"BREXIT" AND THE CONTRACTION OF SYNDICATED LENDING*

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This Version: June 2018

Abstract

We analyze the effect of policy uncertainty on global syndicated loan markets using the "Brexit vote" – the vote of the UK citizens to leave the European Union – as a laboratory. Issuances in the UK syndicated loan market drop by 23% after the Brexit vote 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 analyze a novel channel, market attractiveness: firm-bank combinations that used to issue loans in both the UK market and other markets do not decrease their issuances in the UK market more than in other markets after the Brexit referendum – suggesting that the UK market did not significantly lose attractiveness relative to other international markets. We also document a strong decrease in the issuance of British pounds denominated loans after the Brexit for the same firm-bank combinations who switch into alternative currencies such as the US Dollar and the Euro. 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 Diana Bofim, Patricia Boyallian, Judy Chalabi, Olivier de Jonghe, Frederik Eidam, Falko Fecht, Manasa Gopal, Ulrich Hege, Emanuel Mönch, Anand Srinivasan, Martin Schmalz, Laura Starks, Jing Zeng, and the seminar participants at Frankfurt School of Finance & Management, University Duisburg-Essen, University Munich, Conference at the German Finance Ministry, FIRS Conference 2017, CAF Summer Finance Research Conference 2017, 3rd IWH-FIN-FIRE Workshop on "Challenges to Financial Stability" and 9th European Banking Center Network Conference for helpful comments and suggestions.
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1. Introduction

In a referendum held on June 23, 2016, United Kingdom (UK) citizens unexpectedly voted to leave the European Union (so-called "Brexit vote"). This event had immediate macroeconomic consequences. 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. The "Economic Policy Uncertainty" index compiled by Baker et al. (2016) reached a historical high in the UK, by far exceeding values from the financial and European sovereign debt crisis. Born et al. (2017) estimate an output loss of about 1.3 percent in the third quarter of 2017 due to the Brexit vote, and the decline in investments by firms played an important role (Baker et al., 2016). The uncertainty associated with the Brexit vote thus had an immediate impact on economic activity in the UK. Microeconomic evidence, however, that helps us understand the effect of political uncertainty – and the Brexit vote in particular – on economic activity and global financial markets is still elusive.

In this paper, we investigate the effect of political uncertainty on the global syndicated loan market using the Brexit vote as an exogenous shock. Due to its importance for economic activity, the global syndicated loan market provides an ideal setting to analyze the consequences of an uncertainty shock and how it affects borrowing and lending decisions of national and international borrowers and lenders. We hypothesize that the Brexit vote affected both the supply of and demand for loans by UK banks and firms and thus had immediate real economic consequences. Importantly, it might have also affected the decision of agents to originate loans in UK markets: the high presence of international borrowers and lenders make the UK especially vulnerable to quick withdrawals from both sides. Moreover, the high level of interconnectedness of UK firms and banks in international syndicated loan markets might even challenge the role of the UK as a leading market for loan origination for domestic firms.

This narrative raises several interesting questions: Does the UK syndicated loan market experience a drop in loan issuances after the Brexit vote relative to other loan markets? If yes, is this driven by demand or supply and how can this effect be explained in the cross-section of firms? Is the UK becoming less attractive for global players in the syndicated loan market?[1] 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 originated in other markets around the world, then political uncertainty such as the Brexit vote has implications also on the importance of global financial centers.

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 (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 vote relative to before and relative to a set of comparable syndicated loan markets using a difference-in-difference (DiD) analysis. Our sample period is the January 2014 to December 2017 period, i.e. 30 months before and 18 months after the Brexit vote. 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). Given the number of

[1] 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.

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.

Our first main result is that the number and the volume of syndicated loan issuances in the UK market decrease by about 23% after the Brexit vote relative to the control group of the largest 49 syndicated loan markets worldwide.[2] 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 and autumn 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 of the Brexit referendum. We do not find differences in pre-event trends, suggesting that the key assumption for the internal validity of our DiD estimator is met.

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.[3] 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 (observable and unobservable) variable that affects loan origination. 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. These Top 10 "Siamese Twins" are stable over time and we find very similar results when only focusing

[2] 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.
[3] More precisely, we use the natural logarithm of the quarterly number of loan issuances to compare markets.

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.

What explains the 15% drop in loan issuances in the UK market? We propose three channels: (1) a reduction in loan demand by UK firms; (2) a reduction in credit supply by UK and/or foreign banks; and (3) a decline in the attractiveness of the UK financial market as a financial center in which international and national borrowers and lenders originate loans.

We try to disentangle these competing hypotheses using univariate and multivariate tests. First, we divide all firms in our sample into eight well-defined categories: A firm can either be a UK or non-UK firm, and both types of firms can (1) borrow from a UK or non-UK bank, and (2) do this in GBP or not in GBP. We document that that UK market share based on all loans issued in the UK market firms in these categories decreased 1.69 percentage points after the Brexit vote relative to before which corresponds to a drop of about 23%, which is similar to our previous analysis on the country level.

Our second main result is that this decline in loan issuances is driven by a decline in GBP denominated loans by UK firms both from UK and non-UK Lenders, where the largest decline is coming from domestic firm-bank combinations, rather than from a decline of the share of those loans which has ultimately been issued in UK markets. In other words, our univariate tests suggest that policy uncertainty through the Brexit vote does not affect the attractiveness of the UK as market for loan syndication during our sample period.

We then we use a modified Khwaja-Mian (2008) estimator and aggregate our data on a firm x bank x market x currency x half-year level. Market is the market where is syndicated loan is originated. We consecutively saturate our model with firm cluster (i.e. industry x borrower country) fixed effects to control for firm demand (under the assumption that firm demand operates on the industry-country level), currency fixed effects and then bank fixed effects to control for bank loan supply and to finally isolate the market attractiveness channel as the remaining variation shows whether there is a change in lending in the UK market within a group of firms, banks and currencies. Our results suggest an important demand effect in the decline of syndicated lending: the change in the likelihood that a loan is issued in the UK market relative to the unconditional likelihood that a loan is issued is cut in half once we include firm cluster fixed effects. Once we add currency fixed effects the coefficient becomes very small and statistically insignificant. That is, within a firm-cluster x currency combination, there is no significant change in lending in the UK relative to other syndicated loan markets suggesting that – at least during our sample period – bank loan supply as well as at the attractiveness of the UK syndicated loan market remained unaffected.

We now have a closer look at the importance of exchange rate effects as a driver of syndicated loan origination. The uncertainty surrounding the Brexit vote caused a substantial decline in the GBP relative to other major currencies such as the USD or the Euro. Our tests support the interpretation that lending in GBP dropped substantially: Even within the same firm cluster x bank x market, we observe a decline in lending in GBP by about 15% relative to the unconditional likelihood of issuing a loan. If GBP becomes less attractive due to the uncertainty associated with a Brexit, do firms switch to other currencies and in which currency are they now more likely to issue loans? Our analysis shows that USD denominated loans increase by about 10.5% after the Brexit vote, followed by loans issued in Euro and other currencies.

Our paper relates to several strands of literature. It is related to a large macroeconomic literature on the effects of political uncertainty (e.g. Bernanke, 1983; Bloom, 2009; and Bachmann et al., 2013). More recent papers find substantial effects of the Brexit vote on various financial and macroeconomic indicators, such as stock returns (Ramiah et al., 2016), inflation (Breinlich et al., 2017) and GDP performance (Born et al., 2017). Microeconomic support is provided e.g. by Julia and Yook (2012) and Gulen and Ion (2016) who investigate the effect of political uncertainty on domestic firms. They document effects on investment behavior around election cycles or when political uncertainty as measured by the Bloom et al. (2016) index is high. Campello et al. (2018) investigate cross-border spillovers after the Brexit vote and find large effects on employment, investment, R&D and savings of US firms with exposures to the UK. We show that political uncertainty affects the behavior of both domestic and foreign borrowers and lenders in the global syndicated loan market.

It also 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 et al., 2011; Laeven and Giannetti, 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. (2017) 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.

