"BREXIT" AND THE CONTRACTION OF SYNDICATED LENDING*

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This Version: March 2017

Abstract

Using the syndicated loan market as a laboratory, we analyze the effect of the Brexit referendum on corporate loan origination. Issuances in the UK syndicated loan market dropped by 20% after the Brexit referendum relative to a set of comparable syndicated loan markets. We propose a new matching strategy – "Siamese Twins Matching" – to identify appropriate counterfactuals for the UK market. We further document a novel channel, market attractiveness, that plays an important role beyond standard demand and supply factors: firm-bank combinations that used to issue loans in both the UK market and other markets decrease their issuances in the UK market more than in other markets after the Brexit referendum. Our results help to understand the dynamics of competition between financial centers and the role of policy uncertainty shocks in this competition.

*We would like to thank Judy Chalabi, Frederik Eidam, Falko Fecht, Manasa Gopal, Ulrich Hege, Emanuel Mönch, Martin Schmalz, Laura Starks, Jing Zeng, and the seminar participants at Frankfurt School of Finance & Management, University Duisburg-Essen, University Munich, and Conference at the German Finance Ministry for helpful comments and suggestions.

1. Introduction

Since the late 1950s, the City of London has become the second most important financial center after New York. Due to increasing regulatory pressure following the Great Depression of the 1930s, US banks started to shift financial services transactions to London thereby developing the "Eurodollar" market.[1] Due to the concentration of financial services by banks globally, London became, among others, the leading center for international lending in the 1990s (Michie, 2005).[2] The depth of its financial markets, its labor force and its political and regulatory stability made London attractive as a financial center.

In a referendum held on June 23, 2016, United Kingdom (UK) citizens voted to leave the European Union (so-called "Brexit") with – at least as of now – unknown impact on the UK economy as well as London as a financial center. The cost to insure against a UK default, for example, increased by almost 80% on the day after the referendum, reflecting the elevated uncertainty among market participants. Moreover, the "Economic Policy Uncertainty" index compiled by Baker, Bloom, and Davis (2016) reached a historical high in the UK, even exceeding values from the financial crisis and the European sovereign debt crisis.

In this paper, we investigate the impact of the Brexit referendum on the global syndicated loan market. Importantly, we hypothesize that the surprising outcome of the referendum not only directly affected UK banks and firms but also affected the attractiveness of London as a financial center. The high presence of international borrowers and lenders make the UK especially

[1] An early literature investigates motives of banks to expand internationally. Several papers argue that banks tend to "follow their customers" into non-domestic markets (such as in Fieleke, 1977). Goldberg and Saunders (1980) find corroborating evidence for US banks' expansion into the United Kingdom (UK). Other factors might be differences in the regulatory and supervisory framework or other micro- or macroeconomic factors (see, e.g., Graham and Krugman, 1995). These benefits have to offset important costs of foreign banks in non-domestic markets such as elevated informational asymmetries, cultural or bureaucratic barriers (as described in, for example, Khanna and Palepu, 1999, Buch, 2003, Petersen and Rajan, 2002, or Mian, 2006). More recently, Haselmann and Wachtel (2011) argue that the presence of foreign banks in large global syndicated loan markets can also to some extent be explained by risk taking behavior of multinational banks.

[2] London gained similar importance in other international financial services transactions such as equity and debt issuances, derivatives or foreign exchange transactions (CSFI, 2003).

vulnerable to a quick withdrawal from both the demand and supply sides. Moreover, the high level of interconnectedness of UK firms and banks in international syndicated loan markets might challenge the role of the UK as a leading market for loan origination. The UK market therefore provides an ideal laboratory to analyze how a shock to policy uncertainty affects borrowing and lending decisions by national and international borrowers and lenders.

This narrative raises several interesting questions: Does the UK syndicated loan market experience a drop in loan issuances after the Brexit referendum relative to other loan markets? And if yes, is this decrease driven by a lower demand of UK firms who decide to postpone investments until the uncertainty is resolved, or because of a lower supply of loans by UK banks, and, particularly those with a strong focus on UK business? Or is the UK becoming less attractive for syndicated lending such that even non-UK firms or banks retrench?[3] Disentangling demand, supply, and the attractiveness of the UK market is of crucial importance: if loans that were usually issued in the UK market are now being issued in other markets around the world, then this clearly points to the impact of the Brexit referendum on London as a financial center.

In a first step, we provide a few stylized facts how the global syndicated loan market has developed over the last 15 years. During the 2000 to 2015 period, the UK ranked third in terms of number of issuances and issuance volume (behind the US and Japan). During this time period, UK issuance volume was equal to US$ 194bn per annum (in 2015 US$), composed of 509 syndicated loans per annum with an average loan volume of US$ 384 million (in 2015 US$). The UK market is more international than the US and Japan. More than 17% of loans are issued by non-UK borrowers (US: 6%, Japan: 4%), 56% of the loans are at least partially funded by non-UK banks (US: 24%, Japan: 6%), and 35% of loans are in a non-local currency, i.e. non-GBP

[3] One example for the latter point would be if firm A (for example, a German shipping company) that used to borrow from bank B (for example, a Norwegian bank) in the UK and US syndicated loan markets before the Brexit referendum reduces its borrowing from exactly the same bank in the UK market but not in the US syndicated loan market.

(US: 1%, Japan: 8%). Overall, the UK is one of the leading markets for global syndicated lending with a high presence of both international firms and lenders.

Our empirical analysis of the impact of the Brexit decision on the global syndicated loan market proceeds in two steps. First, we investigate the change in lending in the UK syndicated loan market after the Brexit referendum relative to before and relative to a set of comparable syndicated loan markets. Given the number of arguably heterogeneous loan markets, we propose a new method to construct a control group that is comparable to the UK. Second, we analyze the drivers of this development – i.e. disentangling demand, supply, and market attractiveness – using a Khwaja-Mian (2008) type estimator.

In a first step, we compare changes in loan issuance in the UK pre- and post-referendum to the changes in other syndicated loan markets using a difference-in-difference (DiD) analysis. We define a loan to be issued in the UK syndicated loan market if it is issued under UK civil law – this is the standard definition for the "loan market" in the major data bases (Dealscan, SDC). Our data includes syndicated loan issuances from January 2014 to December 2016, i.e. 30 months before the Brexit referendum and 6 months after the Brexit referendum. We find that both the number and the volume of syndicated loan issuances drop by 20% ($p<0.01$) after the Brexit referendum relative to the control group of the largest 49 syndicated loan markets worldwide.[4] Our results are robust to the inclusion of country and year fixed effects. We also control for loan market seasonality by including country x quarter-of-the-year fixed effects to rule out that our results are driven by generally low activity in the summer months in the UK.

The DiD analysis relies on the assumption that the other 49 syndicated loan markets worldwide provide a good counterfactual to what would have happened in the UK in the absence

[4] The volume is measured in US-dollars, implying that the drop in the GBP-equivalent volume is somewhat lower. Most of our inferences are based on the number of loans to avoid currency effects.

of the Brexit referendum. Reassuringly, we do not find differences in pre-event trends – suggesting that the key assumption for the internal validity of our DiD estimator is fulfilled.

To further increase the credibility of our results, we propose a new matching method to determine those syndicated loan markets that provide the best counterfactual to the UK syndicated loan market. To do that, we match the UK market to those markets that had a similar development as to the number of loan issuances per quarter as the UK market before the Brexit referendum.[5] The method matches on the pre-event *path* of the *outcome* variable. Unlike our approach, standard matching estimators crucially rely on the econometrician's ability to observe and choose the outcome-relevant determinants (Roberts and Whited (2012)). By matching on the path of the outcome variable, we implicitly match on any important variable that affects outcomes. We find that France, Germany, US, Italy, and the Netherlands provide the best fit to the UK market, followed by Australia, Norway, Spain, Canada, and Sweden.[6] These Top 10 "Siamese Twins" are stable over time and we find very similar results when only focusing on the 2011-2015 period. Our matching method is potentially applicable to a wide range of panel set-ups in finance and economics research where pre-event data is available for multiple periods.

The 20% drop in issuance in the UK market relative to other markets is consistent with a demand narrative (UK firms having lower credit demand as a consequence of the Brexit referendum), a credit supply narrative (UK banks cutting credit supply), or an explanation based on a decrease in the attractiveness of the UK financial market to originate loans.

To disentangle these competing hypotheses, we use a modified Khwaja-Mian (2008) estimator and estimate changes in loan issuances within *industry x borrower country x bank* clusters. Aggregating data into *industry x borrower country x bank* clusters, instead of firm x

[5] More precisely, we use the natural logarithm of the quarterly number of loan issuances to compare markets.
[6] Markets with the lowest correlation with the UK market are Philippines, Argentina, and Columbia and some of the largest markets, such as Japan or China, are not among the Top 10 in terms of correlation with the UK market. This makes intuitive sense as activities in these economies are less correlated with the UK economy.

bank clusters as in the original Khwaja-Mian (2008) approach, accommodates the fact that syndicated loan issuances are less frequent on the firm level. Our implicit assumption is that firm demand shocks operate on the *industry x borrower country* level.[7]

In a univariate setup, UK firms are 30% less likely to issue a loan in the global (UK and non-UK) syndicated loan market after the referendum relative to before the referendum. UK banks are 32% less likely to provide loans while it becomes 28% less likely for a loan to be issued in the UK market.[8] Using a Khwaja-Mian type estimator, we find evidence for significant credit supply effects, with UK banks decreasing loan issuance by 24% relative to non-UK banks on average within an *industry x borrower country* cluster.

Furthermore, we uncover a new market attractiveness channel that plays an important role beyond standard demand and supply factors: loan issuances decrease by 11% more in the UK market compared to other comparable syndicated loan markets after controlling for demand effects via *industry x borrower country* fixed effects. Controlling for bank supply via bank fixed effects hardly decreases the economic magnitude of this effect. We still find that UK loan issuances decrease by 7% relative to other markets, albeit these results are marginally statistically insignificant when looking at only two quarters post-Brexit.

Our results suggest that firm-cluster/bank combinations that used to issue loans in both the UK market and other markets decrease their issuances in the UK market more than in other markets after the Brexit referendum. As an example, Dell used to issue loans with Barclays as a lead arranger in both the US market as well as in the UK market before the referendum. After the referendum, Dell issued another syndicated loan in September 2016 with Barclays as the lead arranger and this loan was issued in the US market. We find that this is not an isolated case, but

[7] A similar approach of aggregating data on a coarser level than the Khwaja-Mian *firm x bank* level has been applied by Acharya et al. (2016), Gropp et al. (2016), as well as Degryse et al. (2016), among others.

[8] The 28% number is an average decrease in issuances on the *industry x borrower country x bank* level and thus deviates from the average decrease in the UK market of 20%. This implies that *industry x borrower country x bank* clusters with a high number of issuances pre-referendum saw a smaller drop than *industry x borrower country x bank* clusters with a low number of issuances pre-referendum.

we observe this pattern systematically across our data set. Neither demand effects (Dell continues to borrow after the referendum) nor supply effects (Barclays continues to lend after the referendum) are able to explain this issuance behavior. These results indicate that the UK market lost attractiveness relative to other market after the Brexit referendum.

