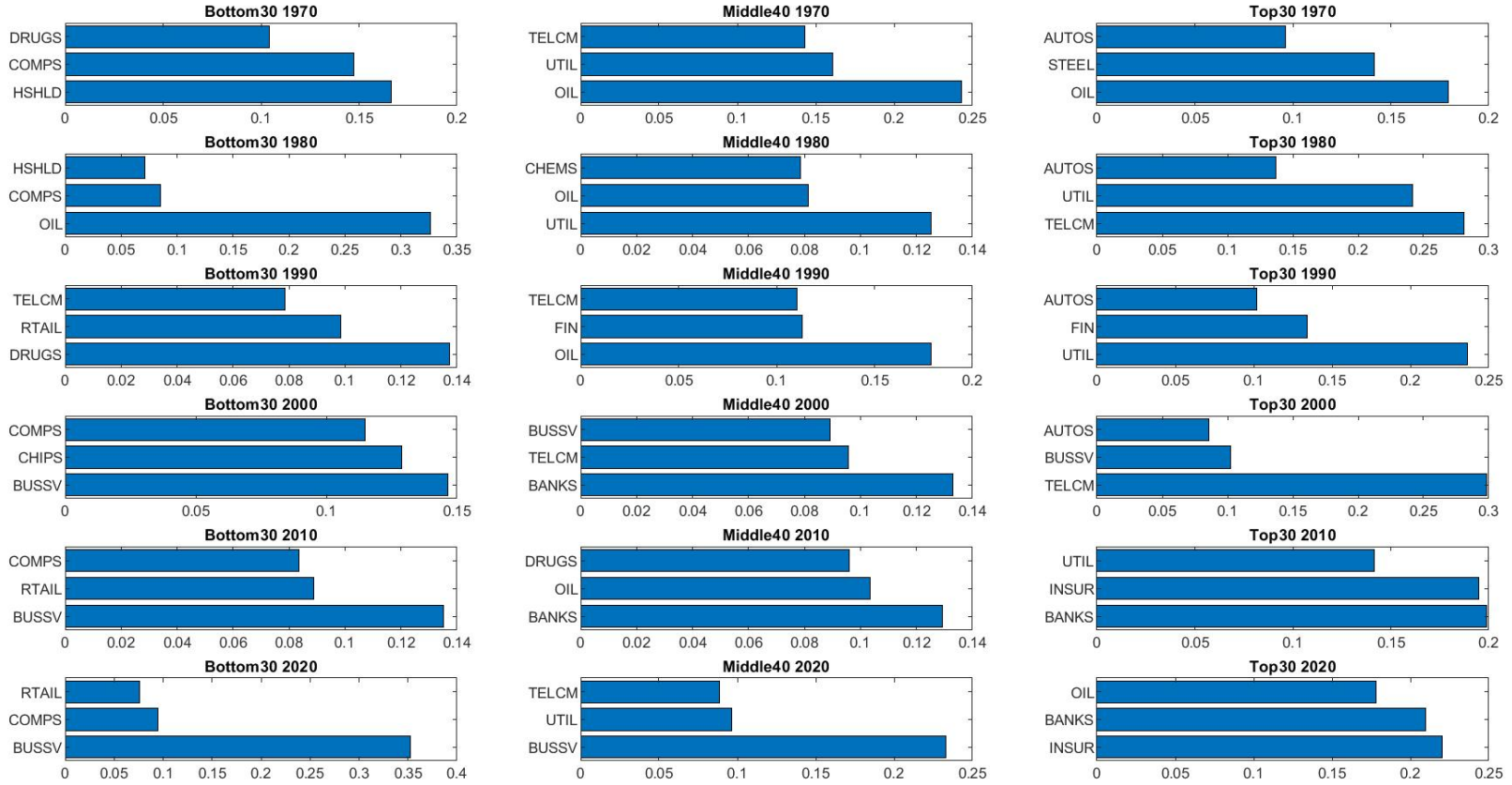


Figure 2: Top industries in size univariate sort portfolios

For each of the size univariate sort portfolios (bottom30, middle40, top30), this figure reports the three most represented (with respect to market capitalization) industries and the share of the given univariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.



1.75

Figure 3: Top industries in book-to-market value univariate sort portfolios

For each of the BE/ME univariate sort portfolios (bottom30, middle40, top30), this figure reports the three most represented (with respect to market capitalization) industries and the share of the given univariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

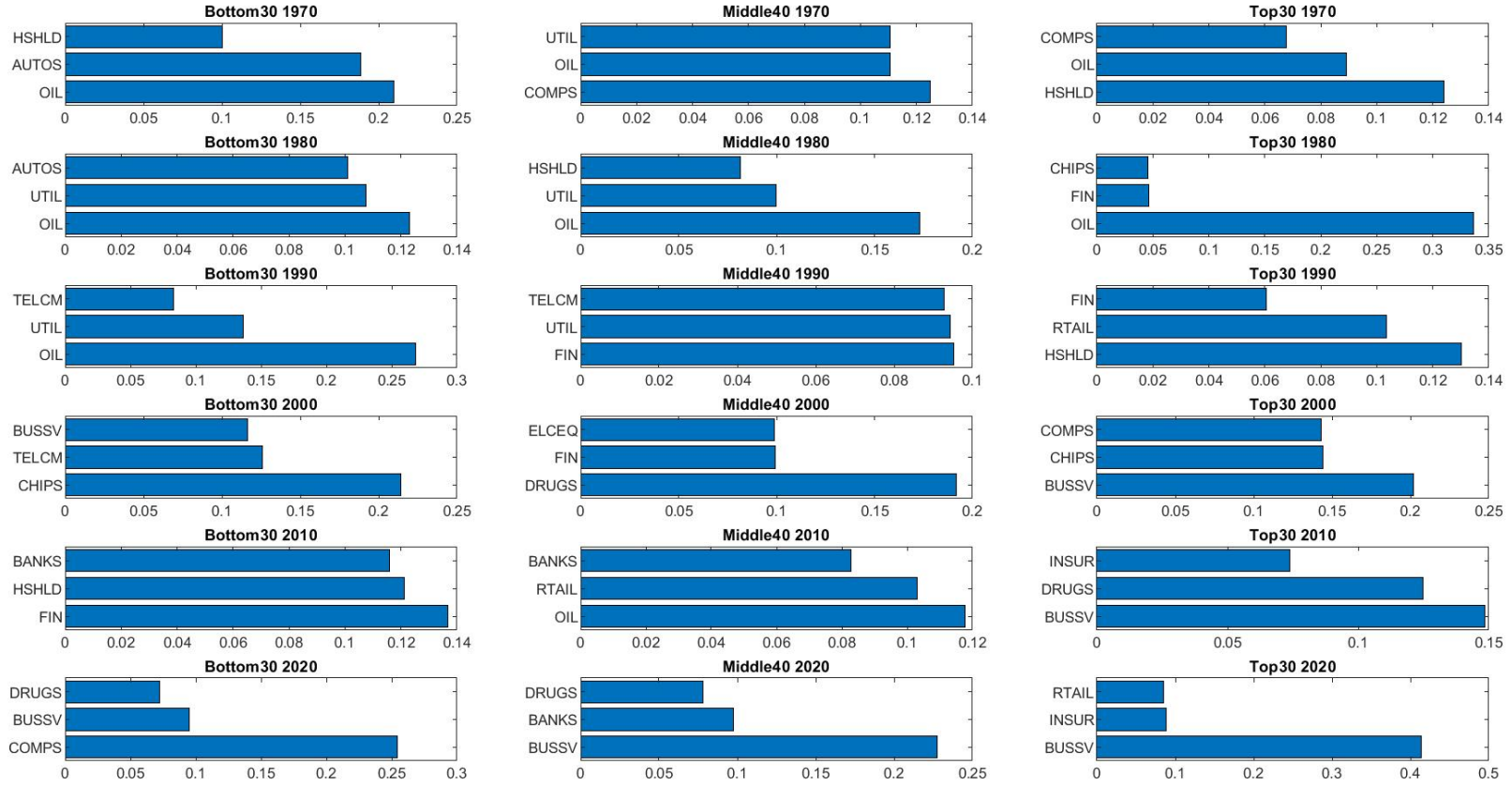


Figure 4: Top industries in investment univariate sort portfolios

For each of the INV univariate sort portfolios (bottom30, middle40, top30), this figure reports the three most represented (with respect to market capitalization) industries and the share of the given univariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

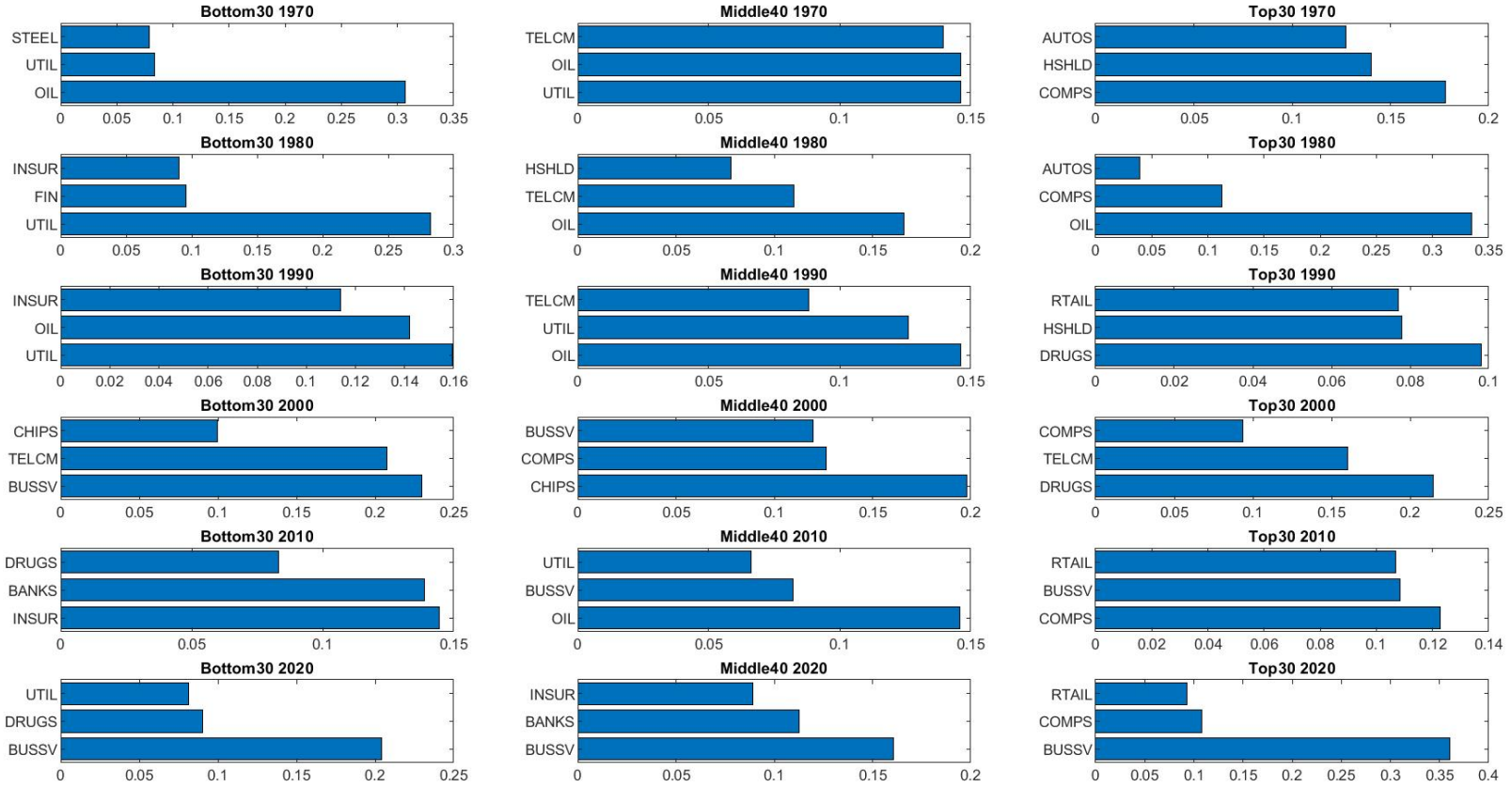


Figure 5: Top industries in operating profitability univariate sort portfolios

For each of the OP univariate sort portfolios (bottom30, middle40, top30), this figure reports the three most represented (with respect to market capitalization) industries and the share of the given univariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

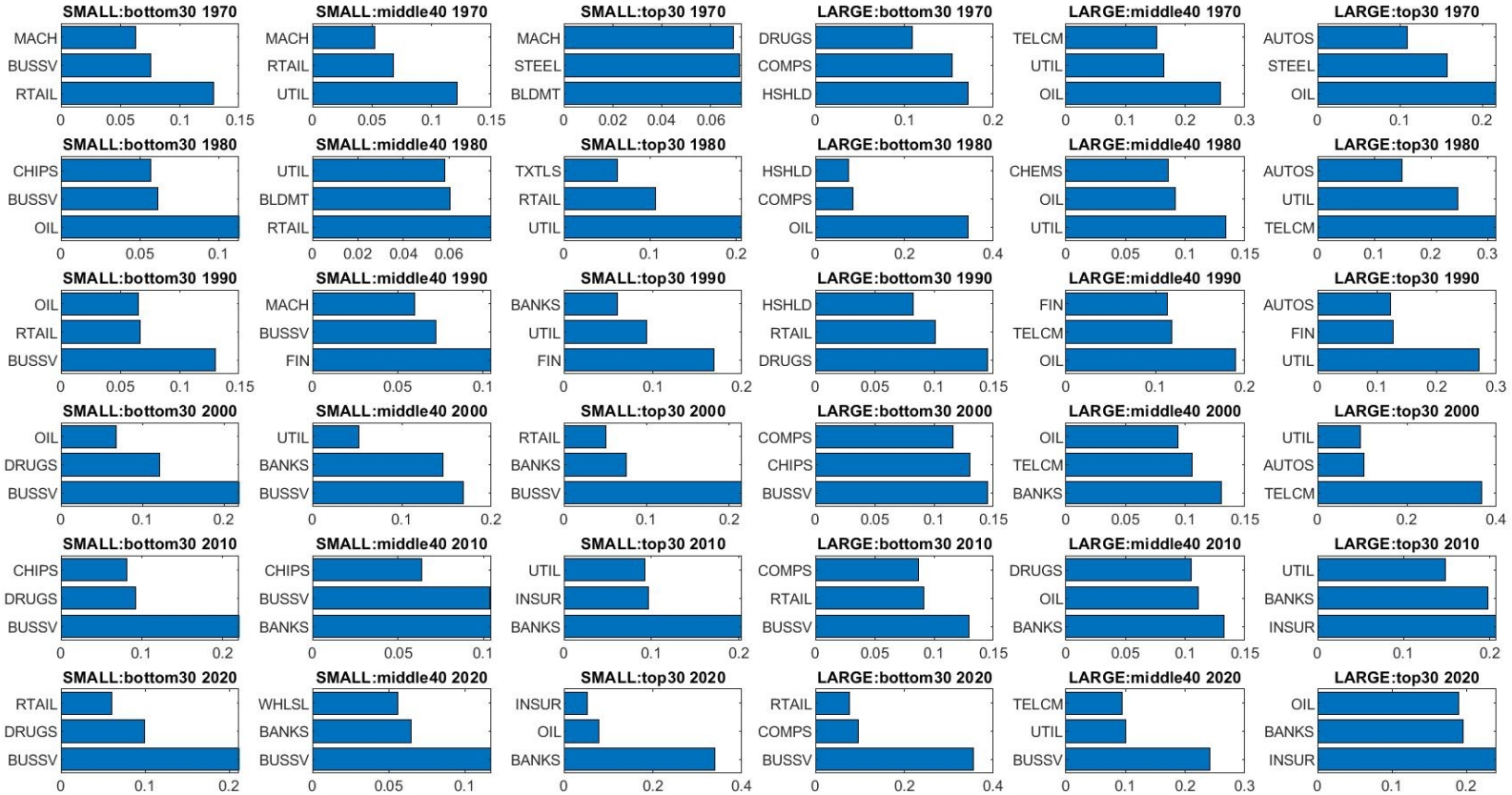


Figure 6: Top industries in size/book-to-market bivariate sort portfolios

For each of the six size/book-to-market bivariate sort portfolios, this figure reports the three most represented (with respect to market capitalization) industries and the share of the given bivariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