The paper proceeds as follows. Section 2 provide background information regarding the Brexit referendum, we describe the data in Section 3 and provide some stylized facts about the global syndicated loan market in Section 4. We analyze the impact of the Brexit vote on syndicated lending in Section 5 and Section 6 concludes.

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 December 2017. 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 2017 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, our data -

collected in April 2018 – might miss some deals from the fourth quarter of 2017. 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.[4] 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 identifying domestic and foreign borrowers or lenders, we use the country information of their respective ultimate parent company.[5]

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. Our final sample comprises 43,581 loans to 16,769 firms from 971 lenders in 11 markets issued between January 2014 and December 2017.

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.*

[4] 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.
[5] We define lead lender as the main lender.

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.[6] 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.[7] 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.

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]

[6] Note that loan volume is always winsorized and the 1% and 99% percentiles, unless otherwise noted.

[7] The top 20 syndicated markets are: the US, Japan, the UK, Canada, France, Germany, Australia, Spain, China, the Netherlands, Hong Kong, India, Italy, Taiwan, Switzerland, Russia, Singapore, Sweden, South Korea, and Norway.

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: About 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 (2008) 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 Q12014-Q32017 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 the indexed UK number of issuances remains below the indexed number of non-UK issuances throughout the entire post-Brexit referendum period. 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 and its share never fully recovers.

[Figure 4]

We continue by estimating the following DiD regression:

$$Y_{m,t} = \beta_1 \cdot \text{UK Market}(0/1) \cdot \text{PostBrexit }(0/1) + \beta_2 \cdot \text{Controls}_{m,t} + \eta_m + \eta_t + \varepsilon_{m,t}, \qquad (1)$$

where $Y_{m,t}$ is either the natural logarithm of the number of syndicated loans issued in market *m* in quarter *t* or the natural logarithm of the volume of syndicated loans issued in market *m* in quarter *t*. The dummy variable *UKMarket(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.[8] We use market (η_m) and quarter fixed effects (η_t), thus providing more granular controls than simple *UKMarket(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

[8] 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.

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 natural logarithm of the number of quarterly syndicated loan issuances in the UK and the natural logarithm of the number of quarterly syndicated loan issuances in market c:

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

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 (2012). Table 2 provides the results.[9]

[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

[9] We find similar results when matching based on the paths of changes in the natural 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.

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.

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 -0.256 ($p<0.10$). This suggests that the number of loan issuances in the UK market Post-Brexit referendum decreases by exp(-0.256)-1= -23% 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 includes the third quarter twice (2016, 2017), the analysis therefore rules out that the results are driven by third quarters being generally lower-issuance quarters in the UK. Reassuringly, results hardly change. Column (3) uses only European countries as a control group. Again, the results point to a significant decrease of approximately 23% in the number of UK issuances post Brexit referendum.

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 -0.268 ($p<0.01$), 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 significant 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 (firm/bank combinations moving from the UK to another market).

5.2.1. Univariate tests

Before turning to the regression analysis, a univariate analysis provides first insights into the effect of the Brexit referendum on firms, banks and markets. The idea is simple: we document the average number of loans issued per annum within the 2.5 years before and 1.5 years after the Brexit vote (*Loans p.a. (#)*), the percentage share of those loans that have been issued in the UK market (*Mkt Share UK*) and calculate the percentage change of both measures in the post vs. the pre-Brexit vote period. Importantly, we can do this for all firms as we can group them in eight well-defined categories: A firm can either be a UK or non-UK firm, and both types of firms can (1) borrow from a UK or non-UK bank, and (2) do this in GBP or not in GBP. We report these statistics in Table 4.

[Table 4]

For example, UK firms borrowing from UK banks and in GBP have issued, on average, 274 loans p.a. before the Brexit vote, and 99.56% of these loans have been issued in the UK market. Similarly, UK firms have issued 182 loans p.a. borrowing from non-UK banks and not in GBP, and about half (55.6%) of these loans have been issued in the UK market. Non-UK firms issue predominantly outside the UK market unless they issue loans in GBP. For example, non-UK firms issue about 9,640 loans p.a. with non-UK banks and in currencies other than GBP, and 0.68% of these loans are issued in the UK market. These statistics are related to loan issues prior to the Brexit referendum.

Columns (3) and (4) show the same metrics for loans issued after the Brexit vote and columns (5) and (6) the respective percentage change. Most of the loans that are issued in GBP during our sample period are to UK firms – and, thus, our analysis will put more weight on those firms – however, we observe a strong decline in GBP denominated loans both by UK and non-UK firms. For example, the number of GBP denominated loans to UK firms by UK and non-UK banks drops by about 37% and 11%, respectively. Interestingly, the share of the loans issued in the UK market hardly changes (even increases somewhat). Based on the total number of loans issued in the post- versus pre-Brexit vote period, the UK market share decreases by 1.69% (7.43% - 5.74%).

To understand the determinants of the UK market share in syndicated lending, we define the UK market share as

$$MktShareUK_t = \frac{\sum_i N^i_{UK,t}}{\sum_i N^i_{WW,t}} = \frac{\sum_i N^i_{WW,t} \cdot MktShareUK^i_t}{\sum_i N^i_{WW,t}}$$

Where $N_{UK,t}$ is the number of facilities originated in the UK market in period t in category i, where i denotes our eight groups (e.g. UK firm-UK bank-GBP). $N_{WW,t}$ is the number of facilities originated worldwide in period t in category i. A drop in the UK market share can either be driven by a drop in loans in the category that usually takes place in the UK (here: UK firm) or by a change in market share in one or both the categories (e.g. UK firms and/or non-UK firms switching from the UK market to another market). Changes in the UK market share can thus be decomposed into (1) changes in the number of loans issued in a category, (2) changes in the market share of the UK in a particular category, and (3) an interaction term between both.[10] We show the decomposition for the number of loans and changes in the market share in columns (7) and (8).

The results are striking. About 1.45 percentage points of the 1.69% decline can be explained by a decline in GBP denominated loans by UK firms from both UK and non-UK banks, where the largest decline is coming from domestic firm-bank combinations. In fact, the second most important factor is the decline in loans of UK firms in non-GBP denominated loans suggesting possible demand effects related to borrowing by UK firms after the Brexit vote. The explanatory of the change in market share is very small (column (8))

5.2.2. Methodology

In the following, we use a modified Khwaja and Mian (2008) estimator to further disentangle these alternatives in a regression framework. We construct a new variable $Loan(0/1)_{f,b,m,t}$, which is a dummy variable that equals one if at least one loan has been issued to firm f by bank b in market m in half year t.[11] We focus on the likelihood that a loan is originated instead of loan volume to avoid confounding effects, e.g. due to a devaluation of the British pound.[12]

[10] We show a detailed decomposition in Appendix B attached to this paper.

[11] If we do not observe a loan issuance to firm f by bank b in market m in half year t, then $Loan(0/1)_{f,b,m,t}$ is equal to zero. Firm/bank/market combinations that have zero issuances in every single half year are dropped as they would be absorbed by our fixed effects anyway.

[12] In our tests, we use firm industry x country cluster fixed effects to accommodate the fact that syndicated loan issuances might be less frequent on the firm level. Our implicit assumption is that firm demand shocks operate on the industry x borrower-country level. The results are very similar, i.e. the level of aggregation is not driving our results.

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 our data, this would be a clear indication of – in our setting the UK Market – losing attractiveness as a place to originate loans. An alternative explanation, however, could be that this effect is masking a structural change as to the currency in which loans are issued. The British pound (GBP) has greatly devaluated since the Brexit vote and loans denominated in GBP might have become less attractive. If these loans are also issued predominantly in the UK market, the market attractiveness effect would be spurious.

$$\Delta \text{Loan(0/1)}_{f,b,c,m} = \beta \cdot \text{UK Market(0/1)} + \eta_f + \eta_b + \eta_c + \varepsilon_{f,b,c,m}$$

The main dependent variable *Loan(0/1)* now equals to one if firm *f* receives at least one loan from bank *b* in currency *c* in market *m* in half-year *t* and zero otherwise. Following Betrand, Duflo, and Mullainathan (2004), we collapse our data on a *firm x bank x currency x market* level into a pre- and post-Brexit period to account for possible autocorrelation in the standard errors. $\Delta Loan(0/1)_{f,b,c,m}$ is thus the change in the likelihood of loan issuance in the post- versus pre-Brexit period. *UKMarket(0/1)* is a dummy equal to one for the UK syndicated market. A negative β implies that the likelihood of loan issuance decreases more in the UK syndicated market compared to other syndicated markets after controlling for loan demand via firm cluster fixed effects (η_f), bank supply with bank fixed effects (η_b) and a currency fixed effect (η_c) to control for a shift from GBP denominated loans into other currencies.

