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The Great Trade Collapse, its aftermath and the determinants of UK export margins: a cohort- and firm-level matching approach.

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Abstract

This paper uses a detailed dataset of UK firms between 2005-16, to investigate how export participation and export values were affected by the 2008 crisis and particularly the post-crisis recovery period. Viewing the post-crisis period as a treatment compared to before the crisis, we compare firm export propensity and export values using a propensity score matching approach. We conclude that the underlying relationships between size, productivity, creditworthiness and exports remained remarkably consistent throughout the period. After correcting for TFP and credit scores, we find relatively constant export propensity across the whole time period, except for younger firms in services industries, whose export propensity increased. Our results suggest that the slowdown in trade in this period has not been attributable to a change in underlying firm export behaviour.[1]

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KEYWORDS: Extensive Margins, Intensive Margins, Crisis, Credit Score
JEL Classification: F1, F2, F3, F4, E00

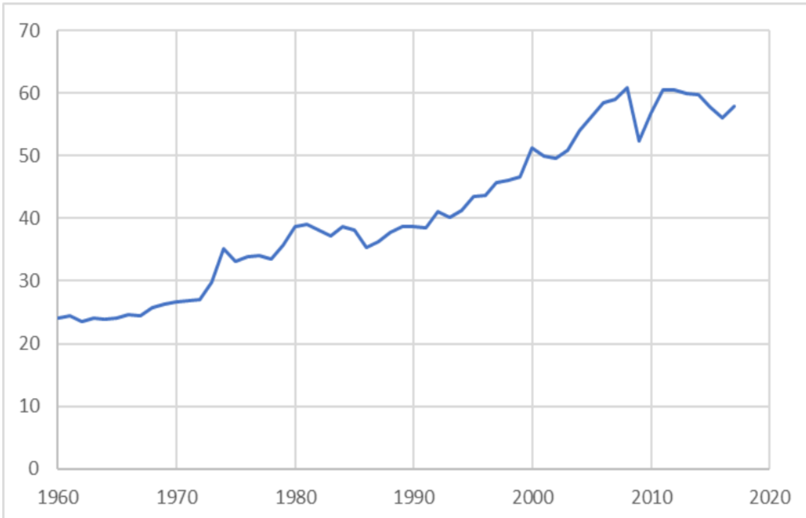
1 Introduction

This paper focuses on the changes in UK export performance following the 'Great Trade Collapse' linked with the 2008 global crisis. While global trade recovered rapidly from the immediate fall, both global trade and British exports have flatlined after the recovery, in sharp contrast to the period before. Looking at the general picture: the 2008 Great Recession led to a sharp contraction in trade for many economies: 'the Great Trade Collapse' ('GTC'), which has been well covered in the economic literature (Alessandria et al., 2010; Alessandria, 2013; Crowley and Luo, 2011; Eaton et al., 2016). In the months following the collapse of Lehman Brothers in September 2008, the volume of world trade shrank by over 30%, compared to a drop of about 3% in world GDP. A notable feature of this was the synchronous timing across all major economies, probably reflecting the degree of integration of global supply chains. The recovery was also sharp - hence leading to a 'bullwhip' description. Explanations for these dynamics include synchronised destocking of durable goods and falling investment (since such goods tend to be more trade-intensive than other elements of GDP) (Alessandria et al., 2010; Crowley and Luo, 2011), with subsequent restocking, but also financial constraints (Amiti and Weinstein, 2011) and subsequent losses of trust in international suppliers. However, this is not the full story. Plotting the relationship between trade and global GDP, in Figure (1) below, we can see that the almost continuous and sharp growth in trade relative to GDP from the mid 1980s until 2008 was not resumed after the bullwhip recovery: in fact, the post-crisis period can be seen as one of trade stagnation.

It follows that the 2008 recession should be seen as a significant long-term structural break in the decades-long trend to greater global integration[2]. An important question is whether the change represents simply the demand effects of recession and recovery, perhaps combined with the effects of a slowdown in productivity and investment, or whether something more fundamental has changed on the trade side.

[2] Jacks et al. (2011) interpret this as a revealed increase in real trade costs

Figure 1: Growth over time in world trade as a percent of GDP.