Our paper relates to several strands of literature. First, it relates to the literature on domestic credit supply shocks (Khwaja and Mian, 2008; Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014) as well as the literature on international spill-over effects (Peek and Rosengreen, 1997, 2000; Schnabl, 2009; Puri, Rocholl, and Steffen, 2011; Laeven and Gianetti, 2012). While these papers focus on credit supply in the cross-section of banks, we look at loan issuances in the cross-section of different syndicated loan markets. We therefore focus on shocks to the attractiveness of a particular market – the UK syndicated loan market – vis-à-vis other international lending markets. Second, our paper is related to the literature on the global syndicated loan market. Carey and Nini (2007) and Berg et al. (2016) analyze pricing differences across markets while Giannetti and Yafeh (2012) analyze the role of cultural differences in the international syndicated loan market. We add to this literature by analyzing loan issuance decisions after the Brexit referendum shock. Overall, our paper adds to our understanding of the choice of a particular syndicated loan market where borrowers and lenders like to contract. We document that this market-choice is significantly affected by the Brexit referendum, thereby highlighting some of the consequences of the Brexit referendum for the UK financial services industry.

2. Institutional Environment – The Brexit Decision

2.1. Why the referendum?

Successive treaties since 1975 have transformed the European Union from a trading arrangement to a political union, giving Brussels influence over many areas of policy. Too much political influence from Brussels has been seen as problematic by many British citizens, threatening the re-election of the UK prime minister David Cameron. Thus, in January 2013, David Cameron made a pledge to hold an "in or out" referendum to decide whether the UK should leave or remain in the European Union, if the Conservatives won the 2015 election (which he did). He set 23 June 2016 as referendum date.

2.2. What happened?

A referendum was held on Thursday 23 June 2016, to decide whether the UK should leave or remain in the European Union. In an unexpected outcome, UK citizens voted to leave the EU with a 52% (to 48%) majority. The referendum turnout was 71.8%, with more than 30 million people voting. While voters in England and Wales voted to leave the EU (with about 53%, on average), Scotland and Northern Ireland voted to remain in the EU (with 62% and 56%, respectively).

2.3. How was the reaction?

The unexpected vote to leave the EU increased uncertainty around the world. Since the vote was politically motivated, we rely on a newly developed measure by Baker, Bloom and Davis (2016) that measures the economic political uncertainty based on newspaper coverage frequency. This measure captures the actors of events, the type of actions as well as the possible economic consequences. Figure 1 shows the Economic Policy Uncertainty (EPU) index for Europe and the UK in Panel A and for the US in Panel B from January 1987/1985 to October 2016. The index increased by 166% from May to July 2016 for UK, causing the biggest increase in the index since its first recording. By October 2016, it recovered quickly dropping by 67% relative to July 2016. The Brexit seems to have been an event with the highest political uncertainty for the UK, even higher than the global financial crisis 2008 or sovereign debt crisis. Also on the European level, the EPU index for Europe increased by 111% between May and July 2016 relative to an increase of 70% when Lehman Brothers filed for bankruptcy in September 2008. Panel B shows the EPU index for the US, revealing that the US was also affected by the Brexit referendum similar to other events such as the dotcom bubble or Lehman Brothers' bankruptcy.

[Figure 1]

2.4. What was the reaction of the Bank of England?

Economic indicators were pointing to a sharp slowdown in the economy in the second half of 2016 as well as in 2017. The Bank of England highlighted an expected decrease in demand and an increase in unemployment that might lead to an increase in GDP in 2017 (2018) of only about 0.8% (1.8%) - in contrast to the 2.3% growth projected for 2017 and 2018. The inflation rate is expected to be above the target rate of 2% mainly due a weaker currency making imported goods and services more expensive.

The Monetary Policy Committee thus lowered interest rates from 0.5% to 0.25% to avoid a recession and stimulate investments on August 4, 2016. Moreover, the BoE announced to increase its Quantitative Easing (QE) program by 80 billion GBP to 435 billion GBP and an investment-grade corporate bond buying program of UK based firms of about 10 billion GBP starting in September 2016. In addition to that, it announced a program that is supposed to help banks expand lending to firms and households at lower rates.

3. Data

To investigate the effect of the Brexit referendum on global syndicated loan markets, we collect data for all syndicated loans issued by private and public companies in all available countries during the period 2000 to 2015 from Dealscan database maintained by the Loan Pricing Corporation (LPC Dealscan). As Dealscan reports syndicated loans with a lag of up to 6 months only, we additionally collect more recent data for the time period from January 2014 to December 2016 from SDC Platinum of Thomson Reuters to be able to capture the effect of

Brexit. SDC has a small lag of 1-2 month in reporting syndicated loan data, implying that our data collected in January 2017 likely misses some deals from end of 2016. However, we could not find any difference in the delay of reporting for the UK versus non-UK market, implying that any differences between the UK and non-UK market should not be affected. We also compare Dealscan with SDC Platinum for the years 2014-2015 and find that both data bases report virtually the same syndicated loans. The analysis on the historical development of syndicated loan markets solely relies on Dealscan; and the analysis on the Brexit referendum itself relies on SDC Platinum.

The data contains all spreads and fees as well as other relevant loan characteristics such as maturity, loan size, facility type, collateral, and covenants. For now, we require only the loan amount to be available.[9] LPC Dealscan also contains information on the country of syndication, the country of the borrower and the country of the lender as well as the currency denomination of each loan. To make sure that we are actually dealing with a foreign borrower or lender, we use the country information of the ultimate parent company of the borrower or lender.[10]

To document the historical development of the global syndicated loan markets, we focus on term and revolver loans issued between January 2000 and December 2015 from LPC Dealscan for which detailed country data is given. Overall, the sample consists of 191,424 loans to 49,528 firms from 1,922 lenders in 160 countries. Our sample is representative, comprising about 83% of total loan volume issued between January 2000 and December 2015.

[9] The loan amount is the dependent variable in some specifications. As we aggregate our loan level data on the quarter level, loan characteristics are absorbed by our quarterly fixed effects.
[10] Note that we define lead lender as the main lender.

4. Historical Development of Syndicated Loan Markets – Stylized Facts

Before we analyze the impact of Brexit on the UK syndicated loan markets, we establish a few stylized facts as to how the global syndicated loan market developed over the last two decades, with a particular focus on their exposure to foreign borrowers, lenders and currencies.

Stylized Fact 1*: The UK is the third largest syndicated market with a share in loan issuance volume of 6.2%. The US accounts for almost 50% of loan issuance volume, while the top 5 syndicated loan markets (US, Japan, UK, Canada and France) account for around 70% of loan issuance volume.*

We determine the largest syndicated loan markets based on their total loan volume between 2000 and 2015. Not surprisingly, the US turns is the largest market when we rank countries based on their total loan volume in US$ billions in Table 1.[11] The second and third largest markets are Japan and the UK, followed by Canada and France. Table 1 also shows the total number and total volume of deals in US$ billions for the top 20 syndicated markets and the remaining 140 countries in "Rest of the World" between 2000 and 2015, followed by the percentage in total volume of deals as well as the cumulative percentage.[12] The top 5 syndicated markets account for almost 70% of the world market, while the top 20 markets account for over 90% of the market based on volume in total. Perhaps surprisingly, Hong Kong, Switzerland, and Singapore, known as global financial centers, do not appear among the top 10 of syndicated loan markets. The next column of Table 1 shows the average loan size in US$ millions, indicating that loans originated in European syndicated markets are, on average, larger.

[11] Note that loan volume is always winsorized and the 1% and 99% percentiles, unless otherwise noted.
[12] The top 20 syndicated markets are: the US, Japan, the UK, Canada, France, Germany, Australia, Spain, China, the Netherlands, Hong Kong, India, Italy, Tawain, Switzerland, Russia, Singapore, Sweden, South Korea, and Norway.

Stylized Fact 2*: The UK was the second biggest market after the US up to 2007 but lost some of its share after the global financial crisis and resumed its second position in 2015.*

Although the US has dominated the global syndicated loan market over the past with an annual loan volume of $1,346 billion (around 10% of US GDP) on average and a share of around 50% in the average total loan volume in the global syndicated market, its share in the global syndicated market has declined over the past 15 years from around 70% in 2000 to 50% in 2015 (see Figure 2).

[Figure 2]

Figure 2 shows the top 5 syndicated loan markets in terms of loan volume over time, where Panel A presents the total loan volume in 2015 US$ millions, using US CPI, and Panel B the share of the top 5 syndicated markets in the total loan volume. Panel A reveals that the US remained the largest market even when its loan volume sharply dropped in 2008 and 2009 due to the global financial crisis. While the UK was the second largest market until 2007, Japan gained in volume when the European sovereign debt crisis unfolded. In 2014, the UK recovered, resuming its second positions, closely followed by Japan and Canada. The size of the Canadian and French syndicated markets remained relatively stable over time.

Stylized Fact 3*: Among the top 5 syndicated loan markets, the UK is the most international market: Above 17% of loans are issued by non-UK firms, 56% of lenders are non-UK banks or institutions, 36% of loans are issued in a currency other than the GBP.*

The UK has been regarded as a highly international market which also extends to the syndicated loan markets as well. The last three columns of Table 1 present the exposure of the top 20 syndicated markets to foreign borrowers, lenders and currencies based on the total loan volume of the respective country. The UK has the highest exposure to foreign borrowers, lenders and currencies among the top 5 syndicated markets. Above 17.4% of the borrowers and 56% of the lenders in the UK have headquarters in a foreign country compared to only 4% to 6% of foreign borrowers and 6% to 48% of foreign banks in the US, Japan, Canada and France. 36% of all deals in the UK are carried out in a foreign currency relative to just above 1% in the US and 32% in Canada. Japan has the least international market with the lowest percentages of foreign borrowers, lenders and currencies.

[Figure 3]

Figure 3 presents additional evidence that the UK remained highly international over the past 15 years among the top 5 syndicated markets. Panel A of Figure 3 shows the percentage of foreign borrowers suggesting that the UK had a higher exposure to foreign borrowers. The US became more international over time with increased loan volume of foreign borrowers (from around 3% in 2000 to 7% in 2015). Perhaps not surprisingly, the exposure to foreign borrowers in France greatly increased after the introduction of the euro from 3% in 2000 to almost 17% in 2002, however, stabilized below 10% after that.

Panel B of Figure 3 shows that the UK mostly dominates the other large markets with respect to the percentage of foreign lenders. The UK had a share of foreign lenders of at least 45% and as high as 72% in 2000. In general, all the top 5 markets are more exposed to foreign lenders than to foreign borrowers. Japan and Canada experienced a decline in the percentage of foreign lenders of the past 20 years, while the US profited from a slight increase from 16% in 2000 to 32% in 2015. The percentage of foreign lenders in France does not exhibit a particular trend, except for the drop from 46% to 27% from 2008 to 2009 because US and UK banks, having the largest share in France, withdrew from these markets during the global financial crisis. Japan is a large but domestic market with only a small percentage of foreign borrowers or lenders.

Panel C shows the percentage of foreign-currency denominated loans in the top 5 syndicated markets. The US has the lowest percentage of foreign currency deals (below 1%) with

US dollars dominating syndicated deals worldwide. Before the 2000s, the US dollars totally dominated all the other markets, but since then, other currencies such as the Euro and UK Pounds have established increasing presence. Since 2007, the UK has the highest percentage of foreign-currency deals, while the percentage has greatly decreased for Japan and France. For Canada, the percentage of foreign-currency deals decreased between 2000 and 2007 and has increased since then. The UK market is thus the most international financial center of the top 5 syndicated loan markets (6.13% in terms of loan volume).

UK lenders are among the largest foreign capital providers in global (non-UK) syndicated loan markets with the highest presence of UK banks in the largest syndicated markets before US banks. UK banks issued only 28% of their loan volume in the UK between 2000 and 2015, and 30% in the US. UK firms issue almost 15% of their loan volume outside the UK, while US firms issue only 3% outside the US.