Our analysis proceeds in four steps: First, we estimate a baseline effect without any control variables or fixed effects documenting the change in the likelihood that a loan is issued in the UK market after the Brexit vote relative to before and relative to other markets. This effect can be due to either a demand, supply, currency or market attractiveness effect. We then use the within-firm Khwaja-Mian (2008) estimator and include the firm-cluster fixed effect ($\boldsymbol{\eta_f}$) to control for loan demand within a firm-cluster. In a third step, we include a currency fixed effect ($\boldsymbol{\eta_c}$) to evaluate whether there is a decline in loan issuances in the UK market for the same firm cluster within the same currency. Finally, we include bank fixed effects ($\boldsymbol{\eta_b}$) to control for supply of loans by banks.

We now turn our focus on the currency, in which the loans are originated, and investigate whether loans are less likely to be issued in GBP after the Brexit vote holding everything else constant. We run the following regression:

$$\Delta \text{Loan}(0/1)_{f,b,c,m} = \beta \cdot \text{GBP}(0/1) + \eta_f + \eta_b + \eta_m + \varepsilon_{f,b,c,m},$$

where *GBP(0/1)* is a dummy variable that equals one if the loan is denominated in GBP and zero otherwise. Similar to our analysis before, we saturate a baseline model consecutively with firm cluster and bank fixed effects to control for any demand and supply effects that might drive our results. Thus, we can have the same firm cluster that receives a loan from the same bank in US dollars and British pounds before and only in US dollars after the Brexit vote. When we add market fixed effects, we additionally control for the market in which the loan is syndicated. This analysis helps us evaluating whether there was a shift from loans denominated in British pounds to loans in other major currencies such as US dollars or euros after the Brexit for the same firm cluster-bank combinations within the same market.

5.2.3 Multivariate results

The results of our multivariate tests are reported in Table 5. As control group, we use the Siamese Twin countries discussed in the previous section. Our analysis is carried out at the firm-bank-currency-market-half-year level and our sample comprises 58,430 observations. We cluster standard errors at the bank level in all regressions. Panel A of Table 5 shows regression results for equation (4), relying on Khwaja and Mian (2008) to control for demand side effect, while Panel B presents regression results for the market attractiveness narrative as in equations (5).

[Table 5]

Column (1) in Panel A reports baseline regression results without controls or fixed effects. In column (1) of Panel A, we observe a negative coefficient of *UKMarket(0/1)* of -0.058 which is significant at the 1 percent level. I.e. the likelihood that a loan is issued in the UK syndicated loan market is 5.8% lower in the post-Brexit vote period. Compared to an unconditional likelihood that a loan is issued of 17%, these effects represent a relative likelihood in loan issuance in the UK syndicated loan market of approximately 34% - and an economically large effect. In column (2), we add firm cluster fixed effects. Overall, we have 2,295 SIC 3-country (i.e. firm) clusters. The coefficient of *UKMarket(0/1)* drop substantially to -0.023, which is still statistically significant and represents about 14% relative to the unconditional mean. In other words, a substantial part of the drop in lending in the UK market can be explained by a drop in firm demand. In column (3), we add currency fixed effects and the coefficient becomes very small and statistically insignificant. That is, within a firm-cluster x currency combination, there is no significant change in lending in the UK relative to other syndicated loan markets. We add bank fixed effects in column (4) as additional control for bank loan supply, which does not change the coefficient. Bank supply does not play a major role once we control for currency effects. In summary, we do not find evidence that policy uncertainty through the Brexit vote affects the attractiveness of the UK as market for loan syndication during our sample period. As expected, loan demand drops substantially, as, for example, firms might hold-off investments due to uncertainty regarding the exchange rate or how the negotiations regarding trade relationships with the EU are going to develop. We investigate possible drivers of loan demand further below in this paper.

We now have a closer look at the importance of exchange rate effects as a driver of syndicated loan origination. The uncertainty surrounding the Brexit vote caused a substantial decline in the GBP relative to other major currencies such as the USD or the Euro. Our previous results already showed that currency effects are an important driver of the decline in loan issuances, we now try to quantify this effect. Similar to our previous test, our approach is to identify whether there is a shift from GBP to other currencies within a firm cluster-bank combination and within a market. Regression results from equation (5) are shown in Panel B of Table 5.

We report the results from a baseline model without control variables and fixed effects in column (1). On average, GBP denominated loans drop about 6.5% after the Brexit vote relative to other currencies. Given an unconditional likelihood of issuing a loan of 17%, the coefficient represents about 38% of this likelihood. We first add firm fixed effects in column (2) and, as expected, the coefficients drop to 0.035 but is still highly significant. In column (3), we estimate the currency effect within a firm cluster-bank combination. The coefficient drops to 0.029 (or 17% relative to the unconditional likelihood). That is, within the same firm-cluster-bank combination, we observe a substantial decline in GBP syndicated loans. Finally, we include market of syndicated fixed effects (11 clusters, UK and 10 twins). The coefficient drops by about 10% to 0.026 and remains highly statistically significant. Even with the same firm cluster x bank x market, we observe a decline of 2.6% or 15% relative to the unconditional mean.

We keep our focus on the exchange rate effect and ask – given the substantial decline in loan issuances in GBP – do firms switch to other major currencies (such as the USD or Euro) to avoid the uncertainty associated with the Brexit vote? From our sample at the firm – bank – currency – market – half-year level, we keep those firms that had at least one loan denominated in GBP before the Brexit vote. We include firm-cluster and bank fixed effects to control for loan demand and supply and investigate the change in GBP denominated loans after the Brexit vote relative to other currencies (column (1)), the change in loans made in USD, Euro and other currencies relative to GBP (column (2)), and whether the change in GBP denominated loans is larger for UK firms compared to other firms (column (3)). We report the results in Table 6.

[Table 6]

Consistent with our analysis above, GBP denominated loans drop about 6% relative to other currencies in the post-Brexit vote period. USD denominated loan experience the largest increase (about 10.5%), followed by Euro denominated loans (2.5%) and other currencies (3.2%). Interestingly, we do not find any differential effect for UK versus non-UK firms w.r.t. to the decline in GBP denominated loans. Taken together, among those group of firms that have issued GBP denominated loans before the crisis, we observe a change in the composition of currencies in which they issue loans, with an increase particularly in USD and Euro denominated loans.

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 23 % 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 do not observe a significant decline in lending by international firms and from international banks in the UK syndicated loan market. Taken together, these results suggest that the Brexit referendum primarily affected UK banks and borrowers with – so far – limited consequences for international activities in the UK syndicated loan market. The starkest effect comes from the drop in GBP-lending. This drop cannot be attributed to pure demand factors (UK firms usually borrowing more in GBP and not borrowing anymore post-referendum) or supply factors (UK banks usually lending more in GBP and not lending anymore post-referendum) but even holds with firm, bank, and market fixed effects.