Note: source World Bank

It is upon this postcrisis period that we particularly focus. Our contribution is to use a disaggregated firm-level dataset for the UK for the period 2005-16 inclusive, so covering periods before, during and after the crisis, but stopping at the time of the Brexit vote, which produced another shock (Hosoe, 2018). Using propensity score matching, we can compare firms' export behaviour - in terms of both export propensity and export values - over the period, including disaggregation of trade behaviour by firm cohort and industry. Indeed, this paper addresses this change, at least in the case of the United Kingdom.[3] This is the first paper, as far as we are aware, to estimate the effect of the crisis and its aftermath on both the extensive and intensive margins of UK exports, using firm-level data for the period 2005 to 2016. This enables us to compare the post-crisis period with the period just before the crisis. In particular, we focus upon whether or not firm-level export behaviour has changed in terms of the responses of export participation and export values to key variables, such as productivity, firm size and financial performance. In addition, we utilise a much more disaggregated approach, taking account of firm cohorts, following Sedláček and Sterk (2017),

[3]Comparing UK export data in Appendix Figure A1 with Figure 1 shows that UK trade followed similar dynamics to global trade throughout this period.

as well as inter-industry differences. We explicitly treat the crisis and the recovery period as treatments upon firms, and hence are able to utilise a difference-in-differences ('diff-in-diff') approach, using pairwise propensity score matching of firms to control for a number of explanatory variables and discern whether or not behaviour has changed between these periods.

As in the previous literature (see Section 2 below) places considerable emphasis on the roles of finance in exports and the GTC, we take explicit account of financial data - in this case, by directly utilising for the first time in this context firms' credit score data.

Our overall conclusion is that, in fact, many of the underlying relationships are relatively stable over the three periods: pre-crisis (up to 2008), the crisis (2009-10), and post-crisis (2011 onwards). Larger or higher-productivity firms are more likely to export, and to export more. Firms with better credit scores are also likelier to export. Moreover, far from the crisis worsening credit scores, these improved on average both during and after the crisis, probably reflecting tougher selection effects from competitive pressures during the crisis. In addition, the impact of credit scores on export propensity was somewhat reduced following the crisis.

In addition, although export performance has been slow throughout the period, our paper indicates that, in fact, there has still been a tendency for export participation to grow. Part of this reflects the growth in total factor productivity during the recovery - which has, admittedly, been slower than before the crisis, hence perhaps explaining a slower trend growth in trade, as a consequence of the productivity slowdown.

Analysis of firms' export propensity shows that this has remained relatively steady in most sectors and cohorts, with the marked exception of younger firms in the services sector, which are more likely to be exporters in the post-crisis period.

In our focus on the United Kingdom, it is worth considering that the UK has a particularly strong concentration of financial services, which were hard hit during the crisis (affecting government finances and demand), but that it is also relatively flexible, with employment recovering faster than elsewhere in Europe (arguably at the cost of reduced wages and greatly slowed productivity).

The structure of our paper is as follows: - Section 2 reviews the background and literature, as well as the UK case in more detail. Section 3 outlines our data sources, including the use of firm-level financial data. Section 4 lays out our empirical methodology and results. This confirms the results in much of the literature, that export propensity is increasing with respect to TFP, foreign ownership, firm size and credit score, and suggests that, on average, export propensity was slightly higher, once correcting for these factors, during and after the crisis compared to before.

2 Background and Literature on the Great Trade Recession and increasing trade costs

We start by considering potential reasons discussed in the literature as to the impact of the Great Trade Collapse on different firms' exports, and also for the weakness of trade after the immediate recovery.

It is perhaps no surprise that financial risk and financing costs should be mentioned as potential contributory factors in both the crisis and the subsequent trade slowdown. After all, the origins of the 2008 crisis were linked to bank instability, and even though central banks responded (to varying degrees) with interest rate cuts and aggressive quantitative easing to attempt to maintain the supply of credit, business credit has been less available than before the crisis. We discuss the specific case of the United Kingdom in a separate subsection, but many of the same points apply internationally. This is important because the role of credit in promoting trade has increasingly been acknowledged: notably, in the recent literature, by Chaney (2013) and Manova (2013), who both introduce credit constraints into a heterogeneous firm model à la Melitz (2003). The liquidity needed to cover costs associated with establishment in a foreign market must be paid up-front, requiring access to either internal capital or credit.