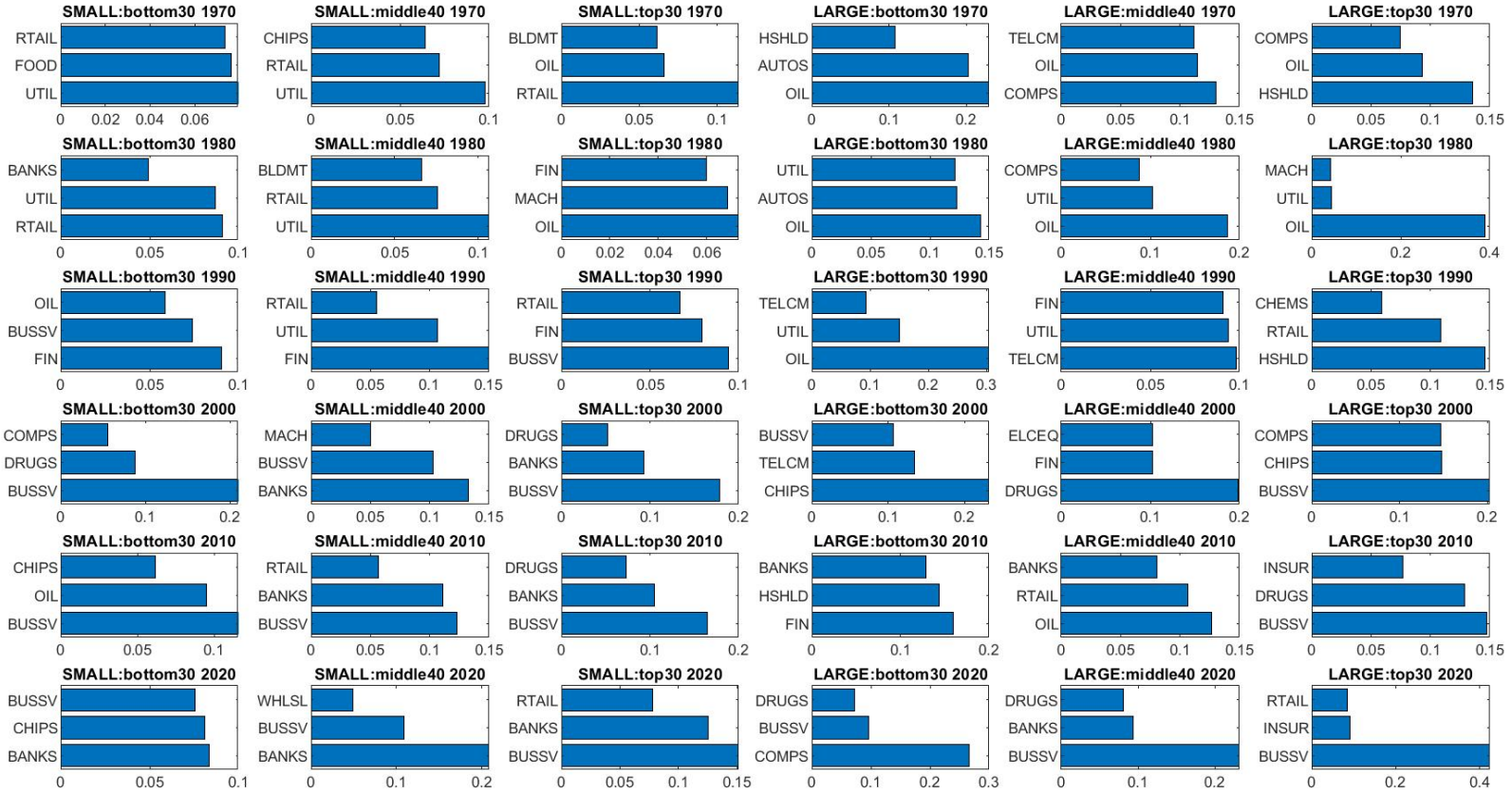


Figure 7: Top industries in size/investment bivariate sort portfolios

For each of the six size/investment bivariate sort portfolios, this figure reports the three most represented (with respect to market capitalization) industries and the share of the given bivariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

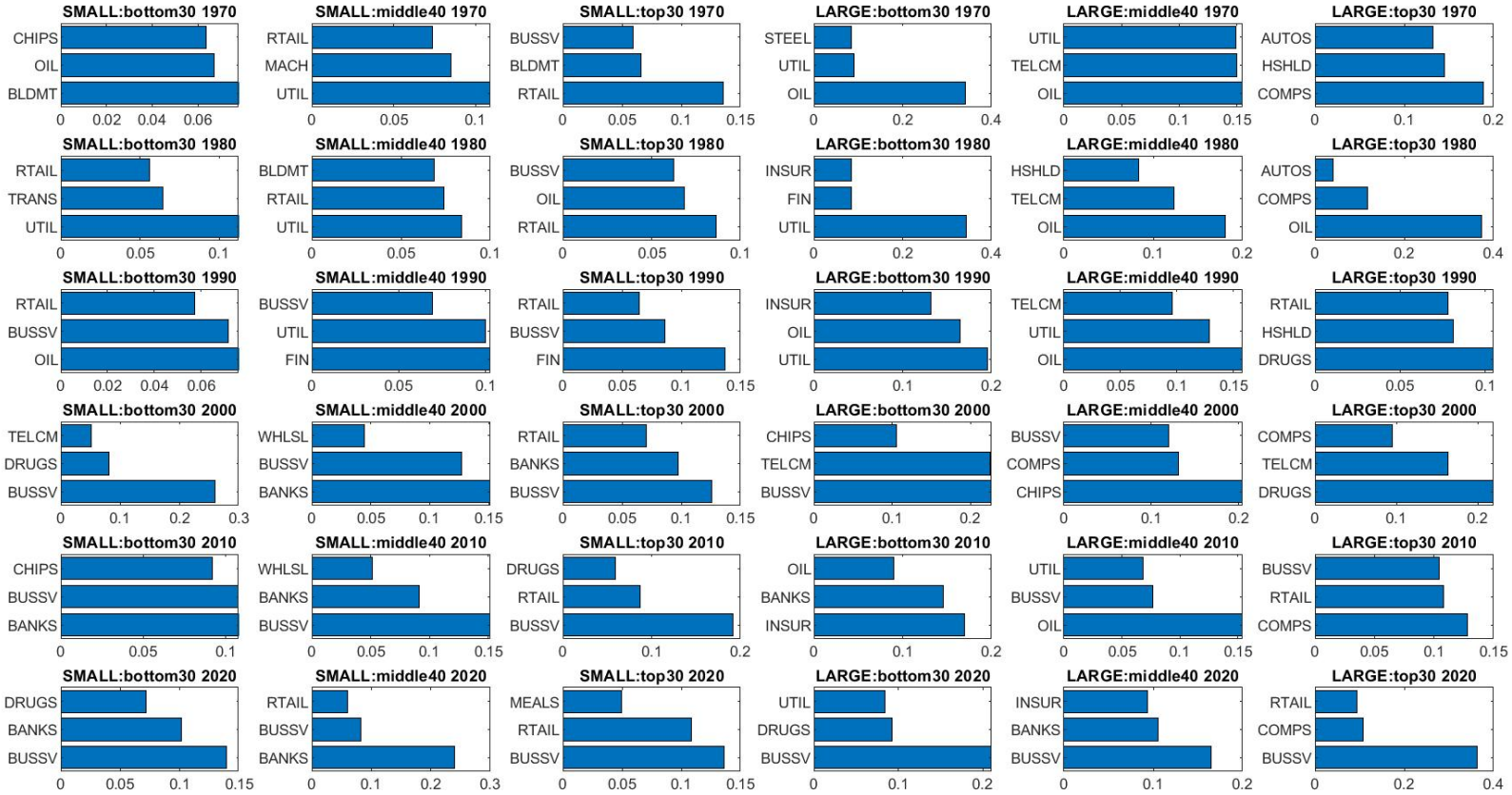


Figure 8: Top industries in size/operating profitability bivariate sort portfolios

For each of the six size/operating profitability bivariate sort portfolios, this figure reports the three most represented (with respect to market capitalization) industries and the share of the given bivariate sort portfolio's market capitalization assigned to these industries. Results are reported at 5 year intervals between 1970 and 2020.

Table 3: Regressions of returns to univariate SIZE sort portfolios on returns to industries most represented in a given bucket between 1970 and 2020.

This table summarizes the results of regressing returns to univariate sort portfolios constructed with respect to the size characteristic on returns to industries which were found to be most represented in the given univariate sort bucket between 1970 and 2020. Weekly frequency.

Bottom 30		Middle 40		Top 30	
α	0.03	α	0.02	α	- 0.01
	1.36		1.42		- 0.67
RTAIL	***- 0.07***	UTIL	***0.07***	OIL	***0.14***
	- 4.42		***7.08***		***33.25***
BLDMT	***0.25***	RTAIL	0.01	HSHLD	***0.10***
	15.59		1.48		***15.54***
CHIPS	0.01	BLDMT	***0.26***	COMPS	***0.07***
	0.68		***28.33***		***12.92***
MACH	***0.22***	OIL	***0.09***	UTIL	***0.07***
	12.83		***12.73***		***10.36***
FIN	***0.16***	FIN	***0.15***	TELCM	***0.14***
	9.35		***13.40***		***21.83***
BUSSV	***0.26***	BUSSV	***0.21***	BUSSV	***0.11***
	14.31		***18.51***		***14.08***
BANKS	0.01	BANKS	***0.04***	CHIPS	***0.08***
	0.43		***3.87***		***12.66***
DRUGS	- 0.01	CHIPS	***0.11***	DRUGS	***0.12***
	- 0.84		***13.53***		***20.52***
				RTAIL	***0.15***
					22.70
N	2661	N	2661	N	2661
R^2(%)	78.89	R^2(%)	90.63	R^2(%)	94.71
R^2_{48KF}(%)	87.27	R^2_{48KF}(%)	94.98	R^2_{48KF}(%)	96.80

Table 4: Regressions of returns to univariate BEME sort portfolios on returns to industries most represented in a given bucket between 1970 and 2020.

This table summarizes the results of regressing returns to univariate sort portfolios constructed with respect to the book-to-market value characteristic on returns to industries which were found to be most represented in the given univariate sort bucket between 1970 and 2020. Weekly frequency.

Bottom 30		Middle 40		Top 30	
α	- 0.01	α	0.02	α	***0.06***
	- 1.07		1.54		***3.49***
HSHLD	***0.13***	OIL	***0.15***	OIL	***0.10***
	19.69		***28.06***		***12.26***
COMPS	***0.09***	UTIL	***0.15***	STEEL	***0.11***
	15.34		***19.85***		***15.48***
DRUGS	***0.19***	TELCM	***0.10***	AUTOS	***0.09***
	31.17		***13.97***		***12.16***
OIL	***0.09***	CHEMS	***0.15***	TELCM	***0.10***
	21.64		***23.16***		***8.71***
RTAIL	***0.16***	FIN	***0.12***	UTIL	***0.10***
	22.78		***14.98***		***8.28***
TELCM	***0.06***	BANKS	***0.15***	FIN	***0.12***
	9.72		***22.73***		***9.71***
BUSSV	***0.19***	BUSSV	***0.10***	BUSSV	***- 0.02***
	24.48		***14.99***		***- 2.06***
CHIPS	***0.09***	DRUGS	***0.02***	BANKS	***0.26***
	14.28		***2.79***		***24.60***
				INSUR	***0.10***
					7.90
N	2661	N	2661	N	2661
R^2(%)	95.16	R^2(%)	93.61	R^2(%)	89.09
R^2_{48KF}(%)	96.05	R^2_{48KF}(%)	95.13	R^2_{48KF}(%)	90.82

Table 5: Regressions of returns to univariate INV sort portfolios on returns to industries most represented in a given bucket between 1970 and 2020.

This table summarizes the results of regressing returns to univariate sort portfolios constructed with respect to the investment characteristic on returns to industries which were found to be most represented in the given univariate sort bucket between 1970 and 2020. Weekly frequency.

Bottom 30		Middle 40		Top 30	
α	***0.06***	α	0.02	α	***- 0.03***
	4.00		1.64		***- 2.66***
OIL	***0.14***	COMPS	***0.04***	HSHLD	***0.02***
	23.64		***8.87***		***2.39***
AUTOS	***0.09***	OIL	***0.12***	OIL	***0.10***
	14.03		***26.56***		***19.41***
HSHLD	***0.11***	UTIL	***0.08***	COMPS	***0.10***
	12.62		***11.35***		***14.05***
UTIL	***0.10***	HSHLD	***0.11***	FIN	***0.14***
	10.13		***16.58***		***16.78***
TELCM	***0.07***	FIN	***0.09***	CHIPS	***0.11***
	8.00		***11.95***		***14.46***
CHIPS	***0.08***	TELCM	***0.10***	RTAIL	***0.11***
	10.02		***14.70***		***12.71***
BUSSV	***0.11***	DRUGS	***0.09***	BUSSV	***0.24***
	10.04		***15.85***		***23.65***
FIN	***0.09***	ELCEQ	***0.08***	DRUGS	***0.12***
	9.06		***13.98***		***16.39***
BANKS	***0.05***	RTAIL	***0.10***	INSUR	***0.07***
	6.53		***14.83***		***7.54***
COMPS	***- 0.02***	BANKS	***0.09***		
	- 2.56		***15.75***		
DRUGS	***0.09***	BUSSV	***0.04***		
	10.97		***5.52***		
N	2661	N	2661	N	2661
R^2(%)	89.74	R^2(%)	94.60	R^2(%)	93.88
R^2_{48KF}(%)	91.54	R^2_{48KF}(%)	95.44	R^2_{48KF}(%)	94.60

Table 6: Regressions of returns to univariate OP sort portfolios on returns to industries most represented in a given bucket between 1970 and 2020.

This table summarizes the results of regressing returns to univariate sort portfolios constructed with respect to the operating profitability characteristic on returns to industries which were found to be most represented in the given univariate sort bucket between 1970 and 2020. Weekly frequency.

Bottom 30		Middle 40		Top 30	
α	***- 0.04***	α	0.01	α	***0.02***
	- 2.41		1.19		***1.98***
OIL	***0.05***	UTIL	***0.05***	COMPS	***0.07***
	6.86		***7.12***		***11.78***
UTIL	***0.04***	OIL	***0.13***	HSHLD	***0.15***
	4.38		***28.61***		***20.37***
STEEL	***0.12***	TELCM	***0.12***	AUTOS	***0.06***
	19.70		***16.48***		***12.71***
FIN	***0.18***	HSHLD	***0.08***	OIL	***0.14***
	16.63		***12.96***		***30.22***
INSUR	***0.10***	CHIPS	***0.09***	DRUGS	***0.17***
	9.32		***14.72***		***24.86***
BUSSV	***0.18***	COMPS	***0.06***	RTAIL	***0.13***
	16.49		***10.22***		***15.80***
TELCM	***0.08***	BUSSV	***0.14***	TELCM	***0.08***
	8.37		***16.65***		***10.84***
CHIPS	***0.13***	BANKS	***0.14***	BUSSV	***0.17***
	16.51		***22.92***		***20.58***
BANKS	***0.04***	INSUR	***0.12***		
	4.09		***14.42***		
DRUGS	***0.03***				
	3.93				
N	2661	N	2661	N	2661
R^2(%)	91.81	R^2(%)	93.89	R^2(%)	93.23
R^2_{48KF}(%)	92.95	R^2_{48KF}(%)	95.53	R^2_{48KF}(%)	94.54

Table 7: Regressions of returns to bivariate SIZE/BEME sort portfolios on returns to industries most represented in a given bucket.

This table summarizes results of regressing returns to bivariate sort portfolios constructed with respect to the size and book-to-market value characteristics on returns to industries which were found to be most represented in the given bivariate sort bucket between 1970 and 2020. Weekly frequency.