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 5 quarters after the Brexit referendum. Effects in the coming quarters 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 natural logarithm of the number of issuances in the UK syndicated loan market with time series of the natural 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 2017. Detailed variable definitions can be found in Table A.1 of the Appendix. 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 - Q4/2017)

	(1)	(2)	(3)	(4)
	Baseline	Controlling for seasonality	Control group: Europe	Control group: Top 10 Siamese Twins
UK(0/1) x PostBrexit(0/1)	-0.256***	-0.235***	-0.275***	-0.268***
	(-3.04)	(-3.47)	(-3.59)	(-3.99)
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)	656	656	256	176
Adjusted R2	0.959	0.986	0.951	0.991

Panel B: Log Loan Volume Panel (Q1/2014 - Q4/2017)

	(1)	(2)	(3)	(4)
	Baseline	Controlling for seasonality	Control group: Europe	Control group: Top 10 Siamese Twins
UK(0/1) x PostBrexit(0/1)	-0.253**	-0.233*	-0.174	-0.303**
	(-2.04)	(-1.80)	(-1.63)	(-2.44)
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)	656	656	256	176
Adjusted R2	0.963	0.978	0.921	0.989

Table 4: Loan Issuance post-Brexit – Univariate Analysis

This table shows the average number of loans issued per annum within the 2.5 years before and 1.5 years after the Brexit vote (*Loans p.a. (#)*), the percentage share of those loans that have been issued in the UK market (*Mkt Share UK*) and calculate the percentage change of both measures in the post vs. the pre-Brexit vote period (2014-2017). The table reports statistics separately for UK firms and non-UK firms that borrow from UK and non-UK banks in GBP or non-GBP. Column *Change* reports the percentage change in numbers of loans and UK market share in the post vs. the pre-Brexit vote period. Column *Contribution to change* decomposes the change in the UK market share into (1) changes in the number of loans issued in a category (*Loans p.a. (#)*)), (2) changes in the market share of the UK in a particular category (*Mkt Share UK)*.

	Pre-Brexit		Post-Brexit		Change Δ		Contribution to change	
Category	Loans p.a. (#)	Mkt Share UK	Loans p.a. (#)	Mkt Share UK	Loans p.a. (#)	Mkt Share UK	Loans p.a. (#)	Mkt Share UK
UK Firms								
UK Bank / GBP	274	99.56%	171	100.00%	-37.47%	0.44%	**-1.05%**	0.01%
Non-UK Bank / GBP	270	99.41%	241	99.45%	-10.73%	0.04%	**-0.40%**	0.00%
UK Bank / Non-GBP	54	80.15%	36	75.93%	-33.82%	-5.27%	-0.15%	-0.02%
Non-UK Bank / Non-GBP	182	55.60%	183	58.18%	0.73%	4.64%	-0.05%	0.04%
Non-UK Firms								
UK Bank / GBP	13	81.82%	7	81.82%	-44.44%	0.00%	-0.05%	0.00%
Non-UK Bank / GBP	47	50.00%	46	34.78%	-2.54%	-30.43%	-0.02%	-0.07%
UK Bank / Non-GBP	192	4.18%	202	6.60%	5.43%	58.09%	0.00%	0.04%
Non-UK Bank / Non-GBP	9,640	0.68%	10,461	0.68%	8.51%	0.83%	0.01%	0.01%
Total	**10,672**	**7.43%**	**11,347**	**5.74%**	6.32%	**-1.69%**	**-1.71%**	**0.02%**

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 likelihood of loan issuance pre- and post-Brexit on a UK Market(0/1) dummy (Panel A) and a GBP(0/1) dummy (Panel B). The analysis is based on data on firm-bank-currency-market-half year level between 2014 H1 and 2017 H2 that is collapsed to a pre- and post-Brexit period. The dependent variable is based on pre- and post-Brexit difference (ΔLoan(0/1)) of the dummy variable Loan(0/1) that equals one if at least one loan has been issued to firm *f* from bank *b* in currency *c* in market *m* in half year *t* and zero otherwise. Column (1) of Panel A presents baseline results with a UK Market(0/1) dummy; column (2) controls for the demand side with firm cluster (industry and country of the borrower) fixed effects; column (3) additionally controls for currency effects with currency fixed effects; and column (4) additionally controls for the supply side with bank fixed effects. Column (1) of Panel B presents baseline results with a GBP(0/1) dummy; column (2) controls for the demand side with firm cluster (industry and country of the borrower) fixed effects; column (3) additionally controls for the supply side with bank fixed effects; and column (4) additionally controls for market fixed effects. Detailed variable definitions can be found in Table A.1 of the Appendix. The Top 10 Siamese Twin countries as listed in Table 2 constitute the control group. Below each regression, we report the average unconditional likelihood of loan issuance between 2014 H1 and 2017 H2. 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: Market Attractiveness (H1/2014 - H22017)

	(1) Baseline	(2) Khwaja Mian (2008)	(3) Extended Khwaja Mian (2008)	(4) Extended Khwaja Mian (2008)
UK Market (0/1)	-0.058***	-0.023***	-0.003	0.000
	(-8.86)	(-2.96)	(-0.32)	(0.05)
Firm Cluster Fixed Effects	No	Yes	Yes	Yes
Currency Fixed Effects	No	No	Yes	Yes
Bank Fixed Effects	No	No	No	Yes
Firm Clusters	2,295	2,295	2,295	2,295
Banks	971	971	971	971
Currency	25	25	25	25
Observations	58,430	58,430	58,430	58,430
R2	0.004	0.206	0.208	0.233
Unconditional Loan (0/1)	17%	17%	17%	17%

Panel B: Currency Effects (H1/2014 - H22017)

	(1) Baseline	(2) Khwaja Mian (2008)	(3) Extended Khwaja Mian (2008)	(4) Extended Khwaja Mian (2008)
GBP(0/1)	-0.065***	-0.035***	-0.029***	-0.026***
	(-9.43)	(-7.71)	(-4.98)	(-4.45)
Firm Cluster Fixed Effects	No	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes
Country Fixed Effects	No	No	No	Yes
Firm Clusters	2,295	2,295	2,295	2,295
Banks	971	971	971	971
Markets	11	11	11	11
Observations	58,430	58,430	58,430	58,430
R2	0.004	0.206	0.231	0.233
Unconditional Loan(0/1)	17%	17%	17%	17%

Table 6: Loan Issuance post-Brexit – Currency Effects

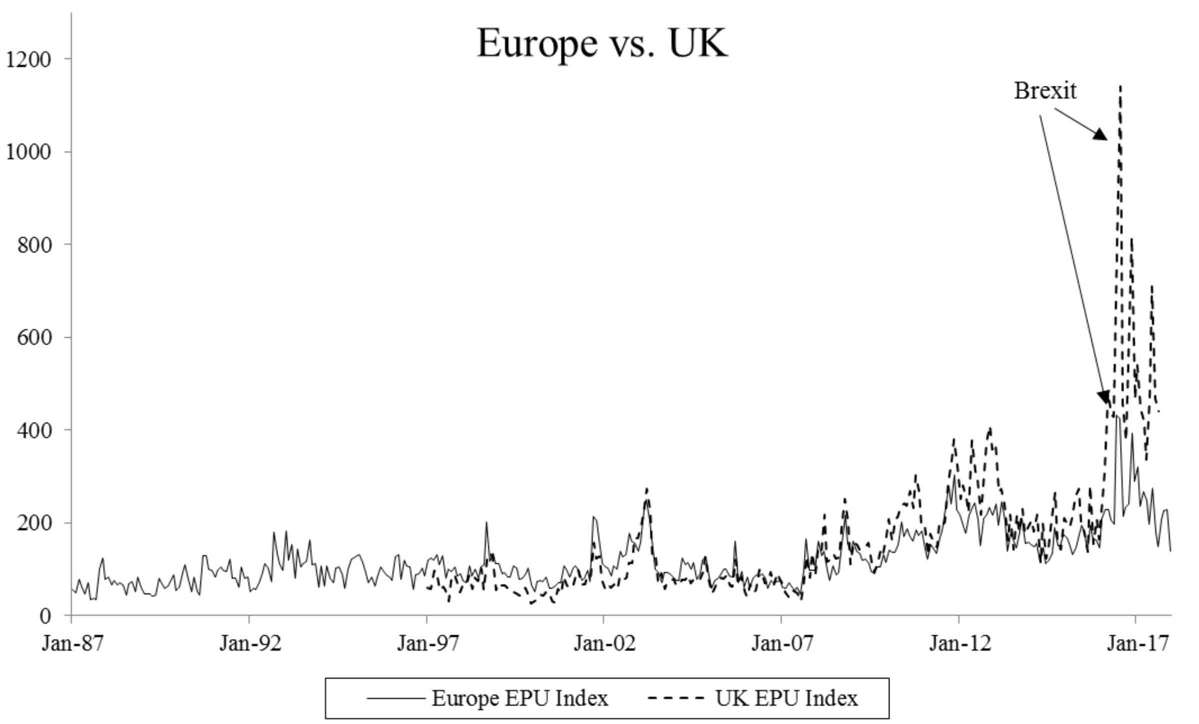
UPDATEd: This table provides results of difference-in-differences regressions of the change in the likelihood of loan issuance pre- and post-Brexit on a GBP(0/1) that equals one if a loan is denominated in British pounds, a USD (0/1) that equals one if a loan is denominated in US dollars, a EURO(0/1) that equals one if a loan is denominated in euros and OTHER (0/1) for all other currencies. The analysis is based on data on firm-bank-currency-market-half year level between 2014 H1 and 2017 H2 that is collapsed to a pre- and post-Brexit period, only for firms that have received at least one loan in British pounds before the Brexit.The dependent variable is based on pre- and post-Brexit difference (ΔLoan(0/1)) of the dummy variable Loan(0/1) that equals one if at least one loan has been issued to firm *f* in currency *c* from bank *b* in market *m* in half year *t* and zero otherwise. Column (1) of Panel A presents baseline results with a GBP(0/1) dummy and controls for the demand side with firm cluster fixed effects; column (2) additionally controls for the supply side with bank fixed effects; columns (3) and (4) repeat the analysis and use USD(0/1), EURO(0/1) and OTHER(0/1) as explanatory variables and GBP(0/1) loans as the reference group, Columns (5) and (6) interact the GBP(0/1) dummy with a UK Firm(0/1) that equals one for UK firms. Detailed variable definitions can be found in Table A.1 of the Appendix. The Top 10 Siamese Twin countries as listed in Table 2 constitute the control group. Below each regression, we report the average unconditional likelihood of loan issuance between 2014 H1 and 2017 H2. 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.