However, while we know that costs of access to credit are important elements of both market entry and ongoing trade costs, the role of these in the changes of export behaviour during and - importantly - after the Great Trade Collapse are perhaps less certain. Evidence that crises affect export behaviour at least partially due to access to trade finance comes from various sources: Ahn et al. (2011) emphasise the importance of financial factors and trade finance as primary causes of this collapse in exports, and Amiti and Weinstein (2011) analysing a panel of Japanese firms, show that health of financial institutions is an important determinant of firms' exports during 1990-2010 crises. Looking at crises more generally, Iacovone et al. (2019) studied the impact of 23 banking crises on export growth in both developing and developed countries, showing that sectors that are more dependent on banking credits are more influenced by crises: that is, they suffer a lower growth rate than other sectors. Effects of a crisis on exporting via credit rationing have been examined by a number of papers. Minetti and Zhu (2011) consider firms' decision to export in more than one market in a credit rationing environment, and the results suggest a negative effect of credit rationing on export participation. Similar results are reported by Berman and Héricourt (2010) for cross-country evidence from developing countries. Paravisini et al. (2015) show that a 10% reduction in the supply of credit reduces the volume of exports in the year after the shock by 1.95%, while no effect is estimated for the probability of exporting. On the other hand, using systemic and bank-specific shocks Carvalho et al. (2013) highlight the fact that bank distress is associated with investment cuts to those borrower firms which are more bank dependent. Görg and Spaliara (2018) highlight that deterioration of firms' financial position increases the likelihood of export exit particularly during the financial crisis. Chodorow-Reich (2014) analyses the effect of 2008–9 crisis on employment in non-financial firms, emphasizing that effects vary according to firm size. More recently, Huang et al. (2017) show that Chinese firms that are able to issue stocks (as a mode of external finance) are more likely to engage into export activity.

The burgeoning literature on the effects of firm heterogeneity, following Melitz (2003) indicates both theoretical and empirical reasons to believe that export participation is positively associated with both firm size and total factor productivity (TFP). In this UK, there has been considerable literature on the 'productivity puzzle', such as by Harris and Moffat (2016); Douch et al. (2019), who suggest that both manufacturing and services experienced a significant fall in productivity post-2008, although this is mainly in service sector and is mainly found among younger, smaller firms. A recent OECD report highlights that the main contributor to this decline is non-financial services and in particular information and communication sectors (Remes et al., 2018).

Other factors affecting export propensity include foreign ownership (Manova et al., 2009), and that the probability of exporting increases with age.

It is also sensible to consider the role of firm cohorts in export behaviour, where firm cohort is interpreted in terms of the year of establishment. In the context of comparing periods before, during and after the crisis, different cohorts will be distinguished in any of these periods by age. A firm which is new during a crisis may well differ in a number of ways from one which is of similar age during the pre-crisis period. It is perhaps no surprise that the immediate crisis led to lowered export probability for young firms compared to older ones. First, new firms lack a credit history, so if lenders are more wary of risky ventures during or after a crisis, they may well find access to capital is rationed. Second, because market entry may require an investment in search capital, this may become sunken after firms have found partners (Edwards, 2010) but not for newer entrants: hence firms who have not yet entered export markets may respond to uncertain conditions by delaying entry.[4] In addition, as Sedláček and Sterk (2017) stress, cohorts of firms established during recessionary conditions are likely to target smaller, slower-growing and more niche markets, rather than mass markets. This again leads to a potential qualitative difference compared to firms established in the boom years.

2.1 The Case of the UK

Figure (1) in Section 1 reported the stagnation of the share of world trade volumes, showing the pattern of a short-term but very sharp collapse, followed by recovery and then stagnation. Not surprisingly, Figure (A1) in the Appendix shows that UK firms' exports have followed a very similar path, at least since 2005.

Compared to the Eurozone, the banking crisis in the UK was particularly severe early on, with the Northern Rock crisis of autumn 2007, and several banks needing state aid to survive.

[4] Graziano et al. (2018) use a real options model to explain how anticipation of another potential crisis (Brexit) is delaying firm entry into exporting.

Subsequently, the UK followed a more accommodating monetary and (initially) fiscal policy than the Eurozone, with quantitative easing and a fall in sterling assisting exporters.

The drop in the supply of finance as banks restructured their finances has resulted in firms facing increasing transaction costs from trade, since banks have increased the collateral required to access finance for trade. To some extent, central bank interest rate reductions may have ameliorated the situation, but often commercial banks did not pass these cuts to firms and consumers. For consumers this led to a rise in the savings rate, from almost 0% to 7% during the crisis. On the other hand, this has led to increased financial costs and relatively higher risks for many firms. Arguably this is one of the factors (alongside falls in demand, particularly for durables and investment goods), which caused a drop in exports. Against this, the policy response of lowering interest rates, quantitative easing and allowing sterling to fall would be expected to have cushioned the shock. Other schemes that helped companies with their obligations may also have played a crucial role - for example, tax payment extensions - these might have allowed firms to sustain their trade activities, despite lower access to finance (Arrowsmith et al., 2013).