S Lo		S Mid		S Hi		L Lo		L Mid		L Hi	
α	***- 0.05***	α	***0.07***	α	***0.10***	α	- 0.01	α	0.01	α	***0.04***
	- 1.97		***3.92***		***5.08***		- 0.52		0.89		***2.02***
RTAIL	***0.03***	UTIL	0.02	BLDMT	***0.16***	HSHLD	***0.15***	OIL	***0.15***	OIL	***0.10***
	2.16		1.93		***10.30***		***22.08***		***28.95***		***12.83***
BUSSV	***0.45***	RTAIL	***- 0.06***	STEEL	***0.12***	COMPS	***0.10***	UTIL	***0.16***	STEEL	***0.09***
	24.44		***- 5.02***		***11.94***		***16.77***		***20.89***		***11.33***
MACH	***0.35***	MACH	***0.18***	MACH	***0.10***	DRUGS	***0.20***	TELCM	***0.12***	AUTOS	***0.09***
	20.90		***13.45***		***5.82***		***32.89***		***15.45***		***10.94***
OIL	***0.03***	BLDMT	***0.18***	UTIL	***0.04***	OIL	***0.09***	CHEMS	***0.15***	TELCM	***0.11***
	2.61		***13.94***		***3.00***		***22.89***		***22.14***		***9.32***
CHIPS	***0.06***	FIN	***0.12***	RTAIL	***- 0.05***	RTAIL	***0.17***	FIN	***0.11***	UTIL	***0.11***
	4.44		***8.90***		***- 4.07***		***24.55***		***13.90***		***8.67***
DRUGS	***0.07***	BUSSV	***0.11***	TXTLS	***0.15***	BUSSV	***0.18***	BANKS	***0.16***	FIN	***0.08***
	5.28		***8.23***		***17.16***		***22.47***		***23.26***		***6.56***
		BANKS	***0.04***	FIN	***0.11***	CHIPS	***0.09***	DRUGS	***0.03***	INSUR	***0.11***
			3.99		***7.44***		***14.26***		***4.54***		***9.04***
		CHIPS	***0.02***	BANKS	***0.11***			BUSSV	***0.08***	BANKS	***0.31***
			1.97		***8.07***				***11.38***		***28.06***
		WHLSL	***0.25***	BUSSV	***0.09***						
			17.00		***6.95***						
				INSUR	- 0.01						
					- 0.80						
				OIL	***0.03***						
					3.15						
N	2661	N	2661	N	2661	N	2661	N	2661	N	2661
R^2(%)	81.97	R^2(%)	86.15	R^2(%)	83.75	R^2(%)	94.94	R^2(%)	93.46	R^2(%)	88.66
R^2_{48}(%)	89.74	R^2_{48}(%)	90.63	R^2_{48}(%)	88.30	R^2_{48}(%)	96.07	R^2_{48}(%)	94.88	R^2_{48}(%)	89.78

Table 8: Regressions of returns to bivariate SIZE/INV sort portfolios on returns to industries most represented in a given bucket.

This table summarizes results of regressing returns to bivariate sort portfolios constructed with respect to the size and investment characteristics on returns to industries which were found to be most represented in the given bivariate sort bucket between 1970 and 2020. Weekly frequency.

S Lo		S Mid		S Hi		L Lo		L Mid		L Hi	
α	***0.06***	α	***0.09***	α	***- 0.04***	α	***0.05***	α	0.01	α	***- 0.03***
	2.30		***5.05***		***- 1.90***		***3.45***		0.96		***- 2.27***
UTIL	***0.06***	UTIL	***0.02***	RTAIL	- 0.02	OIL	***0.15***	COMPS	***0.05***	HSHLD	0.01
	3.21		***2.22***		- 1.62		***24.11***		***9.61***		1.55
FOOD	- 0.01	RTAIL	***- 0.06***	OIL	***0.03***	AUTOS	***0.08***	OIL	***0.12***	OIL	***0.08***
	- 0.55		***- 4.85***		***3.47***		***12.78***		***25.82***		***12.58***
RTAIL	***0.03***	CHIPS	0.01	BLDMT	***0.21***	HSHLD	***0.14***	TELCM	***0.11***	COMPS	***0.12***
	1.88		0.84		***14.25***		***15.08***		***15.88***		***15.86***
BANKS	***0.10***	BLDMT	***0.19***	MACH	***0.22***	UTIL	***0.10***	UTIL	***0.09***	UTIL	0.01
	6.59		***14.62***		***13.62***		***10.60***		***13.18***		0.57
FIN	***0.21***	FIN	***0.11***	FIN	***0.17***	TELCM	***0.08***	FIN	***0.07***	MACH	***0.07***
	11.11		***8.04***		***10.82***		***8.87***		***8.72***		***6.11***
BUSSV	***0.25***	BANKS	***0.06***	BUSSV	***0.37***	CHIPS	***0.08***	DRUGS	***0.14***	RTAIL	***0.13***
	11.93		***5.92***		***25.32***		***9.33***		***24.20***		***14.26***
OIL	***0.15***	BUSSV	***0.10***	BANKS	- 0.02	BUSSV	***0.08***	ELCEQ	***0.09***	CHEMS	0.01
	13.12		***7.06***		- 1.37		***7.29***		***15.77***		1.07
DRUGS	***- 0.03***	MACH	***0.16***	DRUGS	0.01	FIN	***0.08***	RTAIL	***0.14***	BUSSV	***0.23***
	- 1.67		***11.89***		1.05		***7.64***		***20.62***		***22.24***
COMPS	0.01	WHLSL	***0.26***			BANKS	***0.05***	BANKS	***0.10***	CHIPS	***0.10***
	0.97		***18.11***				***6.33***		***17.00***		***12.28***
CHIPS	***0.11***					COMPS	***- 0.02***	BUSSV	***0.02***	DRUGS	***0.13***
	7.26						***- 2.26***		***3.24***		***16.53***
						DRUGS	***0.10***			INSUR	***0.11***
							12.23				***11.83***
N	2661	N	2661	N	2661	N	2661	N	2661	N	2661
R^2(%)	75.60	R^2(%)	85.76	R^2(%)	84.96	R^2(%)	89.17	R^2(%)	94.18	R^2(%)	93.00
R^2_{48}(%)	87.46	R^2_{48}(%)	90.32	R^2_{48}(%)	91.27	R^2_{48}(%)	90.95	R^2_{48}(%)	95.66	R^2_{48}(%)	94.09

Table 9: Regressions of returns to bivariate SIZE/OP sort portfolios on returns to industries most represented in a given bucket.

This table summarizes results of regressing returns to bivariate sort portfolios constructed with respect to the size and operating profitability characteristics on returns to industries which were found to be most represented in the given bivariate sort bucket between 1970 and 2020. Weekly frequency.

S Lo		S Mid		S Hi		L Lo		L Mid		L Hi	
α	- 0.03	α	***0.07***	α	***0.05***	α	***- 0.04***	α	0.01	α	0.02
	- 1.00		***4.14***		***2.38***		***- 2.49***		0.56		1.58
BLDMT	***0.25***	UTIL	0.01	RTAIL	- 0.01	OIL	***0.05***	OIL	***0.13***	COMPS	***0.08***
	15.12		0.86		- 0.64		***6.42***		***28.56***		***13.19***
OIL	***0.09***	MACH	***0.16***	BLDMT	***0.38***	UTIL	***0.05***	TELCM	***0.13***	HSHLD	***0.16***
	8.08		***13.42***		***28.82***		***4.96***		***18.28***		***21.50***
CHIPS	***0.15***	RTAIL	***- 0.05***	BUSSV	***0.25***	STEEL	***0.11***	UTIL	***0.06***	AUTOS	***0.06***
	11.33		***- 4.10***		***18.16***		***16.61***		***7.47***		***11.44***
UTIL	- 0.02	BLDMT	***0.19***	OIL	***0.11***	FIN	***0.18***	HSHLD	***0.10***	OIL	***0.14***
	- 1.30		***14.93***		***12.42***		***16.15***		***14.77***		***30.78***
TRANS	***0.10***	FIN	***0.09***	FIN	***0.12***	INSUR	***0.12***	CHIPS	***0.09***	DRUGS	***0.18***
	5.92		***7.26***		***7.81***		***10.86***		***14.15***		***26.43***
RTAIL	***- 0.08***	BUSSV	***0.11***	BANKS	***0.05***	BUSSV	***0.14***	COMPS	***0.07***	RTAIL	***0.13***
	- 4.85		***9.58***		***4.02***		***12.75***		***11.32***		***15.73***
BUSSV	***0.36***	BANKS	***0.07***	DRUGS	***- 0.07***	TELCM	***0.11***	BUSSV	***0.12***	TELCM	***0.08***
	19.17		***6.93***		***- 6.10***		***11.10***		***14.82***		***11.68***
DRUGS	- 0.00	WHLSL	***0.26***	MEALS	***0.12***	CHIPS	***0.14***	BANKS	***0.13***	BUSSV	***0.15***
	- 0.27		***18.41***		***10.31***		***16.61***		***21.91***		***18.24***
TELCM	***0.05***					BANKS	***0.04***	INSUR	***0.11***		
	2.75						***4.57***		***13.91***		
BANKS	***0.05***					DRUGS	***0.04***				
	4.16						***4.39***				
N	2661	N	2661	N	2661	N	2661	N	2661	N	2661
R^2(%)	79.69	R^2(%)	86.37	R^2(%)	84.61	R^2(%)	91.36	R^2(%)	93.85	R^2(%)	93.28
R^2_{48}(%)	88.15	R^2_{48}(%)	90.83	R^2_{48}(%)	92.13	R^2_{48}(%)	92.12	R^2_{48}(%)	95.47	R^2_{48}(%)	94.58

Table 10: Regressions of returns to US common factors on returns to industries most represented in the top-30 and bottom-30 buckets constructed with respect to the given characteristics.

This table summarizes results of regressing returns to US commonly used factors on returns to industries which were found to be most represented in the top-30 and bottom-30 sort buckets constructed with respect to the relevant characteristics. Time period is between 1970 and 2020 and weekly frequency returns are used.

SMB		HML		RMW		CMA	
α	0.03	α	0.10	α	0.07	α	0.09
	1.55		5.97		4.36		6.96
RTAIL	- 0.08	HSHLD	- 0.07	OIL	0.07	OIL	0.03
	- 5.47		- 6.52		9.83		5.17
BLDMT	0.22	COMPS	- 0.04	UTIL	- 0.01	AUTOS	0.05
	15.48		- 4.80		- 1.16		7.51
CHIPS	- 0.02	DRUGS	- 0.19	STEEL	- 0.06	HSHLD	0.04
	- 1.72		- 19.54		- 8.34		4.05
MACH	0.14	OIL	0.03	FIN	- 0.13	UTIL	0.05
	8.56		3.48		- 11.56		5.62
FIN	0.03	RTAIL	- 0.08	INSUR	- 0.02	TELCM	0.04
	2.03		- 6.89		- 2.09		4.90
BUSSV	0.16	TELCM	0.05	BUSSV	- 0.03	CHIPS	- 0.02
	9.76		4.75		- 2.97		- 2.22
BANKS	- 0.06	BUSSV	- 0.26	TELCM	- 0.05	BUSSV	- 0.14
	- 4.51		- 20.46		- 5.27		- 13.27
DRUGS	- 0.08	CHIPS	- 0.06	CHIPS	- 0.06	FIN	- 0.01
	- 6.50		- 6.66		- 6.32		- 1.25
OIL	- 0.07	STEEL	0.06	BANKS	0.05	BANKS	- 0.01
	- 6.81		8.82		5.35		- 0.89
HSHLD	- 0.17	AUTOS	0.06	DRUGS	0.02	COMPS	- 0.06
	- 11.99		7.72		1.74		- 8.22
COMPS	- 0.05	UTIL	0.09	COMPS	- 0.02	DRUGS	- 0.05
	- 4.17		7.92		- 2.47		- 6.39
UTIL	- 0.03	FIN	0.01	HSHLD	0.16	RTAIL	- 0.02
	- 2.26		1.01		16.06		- 2.44
TELCM	- 0.09	BANKS	0.25	AUTOS	0.03	INSUR	0.03
	- 6.54		23.73		3.62		2.52
		INSUR	0.09	RTAIL	0.08		
			6.87		7.54		
N	2661	N	2661	N	2661	N	2661
R^2(%)	29.13	R^2(%)	62.46	R^2(%)	35.83	R^2(%)	38.03
R^2_{48}(%)	58.22	R^2_{48}(%)	65.92	R^2_{48}(%)	44.36	R^2_{48}(%)	42.57

Table 11: Regressions of returns to US common factors on returns to industries most represented in the top-30 and bottom-30 buckets constructed with respect to size and the given characteristics.

This table summarizes results of regressing returns to US commonly used factors on returns to industries which were found to be most represented in the top-30 and bottom-30 sort buckets constructed with respect to size and the relevant characteristics. Time period is between 1970 and 2020 and weekly frequency returns are used.

SMB		HML		RMW		CMA	
α	0.04	α	0.10	α	0.07	α	0.09
	1.79		5.98		4.58		6.82
RTAIL	- 0.07	RTAIL	- 0.08	BLDMT	0.02	UTIL	0.05
	- 4.98		- 7.29		2.26		4.77
BUSSV	0.16	BUSSV	- 0.27	OIL	0.04	FOOD	0.05
	9.93		- 20.83		6.41		4.68
OIL	- 0.06	OIL	0.02	UTIL	- 0.01	RTAIL	- 0.03
	- 6.05		3.03		- 0.81		- 3.14
DRUGS	- 0.07	DRUGS	- 0.19	TRANS	0.02	FIN	- 0.01
	- 5.47		- 19.34		2.23		- 1.36
UTIL	- 0.02	HSHLD	- 0.08	BUSSV	- 0.08	BUSSV	- 0.15
	- 1.52		- 7.33		- 6.91		- 13.69
BLDMT	0.25	COMPS	- 0.04	DRUGS	0.03	DRUGS	- 0.06
	17.09		- 4.47		2.99		- 7.11
FIN	0.04	CHIPS	- 0.06	BANKS	0.05	OIL	0.02
	2.70		- 6.74		5.39		3.06
BANKS	- 0.04	BLDMT	0.05	FIN	- 0.16	BANKS	- 0.01
	- 3.08		4.40		- 13.77		- 0.94
STEEL	0.08	STEEL	0.05	TELCM	- 0.06	CHIPS	- 0.02
	7.85		7.15		- 6.12		- 2.93
INSUR	- 0.05	UTIL	0.09	INSUR	- 0.04	AUTOS	0.04
	- 3.35		7.66		- 3.12		6.46
HSHLD	- 0.16	FIN	0.01	RTAIL	0.07	TELCM	0.04
	- 10.91		1.12		6.75		4.62
COMPS	- 0.05	BANKS	0.24	COMPS	- 0.05	HSHLD	0.02
	- 4.46		22.93		- 6.72		2.22
CHIPS	0.00	INSUR	0.08	HSHLD	0.16	COMPS	- 0.06
	0.03		6.03		15.15		- 8.02
TELCM	- 0.10	TELCM	0.05			MACH	0.03
	- 7.26		5.04				3.05
AUTOS	0.00	AUTOS	0.05			INSUR	0.02
	0.33		6.40				1.74
N	2661	N	2661	N	2661	N	2661
R^2(%)	29.11	R^2(%)	62.72	R^2(%)	33.25	R^2(%)	38.71
R^2_{48}(%)	58.22	R^2_{48}(%)	65.92	R^2_{48}(%)	44.36	R^2_{48}(%)	42.57

Table 12: Regressions of developed countries factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *developed countries* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.123	0.013	0.061	0.023	0.016	0.009	-0.078
	5.803	0.477	***2.598***	1.389	0.884	***10.746***	-1.467
Automobiles Components	-0.017	0.016	0.033	0.007	-0.069	-0.003	-0.232
	-0.688	0.516	1.220	0.385	***-3.215***	***-2.692***	***-3.766***
Banks	0.034	0.033	0.343	-0.223	0.089	0.000	-0.229
	0.957	0.718	***8.798***	***-8.032***	***2.866***	-0.091	***-2.569***
Capital Goods	0.044	0.186	0.244	0.013	0.294	0.002	-0.029
	0.839	***2.749***	***4.199***	0.305	***6.390***	0.761	-0.215
Commercial Professional Services	0.320	0.049	-0.082	0.016	0.007	0.001	0.107
	9.353	1.122	***-2.190***	0.610	0.220	0.433	1.246
Consumer Durables Apparel	-0.027	-0.129	0.130	-0.023	0.071	0.000	0.063
	-0.655	***-2.466***	***2.884***	-0.731	***1.999***	0.033	0.609
Consumer Services	0.019	0.028	-0.133	0.033	-0.074	0.000	0.044
	0.414	0.495	***-2.700***	0.944	***-1.882***	-0.109	0.392
Diversified Financials	0.102	-0.155	-0.110	-0.096	-0.171	0.001	-0.342
	2.072	***-2.460***	***-2.022***	***-2.478***	***-3.985***	0.649	***-2.755***
Energy	0.072	-0.013	0.103	-0.046	-0.006	0.000	-0.182
	5.140	-0.751	***6.740***	***-4.207***	-0.458	-0.095	***-5.195***
Food Staples Retailing	0.013	0.103	0.072	-0.022	0.094	0.002	-0.016
	0.408	***2.471***	***1.994***	-0.867	***3.294***	1.438	-0.191
FoodBeverage Tobacco	-0.245	0.009	-0.136	0.153	-0.016	-0.003	0.096
	-5.229	0.144	***-2.640***	***4.172***	-0.381	-1.639	0.811
Health Care Equipment Services	0.166	0.013	-0.080	-0.034	0.003	0.000	0.204
	5.054	0.300	***-2.202***	-1.325	0.119	-0.022	***2.465***
Household Personal Products	0.035	-0.070	-0.026	0.088	-0.007	-0.002	0.057
	1.521	***-2.359***	-1.040	***4.874***	-0.340	***-1.812***	0.981
Insurance	0.215	-0.268	0.177	-0.024	0.023	0.000	-0.263