Dependent Variable: ΔLoan(0/1)	(1) Khwaja Mian (2008)	(2) Extended Khwaja Mian (2008)	(3) Khwaja Mian (2008)	(4) Extended Khwaja Mian (2008)	(5) Khwaja Mian (2008)	(6) Extended Khwaja Mian (2008)
GBP (0/1)	-0.062***	-0.060***			-0.057***	-0.054***
	(-6.98)	(-6.81)			(-4.05)	(-3.89)
USD (0/1)			0.108***	0.105***		
			(10.03)	(9.94)		
EURO (0/1)			0.027**	0.025**		
			(2.38)	(2.22)		
OTHER (0/1)			0.031**	0.033**		
			(2.01)	(2.18)		
GBP (0/1) * UK Firm (0/1)					-0.007	-0.010
					(-0.38)	(-0.55)
Firm Cluster Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes
Firm Clusters (SIC3)	261	261	261	261	261	261
Banks						
Markets						
Observations	4,599	4,599	4,599	4,599	4,599	4,599
R2	0.322	0.372	0.329	0.378	0.322	0.372
Unconditional Loan (0/1)						

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 December 2017.

Panel A



Panel B

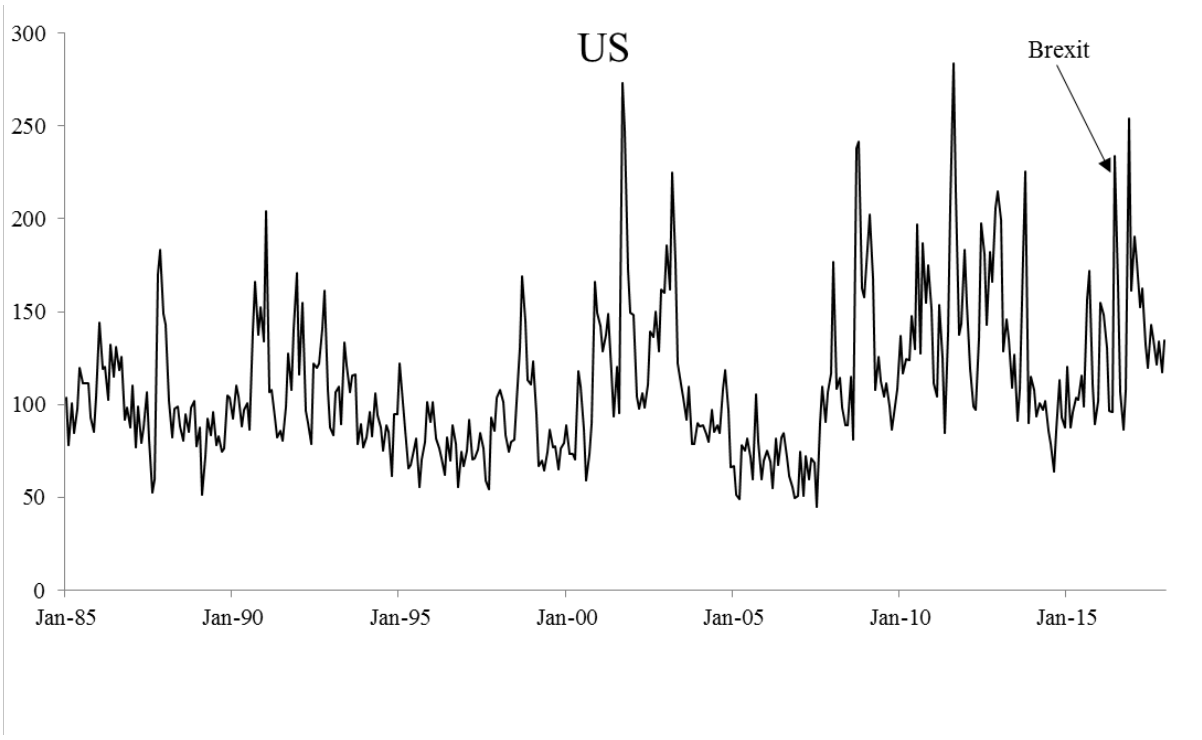
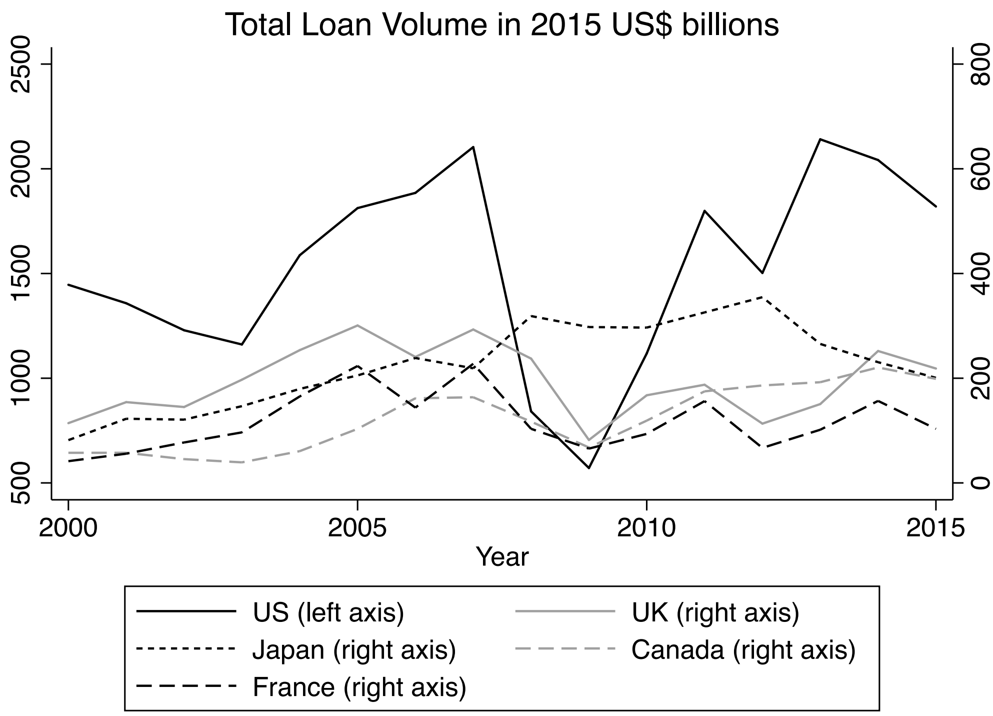