Despite financial easing and a falling pound, Figure (A1) shows that export values remained stagnant, once they had recovered from the financial crisis. We note that this figure, which is for the United Kingdom, reflects the trends seen in Figure 1 for global trade.

In the subsequent sections, we analyse how differences between firms in terms firms' potential credit accessibility, age, and size and ownership status resulted in different export performance.

3 Data sources and variables.

We use UK firm level data, from the FAME database, covering the period from 2005 to 2016 inclusive. This data precedes the Brexit vote (except the very final year). This database includes information on exports, gross output and other firm-specific characteristics, such as firms' geographic location, number of employees *etc.*. We can also distinguish firms based on their ownership status, such as whether a firm is domestically or foreign-owned.

Table (A1) in the Appendix reports summary statistics of the main variables of interest, based on the whole sample. Firms engaged in trade account for about 46% of the sample. This is in line with Greenaway and Kneller (2008) who find that about 75% exported in at least 1 year, although the percentage exporting in any given year is lower than this. Moreover, these figures are also in line with Germany, where about 45% are exporters (Wagner, 2003). Countries such as Spain (about 62% exporters Delgado et al. (2002)) and Sweden (about 90%, Greenaway et al. (2005)) are more export-oriented because smaller economies tend to be more open.

Since there is no common agreement on the most appropriate measure of productivity, we use four different measures:- i.e. total factor productivity (TFP), as measured by Levinsohn and Petrin (2003), by Olley and Pakes (1996) and also by Ackerberg et al. (2015), as well as standard labour productivity.

The credit score is derived from CRIF and is discussed below and in the Appendix. It ranges from a minimum of 6 up to a maximum of 99 and has a mean value of about 85. A higher score implies better creditworthiness.

Table (1), below, shows the main differences in the value of key firm level variables between firms active before, during and after the financial crisis (2009-2010).

We start by comparing the Crisis period (2009-10) with the Pre-Crisis period, as shown in Columns (1)-(3). Variables in monetary units have been deflated by sectoral output PPI indices.

Probability of being an exporter (first row), was about 0.68% higher during the financial crisis than in the average of the period before it. Export value (second row) was also somewhat higher during the crisis than the average of the period before, although this is statistically insignificant. Domestic sales were lower (again not significant). The productivity measures - labour productivity (insignificantly) and three measures of TFP (highly significantly) fell in the crisis. Domestic sales and number of employees were, however, lower during the crisis than before.

In comprehending this, it is worth bearing in mind that the pre-crisis period is the average for 2005-8 inclusive, while as Figure (A1) in the Appendix shows, there was a spike in exports in 2007-8, before the fall 2009. The crisis may have been marked, but it was starting from levels well above the average of the 4 years previously.

There may be some sign of firm selection effects at play during the crisis: for example ln(Credit Score) was actually higher on average than before the crisis, and firm age increased, possibly indicating selection effects in terms of fewer startups and maybe closure among the least creditworthy firms. We will investigate this later in the paper.

Turning now to Columns (4)-(5): comparing the post-crisis years (2011-16) with the period before the crisis, the average export probability was 3.94% higher than before the crisis (though perhaps more in line with that in 2008). However, export value is insignificantly higher after the crisis than before, while domestic sales are barely changed. Productivity is higher after the crisis than before, but only by 1.85% on the $ln(TFP_{AFC}$ measure, which is often regarded as the most reliable. Compared with the peak in 2008, these figures emphasise Britain's sluggish productivity performance.

Firms in the postcrisis period tend to be larger, older and have better credit scores than before the crisis, perhaps indicating continuing selection effects.

Table 1: Key Firm Level Variable Mean-difference Between Pre- and Post-Crisis periods