Continuation of Table 12

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
	6.362	***-6.208***	***4.784***	-0.928	0.791	0.262	***-3.100***
Materials	-0.066	0.098	-0.024	-0.037	-0.069	-0.001	-0.007
	-2.135	***2.494***	-0.702	-1.536	***-2.575***	-0.668	-0.096
Media Entertainment	-0.029	0.086	0.041	-0.020	-0.003	0.000	0.028
	-0.825	***1.889***	1.049	-0.732	-0.088	-0.223	0.316
PharmaceuticalsBiotechnology Life Sciences	-0.031	0.117	-0.126	-0.094	-0.025	-0.001	0.053
	-1.443	***4.310***	***-5.397***	***-5.670***	-1.344	-0.730	0.984
Real Estate	-0.090	0.133	-0.047	0.021	-0.030	0.002	-0.047
	-2.938	***3.397***	-1.411	0.887	-1.114	***1.844***	-0.607
Retailing	0.113	0.028	-0.089	0.106	-0.029	-0.003	-0.071
	3.174	0.614	***-2.279***	***3.803***	-0.939	***-2.166***	-0.799
Semiconductors Semiconductor Equipment	0.046	-0.057	0.008	0.017	-0.052	0.001	0.025
	2.295	***-2.231***	0.370	1.085	***-3.013***	0.645	0.493
Software Services	0.145	-0.126	-0.245	0.074	-0.165	0.001	0.262
	4.835	***-3.282***	***-7.461***	***3.182***	***-6.324***	0.787	***3.480***
Technology Hardware Equipment	-0.036	0.095	-0.090	-0.024	0.016	0.001	0.035
	-1.126	***2.323***	***-2.558***	-0.946	0.561	0.954	0.442
Telecommunication Services	0.083	-0.109	0.018	-0.034	0.049	-0.002	0.156
	2.389	***-2.449***	0.470	-1.241	1.621	-1.141	***1.785***
Transportation	-0.015	0.060	0.008	0.083	-0.036	0.000	0.098
	-0.347	1.106	0.167	***2.507***	-0.975	-0.292	0.915
Utilities	0.126	-0.191	0.006	0.082	0.077	0.002	0.228
	3.437	***-4.085***	0.156	***2.873***	***2.408***	1.616	***2.478***
N	563	563	563	563	563	563	563
R^2(%)	95.03	25.19	66.02	50.97	34.08	3.89	43.47

Table 13: Regressions of developed countries excl. US factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *developed countries excluding US* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.098	0.041	0.068	0.031	0.017	0.009	-0.012
	3.671	1.313	***2.569***	1.639	0.864	***10.746***	-0.236
Automobiles Components	0.065	-0.072	0.056	0.038	-0.046	-0.003	-0.218
	2.106	***-1.993***	***1.834***	***1.733***	***-2.071***	***-2.692***	***-3.596***
Banks	0.000	-0.014	0.264	-0.222	0.099	0.000	-0.221
	-0.010	-0.263	***5.944***	***-7.014***	***3.091***	-0.091	***-2.525***
Capital Goods	0.127	0.189	0.323	-0.095	0.233	0.002	-0.018
	1.909	***2.435***	***4.879***	***-2.016***	***4.874***	0.761	-0.135
Commercial Professional Services	0.278	-0.087	-0.159	0.080	-0.052	0.001	0.111
	6.480	***-1.732***	***-3.723***	***2.616***	***-1.677***	0.433	1.312
Consumer Durables Apparel	0.020	-0.210	0.111	-0.045	0.033	0.000	0.070
	0.398	***-3.476***	***2.155***	-1.236	0.896	0.033	0.691
Consumer Services	-0.140	0.048	-0.094	0.048	-0.005	0.000	-0.005
	-2.487	0.730	***-1.676***	1.198	-0.131	-0.109	-0.046
Diversified Financials	0.153	-0.139	-0.144	-0.022	-0.193	0.001	-0.274
	2.464	***-1.909***	***-2.328***	-0.508	***-4.314***	0.649	***-2.248***
Energy	0.049	-0.012	0.068	-0.020	-0.001	0.000	-0.142
	2.796	-0.603	***3.907***	-1.603	-0.106	-0.095	***-4.127***
Food Staples Retailing	0.247	0.095	0.084	-0.029	0.086	0.002	0.014
	6.013	***1.971***	***2.038***	-0.984	***2.909***	1.438	0.173
FoodBeverage Tobacco	-0.290	0.199	-0.274	0.152	-0.092	-0.003	0.149
	-4.926	***2.880***	***-4.674***	***3.656***	***-2.160***	-1.639	1.288
Health Care Equipment Services	0.083	0.061	-0.045	-0.002	0.045	0.000	0.165
	2.008	1.257	-1.083	-0.060	1.524	-0.022	***2.037***
Household Personal Products	0.037	-0.055	-0.057	0.058	-0.017	-0.002	0.089
	1.282	-1.629	***-1.987***	***2.799***	-0.827	***-1.812***	1.563
Insurance	0.168	-0.379	0.157	-0.023	-0.007	0.000	-0.269

Continuation of Table 13

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
	3.969	***-7.629***	***3.724***	-0.759	-0.241	0.262	***-3.228***
Materials	0.006	0.075	-0.029	-0.083	-0.084	-0.001	-0.068
	0.154	***1.659***	-0.750	***-3.011***	***-3.027***	-0.668	-0.893
Media Entertainment	0.079	0.144	-0.034	0.017	0.004	0.000	0.041
	1.766	***2.742***	-0.751	0.537	0.126	-0.223	0.466
PharmaceuticalsBiotechnology Life Sciences	-0.047	0.085	-0.063	-0.037	0.007	-0.001	0.076
	-1.778	***2.701***	***-2.360***	***-1.936***	0.383	-0.730	1.442
Real Estate	-0.066	0.138	-0.119	0.087	-0.088	0.002	0.007
	-1.717	***3.074***	***-3.111***	***3.194***	***-3.183***	***1.844***	0.092
Retailing	-0.079	0.057	-0.070	0.029	-0.060	-0.003	-0.062
	-1.760	1.081	-1.573	0.912	***-1.881***	***-2.166***	-0.711
Semiconductors Semiconductor Equipment	0.006	-0.074	0.014	0.029	-0.048	0.001	-0.010
	0.232	***-2.512***	0.545	***1.655***	***-2.676***	0.645	-0.205
Software Services	0.028	-0.100	-0.111	0.063	-0.075	0.001	0.152
	0.742	***-2.264***	***-2.962***	***2.350***	***-2.788***	0.787	***2.055***
Technology Hardware Equipment	-0.025	0.165	-0.070	-0.037	0.029	0.001	0.080
	-0.629	***3.523***	***-1.755***	-1.317	0.990	0.954	1.019
Telecommunication Services	0.169	-0.197	0.089	-0.061	0.090	-0.002	0.049
	3.871	***-3.850***	***2.040***	***-1.987***	***2.872***	-1.141	0.574
Transportation	0.017	0.127	0.045	0.073	0.001	0.000	0.109
	0.310	***2.029***	0.855	***1.919***	0.037	-0.292	1.043
Utilities	0.139	-0.214	0.061	0.020	0.120	0.002	0.199
	3.018	***-3.976***	1.332	0.610	***3.636***	1.616	***2.202***
N	563	563	563	563	563	563	563
R^2(%)	92.77	45.34	50.69	37.42	29.23	3.89	40.38

Table 14: Regressions of North American factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *North American* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.148	0.003	0.059	-0.004	0.022	0.009	-0.140
	4.243	0.094	***1.763***	-0.150	0.883	***10.746***	***-2.201***
Automobiles Components	-0.095	0.047	-0.019	-0.019	-0.077	-0.003	-0.222
	-2.369	1.139	-0.497	-0.668	***-2.675***	***-2.692***	***-3.015***
Banks	0.028	0.162	0.388	-0.215	0.065	0.000	-0.236
	0.478	***2.704***	***6.907***	***-5.221***	1.561	-0.091	***-2.219***
Capital Goods	-0.087	0.006	0.113	0.196	0.333	0.002	-0.025
	-1.005	0.067	1.353	***3.200***	***5.400***	0.761	-0.155
Commercial Professional Services	0.356	0.294	0.033	-0.008	0.063	0.001	0.142
	6.337	***5.097***	0.604	-0.194	1.577	0.433	1.387
Consumer Durables Apparel	-0.054	-0.069	0.147	0.051	0.086	0.000	0.087
	-0.802	-0.992	***2.269***	1.062	***1.791***	0.033	0.710
Consumer Services	0.186	0.119	-0.158	0.014	-0.125	0.000	0.077
	2.526	1.574	***-2.224***	0.272	***-2.389***	-0.109	0.570
Diversified Financials	0.044	-0.209	-0.041	-0.204	-0.136	0.001	-0.440
	0.548	***-2.513***	-0.523	***-3.565***	***-2.363***	0.649	***-2.971***
Energy	0.119	0.053	0.169	-0.060	0.014	0.000	-0.239
	5.187	***2.258***	***7.673***	***-3.703***	0.876	-0.095	***-5.704***
Food Staples Retailing	-0.224	-0.127	0.020	-0.075	0.082	0.002	-0.055
	-4.175	***-2.297***	0.384	***-1.982***	***2.142***	1.438	-0.558
FoodBeverage Tobacco	-0.225	-0.167	0.070	0.127	0.089	-0.003	0.002
	-2.934	***-2.112***	0.948	***2.343***	1.620	-1.639	0.016
Health Care Equipment Services	0.244	0.015	-0.106	-0.062	-0.050	0.000	0.248
	4.527	0.270	***-2.029***	-1.625	-1.307	-0.022	***2.513***
Household Personal Products	0.043	-0.081	0.022	0.116	0.006	-0.002	0.011
	1.122	***-2.066***	0.605	***4.322***	0.210	***-1.812***	0.152
Insurance	0.285	-0.103	0.248	-0.021	0.071	0.000	-0.230

Continuation of Table 14

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
	5.153	***-1.802***	***4.646***	-0.537	***1.793***	0.262	***-2.273***
Materials	-0.078	0.180	-0.025	-0.086	-0.089	-0.001	0.066
	-1.543	***3.470***	-0.522	***-2.412***	***-2.484***	-0.668	0.718
Media Entertainment	-0.133	-0.047	0.100	-0.088	-0.008	0.000	-0.011
	-2.267	-0.775	***1.770***	***-2.128***	-0.183	-0.223	-0.098
PharmaceuticalsBiotechnology Life Sciences	-0.032	0.166	-0.231	-0.148	-0.056	-0.001	0.046
	-0.919	***4.627***	***-6.858***	***-6.004***	***-2.244***	-0.730	0.722
Real Estate	-0.102	0.089	0.099	-0.088	0.068	0.002	-0.146
	-2.032	***1.734***	***2.041***	***-2.481***	***1.917***	***1.844***	-1.590
Retailing	0.312	0.156	-0.098	0.237	-0.013	-0.003	-0.087
	5.351	***2.602***	***-1.733***	***5.736***	-0.317	***-2.166***	-0.813
Semiconductors Semiconductor Equipment	0.093	-0.008	0.004	0.000	-0.054	0.001	0.055
	2.836	-0.244	0.127	0.009	***-2.316***	0.645	0.910
Software Services	0.243	-0.074	-0.427	0.050	-0.256	0.001	0.397
	4.954	-1.471	***-9.016***	1.446	***-7.339***	0.787	***4.427***
Technology Hardware Equipment	-0.059	-0.017	-0.097	-0.026	0.000	0.001	-0.016
	-1.124	-0.314	***-1.913***	-0.703	0.008	0.954	-0.167
Telecommunication Services	-0.013	-0.054	-0.085	0.031	-0.017	-0.002	0.236
	-0.222	-0.922	-1.555	0.763	-0.420	-1.141	***2.264***
Transportation	-0.056	-0.077	-0.080	0.132	-0.070	0.000	0.096
	-0.807	-1.074	-1.194	***2.675***	-1.411	-0.292	0.750
Utilities	0.134	-0.189	-0.047	0.162	0.048	0.002	0.294
	2.243	***-3.062***	-0.815	***3.826***	1.119	1.616	***2.675***
N	563	563	563	563	563	563	563
R^2(%)	87.83	35.82	62.15	40.73	31.96	3.89	38.68

Table 15: Regressions of European factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *European* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.093	0.070	0.035	0.050	0.020	0.009	0.030
	2.266	***1.973***	0.996	***1.846***	0.820	***10.746***	0.462
Automobiles Components	0.004	-0.058	0.001	0.047	-0.044	-0.003	-0.166
	0.093	-1.417	0.034	1.483	-1.535	***-2.692***	***-2.217***
Banks	-0.005	-0.059	0.266	-0.270	0.112	0.000	-0.319
	-0.078	-0.984	***4.501***	***-5.906***	***2.714***	-0.091	***-2.948***
Capital Goods	0.088	0.281	0.232	-0.045	0.209	0.002	-0.035
	0.858	***3.162***	***2.634***	-0.654	***3.407***	0.761	-0.217
Commercial Professional Services	0.458	-0.095	-0.115	0.065	-0.077	0.001	0.113
	6.924	***-1.657***	***-2.011***	1.484	***-1.938***	0.433	1.078
Consumer Durables Apparel	0.177	-0.170	0.187	-0.121	0.046	0.000	-0.019
	2.240	***-2.471***	***2.743***	***-2.291***	0.971	0.033	-0.156
Consumer Services	-0.161	0.092	-0.028	0.056	0.009	0.000	0.021
	-1.854	1.221	-0.373	0.961	0.173	-0.109	0.154
Diversified Financials	0.197	-0.059	-0.130	0.027	-0.225	0.001	-0.333
	2.062	-0.708	-1.583	0.418	***-3.906***	0.649	***-2.210***
Energy	0.026	-0.011	0.067	-0.015	-0.002	0.000	-0.118
	0.983	-0.477	***2.901***	-0.850	-0.124	-0.095	***-2.777***
Food Staples Retailing	0.114	-0.006	0.046	-0.027	0.079	0.002	-0.080
	1.810	-0.114	0.848	-0.629	***2.082***	1.438	-0.803
FoodBeverage Tobacco	-0.242	0.156	-0.265	0.118	-0.165	-0.003	0.100
	-2.671	***1.982***	***-3.395***	***1.957***	***-3.033***	-1.639	0.702
Health Care Equipment Services	0.066	0.023	-0.096	-0.025	0.020	0.000	0.169
	1.044	0.406	***-1.751***	-0.596	0.534	-0.022	***1.679***
Household Personal Products	0.010	-0.151	-0.096	0.094	-0.001	-0.002	0.054
	0.214	***-3.894***	***-2.491***	***3.142***	-0.044	***-1.812***	0.767
Insurance	0.349	-0.288	0.304	-0.101	-0.002	0.000	-0.293
	5.355	***-5.079***	***5.413***	***-2.324***	-0.043	0.262	***-2.844***

Continuation of Table 15

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
Materials	-0.011	0.011	0.055	-0.048	-0.016	-0.001	0.013
	-0.182	0.218	1.065	-1.203	-0.447	-0.668	0.141
Media Entertainment	0.061	0.124	0.093	-0.081	0.073	0.000	-0.001
	0.878	***2.067***	1.559	***-1.758***	***1.754***	-0.223	-0.013
PharmaceuticalsBiotechnology Life Sciences	-0.061	0.069	-0.099	-0.029	-0.002	-0.001	0.085
	-1.483	***1.940***	***-2.789***	-1.043	-0.062	-0.730	1.304
Real Estate	-0.163	0.129	-0.136	0.081	-0.079	0.002	0.053
	-2.764	***2.518***	***-2.674***	***2.067***	***-2.227***	***1.844***	0.565
Retailing	-0.124	0.052	-0.088	0.073	-0.086	-0.003	-0.010
	-1.806	0.863	-1.480	1.582	***-2.069***	***-2.166***	-0.090
Semiconductors Semiconductor Equipment	0.103	-0.016	0.101	0.011	-0.050	0.001	-0.070
	2.667	-0.483	***3.039***	0.438	***-2.131***	0.645	-1.153
Software Services	0.065	-0.086	-0.091	0.074	-0.056	0.001	0.169
	1.122	***-1.700***	***-1.831***	***1.915***	-1.623	0.787	***1.852***
Technology Hardware Equipment	-0.258	0.053	-0.240	0.018	0.036	0.001	0.173
	-4.192	0.992	***-4.517***	0.441	0.979	0.954	***1.772***
Telecommunication Services	0.336	-0.053	0.160	-0.091	0.152	-0.002	0.096
	5.010	-0.899	***2.758***	***-2.029***	***3.754***	-1.141	0.902
Transportation	-0.124	0.093	-0.096	0.135	0.005	0.000	0.123
	-1.510	1.304	-1.357	***2.458***	0.110	-0.292	0.948
Utilities	0.233	-0.257	0.097	0.019	0.041	0.002	0.179
	3.302	***-4.170***	1.588	0.398	0.955	1.616	1.605
N	563	563	563	563	563	563	563
R^2(%)	87.33	29.21	54.28	30.17	13.51	3.89	36.01