Figure 2: Top 5 Syndicated Markets

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

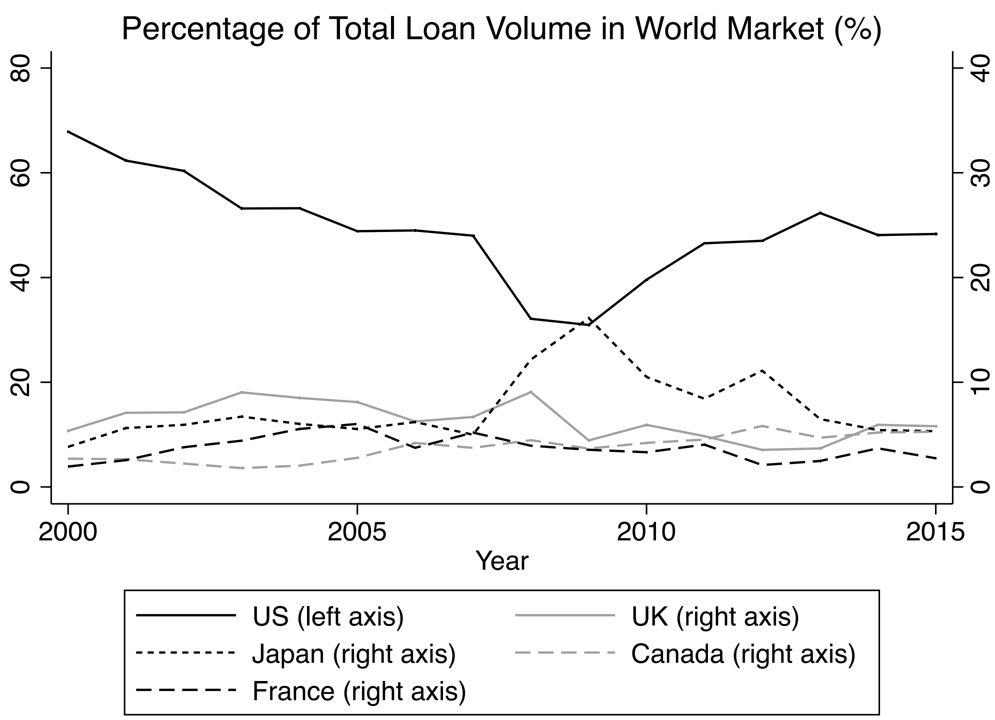
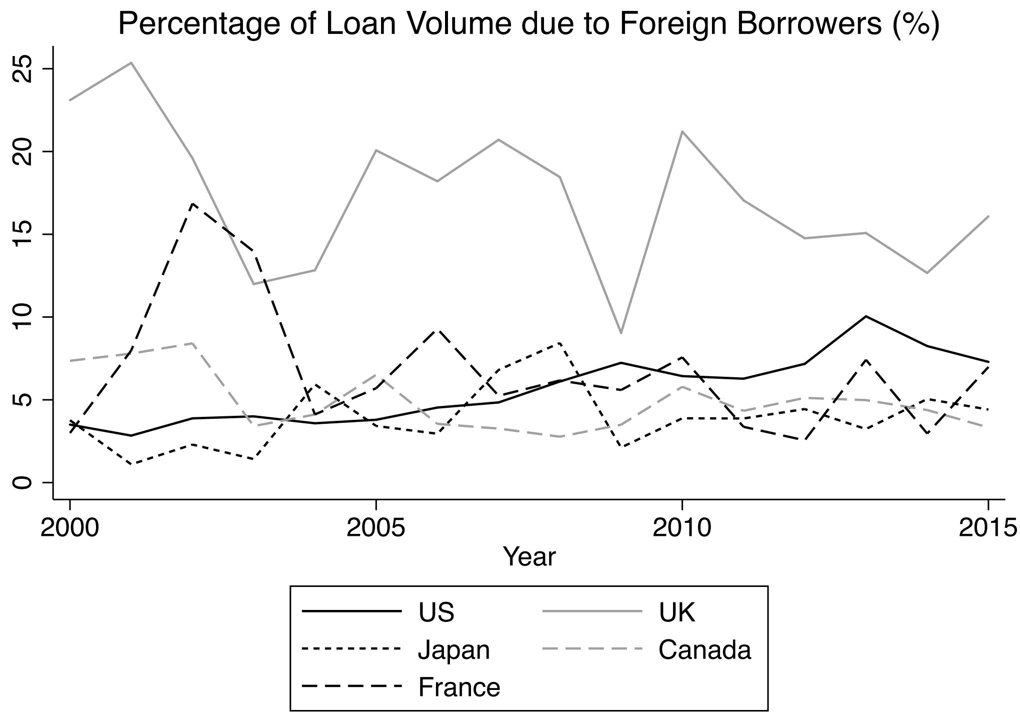


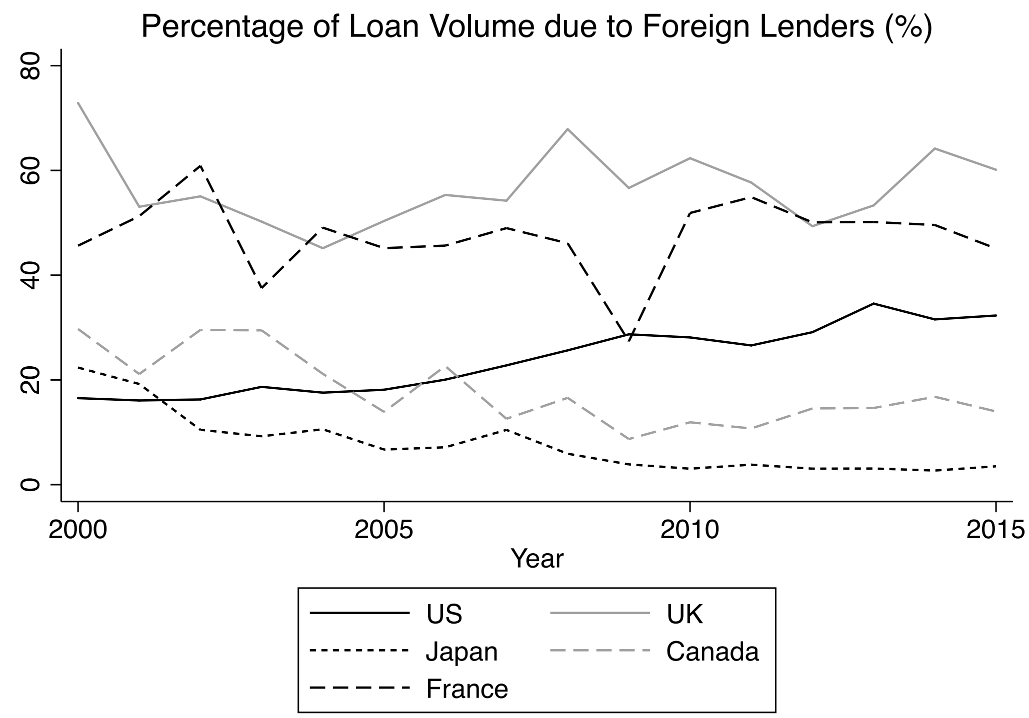
Figure 3: Top 5 Syndicated Markets and Foreign Exposure

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.