Overall, this section shows that the UK is the second most important market for syndicated loans with a high presence of international firms and lenders. The unanticipated announcement of an exit from the European Union and potential changes in the financial market infrastructure that come with it might have considerable consequences for the UK market. The high presence of international borrowers and lenders make the UK especially vulnerable to a quick withdrawal from their side. At the same time, UK lenders and UK firms are highly internationally active, suggesting that the effect of Brexit might spillover outside the UK market borders.

5. The Impact of Brexit on Syndicated Lending

In this section, we present results related to lending in the global syndicated loan market pre- and post Brexit-referendum. We conduct our analyses both on the market/quarter level and, using more granular data, on the sector/borrower-country/bank-quarter level that allows us to disentangle alternative explanations for changes in lending such as demand, supply and market attractiveness using a Khwaja-Mian type estimator.

5.1. Analysis on the market-quarter level

5.1.1. Methodology

We aggregate both the number of syndicated loan issuances and the volume (in US$) of syndicated loan issuances on the market-quarter level. A market is defined in terms of the country in which the syndicated loan was issued. For example, if a Norwegian bank provides a loan to a French firm in the UK market – meaning it is issued under UK law and it will typically be negotiated in London – then this is a UK market syndicated loan.

Panel A of Figure 4 provides a simple plot of the number of syndicated loan issuances in the UK over the 2014-2016 time window and compares this to the aggregate number in all other syndicated loan markets. Both the line for the UK as well as for the other markets is indexed to an average level of one for the year 2014. We can observe a substantial decline in lending in the UK syndicated loan market after the Brexit referendum: the number of issuances drops in the third quarter of 2016 even though global issuance numbers increase, and it drops significantly more for the UK market in the fourth quarter of 2016 relative to non-UK markets. Panel B of Figure 4 depicts the ratio of UK loans to non-UK loans. Again, we observe that the UK share of the global syndicated loan market drops significantly after the Brexit referendum. In both quarters, the UK market loses roughly 0.5% market share, equivalent to approximately 10% of the pre-Brexit market share of the UK syndicated loan market.

[Figure 4]

We continue by estimating the following DiD regression:

$$Y_{c,t} = \beta_1 \cdot \text{UK(0/1)} \cdot \text{PostBrexit (0/1)} + \beta_2 \cdot \text{Controls}_{\text{c,t}} + \alpha_c + \alpha_t + \varepsilon_{\text{c,t}}, \qquad (1)$$

where $Y_{c,t}$ represents either the natural logarithm of the number of syndicated loans issued in market *c* in quarter *t* or the natural logarithm of the volume of syndicated loans issued in market *c* in quarter *t*. The dummy variable UK(0/1) equals one if the loan was issued in the UK syndicated loan market and zero otherwise. The dummy variable PostBrexit (0/1) is zero for all quarters until June 2016 and equals to one from July 2016 onwards.[13] We use market and quarter fixed effects, thus providing more granular controls than simple UK(0/1) and PostBrexit(0/1) dummies. Furthermore, we weight each country by the number of loans issued over the 2014 to 2015 period, thereby ensuring that larger markets (e.g., U.S. or Germany) also receive a larger weight than smaller markets (e.g., Portugal or Romania).

5.1.2. "Siamese Twin"-matching

Until now, the control group consists of either the 49 largest syndicated loan markets worldwide or all European markets. It is not obvious which of these markets provides the best counterfactual to the UK market. In absence of the Brexit-referendum, would the UK market have developed similar as other European markets? Or similar to the US market? Or do other financial centers like Ireland, Luxembourg, Singapore, and Hong Kong provide the best counterfactual? Standard matching methods crucially rely on the ability of the econometrician to observe all outcome-relevant determinants (Roberts and Whited, 2012). They further require the researcher to choose among a potentially large set of variables (in our case, for example, geographical location, financial center status, or size of the market) with no objective measure of which of these variables works best.

We therefore propose a novel method that matches on the *path* of *outcome* variables. By matching on the path of the outcome variable, we implicitly match on any important variable that affects outcomes. In particular, for each market c we calculate the correlation between the logarithm of the number of quarterly syndicated loan issuances in the UK and the logarithm of the number of quarterly syndicated loan issuances in market c:

[13] The Brexit referendum was on June 23rd 2016. Dropping the June observations or defining June as a Post-Brexit month does not affect our results.

$$\rho_c = \rho\left(Y_{c,t}, Y_{UK,t}\right), \tag{2}$$

We then sort countries by correlation with the UK market for the pre-Brexit period of 2000-2015 as well as of the 2011-2015 period. Appendix A provides a methodological background and compares our methodology to the synthetic control estimator by Abadie, Diamand, and Hainmueller. Table 2 provides the results.[14]

[Table 2]

Over the full 2000-2015 period, France, Germany and the US exhibit the largest correlation with the UK market. These three countries are followed by Italy, Netherlands, Australia, Norway, Spain, Canada, and Sweden. Interestingly, the Top 10 countries over the 2000-2015 period are very similar to the Top 10 countries over the 2011-2015 period: only two countries, Hong Kong and Turkey enter the Top 10 over the 2011-2015 period and these two countries are ranked No. 9 and No. 10. This suggests that those countries that track the number of issuances in the UK closely were rather stable over the pre-Brexit period. It is also comforting to see that the countries at the bottom of the list (Philippines, Argentina, Columbia, Malaysia and Portugal) are countries which are very different from the UK market in many respects. In the following, we label the Top 10 markets over the 2000-2015 period "Siamese Twin Markets" to the UK market and use these as our control group in most of the following specifications.

[14] We find similar results when matching based on the paths of changes in the logarithm of quarterly loan issuance (instead of levels). Furthermore, note that a correlation coefficient is invariant to scaling (i.e., x and βx are perfectly correlated) and our approach might therefore match other markets to the UK market which have a similar, but more (or less) volatile development. We therefore repeat the matching using sum of squared differences between the UK path of the outcome variable and other markets. Results are very similar, with 8 out of the top 10 matches using correlation coefficient also being among the top 10 matches using squared differences.

5.1.3. Results

Column (1) of Table 3 provides the results using the natural logarithm of the number of loans as dependent variable.

[Table 3]

Consistent with the descriptive evidence in Figure 4, the coefficient on the interaction term between the UK-dummy and the Post-Brexit dummy is -0.210 ($p<0.01$). This suggests that the number of loan issuances in the UK market Post-Brexit referendum decreases by exp(-0.210)-1= -19% more than in the other 49 markets worldwide, which is a statistically and economically large effect. Column (2) further controls for *country x quarter-of-the-year* fixed effects that accounts for any potential differences in loan market seasonality in the UK vs. other loan markets (Murfin and Petersen (2016)). This is important as our post-Brexit-referendum period does not include a full calendar year but only the two quarters from July-December. Reassuringly, results hardly change. Column (3) uses only European countries as a control group. Again, the results point to a significant decrease in the number of UK issuances post Brexit.

In Panel B of Table 3, we repeat the same analysis using the natural logarithm of the loan volume instead of the number of loans as our dependent variable. While the results are similar to Panel A, they are somewhat noisier as loan volumes are usually driven by a few number of very large loans. All loan volumes are in US$, the results from Panel B are thus also affected by the drop in the GBP relative to the US$ after the Brexit referendum. In the following analysis, we therefore focus on the number of issuances to understand the effect of the Brexit referendum on global syndicated loan markets.

Column (4) in Panel A and B of Table 3 report results using the 10 Siamese Twin markets as a control group. Again, in Panel A we use the natural logarithm of the number of loan issuances as dependent variable. The effect of the Brexit referendum is similar to the baseline result with a coefficient of -0.260 ($p<0.01$), suggesting that our results are robust to excluding markets from the control group that have historically not shown a similar time series pattern as the UK market. This effect extends to Panel B and using the natural logarithm of the loan volume as dependent variable. Overall, our benchmark results suggest that the Brexit referendum caused a massive decline in lending in the UK market relative to other syndicated loan markets.

5.2. Disentangling demand, supply, and attractiveness of UK financial market

The analysis on the country-quarter level provides first evidence how the Brexit referendum affects the global syndicated loan market. However, the results are consistent with a variety of explanations: a demand narrative (UK firms having lower credit demand as a consequence of the Brexit referendum), a credit supply narrative (UK banks cutting credit supply), or an explanation based on a decrease in the attractiveness of the UK financial market to originate loans.

5.2.1. Univariate tests

Before turning to the regression analysis, simple univariate analysis provides first insights into the effect of the Brexit referendum on firms, banks and markets. Panel A of Table 4 shows the average loan amount in US$ millions on the loan issuance level for the pre- and post-Brexit period as well as the all loans. Table A.1 in the Appendix reports definitions of the variables.

[Table 4]

33,049 loans have been issued in the period 2014-2016 where 27,420 loans have been issued in the pre-Brexit period and 5,269 in the post-Brexit period. The average size of a loan is US$ 335 million. Panel A also reports that 7% of loans were issued to UK firms, 17% of loans were issued by UK banks and 7% were issued in the UK syndicated market.

Panel B of Table 4 shows the average probability of loan issuance on *firm cluster x bank x market x quarter* level for the period between the 2014 Q1 and 2016 Q4.[15] The sample consists of

[15] Note that we only use combinations of firm cluster – bank – market that occured at least once in our sample in order to calculate the probability of loan issuance for such a combination for each quarter.

296,700 observations on *firm cluster x bank x market x quarter* level for 2,179 firm-clusters from 867 banks in 11 markets. The post period is defined as of June 24, 2016.[16] The first row shows the average probability of loan issuance for the pre- and post-Brexit which is around 16% without any significant difference. The next rows distinguish the probability of loan issuance by firm domicile, bank domicile and syndicated loan market. We find a significant decrease in the probability of loan issuance between 4 and 5 percentage points for UK firms, UK banks and in the UK market. The effect corresponds to a 25% to 31% decline relative to the unconditional average probability of 16%, which is similar to the country-level effect we have seen in chapter 5. For non-UK firms, non-UK banks and the other markets, we even find a significant but small increase in the Brexit period, resulting in a difference-in-difference effect between 4 and 5 percentage points. The regression analysis will reveal whether the observed effect is coming from the demand side, supply side or simply the attractiveness of the UK market.

5.2.2. Methodology

In the following, we use a modified Khwaja and Mian (2008) estimator to disentangle those alternatives. In particular, we aggregate firms into clusters based on their industry (3-digit SIC code) and firm domicile and construct a new variable $Pr(Loans)_{f,b,m,t}$, which is the probability that a firm-cluster f receives a loan by bank b in market m in quarter t.[17] We focus on the probability that a loan is originated instead of loan volume to avoid confounding effects, e.g. due to a devaluation of the British pound. Aggregating firms into *industry x country* clusters accommodates the fact that syndicated loan issuances are less frequent on the firm level. Our

[16] Note that since the post Brexit period is defined as of June 24, 2016, we count these observations to the third quarter of 2016.

[17] If we do not observe a loan issuance in firm-cluster f by bank b in market m in quarter t, then $Loans_{f,b,m,t}$ is equal to zero. Firm-cluster/bank/market combinations that have zero issuances in every single quarter are dropped as they would be absorbed by our fixed effects anyway.

implicit assumption is thus that firm demand shocks operate on the *industry x borrower-country* level.