Table 16: Regressions of Japanese factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *Japanese* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.060	0.047	0.053	0.001	-0.022	0.009	-0.162
	0.994	0.980	1.133	0.046	-0.665	***10.746***	***-2.591***
Automobiles Components	0.323	-0.144	0.143	0.061	-0.019	-0.003	-0.329
	4.669	***-2.583***	***2.642***	***1.829***	-0.491	***-2.692***	***-4.558***
Banks	0.062	0.080	0.231	-0.216	0.042	0.000	-0.163
	0.614	0.992	***2.948***	***-4.510***	0.750	-0.091	-1.559
Capital Goods	0.736	0.032	0.441	-0.323	0.296	0.002	-0.116
	4.932	0.270	***3.779***	***-4.534***	***3.586***	0.761	-0.748
Commercial Professional Services	-0.037	0.128	-0.084	0.001	-0.036	0.001	0.056
	-0.385	***1.646***	-1.109	0.024	-0.679	0.433	0.552
Consumer Durables Apparel	-0.212	-0.082	-0.021	0.026	-0.007	0.000	0.167
	-1.833	-0.874	-0.234	0.464	-0.103	0.033	1.387
Consumer Services	-0.318	0.155	-0.154	0.105	0.079	0.000	0.100
	-2.514	1.518	-1.557	***1.735***	1.131	-0.109	0.757
Diversified Financials	0.041	-0.273	-0.126	-0.177	-0.220	0.001	-0.171
	0.297	***-2.422***	-1.154	***-2.655***	***-2.851***	0.649	-1.175
Energy	-0.028	-0.049	0.046	0.002	-0.013	0.000	-0.081
	-0.719	-1.555	1.506	0.086	-0.607	-0.095	***-1.980***
Food Staples Retailing	0.832	0.165	0.046	-0.080	0.063	0.002	0.087
	9.004	***2.216***	0.642	***-1.801***	1.226	1.438	0.901
FoodBeverage Tobacco	-0.565	0.151	-0.317	0.202	0.007	-0.003	0.277
	-4.272	1.415	***-3.064***	***3.195***	0.095	-1.639	***2.012***
Health Care Equipment Services	0.204	0.078	-0.003	-0.046	0.135	0.000	0.191
	2.191	1.045	-0.040	-1.042	***2.630***	-0.022	***1.974***
Household Personal Products	0.084	0.014	-0.151	0.063	-0.087	-0.002	0.182
	1.290	0.274	***-2.952***	***2.024***	***-2.406***	***-1.812***	***2.669***
Insurance	-0.318	-0.356	0.047	0.033	0.024	0.000	-0.264
	-3.336	***-4.633***	0.633	0.725	0.457	0.262	***-2.661***

Continuation of Table 16

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
Materials	-0.447	0.089	0.040	0.042	0.021	-0.001	-0.109
	-5.132	1.265	0.584	0.998	0.434	-0.668	-1.203
Media Entertainment	0.135	0.248	-0.273	0.164	-0.120	0.000	0.196
	1.339	***3.040***	***-3.460***	***3.396***	***-2.142***	-0.223	***1.860***
PharmaceuticalsBiotechnology Life Sciences	0.012	0.073	-0.048	-0.043	-0.002	-0.001	0.018
	0.199	1.500	-1.032	-1.496	-0.070	-0.730	0.294
Real Estate	-0.023	0.141	-0.169	0.156	-0.111	0.002	0.004
	-0.263	***2.022***	***-2.506***	***3.794***	***-2.321***	***1.844***	0.049
Retailing	-0.039	-0.042	0.044	-0.016	-0.064	-0.003	-0.200
	-0.386	-0.523	0.565	-0.336	-1.146	***-2.166***	***-1.907***
Semiconductors Semiconductor Equipment	-0.288	0.049	-0.119	0.065	-0.039	0.001	0.088
	-5.097	1.082	***-2.694***	***2.394***	-1.240	0.645	1.492
Software Services	-0.103	-0.046	-0.114	0.133	-0.094	0.001	0.121
	-1.216	-0.675	***-1.733***	***3.302***	***-2.016***	0.787	1.373
Technology Hardware Equipment	0.511	-0.039	0.125	-0.105	0.003	0.001	-0.122
	5.669	-0.539	***1.769***	***-2.446***	0.054	0.954	-1.300
Telecommunication Services	-0.217	-0.179	0.061	-0.021	0.019	-0.002	0.016
	-2.211	***-2.268***	0.793	-0.442	0.346	-1.141	0.161
Transportation	0.404	-0.065	0.140	-0.002	-0.046	0.000	0.062
	3.369	-0.668	1.486	-0.039	-0.699	-0.292	0.497
Utilities	0.001	-0.119	0.082	0.028	0.182	0.002	0.171
	0.007	-1.431	1.019	0.569	***3.189***	1.616	1.586
N	563	563	563	563	563	563	563
R^2(%)	61.53	20.17	26.43	29.07	10.89	3.89	29.14

Table 17: Regressions of Asia Pacific ex Japan factors on 24 industry indices

This table reports the results of regressing Fama-French five factors and the momentum factor on industry indices. The factors are constructed using *Asia Pacific ex Japan* cross-section of stocks as defined by Kenneth French on his website. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
(Intercept)	0.147	-0.026	0.092	0.056	0.049	0.009	0.114
	3.498	-0.587	***2.302***	1.502	1.522	***10.746***	***1.819***
Automobiles Components	0.025	-0.080	0.050	-0.025	-0.061	-0.003	-0.188
	0.521	-1.562	1.089	-0.586	-1.633	***-2.692***	***-2.587***
Banks	-0.030	-0.028	0.159	0.019	0.047	0.000	-0.101
	-0.420	-0.370	***2.382***	0.304	0.875	-0.091	-0.962
Capital Goods	-0.251	-0.073	0.225	-0.208	0.174	0.002	0.049
	-2.394	-0.661	***2.271***	***-2.228***	***2.165***	0.761	0.312
Commercial Professional Services	-0.024	0.116	-0.391	0.172	0.009	0.001	0.163
	-0.347	1.616	***-6.086***	***2.839***	0.172	0.433	1.612
Consumer Durables Apparel	-0.313	0.023	0.138	-0.055	0.017	0.000	0.067
	-3.848	0.270	***1.790***	-0.765	0.273	0.033	0.548
Consumer Services	0.157	-0.129	-0.145	0.099	-0.035	0.000	-0.039
	1.763	-1.368	***-1.718***	1.249	-0.516	-0.109	-0.293
Diversified Financials	0.215	-0.076	-0.132	-0.072	-0.063	0.001	-0.170
	2.200	-0.733	-1.424	-0.819	-0.842	0.649	-1.160
Energy	0.062	0.056	0.063	-0.050	-0.001	0.000	-0.161
	2.245	***1.914***	***2.421***	***-2.013***	-0.068	-0.095	***-3.888***
Food Staples Retailing	0.040	-0.186	0.042	0.042	0.141	0.002	0.025
	0.611	***-2.706***	0.691	0.724	***2.837***	1.438	0.256
FoodBeverage Tobacco	-0.059	0.445	-0.047	-0.045	-0.062	-0.003	-0.031
	-0.641	***4.520***	-0.529	-0.546	-0.866	-1.639	-0.225
Health Care Equipment Services	-0.021	0.001	-0.006	0.048	0.000	0.000	-0.002
	-0.317	0.016	-0.092	0.820	0.009	-0.022	-0.018
Household Personal Products	0.059	-0.061	0.088	-0.075	-0.013	-0.002	0.101
	1.297	-1.257	***2.040***	***-1.826***	-0.359	***-1.812***	1.469
Insurance	0.082	-0.159	-0.025	0.136	-0.087	0.000	-0.197

Continuation of Table 17

	Mkt_RF	SMB	HML	RMW	CMA	RF	WML
	1.223	***-2.240***	-0.393	***2.289***	***-1.694***	0.262	***-1.968***
Materials	0.456	0.057	-0.259	0.166	-0.207	-0.001	-0.054
	7.466	0.879	***-4.483***	***3.040***	***-4.420***	-0.668	-0.588
Media Entertainment	0.011	0.048	-0.210	0.167	-0.077	0.000	0.032
	0.159	0.642	***-3.127***	***2.639***	-1.422	-0.223	0.303
PharmaceuticalsBiotechnology Life Sciences	-0.045	0.071	0.012	-0.008	0.084	-0.001	0.150
	-1.063	1.584	0.306	-0.213	***2.602***	-0.730	***2.383***
Real Estate	0.235	0.028	0.124	-0.102	-0.110	0.002	-0.116
	3.887	0.440	***2.158***	***-1.889***	***-2.382***	***1.844***	-1.284
Retailing	-0.012	0.008	-0.137	0.008	0.006	-0.003	0.007
	-0.167	0.113	***-2.051***	0.132	0.110	***-2.166***	0.070
Semiconductors Semiconductor Equipment	-0.021	-0.052	-0.034	0.027	-0.107	0.001	0.027
	-0.541	-1.242	-0.905	0.770	***-3.512***	0.645	0.461
Software Services	0.047	-0.050	-0.085	0.034	-0.046	0.001	0.138
	0.789	-0.790	-1.512	0.644	-1.005	0.787	1.557
Technology Hardware Equipment	0.217	0.036	0.154	-0.134	0.118	0.001	0.054
	3.427	0.533	***2.570***	***-2.384***	***2.434***	0.954	0.574
Telecommunication Services	0.151	-0.178	0.016	-0.011	0.053	-0.002	0.165
	2.190	***-2.449***	0.253	-0.179	1.003	-1.141	1.600
Transportation	0.136	0.179	0.229	0.001	0.015	0.000	-0.111
	1.611	***2.005***	***2.873***	0.009	0.231	-0.292	-0.884
Utilities	-0.110	-0.129	0.009	-0.016	0.164	0.002	0.243
	-1.518	***-1.682***	0.132	-0.248	***2.945***	1.616	***2.245***
N	563	563	563	563	563	563	563
R^2(%)	84.87	12.85	27.32	12.33	26.43	3.89	21.54

Table 18: Regressions of returns to geographic factors on 24 industry indices

This table reports the results of regressing returns to geographic factors on industry indices. The returns to geographic factors are constructed in line with Dumas et al. (2020) methodology using a global cross-section of stock returns and Factset GeoRev dataset on the sources of company's revenue. Industry classification resulting in 24 assignment groups at GIC Industry Group level is used. Industry indices are equal weighted. Time period between January 2009 and December 2014. Weekly frequency.

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Malaysia	Singapore	UK	US	RestOfWorld
α	- 0.03	0.04	0.03	***- 0.18***	- 0.14	- 0.08	- 0.11	- 0.14	***- 0.33***	- 0.09	- 0.09	- 0.00	0.05	***- 0.11***
	- 0.26	0.29	0.37	***- 2.00***	- 1.39	- 0.76	- 0.79	- 0.98	***- 2.70***	- 1.18	- 1.23	- 0.02	0.74	***- 2.54***
Automobiles Components	- 0.09	0.04	***0.12***	0.02	- 0.01	- 0.10	***- 0.34***	- 0.07	***0.57***	0.06	0.01	***0.24***	- 0.12	0.04
	- 0.79	0.29	***1.68***	0.20	- 0.09	- 0.89	***- 2.37***	- 0.43	***4.56***	0.71	0.08	***2.15***	- 1.63	0.94
Banks	0.08	- 0.26	***- 0.24***	- 0.06	0.20	0.12	0.25	***0.55***	0.15	***- 0.27***	0.07	0.00	- 0.14	- 0.03
	0.51	- 1.31	***- 2.18***	- 0.44	1.25	0.75	1.18	***2.41***	0.78	***- 2.16***	0.56	0.00	- 1.24	- 0.46
Capital Goods	***- 0.58***	- 0.52	***- 0.54***	- 0.03	0.05	0.26	***1.04***	- 0.03	***1.34***	***0.34***	- 0.07	- 0.41	0.14	- 0.04
	- 2.21	- 1.61	***- 3.09***	- 0.14	0.19	1.00	***3.03***	- 0.08	***4.49***	***1.72***	- 0.38	- 1.51	0.80	- 0.43
Commercial & Profess Serv	***0.32***	0.29	***0.17***	***- 0.26***	***0.66***	***0.81***	***- 1.47***	***0.60***	- 0.12	***- 0.31***	***- 0.26***	***0.89***	***0.54***	0.04
	2.08	1.54	***1.73***	***- 2.02***	***4.49***	***5.27***	***- 7.32***	***2.84***	- 0.71	***- 2.69***	***- 2.42***	***5.71***	***5.38***	0.60
Cons Durables Apparel	- 0.21	0.20	0.02	- 0.01	0.10	0.20	***1.09***	0.14	- 0.29	***- 0.45***	***- 0.27***	0.30	- 0.08	- 0.09
	- 1.08	0.87	0.13	- 0.08	0.55	1.06	***4.30***	0.53	- 1.31	***- 3.07***	***- 1.98***	1.54	- 0.59	- 1.11
Cons Serv	- 0.06	***- 0.52***	- 0.09	***- 0.30***	- 0.16	- 0.30	- 0.08	- 0.28	***- 0.47***	0.04	0.08	0.21	0.22	- 0.12
	- 0.26	***- 1.93***	- 0.65	***- 1.65***	- 0.77	- 1.33	- 0.27	- 0.91	***- 1.88***	0.25	0.49	0.92	1.53	- 1.32
Diversified Financials	- 0.13	- 0.06	0.04	- 0.04	0.06	0.06	0.21	0.14	0.05	***- 0.40***	0.11	0.15	- 0.18	0.02

Continuation of Table 18

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Malaysia	Singapore	UK	US	RestOfWorld
	- 0.62	- 0.22	0.30	- 0.25	0.27	0.29	0.77	0.48	0.19	***- 2.53***	0.75	0.70	- 1.30	0.28
Energy	***0.14***	***0.48***	***0.46***	- 0.10	- 0.06	- 0.06	***- 0.27***	- 0.12	- 0.05	0.10	***0.23***	0.00	0.09	- 0.03
	1.67	***4.67***	***8.33***	- 1.49	- 0.72	- 0.76	***- 2.47***	- 1.03	- 0.52	1.59	***3.80***	0.03	1.58	- 0.91
Food Staples Retailing	0.07	- 0.14	0.00	- 0.13	0.24	0.10	- 0.32	0.21	***1.66***	- 0.15	- 0.05	0.14	***- 0.50***	0.04
	0.41	- 0.69	0.02	- 0.92	1.49	0.62	- 1.45	0.90	***8.68***	- 1.16	- 0.38	0.81	***- 4.50***	0.66
Food Beverage Tobacco	- 0.09	- 0.13	- 0.23	- 0.15	- 0.37	***- 0.45***	0.21	***- 1.02***	***- 0.83***	***1.47***	***0.63***	- 0.03	***- 0.50***	***0.43***
	- 0.36	- 0.44	- 1.46	- 0.76	- 1.58	***- 1.87***	0.66	***- 3.04***	***- 2.98***	***8.05***	***3.60***	- 0.11	***- 3.11***	***4.47***
Health Care Equip Serv	0.06	- 0.23	- 0.02	***0.24***	***0.25***	***0.37***	- 0.19	0.22	0.02	0.05	0.17	***- 0.36***	***0.46***	- 0.03
	0.39	- 1.25	- 0.17	***1.96***	***1.77***	***2.52***	- 0.96	1.08	0.10	0.48	1.63	***- 2.35***	***4.75***	- 0.55
Household Personal Products	0.19	0.03	***0.18***	***0.36***	- 0.10	- 0.08	***0.42***	- 0.11	0.03	- 0.17	0.14	- 0.07	0.08	0.00
	1.30	0.17	***1.92***	***3.04***	- 0.75	- 0.56	***2.25***	- 0.57	0.15	- 1.57	1.40	- 0.46	0.80	0.08
Insurance	- 0.02	0.15	***0.34***	0.15	0.19	0.17	***- 0.70***	***0.38***	***- 0.38***	0.10	- 0.07	0.17	***0.32***	***0.24***
	- 0.14	0.82	***3.42***	1.23	1.31	1.13	***- 3.62***	***1.83***	***- 2.22***	0.87	- 0.70	1.13	***3.29***	***4.08***
Materials	***0.64***	0.27	***0.20***	***0.81***	0.02	- 0.05	***0.67***	- 0.15	***- 0.71***	0.02	- 0.04	- 0.15	***- 0.32***	***0.21***
	4.51	1.54	***2.18***	***6.94***	0.15	- 0.34	***3.61***	- 0.78	***- 4.38***	0.23	- 0.38	- 1.00	***- 3.45***	***3.79***
Media Entertainment	0.06	***- 0.34***	***0.25***	***- 0.49***	***0.28***	***0.32***	0.22	***0.58***	0.08	0.06	- 0.16	0.12	***- 0.36***	0.00
	0.38	***- 1.73***	***2.38***	***- 3.73***	***1.83***	***2.05***	1.06	***2.66***	0.46	0.53	- 1.38	0.73	***- 3.44***	0.08
Pharma Biotech Life Sciences	- 0.14	- 0.04	***- 0.21***	***- 0.35***	- 0.02	- 0.09	0.05	0.13	0.26	***- 0.27***	- 0.14	0.01	- 0.12	***0.12***