	(1) Mean in Pre-Crisis	(2) Mean Crisis	(3) Diff. (2)-(1)	(4) Mean Post-Crisis	(5) Diff. (4)-(1)
Export	0.4376	0.4444	0.0068**	0.4771	0.0394***
Export Value ($000'$)	2506	3004	497	3594	1088
Domestic Sales ($000'$)	17674	15739	-1935	18167	492
ln(Fixed Assets)	3.8946	3.8983	0.0037	4.0128	0.1182***
ln(age)	2.7346	2.7570	0.0225***	2.8552	0.1206***
ln(Number of Employees)	4.2467	4.2000	-0.0467***	4.2725	0.0258***
ln(Credit Score)	4.4070	4.4297	0.0226***	4.4396	0.0325***
ln(Turnover)	6.1530	6.0924	-0.0606***	6.2307	0.0777***
ln(Labour Productivity)	1.9063	1.8923	-0.0139	1.9582	0.0519***
ln(TFP$_{AFC}$)	3.8556	3.7974	-0.0581***	3.8741	0.0185*
ln(TFP$_{LP}$)	5.4337	5.3773	-0.0564***	5.4996	0.0659***
ln(TFP$_{OP}$)	5.4031	5.3470	-0.0560***	5.4689	0.0659***

Note: Where star (* p< 0.1, ** p< .05, *** p<0.01). This table reports the mean difference between firms in the crisis period (2009-2010) versus other periods. This shows that firms in the aftermath of financial crisis tend to be less efficient (low TFP) and small.

Since financial restrictions are one of the main perceived channels by which a crisis is argued to affect export behaviour, we highlight the use of credit score information, as developed by the CRIF Group: a group which supports and insures a range of insurance services, added-value solutions, information services and consumer profiles for the UK insurance industry. This group provides credit information for banks lending to firms, hence providing support for decision management and fraud prevention. This international company operates on four continents serving 3100 banks and financial institutions in 50 countries.

CRIF's credit scores take account of several factors, to calculate the likelihood of failure of the firm, including firms' accounts, county court judgements, subsidiary structure, director and shareholders' history and SIC classification. Moreover, various financial components are included: turnover, working capital, cash and bank deposits, assets and other firm's specific financial variables.

The credit score derived is a subjective measure of the likelihood that firms will eventually became bankrupt in the following twelve months. In other words, the score is 100 minus the estimated probability that a company will obtain ease from its creditors or will eventually close down its activity in the following months. Hence, a high score emphasises a low estimate of failure probability, whereas a low score suggests a high probability of failure. As Table (A1) in the Appendix indicates, the mean value over the whole period is 85.56%, indicating an average perceived probability of 14.44% of failure.

While the formula used to calculate this score is not released to the public, many institutions rely on these scores for company evaluation. Therefore, the score reflects the credit constraint that firms might face on a yearly basis. In fact, it is calculated yearly, hence depending on the market performance firms might face different credit constraints over time.

The result is a score ranging from 1/100 to a maximum of 99/100, which absorbs information on firm characteristics and market potential. In other words, those scoring 1/100 are considered to have the highest likelihood of failure. Therefore, in comparison to other studies this score is firm-specific, varies on a yearly basis and it is a continuous measure of risk that banks and other legal institutions use to determine whether to extend loans to firms.

We investigate the exogeneity of credit scores in the Appendix. Our conclusion is that there may be some endogeneity, but that the great majority of the variation in credit scores is not explained by the other variables in our data set.

4 Methodology and results

4.1 The probability and level of exporting in pre-crisis, crisis and post-crisis periods

Models to explain whether or not firms participate in exporting generally assume that exporters have to cover a combination of additional fixed and variable costs (Chaney, 2013; Manova, 2013). Consequently, when considering the effects of the GTC and recovery periods, one might consider that trade participation will be affected through changes in these costs.

Following Minetti and Zhu (2011), we consider that a firm j will participate in exporting if it believes that its profit from participating in exports is greater than that of not participating (which is effectively the avoidable cost). To derive this, we start by rewriting the difference in expected profit, $\hat{\pi}_{jt}$ as a function of firm-specific characteristics, credit scores and crisis dummies as follows:

$$\begin{aligned} \hat{\pi}_{jt} = \beta_1 ln(Credit\,Score)_{jt} + \beta_2 ln(Credit\,Score)_{jt} \cdot Crisis\,Dummy + \\ + \beta_3 ln(Credit\,Score)_{jt} \cdot PostCrisis\,Dummy + X^{'}_{jt}\beta_x + \gamma_t + \varepsilon_{jt} \end{aligned} \tag{1}$$

where β_1 will capture the average effect of credit constraints on extensive margins, while β_2 captures the additional effect of credit constraints during the recession period. The variable $X^{'}_{jt}$ represents a vector of firm's specific characteristics and γ_t is a year fixed effect. The term ε_{jt} captures any unobserved effect that might affect firms. The Crisis Dummy is equal to one if the year is 2009-2010 and zero otherwise. The PostCrisis dummy is equal to one if the year is 2011-2016, and zero otherwise.