[Figure 5]

Figure 5 illustrates our empirical approach to disentangle the different narratives. Suppose Firm 1 borrows from Bank A (e.g., a US bank) and Bank B (e.g., a UK bank) in the pre-Brexit period but only from Bank A in the post-Brexit period. In the first step, we use the within-firm Khwaja Mian (2008) estimator to disentangle loan demand from loan supply. In other words, Firm 1 continues to have demand for loans but only receives a loan from Bank A. Bank B reduces its supply of loans. This approach allows us to evaluate whether loan originations decreased more for UK lenders ("treated banks") than for non-UK lenders ("control banks") after the Brexit referendum, thereby controlling for changes in loan demand via firm-cluster fixed effects (η_f):

$$\Delta \Pr(Loans)_{f,b,m} = \beta \cdot UKLender(0/1) + \eta_f + \varepsilon_{f,b,m}, \qquad (3)$$

where *UKLender(0/1)* is a dummy equal to one for UK lenders. Following Betrand, Duflo, and Mullainathan (2004), we collapse our data on a *firm cluster x bank x market* level into a pre- and post-period to account for possible autocorrelation in the standard errors. We denote by $\Delta\Pr(Loans)_{f,b,m}$ the change in the probability of loan issuance in the pre Brexit period versus the post Brexit period. A negative β implies that UK lenders experienced a higher drop in the probability of loan issuance than non-UK lenders after controlling for loan demand via firm-cluster fixed effects.

In the second step, we extend the Khwaja Mian (2008) approach to the market level. The treated market is the UK market (i.e., loans issued under UK law) and the control group consists of all other markets. Figure 5 also illustrates this idea. Now, Firm 1 borrows in Market I (e.g., US) and Market II (e.g., UK) in the pre-Brexit period but in the post-Brexit period only borrows in Market I. This approach allows us to evaluate whether loan originations decreased more in the UK market than in other markets after the Brexit referendum, thereby controlling for changes in loan demand via firm-cluster fixed effects:

$$\Delta \Pr(Loans)_{f,b,m} = \beta \cdot UKMarket(0/1) + \eta_f + \varepsilon_{f,b,m}, \qquad (4)$$

where *UKMarket(0/1)* is a dummy equal to one for the UK syndicated market. A negative β implies that the probability of loan issuance decreases by more in the UK syndicated market compared to other syndicated markets after controlling for loan demand via firm-cluster fixed effects.

In the third step, we extend the Kwaja-Mian approach to simultaneously account for firm demand shocks and bank supply shocks. The last row of Figure 5 illustrates the key idea. Suppose that Firm 1 borrows from Bank A in both Market I (for example, US) as well as in Market II (for example, UK) before the Brexit referendum. Further, suppose that Firm 1 continues to borrow from Bank A after the Brexit referendum, however, only in Market I. Neither demand effects (Firm 1 continues to borrow after the referendum) nor supply effects (Bank A continues to lend after the referendum) can explain the example. If this pattern occurs systematically across the data set, this would be a clear indication of Market II losing attractiveness as a place to originate loans. We therefore regress changes in the probability of loan issuances on *firm cluster* and *bank* fixed effects:[18]

[18] Taken literally, the example above implies using *firm x bank* fixed effects. A specification with *firm x bank* fixed effects allows for firm-specific bank supply shocks, while our specification with firm and bank fixed effects assumes that bank supply shocks occur on the bank level.

$$\Delta \Pr(Loans)_{f,b,m} = \beta \cdot UKMarket(0/1) + \eta_f + \eta_b + \varepsilon_{f,b,m} \qquad (5)$$

A negative β implies that loan issuance decreases more for the UK market than for other markets after controlling for loan demand via firm-cluster fixed effects and for loan supply via bank fixed effects.

5.2.3 Multivariate results

Results are presented in Table 5 using only the Siamese Twin countries discussed in the last section. We cluster standard errors on bank level for all regressions. Panel A shows regression results for the supply effect as in equation (3), relying on Khwaja Mian (2008) to control for demand side effect, while Panel B presents regression results for the market attractiveness narrative as in equations (4) and (5), controlling gradually for both demand and supply effects.

[Table 5]

The first column of Panel A reports baseline regression results without fixed effects. In column (2) we add firm cluster fixed effects and in column (3) we distinguish by firm domicile. Results suggest that UK lenders reduce loan issuance by more than non-UK lenders, consistent with univariate results in Table 4. In column (1) of Panel A, we observe a negative and highly significant effect of the UK lender dummy (-5%, $p<0.01$). Once we control for demand side shocks with firm cluster fixed effects, the main effect reduces to 4 percentage points and becomes a bit less significant ($p<0.05$). UK banks reduced their loan issuance by almost 25% more than non-UK banks relative to an average probability of loan issuance of 16% - an economically large effect. Since the main coefficient reduces once we introduce firm cluster fixed effects, part of the reduced loan issuance by UK banks can be attributed to demand side effects.

In column (3), we interact the UK lender dummy with an indicator for non-UK firms such that our main UK lender dummy captures the effect for UK lenders and UK firms post-Brexit. The coefficient becomes more significant and increases to 5 percentage points, indicating that

UK lenders reduce their loan issuance to UK firms by more than non-UK lenders to UK firms. Since the interaction term of the UK lender dummy with the non-UK firm dummy is not significant, it implies that UK lenders reduce their loan issuance independent of the firm domicile.

So far, it seems that UK lenders reduced their loan issuance post-Brexit by more than other lenders, controlling for firm demand. However, we might observe a negative effect because the same lender, in general, reduces its loan issuance to the same firm in the UK market but continues to lend to the same firm in another market. We capture such market attractiveness effects by regressing the change in the probability of loan issuance on the UK market dummy, controlling for both demand and supply effects. Panel B of Table 5 presents results for the baseline regressions without any fixed effects in column (1) and then gradually introduces firm cluster fixed effects in column (2) and bank fixed effects in column (3).

Similar to the univariate results in Table 4, the probability of loan issuance decreases by 5 percentage points more for the UK market relative to other markets ($p<0.01$). This effect corresponds to an almost 30% higher decline in the probability of loan issuance relative to other markets, given an average loan probability of 16%. When we add firm cluster fixed effects in column (2) of Panel B, the effect more than halves to 1.7 percentage points ($p<0.05$), implying a relative reduction by 1.7/16=11%. This suggests that part of the reduced loan issuance in the UK market is driven by a reduced demand for loans. Adding bank fixed effects in column (3), only slightly reduces the main effect to 1.1 percentage points ($p<0.18$), or 1.1/16=7% in relative terms. Reduced loan issuance in the UK market seems not to be driven by reduced loan supply by banks that were particularly active in the UK market. This is consistent with the fact that UK banks reduce their loan volume similarly in the UK and in non-UK markets. The UK market seems to lose its attractiveness relative to other markets, controlling for both demand and supply effects, albeit these results are marginally statistically insignificant when looking at only two quarters post-Brexit.

6. Discussion and Conclusion

In this paper, we investigate the effect of the Brexit referendum on the UK syndicated loan market. We find that the number and volume of issuances in the UK syndicated loan market dropped by 20% after the Brexit referendum relative to a set of comparable syndicated loan markets. Looking at the cross-section, we document the following results: first, the decline is concentrated in lending to domestic firms and by domestic banks. Second, we only observe a small and insignificant decline in lending by international firms and from international banks in the UK syndicated loan market. Taken together, these results suggests that the Brexit referendum primarily affected UK banks and borrowers with – so far – limited consequences for international activities in the UK syndicated loan market.

On the methodology side, we propose a novel matching technique to identify a suitable control group. We argue that syndicated loan markets that have followed a similar path (in terms of number of issuance and issuance volume) as the UK syndicated loan market before the Brexit referendum are likely to be the best counterfactuals for the UK market. Our method thus boils down to matching on the pre-event path of the outcome variable, and choosing the best matches as the control group. This methodology yields France, Germany, USA, Italy, the Netherlands, Australia, Norway, Spain, Canada, and Sweden as the best control countries for the UK. The matching method extends the synthetic control methods and is potentially applicable in other Panel data applications as well.

Our paper provides some initial evidence on the effects of Brexit on the UK as a financial center looking at the first six months after the Brexit referendum. Effects in the coming months are likely to depend on the specific paths chosen by the UK government as well as the actions by national and international banks. Furthermore, while we look at one important market – the syndicated loan market – further research might investigate other markets and players such as bonds, equities, or derivatives markets. The Brexit decision was clearly a disruptive event to the UK financial markets. Given the importance of the UK financial sector both for the UK as well as for international borrowers and lenders, understanding the implications of Brexit on the UK financial services industry is of major importance for the UK and beyond.

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Table 1: Descriptive Statistics of the Top 20 Syndicated Loan Markets

This table reports statistics for the top 20 syndicated loan markets ordered by their total loan volume between 2000 and 2015. "Rest of the World" captures the remaining 140 countries and "Total" the sum of a column. The first column shows country names. The second and third columns show the total volume in 2015 US$ billions between 2000 and 2015 as well as the total number of deals. The next two columns show a country's share in the total loan volume and the cumulative share in the total loan volume. The next column shows the average loan amount in 2015 US$ millions. The last three columns show the percentage of foreign borrowers, of foreign lenders and of foreign-currency denominated loans based on the total loan volume between 2000 and 2015 of the respective country. Note that loan volume is winsorized at the 1% and 99% percentiles.

	Country of Syndication	Total Loan Volume in 2015 US$ billions	Number of Observations	Percentage of Total Loan Volume	Cum. Percentage of Total Loan Volume	Av. Loan Amount in 2015 US$ millions	% of Foreign Borrowers	% of Foreign Lenders	% of Foreign Currencies
1	USA	24,416	86,278	48.92	48.92	283.01	5.72	24.24	1.15
2	Japan	3,604	28,378	7.22	56.14	127.09	4.19	6.24	7.53
3	United Kingdom	3,107	8,147	6.23	62.37	383.75	17.38	56.35	35.47
4	Canada	1,965	6,489	3.94	66.31	302.90	4.56	16.12	31.71
5	France	1,878	5,332	3.76	70.07	354.94	6.42	47.83	7.15
6	Germany	1,721	5,209	3.45	73.52	332.57	7.24	55.42	9.99
7	Australia	1,209	5,023	2.42	75.94	242.06	12.22	38.6	20.42
8	Spain	1,046	3,694	2.10	78.04	283.90	9.65	48.98	10.4
9	China	874	3,189	1.75	79.79	274.75	12.42	14.31	21.29
10	Netherlands	777	2,060	1.56	81.35	378.41	22.91	74.64	27
11	Hong Kong	708	2,641	1.42	82.76	268.54	29.98	93.39	47.19
12	India	657	3,033	1.32	84.08	217.11	10.83	28.59	40.02
13	Italy	654	2,274	1.31	85.39	287.95	17.32	59.37	3.95
14	Taiwan	508	5,486	1.02	86.41	93.10	12.58	11.36	27.01
15	Switzerland	511	729	1.02	87.44	703.43	18.6	85.55	82.35
16	Russia	469	1,388	0.94	88.38	338.67	15.38	87.53	95.88
17	Singapore	370	1,609	0.74	89.12	231.04	34.39	65.91	50.07
18	Sweden	374	889	0.75	89.87	425.10	7.09	74.05	64.87
19	Korea (South)	347	2,493	0.70	90.56	140.47	11.99	32.58	48.77
20	Norway	318	1,073	0.64	91.20	296.95	29.69	61.55	74.65
	Rest of World	4,392	16,010	8.80	100	275.44	15.01	86.62	
	Total	49,908	191,424	100					