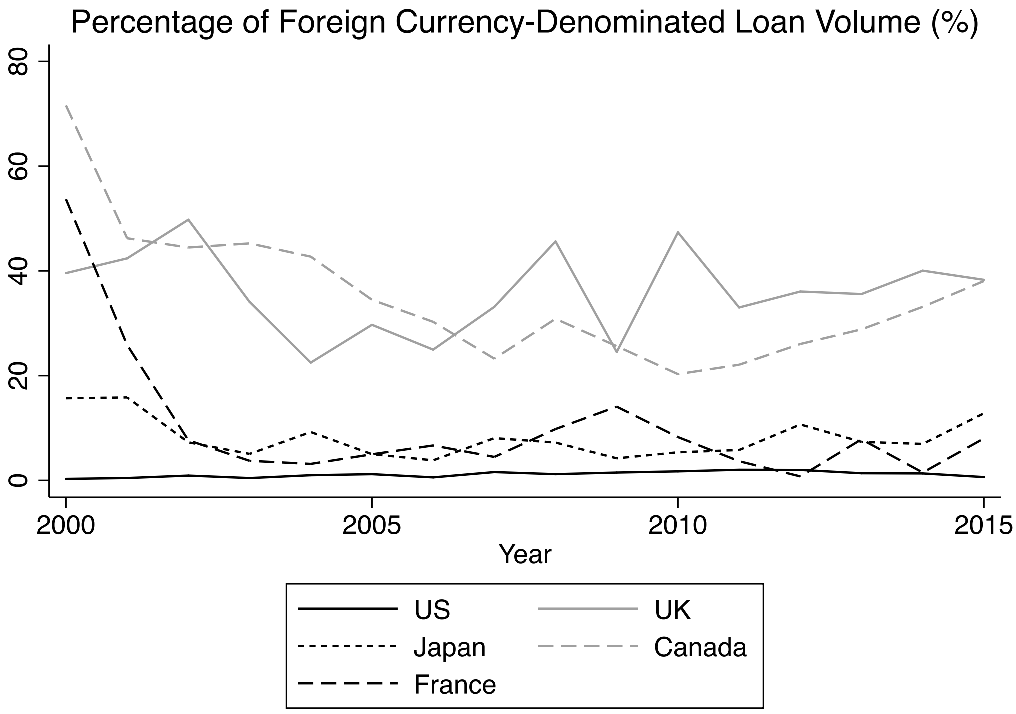
Panel A



Panel B



Panel C

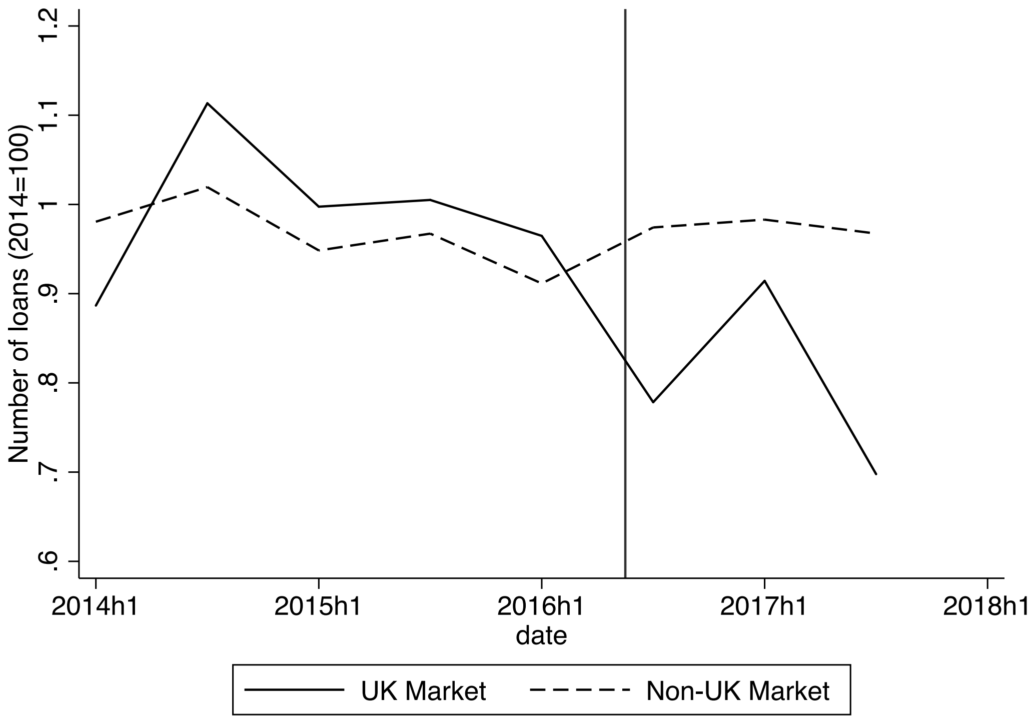


Percentage of Foreign Currency-Denominated Loan Volume (%)
80
60
40
20
0
2000
2005
2010
2015
Year
US
UK
Japan
Canada
France

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 H1/2014- H2/2017 time period in Panel A. The number of loans is indexed to an average level of 1 in the year 2014. Panel B shows the percentage share of the UK in the worldwide syndicated market over the H1/2014- H2/2017 time period.

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

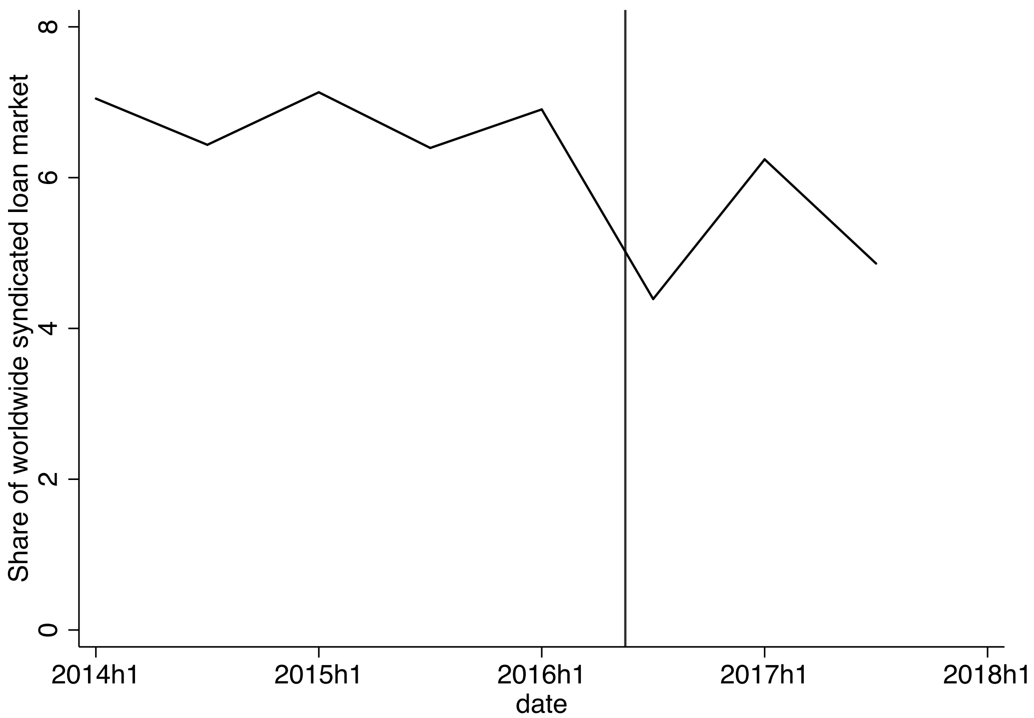
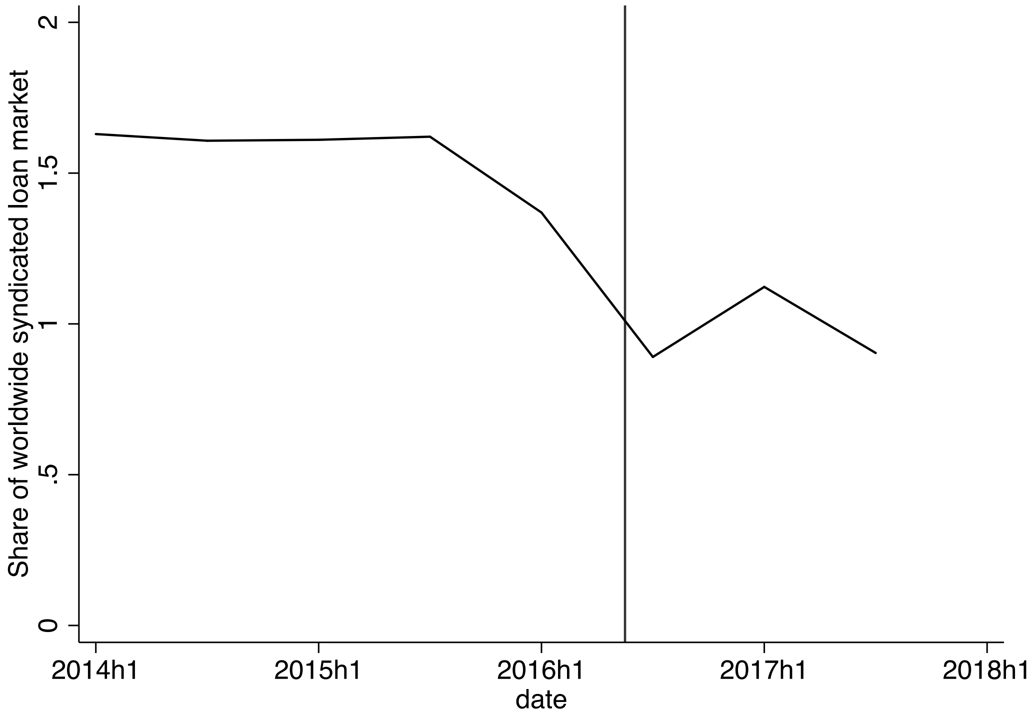