Continuation of Table 18

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Malaysia	Singapore	UK	US	RestOfWorld
	- 1.00	- 0.21	***- 2.21***	***- 2.92***	- 0.13	- 0.63	0.26	0.65	1.59	***- 2.52***	- 1.39	0.07	- 1.22	***2.10***
Real Estate	***0.32***	***0.44***	- 0.01	***0.24***	- 0.11	- 0.21	0.16	- 0.29	***- 0.38***	***0.17***	***0.47***	***- 0.35***	0.11	0.05
	2.29	***2.57***	- 0.15	***2.05***	- 0.82	- 1.48	0.87	- 1.52	***- 2.40***	***1.66***	***4.73***	***- 2.44***	1.22	0.99
Retailing	0.08	***0.37***	0.03	- 0.14	***- 0.43***	- 0.24	***- 0.52***	- 0.30	0.10	0.11	- 0.10	***- 0.51***	***0.66***	- 0.11
	0.47	***1.73***	0.25	- 0.97	***- 2.53***	- 1.38	***- 2.29***	- 1.23	0.48	0.84	- 0.83	***- 2.83***	***5.66***	- 1.56
Semicond & Semicond Equip	- 0.10	0.16	0.06	***0.25***	0.09	0.07	- 0.15	***0.27***	***- 0.51***	***0.13***	- 0.09	0.04	***0.11***	***0.16***
	- 0.98	1.35	0.88	***3.11***	0.94	0.75	- 1.17	***2.04***	***- 4.63***	***1.83***	- 1.30	0.42	***1.68***	***4.06***
Software Serv	0.04	- 0.19	0.05	0.06	0.07	***0.31***	***0.71***	- 0.11	***- 0.44***	0.01	- 0.09	***0.38***	***0.49***	- 0.05
	0.24	- 1.02	0.50	0.53	0.49	***2.05***	***3.65***	- 0.52	***- 2.57***	0.07	- 0.88	***2.47***	***4.98***	- 0.77
Technology Hardware Equip	***0.27***	- 0.24	- 0.10	***0.40***	***- 0.31***	***- 0.46***	- 0.18	***- 0.41***	***0.77***	- 0.17	***0.27***	***- 0.32***	- 0.13	***0.13***
	1.86	- 1.37	- 1.01	***3.40***	***- 2.26***	***- 3.20***	- 0.96	***- 2.08***	***4.72***	- 1.62	***2.59***	***- 2.17***	- 1.42	***2.22***
Telecomm Serv	***0.36***	***0.56***	0.04	***0.49***	***0.59***	***0.59***	- 0.13	***1.11***	***- 0.42***	0.14	0.10	***0.37***	- 0.17	***0.23***
	2.14	***2.71***	0.37	***3.55***	***3.67***	***3.52***	- 0.61	***4.78***	***- 2.17***	1.13	0.86	***2.15***	- 1.57	***3.37***
Transportation	0.22	- 0.00	- 0.10	***0.33***	- 0.19	- 0.14	- 0.29	***- 0.62***	***0.67***	0.15	***0.33***	- 0.06	- 0.05	***- 0.15***
	1.10	- 0.00	- 0.73	***1.98***	- 0.97	- 0.69	- 1.12	***- 2.25***	***2.94***	1.03	***2.34***	- 0.27	- 0.38	***- 1.89***
Utilities	- 0.09	***0.98***	***0.45***	***- 0.42***	0.03	- 0.01	***0.67***	***0.63***	***- 0.48***	- 0.05	***- 0.39***	0.18	***0.37***	- 0.00
	- 0.48	***4.33***	***3.63***	***- 2.73***	0.15	- 0.08	***2.75***	***2.46***	***- 2.28***	- 0.39	***- 2.97***	0.93	***3.03***	- 0.05
N	307	307	307	307	307	307	307	307	307	307	307	307	307	307

Continuation of Table 18

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Malaysia	Singapore	UK	US	RestOfWorld
R^2(%)	76.52	70.98	82.40	81.12	72.79	78.07	73.38	70.47	54.63	56.64	75.00	65.54	84.87	92.96

Appendices

A Geographic factors

In an open economy, individual firm's returns do not reflect solely and fully the business risks of the country of its headquarters (or listing) but rather a mixture of latent geographical factors relevant from the point of view of its operations. To make inferences about the region's risk on the basic of its stock market is, therefore, to ignore the complexity of these underlying relationships. Dumas et al. (2020) aim to overcome this problem by using revenue information about stocks listed worldwide to construct stock market indices, which would better reflect the intrinsic business risks of investing in a given country or region. These synthetic zone factors are called "geographic risks".

Dumas et al. (2020) use World Vest Base to identify thirteen geographic factors: France, Germany, Great Britain, Brazil, United States, Canada, Australia, Malaysia, Singapore, China, Japan, India, and the Rest of the World. In this paper, I use Factset GeoRev dataset to identify sixteen of them: the thirteen from the original work and three additional for Italy, EU15, and the Rest of EU15.

A.1 Data trimming

For all companies covered by the FactSet GeoRev dataset, I collect information about the share of revenue derived from various geographic locations between 2015 and 2019. Information on a total of 61,613 equity ISINs is available across these five years. These are then filtered in three steps aimed to closely mirror these of the original work (Dumas et al., 2020):

1. In the first step ISINs are dropped subject to their static properties obtained from Thomson Reuters's Eikon. First, only stocks listed in one of the 56 countries (28 developed and 28 developing ones) are selected as indicated by

the first two letters of their ISIN[11]. This leaves 54,299 ISINs. Second, I drop ISINs that are not considered ordinary shares by Eikon[12]. This leaves me with 50,502 ISINs. Finally, I delete Chinese Class A shares. This results in 46,485 ISINs. The resulting number of ISINs in each year is summarized in Table A.1 column (1).

2. In the second step ISINs are dropped for specific years depending on their properties in that year. First, I drop all ISINs for which market capitalization information is not available in the given year. This leaves the number of ISIN/year combinations in column (2a). Second, for each country of exchange, I only keep these stocks that are in the top 25th percentile of the market capitalization distribution for that country[13]. This results in the ISIN/year combinations in (2b). Finally, for each company (as identified by FactSet *entity_id*), I only keep the ISIN of the equity issue with the largest market capitalization. This leaves me with yearly ISINs as in (2c).

3. In the third and last step, ISINs are filtered based on the returns data from Eikon. First, I delete stocks for which there is no local currency returns available. Although the geographic factors are constructed using returns derived from USD prices, this step ascertains that the move in these USD prices is not solely a result of the change in the value of the local currency versus the dollar. It results in yearly counts as in (3a). Second, in a given year I only keep ISINs for which there is a whole-year history of returns in that year. This results in counts as per (3b). Finally, I eliminate thinly traded shares i.e. ones that have a zero monthly return in the given currency at least

[11]Developed countries: AU, AT, BE, CA, CY, DK, FI, FR, DE, GR, HK, IE, IL, IT, JP, LU, NL, NZ, NO, PT, SG, KR, ES, SE, CH, TW, GB, US.
Developing Countries: AR, BD, BR, BG, CL, CN, CO, CZ, EG, HU, IN, ID, KE, LT, MY, MX, MA, PK, PE, PH, PL, RO, ZA, LK, TH, TR, VE, ZW

[12]I am keeping only shares that are flagged as *Ordinary Shares* or *Fully Paid Ordinary Shares* according to Eikon's TR.InstrumentType property

[13]This value is higher than the 3rd percentile in (Dumas et al., 2020) and chosen to match the number of ISINs per year for USA in the original paper.

once in a given year. This leaves me with the final number of ISINs each year as given in column (3c).

Year	(1)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
2015	44209	35584	8899	8679	8448	8251	8157
2016	45047	37111	9282	8901	8618	8446	8367
2017	45163	38437	9616	9035	8739	8608	8526
2018	44709	39939	9993	9258	8987	8865	8774
2019	42723	41396	10358	9264	8970	8842	8754

Table A.1: ISINs count per year after each stage of the filtering process

As a result of the filtering process described above, no Venezuelan shares are included in the final sample despite them being initially kept as one of the 56 markets considered.

A.2 Brief summary of methodology

The latent geographic-zone factors are calculated using the following model:

$$R_t = B \times C_t + e_t,$$

where R_t is the vector of firms' returns and B is the matrix of loadings of the firms' returns on the latent zone factors C_t. For a given firm i, its loadings on all the factors are non-negative and equal to the percentage of revenues the firm derives from the given zone. Consequently, they also sum to 1.

To handle missing information about geographical segments and zero-return data points, Dumas et al. (2020) calculate the latent factors using *expectation-maximisation algorithm* as introduced by Brooks and Del Negro (2004) on a year-by-year basis using daily frequency of returns. Because the revenue share coverage

is imbalanced (many more firms sell to the United States than, for example, to Italy), I follow the authors in calculating the latent zone factors for 100 random subsamples of the dataset and calculate the final zone factors C_t as the average of these 100 estimates. The details of the expectation maximisation algorithm and the subsampling can be found in the original paper.

B Robustness results

Table B.1: Regressions of US FF 5 factors on 38 KF industry indices

This table reports the results of regressing Fama-French five factors on industry indices. The five factors are constructed using United States cross-section of stocks. Kenneth French's industry classification resulting in 38 assignment groups is used. Industry indices are equal weighted.

	Mkt_RF	SMB	HML	RMW	CMA	RF
(Intercept)	-0.056	-0.312	-0.135	0.472	-0.261	0.001
	-0.143	-0.704	-0.352	1.634	-0.840	0.105
Agric	-0.011	0.013	-0.009	0.004	-0.001	0.000
	-0.754	0.827	-0.620	0.416	-0.111	0.994
Mines	-0.026	0.010	0.031	-0.008	0.009	0.000
	-2.393	0.815	***2.916***	-0.993	1.112	-0.385
Oil	-0.008	-0.013	0.060	-0.026	0.001	0.000
	-0.734	-1.046	***5.544***	***-3.237***	0.137	-1.022
Stone	0.012	-0.004	0.011	0.005	0.013	0.000
	1.079	-0.278	0.994	0.557	1.408	-1.124
Cnstr	-0.028	-0.010	0.006	-0.004	0.018	0.000
	-1.742	-0.547	0.413	-0.305	1.442	1.212
Food	0.057	-0.035	-0.024	0.038	0.032	0.000
	1.924	-1.064	-0.847	***1.729***	1.376	-0.205
Smoke	0.066	-0.050	-0.018	0.016	0.000	0.000
	5.062	***-3.403***	-1.446	***1.699***	0.047	-1.221
Txtls	0.001	0.013	0.000	0.000	-0.003	0.000
	0.071	0.691	-0.026	0.032	-0.271	-1.533

Continuation of Table B.1

	Mkt_RF	SMB	HML	RMW	CMA	RF
Apprl	-0.001	-0.004	0.026	-0.012	-0.010	0.001
	-0.059	-0.242	1.645	-1.043	-0.763	***1.975***
Wood	-0.008	0.047	-0.013	-0.027	-0.007	0.000
	-0.571	***3.104***	-1.023	***-2.696***	-0.669	1.007
Chair	-0.010	0.016	0.006	0.036	-0.002	0.000
	-0.480	0.705	0.319	***2.383***	-0.095	-0.033
Paper	0.014	-0.035	0.020	0.000	-0.002	0.000
	0.983	***-2.181***	1.487	-0.022	-0.162	-0.044
Print	-0.020	0.040	0.095	0.002	0.040	-0.001
	-1.141	***2.033***	***5.631***	0.191	***2.933***	***-1.887***
Chems	-0.013	0.081	-0.137	-0.106	-0.041	0.000
	-0.639	***3.442***	***-6.700***	***-6.870***	***-2.481***	-0.074
Ptrlm	0.067	-0.037	0.006	-0.024	-0.016	0.000
	4.281	***-2.071***	0.378	***-2.074***	-1.273	0.384
Rubbr	0.035	-0.028	0.013	0.030	0.014	0.000
	1.363	-0.966	0.509	1.618	0.703	0.557
Lethr	0.012	-0.001	-0.028	0.019	-0.011	0.000
	0.819	-0.035	***-1.909***	***1.731***	-0.974	-0.027
Glass	-0.014	-0.004	0.019	-0.007	0.026	0.000
	-0.872	-0.234	1.198	-0.565	***2.052***	-0.782
Metal	0.032	0.023	0.037	0.005	0.031	0.001
	1.583	0.997	***1.842***	0.358	***1.915***	***2.125***
MtlPr	0.020	0.085	-0.009	0.021	-0.006	0.000

Continuation of Table B.1

	Mkt_RF	SMB	HML	RMW	CMA	RF
	0.668	***2.576***	-0.303	0.978	-0.262	0.045
Machn	0.211	0.050	-0.052	-0.031	0.091	0.001
	4.940	1.035	-1.246	-0.999	***2.714***	1.066
Elctr	0.021	-0.037	-0.012	-0.052	-0.068	0.000
	0.582	-0.904	-0.329	***-1.945***	***-2.369***	0.610
Cars	0.035	-0.086	0.095	0.058	-0.031	0.000
	1.124	***-2.421***	***3.076***	***2.498***	-1.269	-0.344
Instr	0.003	0.047	-0.057	-0.039	-0.021	-0.001
	0.065	1.084	-1.497	-1.361	-0.706	-1.602
Manuf	-0.035	0.026	-0.008	0.018	-0.012	-0.001
	-1.787	1.180	-0.410	1.286	-0.781	***-1.847***
Trans	0.048	-0.005	0.025	0.043	0.011	0.000
	1.867	-0.157	1.005	***2.315***	0.551	-0.090
Phone	0.004	0.018	0.017	0.006	0.028	0.000
	0.234	0.879	0.953	0.499	***1.995***	-0.235
TV	-0.035	-0.010	0.038	-0.024	0.047	0.000
	-1.536	-0.398	***1.729***	-1.444	***2.662***	-1.109
Utils	0.179	-0.076	-0.052	0.028	0.014	0.000
	7.685	***-2.914***	***-2.292***	1.616	0.765	0.945
Garbg	-0.025	-0.016	-0.023	0.036	-0.008	0.000
	-1.458	-0.806	-1.369	***2.868***	-0.564	0.646
Steam	0.000	0.000	0.000	0.000	0.000	0.000
	-0.025	-0.569	-0.335	1.415	-1.030	-1.074

Continuation of Table B.1

	Mkt_RF	SMB	HML	RMW	CMA	RF
Whlsl	-0.036	0.061	-0.060	0.050	0.070	-0.001
	-0.911	1.350	-1.536	***1.712***	***2.202***	-1.062
Rtail	0.042	0.086	-0.023	0.122	0.047	-0.001
	1.295	***2.380***	-0.748	***5.171***	***1.839***	-1.140
Money	0.101	-0.005	0.702	-0.194	-0.004	0.000
	2.880	-0.137	***20.509***	***-7.534***	-0.153	0.032
Srvc	0.227	0.068	-0.559	-0.080	-0.297	0.002
	4.607	1.216	***-11.589***	***-2.198***	***-7.646***	***1.659***
Govt	0.005	0.010	-0.016	-0.011	-0.011	0.000
	0.529	0.889	***-1.656***	-1.612	-1.473	-0.909
Other	-0.004	-0.036	0.020	0.017	0.009	0.000
	-0.301	***-2.438***	1.533	***1.764***	0.882	-0.701
N	574	574	574	574	574	574
R^2(%)	89.2	48.3	74.0	48.9	25.6	1.4

Table B.2: Regressions of size univariate sort portfolios on 38 KF industry indices

This table reports the results of regressing univariate sort portfolios with respect to size on industry indices. Univariate sort and industry portfolios are constructed using United States cross-section of stocks. Kenneth French's industry classification resulting in 38 assignment groups is used. Industry indices are equal weighted.