Table 2: Siamese Twins for the UK Syndicated Loan Market

This table provides correlations of the time series of the logarithm of the number of issuances in the UK syndicated loan market with time series of the logarithm of the number of issuances in other markets. The analysis is based on 49 syndicated loan markets worldwide. The 10 markets with the highest correlation with the UK market as well as the 5 markets with the lowest correlation with the UK market are shown in the table below. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	Time period: 2000-2015			**Time period: 2011-2015**	
Rank	Market	Correlation with UK market	Rank	Market	Correlation with UK market
0	United Kingdom	1.00***	0	United Kingdom	1.00***
1	France	0.64***	1	Canada	0.44***
2	Germany	0.58***	2	France	0.43***
3	USA	0.53***	3	Netherlands	0.41***
4	Italy	0.53***	4	Spain	0.40***
5	Netherlands	0.48***	5	Italy	0.40***
6	Australia	0.48***	6	Norway	0.40***
7	Norway	0.48***	7	Germany	0.39***
8	Spain	0.46***	8	USA	0.39***
9	Canada	0.45***	9	Hong Kong	0.36***
10	Sweden	0.41***	10	Turkey	0.35***
…			…		
45	Portugal	-0.03	45	Columbia	-0.02
46	Malaysia	-0.03	46	Kazakhstan	-0.03
47	Columbia	-0.10	47	Romania	-0.07
48	Argentina	-0.16**	48	Greece	-0.12
49	Philippines	-0.20***	49	Russia	-0.29**

Table 3: Loan Issuance post-Brexit – Aggregate Data on the Market/Quarter Level

This table provides results of a difference-in-differences regression of the log number of loan issuance (Panel A) and log loan volume (Panel B) on a UK x Post-Brexit dummy as well as time and market fixed effects. The UK(0/1) dummy is equal to one for issuances in the UK market, defined as issuances under UK law. The analysis is based on collapsed data on the market-quarter level using data from January 2014 to December 2016. Column (1) provides baseline results, column (2) controls for country-specific loan market seasonality, column (3) limits the control group to European countries, and column (4) limits the control group to the Top 10 Siamese Twin countries as listed in Table 2. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Log Number of Loan Issuances (Q1/2014 – Q4/2016)

	(1) Baseline	(2) Controlling for seasonality	(3) Control group: Europe	(4) Control group: Top 10 Siamese Twins
UK(0/1) x PostBrexit(0/1)	-0.210*** (-2.87)	-0.232*** (-2.71)	-0.334*** (-3.91)	-0.260*** (-2.98)
Country fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Country x Quarter-of-the-year fixed effects	No	Yes	Yes	Yes
Observations (Country-quarters)	612	612	192	132
Adjusted R2	0.965	0.984	0.924	0.989

Panel B: Log Loan Volume (Q1/2014 – Q4/2016)

	(1) Baseline	(2) Controlling for seasonality	(3) Control group: Europe	(4) Control group: Top 10 Siamese Twins
UK(0/1) x PostBrexit(0/1)	-0.179* (-1.92)	-0.239*** (-2.83)	-0.181* (-1.92)	-0.308*** (-2.94)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country x Quarter-of-the-year fixed effects	No	Yes	Yes	Yes
Observations (Country-quarters)	612	612	192	132
Adjusted R2	0.957	0.965	0.855	0.983

Table 4: Loan Issuance post-Brexit – Univariate Analysis

This table provides summary statistics on the loan issuance level in Panel A and on firm cluster – bank – market –quarter level in Panel B from January 2014 to December 2016. Panel A shows the average loan amount in US$ millions, the percentage of loans by UK firms, UK lenders and in the UK market pre- and post-Brexit as well as for the total sample. Panel B shows the average probability of loan issuance for a firm cluster – bank – market combination in a quarter collapsed to the pre- and post-Brexit period. The probability is then split between UK and non-UK firms, UK and non-UK lenders as well as in the UK Market and non-UK Markets. Column "Post-Pre" shows the difference between the pre- and post-Brexit average probability of loan issuance. Column "Diff-in-Diff" shows the difference in the difference between the pre and post period for UK vs. non-UK firms, lenders or markets. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Loan Issuance Level

	Pre Brexit			Post Brexit			Total		
	Mean	Std	Obs	Mean	Std	Obs	Mean	Std	Obs
Loan amount in US$ millions	338	880	27,343	323	892	5,611	335	882	32,954
UK Firm (0/1)	0.072	0.26	27,420	0.05	0.22	5,629	0.07	0.25	33,049
UK Lender (0/1)	0.172	0.38	27,420	0.14	0.35	5,629	0.17	0.37	33,049
UK Market (0/1)	0.074	0.26	27,420	0.06	0.24	5,629	0.07	0.26	33,049

Panel B: Firm Cluster - Bank - Market - Quarter Level

	Pre Brexit			Post Brexit			Post-Pre	Diff-in-Diff
	Mean	Std	Obs	Mean	Std	Obs	Difference	UK vs. Non-UK
Pr(Loan)	0.163	0.369	247,250	0.165	0.371	49,450	-0.00163	
Pr(Loan) by Firm Domicile								
UK Firms	0.142	0.349	27,650	0.102	0.302	5,530	-0.0403***	-0.0472***
non-UK Firms	0.166	0.372	219,600	0.172	0.378	43,920	0.00690***	
Pr(Loan) by Bank Domicile								
UK Lenders	0.172	0.377	16,898	0.127	0.333	3,420	-0.0447***	-0.0504***
non-UK Lenders	0.162	0.369	230,352	0.167	0.373	46,030	0.00507***	
Pr(Loan) by Market								
UK Market	0.135	0.342	32,750	0.098	0.297	6,550	-0.0370***	-0.0446***
non-UK Markets	0.167	0.373	214,500	0.175	0.38	42,900	0.00753***	

Table 5: Loan Issuance post-Brexit – Isolating Demand, Supply and Market Attractiveness

This table provides results of difference-in-differences regressions of the change in the probability of loan issuance pre and post Brexit on a UK lender dummy (Panel A) and a UK market dummy (Panel B). The analysis is based on data on firm cluster-bank-market-quarter level between 2014 Q1 and 2016 Q4 that is collapsed to a pre and post Brexit period. Column (1) of Panel A presents baseline results with a UK Lender dummy; column (2) controls for the demand side with firm cluster fixed effects; and column (3) interacts the UK Lender dummy with a non-UK firm dummy. Column (1) of Panel B presents baseline results with a UK Market dummy; column (2) controls for the demand side with firm cluster fixed effects; and column (3) additionally controls for the supply side with bank fixed effects. The Top 10 Siamese Twin countries as listed in Table 2 constitute the control group. Standard errors are clustered at bank level. Robust *t*-statistics are presented in parentheses and ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Supply Effect

	(1) Baseline	(2) Khwaja Mian (2008)	(3) Khwaja Mian (2008) by firm domicile
UK Lender (0/1)	-0.050***	-0.038**	-0.049***
	(-3.28)	(-2.52)	(-4.57)
UK Lender (0/1) × non-UK Firm (0/1)			0.015
			(0.59)
Firm Cluster Fixed Effects	No	Yes	Yes
Firm Clusters	2,179	2,179	2,179
Banks	867	867	867
Markets	11	11	11
Observations	24,725	24,725	24,725
R2	0.002	0.315	0.315
Unconditional Pr(Loan)	16%	16%	16%

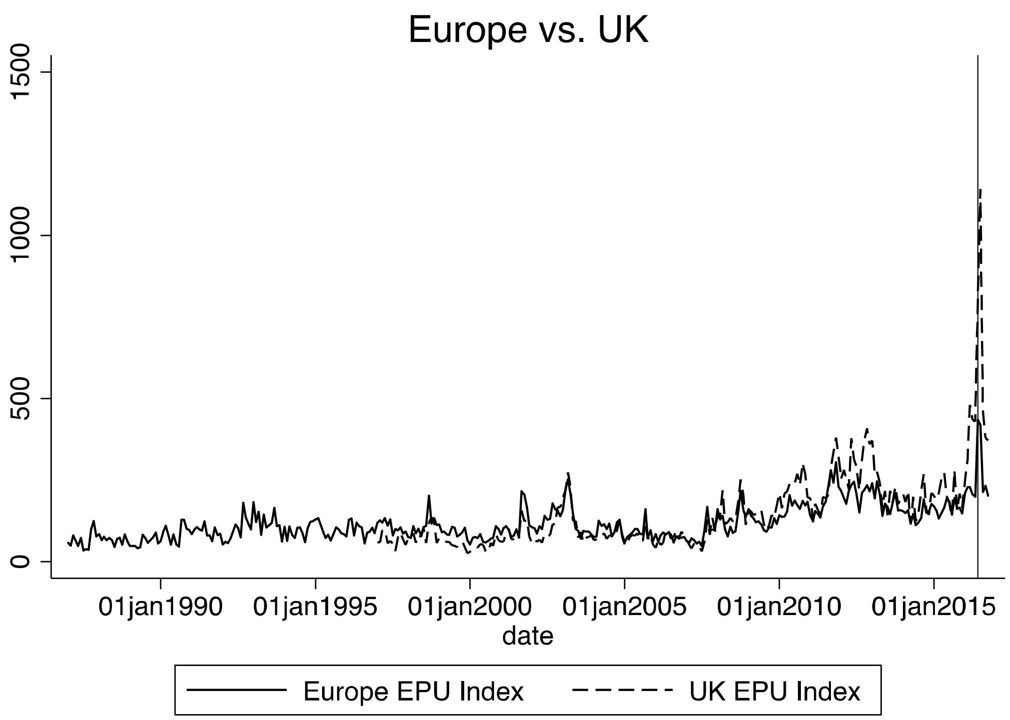
Panel B: Market Attractiveness

	(1) Baseline	(2) Khwaja Mian (2008)	(3) Extended Khwaja Mian (2008)
UK Market (0/1)	-0.045***	-0.017**	-0.011
	(-7.56)	(-2.31)	(-1.33)
Firm Cluster Fixed Effects	No	Yes	Yes
Bank Fixed Effects	No	No	Yes
Firm Clusters	2,179	2,179	2,179
Banks	867	867	867
Markets	11	11	11
Observations	24,725	24,725	24,725
R2	0.003	0.314	0.353
Unconditional Pr(Loan)	16%	16%	16%

Figure 1: Political Uncertainty around Brexit

This figure shows the time-series of the Economic Policy Uncertainty Index based on Baker, Bloom and Davis (2016) for Europe and UK (Panel A) and for US (Panel B) from January 1987/1985 until October 2016.