Figure 5: UK-firm/GBP-loans as a percentage of the worldwide syndicated loan market

This figure depicts UK-firm/GBP/UK-bank-loans (Panel A) and UK-firm/GBP/non-UK-bank-loans (Panel B) as a percentage of the worldwide syndicated loan market between H1/2014- H2/2017.

Panel A: UK-firm/GBP/UK-bank loans as a percentage of the worldwide syndicated loan market



Panel B: UK-firm/GBP/non-UK-bank loans as a percentage of the worldwide syndicated loan market

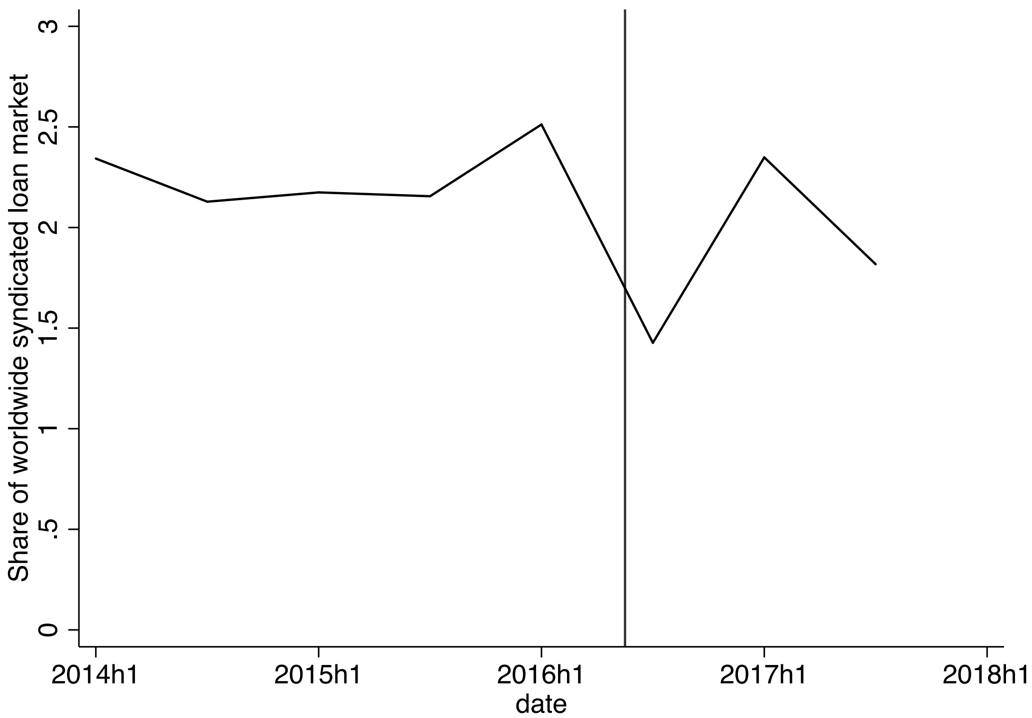


Table A.1: Definition of Variables

Variable	Source	Description
Main Dependent Variable		
Loan (0/1)	Dealscan	Equals one if at least one loan has been issued to firm cluster f from bank b in market m in quarter t.
Main Independent Variables		
Post Brexit (0/1)	Dealscan	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.
GBP (0/1)	Dealscan	Equals one if a loan is denominated in British pounds and zero otherwise.
Firm Characteristics		
Service Industry (0/1)	Dealscan	Equals one if the firm belongs to the transportations, communications, electric, gas and sanitary services, wholesale trade, retail trade, finance, services or public administration industry.
Manufacturing Industry (0/1)	Dealscan	Equals one if the firm belongs to the manufacturing industry.
Other Industry (0/1)	Dealscan	Equals one if the firm belongs to the agriculture, forestry, fishing, mining or construction industry.
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.
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[13], 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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[13] 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.[14] 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 – and thereby potentially increase the power of the difference-in-differences estimator. However, in this

[14] We assume that lambdas are not collinear.

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.[15]

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.

[15] 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.

B. UK Market Share Decomposition

We define the market share of the UK market in the global syndicated loan market at time t as

$$MktShareUK_t = \frac{N_{UK,t}}{N_{WW,t}}$$

where $N_{UK,t}$ is the number of facilities originated in the UK market in period t and $N_{WW,t}$ is the number of facilities originated worldwide in period t. In the following, we classify all loans into several distinct categories i. These categories are discussed in more detail below. As an example, consider the categories "UK firm" and "non-UK firm". A drop in the UK market share can either be driven by a drop in loans in the category that usually takes place in the UK (here: UK firm) or by a change in market share in one or both the categories (e.g. UK firms and/or non-UK firms switching from the UK market to another market). More formally, the market share can be written as:

$$MktShareUK_t = \frac{\sum_i N^i_{UK,t}}{\sum_i N^i_{WW,t}} = \frac{\sum_i N^i_{WW,t} \cdot MktShareUK^i_t}{\sum_i N^i_{WW,t}}$$

Changes in the UK market share can thus be decomposed into 1) changes in the number of loans issued in a category, 2) changes in the market share of the UK in a particular category, and 3) an interaction term between 1) and 2):

$$\begin{aligned}
\Delta MktShareUK &= \frac{\sum_i N^i_{WW,t} \cdot MktShareUK^i_t}{\sum_i N^i_{WW,t}} - \frac{\sum_i N^i_{WW,t-1} \cdot MktShareUK^i_{t-1}}{\sum_i N^i_{WW,t-1}} \\
&= \sum_i \left(\frac{N^i_{WW,t}}{\sum_i N^i_{WW,t}} - \frac{N^i_{WW,t-1}}{\sum_i N^i_{WW,t-1}} \right) \cdot MktShareUK^i_t + \frac{N^i_{WW,t-1}}{\sum_i N^i_{WW,t-1}} \cdot \Delta MktShareUK^i \\
&= \sum_i \left(\frac{N^i_{WW,t}}{\sum_i N^i_{WW,t}} - \frac{N^i_{WW,t-1}}{\sum_i N^i_{WW,t-1}} \right) \cdot MktShareUK^i_{t-1} + \frac{N^i_{WW,t-1}}{\sum_i N^i_{WW,t-1}} \cdot \Delta MktShareUK^i \\
&\quad + \left(\frac{N^i_{WW,t}}{\sum_i N^i_{WW,t}} - \frac{N^i_{WW,t-1}}{\sum_i N^i_{WW,t-1}} \right) \cdot \Delta MktShareUK^i
\end{aligned}$$

The first term in the last equation represents changes in market share due to a change in mix of loan categories. For example, if UK firms predominantly issue in the UK market and UK firm issuance declines post-Brexit referendum, then this is captured by the first term. The second term represents changes in the market share in a given category. For example, if UK firms used to issue in the UK market pre-Brexit referendum, but switch to other markets post-Brexit referendum, then this would be picked up by the second term. The third term contains second-order interaction terms between these two effects that should be close to zero in most setups.