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
(Intercept)	0.106	-0.221	0.078	0.254	-0.664	-0.147	0.153	0.090
	0.602	-0.827	0.200	1.112	***-2.404***	-0.509	0.409	0.222
Agric	0.007	-0.008	-0.011	0.010	-0.001	-0.006	-0.012	-0.015
	1.163	-0.795	-0.772	1.183	-0.130	-0.592	-0.879	-1.001
Mines	0.025	-0.019	-0.018	0.031	-0.015	-0.016	-0.022	-0.016
	5.104	***-2.546***	***-1.704***	***4.965***	***-2.027***	***-2.018***	***-2.117***	-1.387
Oil	0.050	0.019	0.012	0.059	0.011	0.020	0.020	0.010
	10.189	***2.595***	1.062	***9.137***	1.367	***2.514***	***1.919***	0.903
Stone	0.003	0.006	0.005	0.000	0.012	0.007	0.001	0.007
	0.491	0.812	0.471	-0.054	1.524	0.879	0.095	0.608
Cnstr	0.022	-0.007	-0.014	0.032	-0.033	-0.001	-0.008	-0.012
	3.113	-0.680	-0.871	***3.452***	***-2.909***	-0.074	-0.524	-0.701
Food	0.007	0.026	0.034	0.004	0.012	0.038	0.021	0.043
	0.513	1.288	1.167	0.259	0.590	***1.751***	0.753	1.417
Smoke	-0.018	0.024	0.058	-0.020	0.007	0.023	0.042	0.063
	-3.068	***2.719***	***4.548***	***-2.640***	0.725	***2.390***	***3.424***	***4.672***
Txtls	0.005	0.004	0.003	0.004	0.016	-0.003	-0.012	0.014
	0.653	0.373	0.206	0.442	1.406	-0.242	-0.797	0.835
Apprl	0.005	0.006	0.010	0.005	0.006	0.002	0.016	0.007
	0.652	0.590	0.606	0.517	0.518	0.174	1.057	0.411

Continuation of Table B.2

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Wood	0.003	0.014	-0.016	-0.005	0.035	0.015	0.005	-0.025
	0.455	1.560	-1.187	-0.707	***3.720***	1.482	0.387	***-1.811***
Chair	0.001	0.014	0.010	-0.001	0.026	0.003	0.011	0.009
	0.152	1.026	0.463	-0.117	***1.772***	0.173	0.544	0.439
Paper	-0.003	0.010	0.031	-0.001	-0.008	0.010	0.027	0.030
	-0.502	1.014	***2.238***	-0.135	-0.829	0.942	***2.036***	***2.028***
Print	0.016	-0.002	-0.014	0.016	0.020	-0.002	-0.015	-0.016
	2.101	-0.134	-0.794	1.550	1.621	-0.181	-0.931	-0.895
Chems	0.204	0.025	-0.013	0.221	0.087	0.011	0.001	-0.014
	21.843	***1.779***	-0.641	***18.128***	***5.942***	0.683	0.033	-0.644
Ptrlm	-0.024	0.039	0.057	-0.031	0.021	0.039	0.058	0.054
	-3.463	***3.669***	***3.670***	***-3.424***	***1.870***	***3.400***	***3.857***	***3.300***
Rubbr	-0.001	0.018	0.032	-0.004	0.018	0.021	0.030	0.031
	-0.105	1.059	1.270	-0.262	1.007	1.135	1.215	1.151
Lethr	-0.006	0.018	0.022	-0.009	0.005	0.025	0.027	0.017
	-0.975	***1.779***	1.470	-0.996	0.503	***2.302***	***1.897***	1.108
Glass	0.010	-0.009	0.008	0.018	-0.028	-0.004	0.020	0.000
	1.427	-0.787	0.503	***1.862***	***-2.452***	-0.341	1.275	-0.003
Metal	-0.011	0.059	0.034	-0.022	0.066	0.061	0.047	0.024
	-1.152	***4.264***	***1.679***	***-1.868***	***4.590***	***4.012***	***2.410***	1.122
MtlPr	0.013	0.028	-0.007	-0.004	0.084	0.028	-0.008	-0.004
	1.005	1.421	-0.254	-0.257	***4.078***	1.310	-0.292	-0.117
Machn	-0.035	0.201	0.163	-0.073	0.201	0.194	0.187	0.156

Continuation of Table B.2

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
	-1.843	***6.941***	***3.855***	***-2.945***	***6.719***	***6.174***	***4.606***	***3.517***
Elctr	0.093	0.019	0.039	0.107	0.000	0.017	0.046	0.041
	5.728	0.774	1.083	***5.057***	-0.018	0.628	1.330	1.103
Cars	-0.019	0.048	0.097	-0.023	-0.011	0.069	0.096	0.090
	-1.380	***2.227***	***3.121***	-1.277	-0.517	***3.000***	***3.203***	***2.747***
Instr	0.089	0.021	-0.025	0.102	0.034	0.028	-0.015	-0.033
	5.160	0.785	-0.650	***4.539***	1.252	1.000	-0.408	-0.829
Manuf	0.028	-0.026	-0.038	0.038	-0.023	-0.030	-0.031	-0.039
	3.276	***-2.011***	***-1.968***	***3.422***	***-1.679***	***-2.082***	***-1.672***	***-1.922***
Trans	0.003	0.050	0.037	-0.002	0.033	0.050	0.050	0.041
	0.224	***2.917***	1.483	-0.128	***1.871***	***2.661***	***2.059***	1.540
Phone	0.007	0.010	-0.005	0.003	0.030	0.009	-0.007	-0.008
	0.907	0.842	-0.284	0.249	***2.394***	0.708	-0.400	-0.413
TV	0.050	-0.061	-0.034	0.068	-0.067	-0.057	-0.042	-0.037
	4.985	***-3.988***	-1.530	***5.186***	***-4.268***	***-3.446***	***-1.958***	-1.577
Utils	-0.037	0.095	0.185	-0.056	0.067	0.100	0.145	0.199
	-3.596	***6.000***	***8.039***	***-4.130***	***4.090***	***5.863***	***6.562***	***8.243***
Garbg	0.025	-0.032	-0.016	0.035	-0.033	-0.031	-0.023	-0.014
	3.279	***-2.743***	-0.957	***3.479***	***-2.717***	***-2.427***	-1.400	-0.801
Steam	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.424	-0.580	0.239	0.907	***-2.085***	-0.330	0.483	0.266
Whlsl	0.035	0.007	-0.020	0.040	0.000	0.000	-0.004	-0.017
	1.976	0.264	-0.503	***1.730***	0.009	0.010	-0.115	-0.407

Continuation of Table B.2

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Rtail	0.046	0.107	0.038	0.037	0.116	0.115	0.050	0.033
	3.189	***4.887***	1.209	***1.965***	***5.130***	***4.845***	1.628	0.977
Money	0.244	0.150	0.091	0.246	0.228	0.129	0.061	0.120
	15.635	***6.322***	***2.625***	***12.114***	***9.290***	***5.015***	***1.821***	***3.317***
Srvc	0.135	0.232	0.194	0.110	0.270	0.219	0.211	0.176
	6.136	***6.945***	***3.964***	***3.831***	***7.812***	***6.037***	***4.500***	***3.437***
Govt	0.011	0.008	-0.004	0.013	0.009	0.007	0.005	-0.006
	2.661	1.296	-0.386	***2.252***	1.257	0.972	0.579	-0.612
Other	0.001	-0.004	0.018	0.005	-0.021	-0.001	0.012	0.022
	0.110	-0.431	1.409	0.645	***-2.321***	-0.153	0.982	1.639
N	574	574	574	574	574	574	574	574
R^2(%)	98.5	97.1	91.1	97.5	97.2	96.5	93.2	89.6

Table B.3: Regressions of BE/ME univariate sort portfolios on 38 KF industry indices

This table reports the results of regressing univariate sort portfolios with respect to book-equity/market-equity ratio on industry indices. Univariate sort and industry portfolios are constructed using United States cross-section of stocks. Kenneth French's industry classification resulting in 38 assignment groups is used. Industry indices are equal weighted.

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
(Intercept)	-0.129	-0.249	0.223	-0.021	-0.473	-0.021	-0.118	0.301
	-0.581	***-1.752***	1.042	-0.085	***-2.167***	-0.118	-0.661	1.014
Agric	-0.003	0.006	-0.003	-0.003	-0.003	0.010	0.014	-0.013
	-0.378	1.225	-0.368	-0.314	-0.321	1.552	***2.202***	-1.217
Mines	-0.003	-0.002	0.021	-0.003	-0.007	-0.001	0.005	0.027
	-0.544	-0.439	***3.518***	-0.474	-1.201	-0.223	1.109	***3.309***
Oil	-0.008	0.018	0.081	-0.013	0.009	0.018	0.025	0.104
	-1.259	***4.476***	***13.462***	***-1.888***	1.428	***3.599***	***4.939***	***12.515***
Stone	-0.003	0.005	0.009	0.002	-0.008	0.005	0.013	0.008
	-0.388	1.264	1.452	0.320	-1.303	0.922	***2.574***	0.940
Cnstr	0.008	-0.010	0.034	0.026	-0.029	-0.011	-0.009	0.055
	0.934	***-1.789***	***3.897***	***2.516***	***-3.286***	-1.526	-1.183	***4.548***
Food	0.019	0.018	0.005	0.009	0.018	0.036	0.006	0.006
	1.153	***1.705***	0.310	0.460	1.082	***2.673***	0.449	0.249
Smoke	0.017	0.006	-0.011	0.019	0.014	0.010	0.000	-0.019
	2.354	1.275	-1.504	***2.309***	***1.988***	***1.668***	0.060	***-1.895***
Txtls	0.000	0.019	-0.002	-0.003	0.012	0.018	0.010	-0.003
	-0.013	***3.178***	-0.238	-0.275	1.303	***2.393***	1.363	-0.285
Apprl	0.011	-0.005	0.004	0.020	-0.007	-0.014	0.007	0.003
	1.232	-0.792	0.419	***1.915***	-0.732	***-1.889***	0.902	0.284

Continuation of Table B.3

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Wood	0.019	0.009	-0.017	0.019	0.021	0.011	0.003	-0.027
	2.549	***1.895***	***-2.329***	***2.180***	***2.830***	***1.828***	0.412	***-2.703***
Chair	-0.002	0.019	0.007	0.000	0.015	0.028	-0.007	0.011
	-0.157	***2.566***	0.641	0.000	1.303	***2.946***	-0.694	0.672
Paper	0.006	-0.007	0.016	0.009	-0.007	-0.007	-0.006	0.026
	0.761	-1.434	***2.113***	1.032	-0.926	-1.039	-0.971	***2.474***
Print	-0.032	0.001	0.033	-0.034	-0.015	-0.004	0.034	0.026
	-3.246	0.207	***3.529***	***-3.041***	-1.557	-0.502	***4.373***	***2.016***
Chems	0.221	0.073	0.052	0.250	0.134	0.068	0.033	0.060
	18.638	***9.671***	***4.586***	***18.717***	***11.545***	***7.050***	***3.439***	***3.776***
Ptrlm	0.014	0.023	-0.024	0.007	0.023	0.021	0.024	-0.041
	1.521	***3.962***	***-2.820***	0.660	***2.687***	***2.854***	***3.366***	***-3.474***
Rubbr	0.008	0.008	0.017	-0.010	0.030	0.003	0.028	0.010
	0.552	0.856	1.198	-0.608	***2.102***	0.218	***2.396***	0.515
Lethr	0.016	0.000	-0.002	0.019	0.006	0.003	-0.008	-0.003
	1.869	-0.022	-0.264	***2.043***	0.780	0.398	-1.204	-0.262
Glass	-0.011	0.000	0.017	-0.013	-0.001	0.003	-0.009	0.026
	-1.160	0.045	***1.940***	-1.227	-0.062	0.383	-1.200	***2.158***
Metal	0.013	0.038	-0.004	0.003	0.043	0.032	0.032	-0.017
	1.132	***5.117***	-0.351	0.196	***3.793***	***3.376***	***3.412***	-1.125
MtlPr	0.033	0.019	-0.016	0.034	0.020	0.019	0.009	-0.015
	2.026	***1.799***	-1.019	***1.817***	1.210	1.425	0.660	-0.688
Machn	0.110	0.131	-0.080	0.075	0.166	0.139	0.082	-0.133

Continuation of Table B.3

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
	4.569	***8.517***	***-3.434***	***2.749***	***6.997***	***7.117***	***4.217***	***-4.124***
Elctr	0.078	0.065	0.088	0.087	0.075	0.048	0.074	0.090
	3.809	***4.917***	***4.469***	***3.742***	***3.729***	***2.900***	***4.486***	***3.276***
Cars	-0.002	0.023	0.048	0.016	-0.019	0.036	0.023	0.058
	-0.090	***2.019***	***2.792***	0.777	-1.096	***2.498***	1.643	***2.440***
Instr	0.059	0.042	0.050	0.063	0.058	0.047	0.018	0.066
	2.718	***3.012***	***2.403***	***2.550***	***2.722***	***2.663***	1.011	***2.247***
Manuf	-0.023	-0.010	0.036	-0.024	-0.007	-0.008	-0.025	0.059
	-2.135	-1.433	***3.426***	***-1.965***	-0.688	-0.857	***-2.876***	***4.031***
Trans	0.015	0.020	0.006	-0.001	0.034	0.028	0.019	-0.004
	1.020	***2.134***	0.454	-0.059	***2.391***	***2.402***	1.630	-0.218
Phone	0.006	0.016	0.002	0.002	0.017	0.012	0.016	0.001
	0.635	***2.503***	0.235	0.195	***1.728***	1.419	***1.998***	0.066
TV	-0.030	-0.022	0.060	-0.025	-0.046	-0.019	-0.002	0.085
	-2.326	***-2.726***	***4.886***	***-1.754***	***-3.649***	***-1.835***	-0.186	***4.997***
Utils	0.058	0.069	-0.026	0.059	0.059	0.062	0.068	-0.055
	4.445	***8.223***	***-2.093***	***3.964***	***4.591***	***5.803***	***6.416***	***-3.127***
Garbg	0.000	0.008	0.012	0.002	-0.001	0.012	0.011	0.013
	0.048	1.360	1.236	0.159	-0.122	1.546	1.354	0.992
Steam	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-0.243	-1.589	0.571	0.245	***-1.955***	0.006	-0.620	0.552
Whlsl	-0.011	0.014	0.072	-0.014	0.022	-0.019	0.073	0.060
	-0.476	0.994	***3.315***	-0.553	1.011	-1.016	***3.998***	***1.990***

Continuation of Table B.3

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Rtail	0.066	0.069	0.046	0.060	0.072	0.074	0.066	0.044
	3.649	***5.966***	***2.624***	***2.916***	***4.017***	***5.011***	***4.551***	***1.812***
Money	0.002	0.184	0.441	-0.023	0.056	0.180	0.373	0.441
	0.095	***14.582***	***23.207***	-1.038	***2.875***	***11.218***	***23.454***	***16.690***
Srvc	0.392	0.178	-0.035	0.433	0.278	0.181	0.045	-0.051
	14.068	***9.988***	-1.308	***13.767***	***10.171***	***8.007***	***1.990***	-1.381
Govt	0.008	0.001	-0.007	0.007	0.007	0.003	-0.002	-0.008
	1.511	0.356	-1.298	1.187	1.216	0.740	-0.402	-1.076
Other	-0.007	0.005	0.006	-0.007	-0.003	0.010	-0.004	0.011
	-0.924	1.075	0.800	-0.807	-0.397	***1.712***	-0.683	1.087
N	574	574	574	574	574	574	574	574
R^2(%)	97.8	99.0	97.7	97.2	97.8	98.4	98.4	95.6

Table B.4: Regressions of OP univariate sort portfolios on 38 KF industry indices

This table reports the results of regressing univariate sort portfolios with respect to operating profitability on industry indices. Univariate sort and industry portfolios are constructed using United States cross-section of stocks. Kenneth French's industry classification resulting in 38 assignment groups is used. Industry indices are equal weighted.