Panel A



Panel B

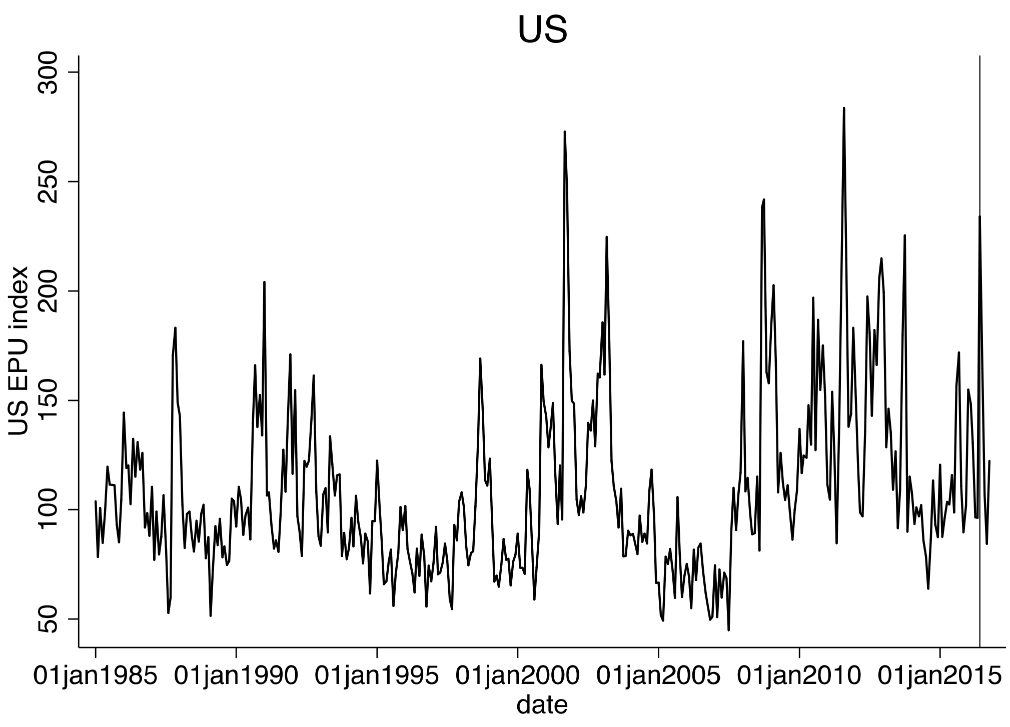
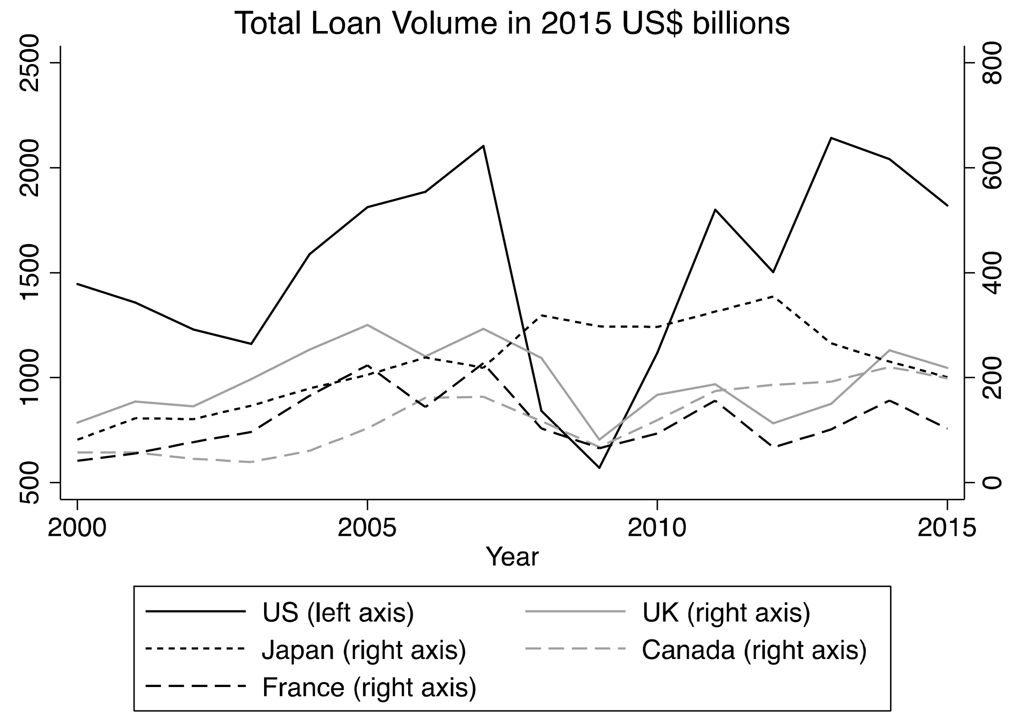


Figure 2: Top 5 Syndicated Markets

This figure shows the annual total loan volume in the global syndicated loan market in 2015 US$ millions between 2000 and 2015 (based on US CPI index). Panel A shows total loan volume for the top 5 syndicated loan markets. Panel B shows the percentage of total loan volume in the global syndicated loan market for each respective country. The values for the US are always on the left axis and for the other countries on the right axis. Note that loan volume is winsorized at the 1% and 99% percentiles.

Panel A



Panel B

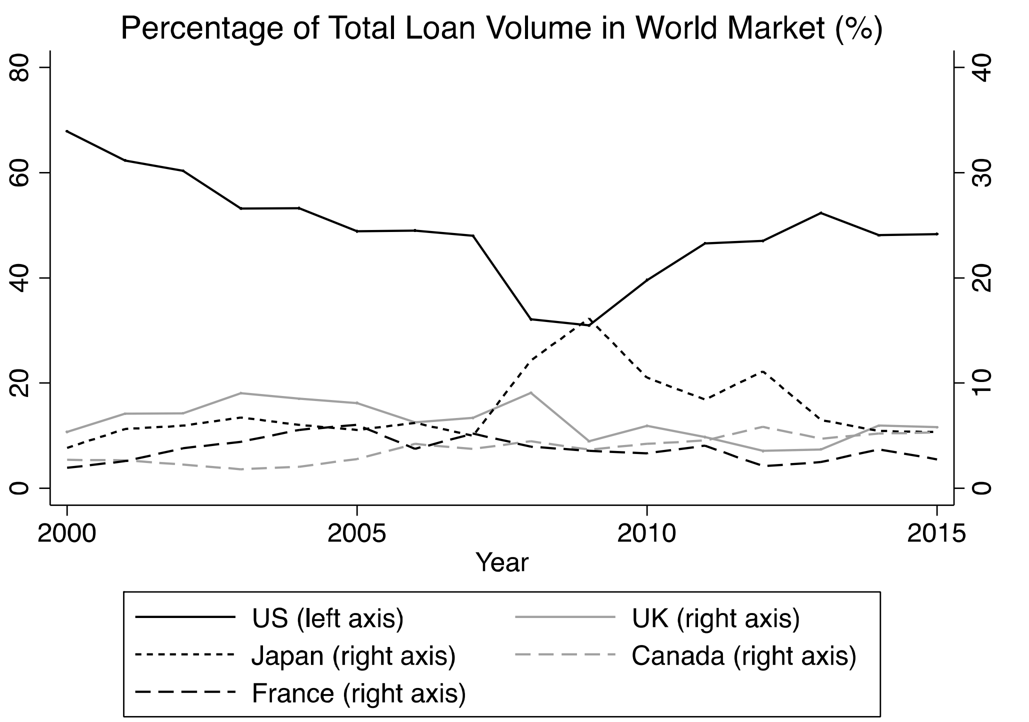
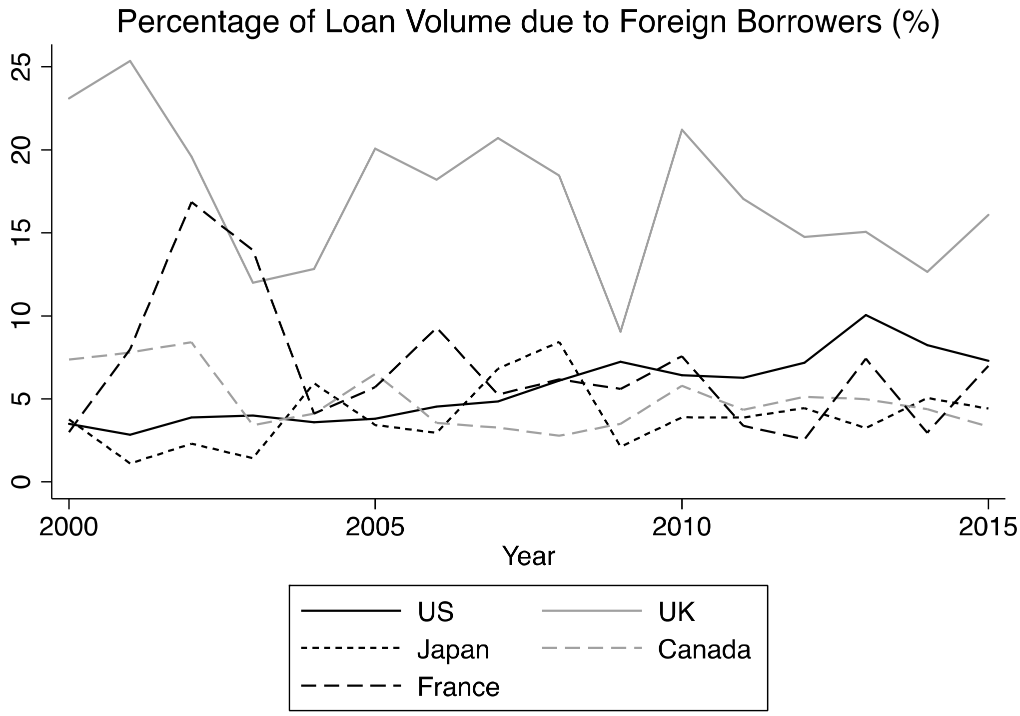


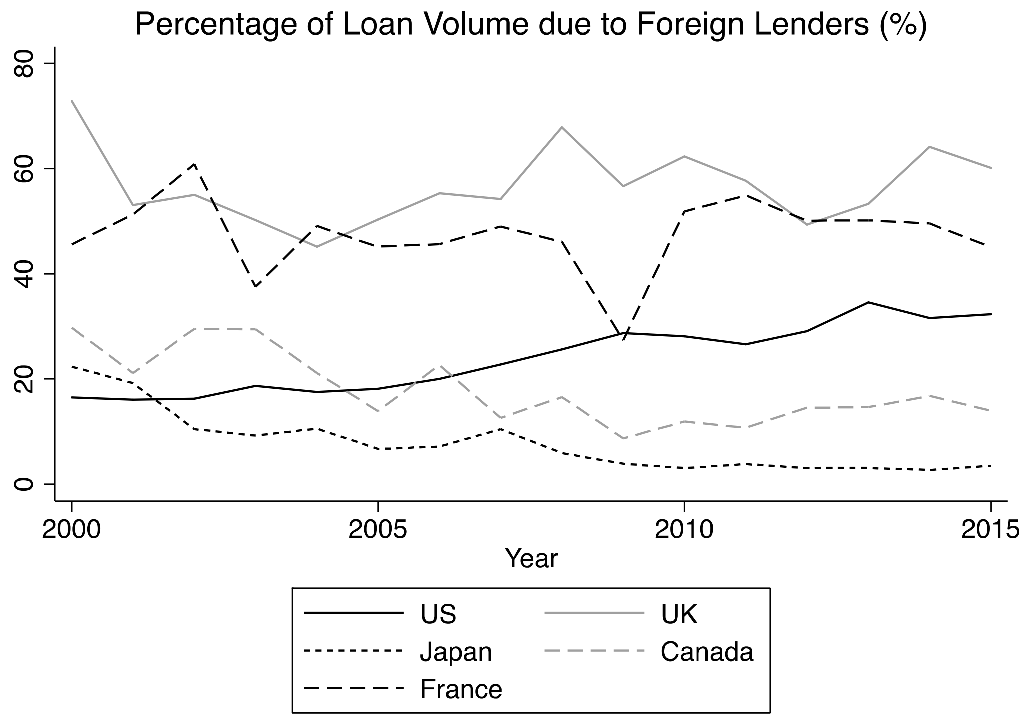
Figure 3: Top 5 Syndicated Markets and Foreign Exposure

This figure shows the exposure of the top 5 syndicated markets to foreign borrowers, foreign lenders and foreign currencies from 2000 to 2015. Panel A shows the annual percentage of loan volume due to foreign borrowers. Panel B shows the annual percentage of loan volume due to foreign lenders. Panel C shows the annual percentage of loan volume due to foreign currencies. Note that loan volume is winsorized at the 1% and 99% percentiles.

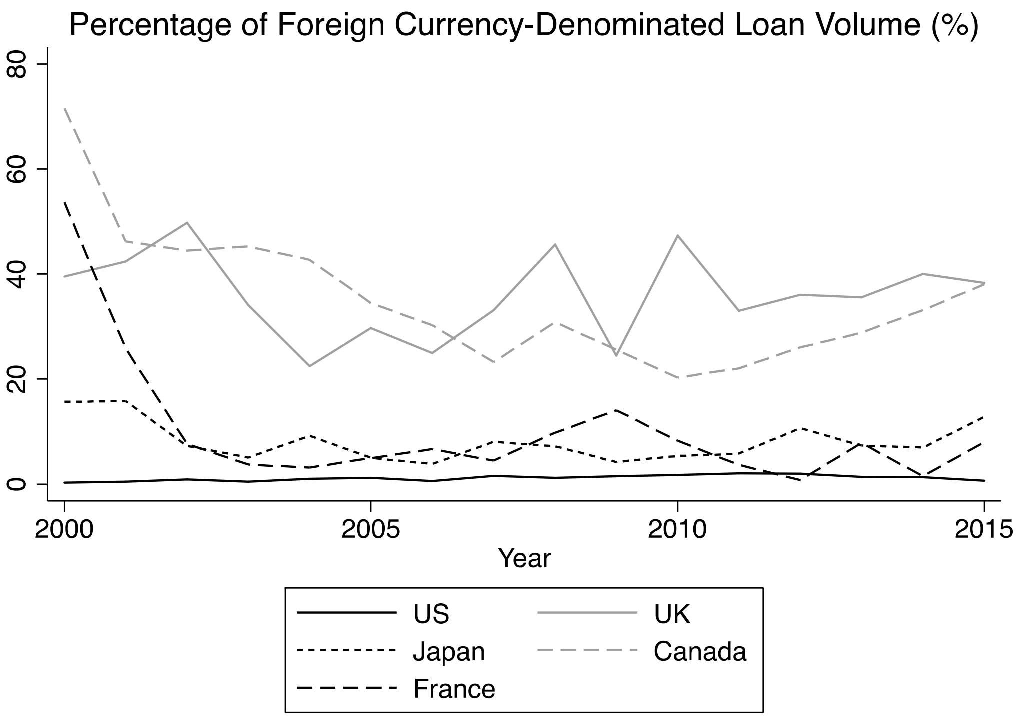
Panel A



Panel B



Panel C

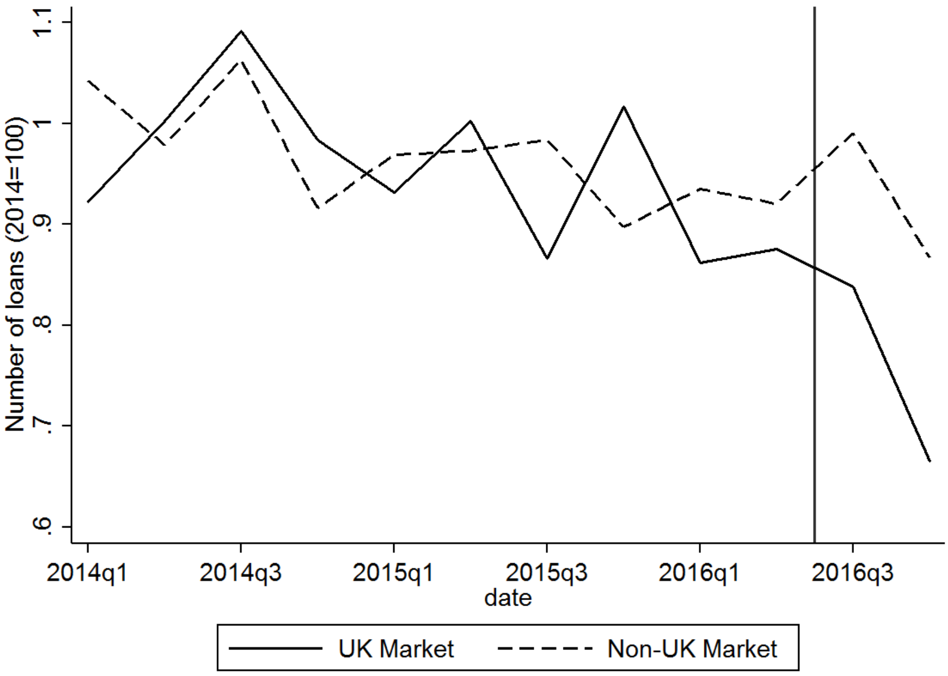


Percentage of Foreign Currency-Denominated Loan Volume (%)
0
20
40
60
80
2000
2005
2010
2015
Year
US
UK
Japan
Canada
France

Figure 4: Size of Syndicated Loan Market before and after Brexit

This figure compares the number of loans issued in the UK syndicated loan market to the number of loans issued in other syndicated loan markets over the 2014-2016 time period. The number of loans is indexed to an average level of 1 in the year 2014.

Panel A: Development of number of loans (indexed to 1 for 2014)



Panel B: Share of UK market as a percentage of worldwide syndicated loan market

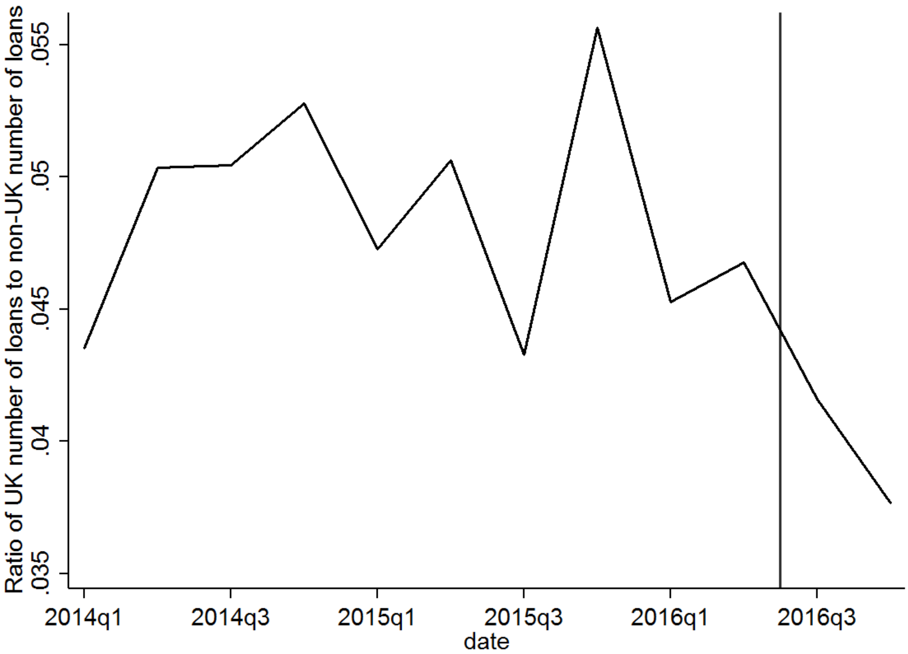


Figure 5: Identification Approach

This figure shows the main identification approach to disentangle demand side and supply side factors as well as market attractiveness to examine the changes in the probability of loan issuance pre- and post-Brexit. Each picture corresponds to equations (3), (4), (5), respectively.

Pre-Period		Post-Period	
Firm 1 Bank A Firm 1 Bank B	→	Firm 1 Bank A	Khwaja Mian
Firm 1 Market I Firm 1 Market II	→	Firm 1 Market I	Khwaja-Mian applied to markets
Firm 1 Bank A Market I Firm 1 Bank A Market II	→	Firm 1 Bank A Market I	Khwaja-Mian within firm x bank

Table A.1: Definition of Variables

Variable	Source	Description
Main Dependent Variable		
Pr(Loan)		The probability of loan issuance in a firm cluster - bank - market combination in a quarter.
Main Independent Variables		
Post Brexit (0/1)		Equals one if a loan has been issued after June 23rd and zero otherwise.
UK Market (0/1)	Dealscan	Equals one if the country of syndication is the United Kingdom and zero otherwise.
UK Firm (0/1)	Dealscan	Equals one if the domicile of the ultimate firm parent is located in the United Kingdom and zero otherwise.
UK Lender (0/1)	Dealscan	Equals one if the domicile of the ultimate lender parent is located in the United Kingdom and zero otherwise.
General Loan Characteristics		
Revolver (0/1)	Dealscan	Loans with type “Revolver/Line < 1 Yr.”, “Revolver/Line >= 1 Yr.”, “364-Day Facility”, “Limited Line” or “Revolver /Term Loan” as indicated in the facility table in Dealscan.
Term Loan (0/1)	Dealscan	Loans with type “Term Loan”, “Term Loan A”-“Term Loan H” or “Delay Draw Term Loan” as indicated in the facility table in Dealscan.
Other Loan (0/1)	Dealscan	Loans that are not classified as either term loans or revolver.
Large Loan (0/1)	Dealscan	Equals one if a loan is above the median (mean) loan amount in a given month of a given country.
Price Terms		
AISD	Dealscan	All-In-Spread-Drawn, defined as the sum of the spread over LIBOR or EURIBOR plus the facility fee.
AISU	Dealscan	All-In-Spread-Undrawn, defined as the sum of the facility fee and the commitment fee.
Spread	Dealscan	Spread over LIBOR, paid on drawn amounts on credit lines.
Facility Fee	Dealscan	Fee paid on the entire committed amount, regardless of usage.
Commitment Fee	Dealscan	Fee paid on the unused amount of loan commitments.
Upfront Fee (UF)	Dealscan	Fee paid upon completion of a syndicated loan.
Utilization fee (UTF)	Dealscan	Fee paid on the entire drawn amount once a certain usage threshold has been exceeded.
Cancellation fee (CAF)	Dealscan	Fee paid if the syndicated loan is cancelled before maturity
Total Cost of Borrowing (TCB)	Dealscan	Total cost of borrowing taking into account the spread, the facility fee, the commitment fee, the letter of credit fee, the utilization fee, the cancellation fee and the upfront fee
Non-Price Terms		
Loan Amount in US$ millions	Dealscan	Facility amount in USD mn as indicated in the field FacilityAmt in the facility table in Dealscan.
Maturity in Months	Dealscan	Loan maturity in months.
Secured (0/1)	Dealscan	Equals one if a loan is secured by collateral and zero otherwise.