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
(Intercept)	0.025	-0.150	0.056	0.089	-0.151	-0.225	0.005	0.081
	0.180	-1.028	0.277	0.468	-0.946	-1.300	0.024	0.362
Agric	0.000	0.002	-0.001	0.002	0.002	0.002	-0.004	-0.001
	0.083	0.427	-0.085	0.348	0.325	0.278	-0.549	-0.143
Mines	0.023	-0.008	-0.010	0.029	-0.004	-0.004	-0.012	-0.011
	5.899	***-2.058***	***-1.857***	***5.520***	-0.948	-0.931	***-2.067***	***-1.866***
Oil	0.052	0.013	0.016	0.062	0.015	0.008	0.020	0.016
	13.359	***3.087***	***2.888***	***11.581***	***3.275***	1.633	***3.360***	***2.612***
Stone	0.000	0.007	0.008	0.001	0.003	0.003	0.013	0.007
	0.102	1.543	1.318	0.106	0.633	0.568	***2.099***	1.123
Cnstr	0.032	-0.016	-0.003	0.036	-0.005	-0.012	-0.010	-0.006
	5.536	***-2.685***	-0.319	***4.713***	-0.798	***-1.648***	-1.175	-0.632
Food	-0.009	0.022	0.061	-0.023	0.019	0.034	0.047	0.060
	-0.895	***2.029***	***4.010***	-1.618	1.573	***2.595***	***3.003***	***3.571***
Smoke	-0.006	0.006	0.024	-0.007	-0.004	0.009	0.013	0.029
	-1.412	1.236	***3.548***	-1.046	-0.844	1.531	***1.938***	***3.905***
Txtls	0.001	0.018	0.000	-0.002	0.014	0.016	0.015	0.001
	0.128	***3.084***	0.039	-0.303	***2.210***	***2.190***	***1.744***	0.129
Apprl	0.008	0.002	0.003	0.012	-0.006	0.001	0.009	0.002
	1.340	0.256	0.307	1.533	-0.903	0.165	1.117	0.181

Continuation of Table B.4

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Wood	0.003	0.006	0.003	0.002	0.009	0.005	0.000	0.004
	0.576	1.120	0.459	0.387	1.589	0.843	-0.020	0.580
Chair	0.007	0.009	0.010	0.008	0.009	-0.003	0.018	0.012
	0.928	1.127	0.950	0.760	1.038	-0.383	1.637	1.008
Paper	-0.003	0.007	0.024	-0.005	0.006	0.007	0.028	0.018
	-0.550	1.419	***3.310***	-0.795	1.002	1.069	***3.725***	***2.206***
Print	-0.007	0.008	0.019	-0.009	0.001	0.006	0.011	0.028
	-1.136	1.258	***2.088***	-1.023	0.083	0.816	1.180	***2.816***
Chems	0.252	-0.024	0.003	0.327	-0.020	-0.032	-0.004	0.006
	33.907	***-3.082***	0.275	***32.394***	***-2.350***	***-3.423***	-0.379	0.470
Ptrlm	-0.013	0.019	0.019	-0.019	0.014	0.015	0.023	0.023
	-2.240	***3.311***	***2.349***	***-2.502***	***2.122***	***2.160***	***2.733***	***2.531***
Rubbr	-0.008	0.027	0.032	-0.018	0.029	0.035	0.024	0.034
	-0.859	***2.794***	***2.404***	-1.420	***2.786***	***3.146***	***1.816***	***2.336***
Lethr	-0.006	0.006	0.022	-0.006	-0.001	0.004	0.021	0.021
	-1.093	1.179	***2.915***	-0.808	-0.198	0.562	***2.685***	***2.495***
Glass	0.014	-0.013	0.007	0.020	-0.011	-0.009	-0.010	0.013
	2.396	***-2.173***	0.894	***2.516***	***-1.650***	-1.328	-1.117	1.403
Metal	-0.011	0.040	0.052	-0.024	0.046	0.028	0.046	0.057
	-1.515	***5.244***	***4.878***	***-2.425***	***5.587***	***3.051***	***4.266***	***4.881***
MtlPr	-0.019	0.046	0.031	-0.025	0.019	0.046	0.062	0.015
	-1.850	***4.229***	***2.033***	***-1.742***	1.610	***3.590***	***4.062***	0.878
Machn	-0.005	0.103	0.086	-0.035	0.111	0.108	0.106	0.077

Continuation of Table B.4

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
	-0.310	***6.522***	***3.916***	***-1.720***	***6.425***	***5.748***	***4.727***	***3.193***
Elctr	0.137	0.016	0.021	0.166	0.022	0.012	0.005	0.028
	10.656	1.201	1.135	***9.535***	1.464	0.770	0.258	1.351
Cars	-0.018	0.048	0.075	-0.027	0.024	0.037	0.066	0.080
	-1.657	***4.113***	***4.639***	***-1.767***	***1.915***	***2.689***	***4.015***	***4.474***
Instr	0.091	0.037	-0.040	0.105	0.034	0.051	0.008	-0.062
	6.670	***2.559***	***-1.997***	***5.656***	***2.174***	***3.031***	0.400	***-2.845***
Manuf	0.019	-0.014	0.000	0.024	-0.008	-0.012	-0.003	-0.003
	2.732	***-1.900***	0.012	***2.592***	-1.026	-1.359	-0.317	-0.240
Trans	-0.017	0.031	0.058	-0.023	0.004	0.036	0.054	0.067
	-1.866	***3.275***	***4.447***	***-1.860***	0.375	***3.174***	***4.054***	***4.614***
Phone	0.003	0.008	0.015	0.000	0.011	0.005	0.015	0.013
	0.527	1.177	1.601	0.054	1.540	0.609	1.604	1.318
TV	0.036	-0.033	-0.009	0.046	-0.019	-0.033	-0.035	0.003
	4.494	***-3.955***	-0.819	***4.215***	***-2.138***	***-3.367***	***-2.963***	0.253
Utils	-0.034	0.097	0.082	-0.054	0.063	0.109	0.099	0.069
	-4.175	***11.278***	***6.804***	***-4.837***	***6.631***	***10.623***	***8.093***	***5.241***
Garbg	0.020	-0.007	-0.004	0.028	-0.013	-0.004	-0.007	-0.001
	3.333	-1.140	-0.426	***3.325***	***-1.902***	-0.531	-0.752	-0.133
Steam	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.058	-1.006	0.382	0.402	-1.030	-1.277	0.079	0.496
Whlsl	0.003	0.054	0.028	-0.015	0.075	0.059	0.005	0.036
	0.217	***3.659***	1.355	-0.768	***4.598***	***3.362***	0.216	1.581

Continuation of Table B.4

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Rtail	0.016	0.068	0.138	0.003	0.055	0.080	0.085	0.154
	1.401	***5.726***	***8.350***	0.192	***4.247***	***5.643***	***5.039***	***8.505***
Money	0.214	0.313	0.075	0.175	0.368	0.341	0.136	0.058
	17.230	***24.153***	***4.140***	***10.392***	***25.967***	***22.150***	***7.391***	***2.951***
Srvc	0.209	0.117	0.172	0.226	0.141	0.094	0.148	0.185
	11.947	***6.406***	***6.775***	***9.514***	***7.061***	***4.329***	***5.695***	***6.649***
Govt	0.002	-0.001	0.001	0.002	0.003	-0.005	-0.001	0.003
	0.456	-0.158	0.121	0.397	0.824	-1.163	-0.220	0.519
Other	0.006	-0.004	0.003	0.007	-0.002	-0.010	0.003	0.005
	1.267	-0.866	0.485	1.068	-0.378	***-1.698***	0.436	0.678
N	574	574	574	574	574	574	574	574
R^2(%)	99.1	98.8	98.0	98.5	98.6	98.3	97.8	97.8

Table B.5: Regressions of INV univariate sort portfolios on 38 KF industry indices

This table reports the results of regressing univariate sort portfolios with respect to investment (change in total assets) on industry indices. Univariate sort and industry portfolios are constructed using United States cross-section of stocks. Kenneth French's industry classification resulting in 38 assignment groups is used. Industry indices are equal weighted.

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
(Intercept)	0.091	-0.112	0.017	0.121	-0.043	-0.103	-0.083	0.039
	0.394	-0.913	0.103	0.411	-0.268	-0.685	-0.491	0.190
Agric	-0.011	0.004	0.007	-0.006	-0.019	0.009	0.015	0.005
	-1.283	0.864	1.113	-0.583	***-3.287***	***1.646***	***2.347***	0.609
Mines	0.029	-0.005	0.000	0.035	0.009	-0.006	-0.008	0.002
	4.646	-1.448	0.068	***4.366***	***2.131***	-1.497	***-1.674***	0.269
Oil	0.064	0.008	0.034	0.080	0.014	0.005	0.013	0.042
	9.929	***2.470***	***7.126***	***9.690***	***3.013***	1.065	***2.707***	***7.307***
Stone	0.007	-0.001	0.003	0.003	0.005	0.003	0.001	0.003
	1.020	-0.310	0.641	0.315	1.146	0.744	0.273	0.489
Cnstr	0.025	0.008	0.004	0.024	0.011	-0.010	0.007	0.016
	2.626	1.513	0.577	***2.025***	***1.739***	-1.542	1.080	***1.916***
Food	0.010	0.033	0.005	0.003	0.031	0.041	0.025	-0.004
	0.589	***3.571***	0.358	0.125	***2.587***	***3.622***	***1.946***	-0.244
Smoke	-0.004	0.005	0.005	-0.008	0.009	0.001	0.010	0.003
	-0.468	1.167	0.942	-0.862	***1.738***	0.196	***1.796***	0.383
Txtls	-0.002	0.006	0.007	-0.009	0.010	0.010	0.000	0.012
	-0.220	1.279	1.055	-0.730	1.552	1.608	0.039	1.377
Apprl	-0.002	0.004	0.007	-0.002	0.003	0.000	0.006	0.009
	-0.215	0.758	1.063	-0.185	0.412	0.074	0.832	1.093

Continuation of Table B.5

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Wood	0.007	0.003	0.003	0.012	-0.001	0.008	0.002	0.000
	0.888	0.783	0.462	1.228	-0.198	1.622	0.373	0.010
Chair	0.007	0.013	-0.004	0.002	0.021	0.014	-0.005	-0.002
	0.536	***1.989***	-0.400	0.135	***2.481***	***1.747***	-0.536	-0.143
Paper	0.019	0.001	-0.002	0.018	0.012	0.000	0.001	-0.004
	2.254	0.218	-0.344	***1.730***	***2.160***	-0.063	0.217	-0.543
Print	0.038	-0.001	-0.020	0.044	0.020	-0.001	-0.013	-0.024
	3.765	-0.100	***-2.635***	***3.348***	***2.786***	-0.112	***-1.795***	***-2.635***
Chems	0.168	0.000	0.205	0.216	0.014	0.004	0.000	0.281
	13.724	-0.072	***22.728***	***13.735***	1.608	0.556	-0.047	***25.749***
Ptrlm	-0.017	0.015	0.009	-0.019	0.002	0.016	0.020	0.003
	-1.843	***3.081***	1.294	-1.613	0.240	***2.636***	***2.893***	0.410
Rubbr	0.006	0.020	0.001	-0.003	0.030	0.037	-0.004	-0.002
	0.400	***2.526***	0.103	-0.163	***2.843***	***3.766***	-0.319	-0.157
Lethr	-0.002	0.003	0.012	-0.003	0.001	0.003	0.009	0.014
	-0.232	0.629	***1.933***	-0.237	0.145	0.487	1.432	***1.813***
Glass	0.013	0.009	-0.014	0.016	0.012	0.002	-0.001	-0.015
	1.394	***1.869***	***-2.046***	1.281	***1.878***	0.380	-0.110	***-1.817***
Metal	-0.010	0.016	0.029	-0.019	0.023	0.012	0.026	0.026
	-0.844	***2.461***	***3.315***	-1.238	***2.718***	1.516	***2.992***	***2.437***
MtlPr	0.007	0.016	0.013	0.015	-0.001	0.026	0.014	0.009
	0.433	***1.742***	1.065	0.667	-0.095	***2.323***	1.146	0.580
Machn	0.020	0.078	0.033	0.003	0.065	0.105	0.051	0.021

Continuation of Table B.5

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
	0.814	***5.879***	***1.785***	0.089	***3.732***	***6.382***	***2.795***	0.942
Elctr	0.095	0.027	0.086	0.107	0.038	0.020	0.051	0.096
	4.465	***2.415***	***5.478***	***3.913***	***2.607***	1.463	***3.278***	***5.096***
Cars	-0.002	0.046	0.019	-0.013	0.042	0.031	0.064	0.006
	-0.108	***4.753***	1.394	-0.570	***3.271***	***2.582***	***4.703***	0.375
Instr	0.095	0.033	0.032	0.107	0.058	0.027	0.040	0.019
	4.197	***2.760***	***1.926***	***3.697***	***3.708***	***1.828***	***2.432***	0.960
Manuf	0.017	-0.001	0.002	0.020	0.009	-0.010	0.000	0.005
	1.477	-0.100	0.202	1.382	1.142	-1.343	0.030	0.475
Trans	0.024	0.015	0.015	0.028	0.013	0.021	0.030	0.001
	1.589	***1.933***	1.323	1.448	1.224	***2.189***	***2.781***	0.058
Phone	0.005	0.019	-0.009	-0.004	0.023	0.022	0.014	-0.017
	0.437	***3.530***	-1.153	-0.315	***3.137***	***3.245***	***1.877***	***-1.821***
TV	0.069	-0.013	-0.010	0.095	0.000	-0.014	-0.026	-0.004
	5.255	***-1.808***	-0.992	***5.601***	-0.042	-1.581	***-2.741***	-0.314
Utils	-0.039	0.100	0.017	-0.067	0.062	0.104	0.078	0.005
	-2.850	***13.865***	***1.718***	***-3.831***	***6.545***	***11.679***	***7.755***	0.396
Garbg	0.008	0.000	0.011	0.005	0.002	-0.009	0.020	0.010
	0.754	0.014	1.484	0.369	0.261	-1.334	***2.714***	1.161
Steam	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.054	-1.024	0.563	0.124	-0.505	-0.843	-0.392	0.688
Whlsl	0.021	0.045	0.017	0.011	0.037	0.051	0.044	0.012
	0.898	***3.580***	0.971	0.374	***2.247***	***3.291***	***2.529***	0.561

Continuation of Table B.5

	Lo30	Med40	Hi30	Lo20	D2	D3	D4	Hi20
Rtail	0.080	0.069	0.037	0.083	0.057	0.085	0.067	0.023
	4.258	***6.898***	***2.657***	***3.425***	***4.350***	***6.899***	***4.864***	1.388
Money	0.132	0.297	0.182	0.091	0.279	0.280	0.303	0.140
	6.426	***27.369***	***12.047***	***3.464***	***19.643***	***20.831***	***20.143***	***7.682***
Srvc	0.098	0.121	0.295	0.108	0.088	0.116	0.159	0.341
	3.396	***7.879***	***13.879***	***2.912***	***4.396***	***6.138***	***7.505***	***13.288***
Govt	-0.005	0.002	0.006	-0.007	0.002	0.002	0.000	0.009
	-0.821	0.715	1.419	-0.974	0.565	0.564	-0.036	***1.838***
Other	0.003	-0.004	0.009	0.003	0.003	-0.015	0.006	0.010
	0.332	-0.932	1.513	0.346	0.542	***-2.893***	1.143	1.440
N	574	574	574	574	574	574	574	574
R^2(%)	97.7	99.1	98.7	96.6	98.6	98.6	98.4	98.3

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6 | Conclusion

This thesis proposes three empirical analyses into information processing by the stock market. The common idea that connects all the studies presented is market efficiency i.e. the fact that information revealed to market participants is quickly discounted into asset prices. Whichever signals market participants receive, these are timely used to adjust their views of the probability of various states of the world in the future. Thus, the realized changes in asset prices can be used to infer the market participants' perception of the impact of the information received.

This thesis contributes to the literature by investigating three different ways in which information processing by the stock market can be used to shed light on matters relevant from the point of empirical asset pricing. The first paper, *Mind the (trade) gap! Stock market implications of barriers to trade*, uses stock market response to the announcement of the United Kingdom's departure from the European Union to measure the impact of Free Trade Agreements on asset prices. The second paper, *Sources of Return Predictability*, shows that the different informational content of days when macroeconomic news is scheduled to be released to the market and days when such news is not scheduled to be released to the market can be used to infer which stock market returns are based on future fundamentals and which ones are not. The third paper, *Old wine in new bottles. Are industry risks still not understood?*, shows that various risk premiums credited to the timing of cash-flows, stock market characteristics, and geographic zones can be in fact combinations of industry-specific risks poorly understood at present.

Taken together these papers contribute to our understanding of information processing by financial markets. They show that building on the idea that information is timely incorporated into asset prices we can use their changes to make various empirical inferences. The methodologies presented in this thesis should be useful for answering various questions of this nature going forward.