Appendix

A. Siamese Twin Matching – Methodology

Notations and difference-in-differences estimator

Suppose that the outcome variable $Y_{i,t}$ is given by a linear factor model with K factors:

$$Y_{i,t} = \rho D_{i,t} + \sum_{k=1}^{K} \beta_{i,k} \lambda_{k,t} + \varepsilon_{i,t} \quad , \varepsilon_{i,t} \text{ i.i.d.} \tag{1}$$

where ρ denotes the treatment effect, $D_{i,t}$ is a treatment indicator which is equal to one for treated unit after the treatment and zero otherwise, $\lambda_{k,t}$ are K unobservable factors[19], and $\beta_{i,k}$ denote the loadings of unit i on factor k. Note that (1) encompasses both time fixed effects ($\beta_{i,k}=1$ for all i) and unit fixed effects ($\lambda_{k,t}=1$ for all t) as special cases. However, it allows the effects of unobserved characteristics to vary over time and is therefore more general than the classical fixed effects difference-in-differences framework. For ease of exposition, we assume that there are two time periods only ($t=0,1$) with $t=0$ being the pre-treatment period and $t=1$ denoting the post-treatment period. Further assume that $i=1,\ldots,N_T$ denote treatment group units and $i=N_T+1, \ldots N_T+N_C$ denote control group units. The difference-in-differences estimator is given by:

$$\hat{\rho} = \left(\overline{Y}_1^T - \overline{Y}_0^T\right) - \left(\overline{Y}_1^C - \overline{Y}_0^C\right) \tag{2a}$$

$$= \rho + \sum_{k=1}^{K} \left(\overline{\beta}_k^T - \overline{\beta}_k^C\right)\left(\lambda_{k,1} - \lambda_{k,0}\right) + \left(\overline{\varepsilon}_1^T - \overline{\varepsilon}_0^T\right) - \left(\overline{\varepsilon}_1^C - \overline{\varepsilon}_0^C\right) \tag{2b}$$

$$\underset{\substack{N_C \to \infty \\ N_T \to \infty}}{\longrightarrow} \rho + \sum_{k=1}^{K} \left(\overline{\beta}_k^T - \overline{\beta}_k^C\right)\left(\lambda_{k,1} - \lambda_{k,0}\right) \tag{2c}$$

where an overbar denotes averages and indices T and C denote the treatment and control group, respectively.

In the presence of time fixed effects and/or unit fixed effects only, the difference-in-differences estimator yields a consistent estimate of ρ because the terms behind the Σ-sign in (2c) are equal to zero. However, if the factors λ are time-varying and average loadings between treatment and control units are different, then a difference-in-differences estimator does not necessarily yield consistent estimates of the treatment effect ρ anymore.

Siamese Twins matching

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[19] The model can be extended to include observable factors in equation (1).

We assume that we can observe outcomes $Y_{i,t}$ for a total of T_0-periods before our difference-in-differences sample period starts, i.e. for the periods $t=-1, -2, ..., -T_0$. The other key assumption we make is the existence of an appropriate control-group match for each treatment-group unit:

Assumption 1: For each treated unit i = 1, ...N_T there exists a unique "Siamese Twin" control group unit $ST(i) \in \{N_T + 1, ..., N_T + N_C\}$ with $\beta_{i,k} = \beta_{ST(i),k}$ for all k. We further assume that the mapping of treatment group units to control group units is a one-to-one (i.e., injective) mapping.

Under Assumption 1 and the linear factor model (1), the following proposition holds:

Proposition 1: If the outcome variable follows a linear factor structure (1) and Assumption 1 holds, then matching each treatment group observation to the control group observations with the lowest mean squared difference in pre-event outcomes paths yields a consistent difference-in-differences estimator for the treatment effect ρ*:*

$$\hat{\rho}_{ST} = \left(\overline{Y}_1^T - \overline{Y}_0^T\right) - \left(\overline{Y}_1^{ST} - \overline{Y}_0^{ST}\right) \underset{N_C \to \infty, N_T \to \infty, T_0 \to \infty}{\longrightarrow} \rho \tag{3a}$$

$$\text{with } \overline{\mathrm{Y}}_{\mathrm{t}}^{\mathrm{ST}} = \frac{1}{N_T} \sum_{i=1}^{N_T} Y_{\gamma(i),t} \qquad \text{(Average over Siamese Twins)} \tag{3b}$$

$$\gamma(\mathrm{i}) = \underset{j}{\operatorname{argmin}} \frac{1}{\mathrm{T}_0} \sum_{t=-1}^{-T_0} \left(Y_{i,t} - Y_{j,t}\right)^2 \qquad \text{(Estimate of Siamese Twin)} \tag{3c}$$

Proof:

Equation (3c) describes the Siamese Twin matching: control group units are matched to treatment group units based on similarity in the paths of the pre-event outcome variable. Using (1), this sum of squared differences can be computed as follows:

$$\frac{1}{T_0} \sum_{t=-1}^{-T_0} \left(Y_{i,t} - Y_{j,t}\right)^2 = \frac{1}{T_0} \left[\sum_{t=-1}^{-T_0} \left(\sum_k \left(\beta_{i,k} - \beta_{j,k}\right) \lambda_{k,t} \right)^2 + \left(\varepsilon_{i,t} - \varepsilon_{j,t}\right)^2 + \sum_k \left(\beta_{i,k} - \beta_{j,k}\right) \lambda_{k,t} \left(\varepsilon_{i,t} - \varepsilon_{j,t}\right) \right] \tag{4a}$$

$$\underset{T_0 \to \infty}{\longrightarrow} \frac{1}{T_0} \sum_{t=-1}^{-T_0} \left(\sum_k \left(\beta_{i,k} - \beta_{j,k}\right) \lambda_{k,t} \right)^2 + \frac{1}{T_0} \sum_{t=-1}^{-T_0} \left(\varepsilon_{i,t} - \varepsilon_{j,t}\right)^2 + 0 \tag{4b}$$

Equation (4a)/(4b) consist of the sum of three terms: the first term represents differences in the path of the outcome variable induced by differences in βs, the second term represents differences

in the path of the outcome variable due to the error term ε in equation (1), and the second is an interaction between the β-difference and the ε-difference that converges to zero for $T_0 \rightarrow \infty$.
Since the error term is *iid* by assumption the second term in (4b) is the same for all *i* and *j*. Differences in the sum of squared differences of the outcome variable are therefore fully driven by the first term in (4b). Under Assumption 1, for each treatment group unit *i* there exists a "Siamese Tiwn" control group unit *ST(i)* with the same factor loadings, i.e. $\beta_{i,k}= \beta_{ST(i),k}$. It therefore follows from (4b) that the estimate of the Siamese Twin $\gamma(i)$ in Proposition 1 converges to the true Siamese Twin *ST(i)* for $T_0 \rightarrow \infty$. Matching on the pre-event path therefore implies matching on a control group observation that has exactly the same loading on each of the *k* factors.[20] We have further assumed that the mapping of treatment group observations to Siamese Twins is a one-to-one match in Assumption 1, implying that $ST(i) \neq ST(j)$ and therefore the number of unique Siamese Twins converges to infinity as the number of treatment group observations converges to infinity. Thus, $\hat{\rho}_{ST} \rightarrow \rho$ for $N_T \rightarrow \infty$, $N_C \rightarrow \infty$ therefore follows directly from (2a)-(2c).

Remarks

- If the residuals ε are not *iid* and, for a particular treatment group unit, there exist several control group units with the same beta-loadings, then the Siamese Twin Matching will match on the control group unit with the lowest variance of the error term.
- Furthermore, assume there exists a control group unit with the same beta-loadings as the control group unit and a high residual variance *ε* ("no bias, large noise"); and another control group unit with a small difference in beta-loadings compared to the treatment unit but a lower residual variance *ε* ("some bias, but small noise"). In this case, the Siamese Twin matching implies a trade-off between bias and precision.
- It is straightforward to incorporate several pre- and/or post-treatment periods. Inference in the Siamese Twins difference-in-differences estimator comes primarily from a large cross-section via (2a)-(2c). A large pre-event time series is needed to identify the correct Siamese Twin $\gamma(i)$ for each treated unit in the last equation of Proposition 1.
- We have split the pre-treatment period into two subperiods, one to find the Siamese Twins and one as the pre-period in the difference-in-differences estimator. One could also use the same time period that is used to find the Siamese Twins as the pre-period –

[20] We assume that lambdas are not collinear.

and thereby potentially increase the power of the difference-in-differences estimator. However, in this case, standard errors cannot be determined with a standard Panel estimator and one would need to be used other methods such as falsification tests.

Comparison to the Synthetic Control Method

In the Synthetic Control (SC) method (Abadie, Diamond, and Hainmueller, 2010), counterfactuals are constructed using a combination of control group units that best fit the pre-event path of the outcome variable. Therefore, both the SC method and the Siamese Twin (ST) method match on the pre-event path of the outcome variable. The Siamese Twin (ST) method differs from the Synthetic Control method in one key aspect: the ST method identifies *one individual* control group unit while the SC method identifies a *combination* of control group units.

This difference has important implications. The SC method is not feasible if $N > T_0$ (i.e. if there are fewer pre-event time periods than cross sectional observations) while the ST method allows $N > T_0$. In most empirical applications, $N > T_0$ seems to be the norm rather than the exception. For example, panel data sets on the firm/year-level (or country-year level) usually have more firms (or countries) than years. In this case, the SC method is overidentified: there can exist many combinations of control group variables that perfectly match the pre-event path of the outcome variable. Abadie and Hainmüller (2010) therefore recommend implementing the SC estimator using a *convex* combination, i.e. weights are required to be between zero and one and need to sum up to one. Using convex combinations allows for N to be somewhat larger than T_0, but comes at the expense of a somehow arbitrary restriction on weights (convex combination) and a significant increase in computational time.

The possibility to allow for $N > T_0$ in the ST method of course comes at the expense of making a somehow stricter assumption on the pool of control group units. While the SC method requires the existence of a linear combination of control group units that matches the outcome path of a particular treatment group unit, the ST method requires the existence of an individual control group unit that matches the paths of a particular treatment group unit. While the ST method is stricter in this regard, it also safeguards against using combinations of control group units that might not represent what a researchers intends them to be. As a purely illustrative example, assume that a universal bank like Citigroup can be represented as 50% Wells Fargo (a commercial bank) + 50% Morgan Stanley (an investment bank). It is not directly obvious whether a conglomerate of Wells Fargo and Morgan Stanley actually behaves like a “sum of the parts", nor is it straightforward to assume that half of Wells Fargo would indeed behave like a scaled-down version of the entire bank. Requiring one matched control group for each treated unit therefore safeguards against extrapolation.

Practical considerations

As with any matching method, a researcher needs to make some practical choices, in particular with respect to the choice of the distance metric, the number of matches, and sampling with or without replacement (see Roberts and Whited (2012) for a detailed discussion).

As distance metric, we have proposed the Euclidian metric in equation (3c) of Proposition 1. However, the proof of Proposition 1 does not rely on this particular choice of a metric. However, more sophisticated metrics such as the Mahalanobis distance are likely to be less important for the ST matching than for traditional matching methods given that matching occurs on the path of a single variable – the outcome variable – only.[21]

As to the number of matches, it is hard to establish an objective rule for the optimal number of matches (see also Roberts and Whited (2012)). Choosing few matches implies a small bias but large variance while many matches decrease variance but might increase bias. In the analysis above, we have chosen the 10 best matches; however, results are robust to choosing 5 or 15 best matches as well.

Following Roberts and Whited (2012) we also suggest matching with replacement. Matching without replacement can make the estimated effect sensitive to the order in which treatment units are matched, see Rosenbaum (1995) and Roberts and Whited (2012). However, it clearly seems sensible to check whether particular control group units are matched to many treatment group observations because the error term of this particular control group can hinder inference even in larger samples.

[21] The Mahalanobis distance overweighs covariates that are uncorrelated with other matching covariates and underweights covariates that are highly correlated with other matching covariates. As an example, assume that matching takes place on body height, shoe size and IQ. In this case, body height and shoe size are likely to be highly correlated and therefore more likely to receive a lower weight than 1/3 while IQ is more likely to receive a weight larger than 1/3. In our case, the averaging in equation (3c) takes place over the same variable – the outcome variable – over different time periods. In our case, the Mahalanobis distance therefore only improves upon the simple Euclidian distance if there is evidence that the outcome variable is highly correlated across some but not all time periods.