However, we do not estimate eq (1) directly. Rather, since the unobserved effect term, ε_{jt}, is assumed to be random, the probability that a firm will export is the probability that

$\varepsilon_{jt} < \hat{\pi}^e_{jt}$, the expected value of $\hat{\pi}_{jt}$ in equation (1). This can be rearranged to yield the probability of exporting for both domestic and foreign firms:

$$\begin{aligned}
Pr(export_{jt} = 1) = \phi(\beta_1 \cdot ln(Credit\,Score)_{jt} + \beta_2 \cdot (ln(Credit\,Score)_{jt} \cdot Crisis\,Dummy)+ \\
+\beta_3 \cdot (ln(Credit\,Score)_{jt} \cdot PostCrisis\,Dummy)+ \\
+\beta_4 \cdot Crisis\,Dummy + \beta_5 \cdot PostCrisis\,Dummy + X'_{jt}\beta_x + Trend_t)
\end{aligned} \tag{2}$$

Here $\Phi(.)$ represents the cumulative distribution function (c.d.f.) of the error term. If this is of standard normal form, then the model can be estimated as a probit. The expected outcome for the $ln(Credit\,Score)$ variable is that firms that are less credit constrained are more likely to be exporters, that is, we expect a positive sign for $\beta_1 > 0$. However, the signs of β_2 and β_3 depend on how the global crisis affected credit constraints. Thus, the magnitude of these effects is expected to be different for domestic and foreign firms.

To investigate the effects on intensive margins of trade we modify eq (3) to account for export values.

$$\begin{aligned}
Value\,of\,Exports = \gamma_1 \cdot ln(Credit\,Score)_{jt} + \gamma_2 \cdot (ln(Credit\,Score)_{jt} \cdot Crisis\,Dummy)+ \\
+\gamma_3 \cdot (ln(Credit\,Score)_{jt} \cdot PostCrisis\,Dummy)+ \\
+\gamma_4 \cdot Crisis\,Dummy + \gamma_5 \cdot PostCrisis\,Dummy + X'_{jt}\gamma_x + Trend_t
\end{aligned} \tag{3}$$

Note that, for the purposes of estimating the effects of the crisis and postcrisis periods, in Equations (2)-(3) we have introduced the crisis and postcrisis dummies in levels terms, and dropped the year fixed effect, due to collinearity.

In this model, we postulate three main routes by which the crisis or post-crisis period might potentially affect export participation. The first is a direct effect, measured by the shift dummies β_4 and interaction effect with credit rating, measured by β_2 and β_3. The third route is an indirect effect, in the sense that values of credit scores and the various explanatory variables in X'_{jt} are changed by the crisis or post-crisis period. In other words, we are testing whether the underlying model of exporting is stable across the three periods of our sample.

4.1.1 Baseline Results

Table (2) below summarises the results of our baseline panel regressions. We will present these results first, and then discuss some of their limitations, which lead us on to the analysis in the next subsection.

Columns (1)-(4) of Table (2), below, break down the effects of the crisis and post-crisis periods upon the probability of exporting or extensive margins. Column (1) reports the result of a probit model without sector dummies. This confirms that export probability is strongly positively linked to credit score, in line with much of the literature, such as Manova (2013). Larger firms, in terms of number of employees, are significantly more likely to export, but the relationship in terms of fixed assets is negative. Strangely, TFP has a statistically significant negative effect, contrary to much of the literature (Melitz, 2003).

Overall, there is a significant positive time trend in export participation, and the Crisis and Post-Crisis periods both fall below that trend (dummies in the first two lines).

Since some of the results in the probit model appear out of line with the literature (effects of fixed assets or productivity), we wish to investigate whether sectoral factors are important here. Consequently, in Column (2), we include sector fixed effects. As is more appropriate in a model with multiple fixed effects, we estimate this using a logit model. Incorporating sector fixed effects corrects the sign of the coefficients on TFP and fixed assets (though number of employees is no longer significant). The negative estimated direct effect of the crisis is no longer significant, and that of the postcrisis period turns positive, indicating that there has been a reorientation of the economy towards less export-orientated sectors, which explained the former negative effect.

The positive and significant coefficient of the age variable in Column (2) confirms that firms that are older are more likely to have entered into trading activities. These results are in line with those reported by Wang (2010) who shows that the probability of exporting increases with age.[5]

Table 2: Export Behaviour and Domestic Sales: crisis and post-crisis periods compared to pre-crisis

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Export (0/1)			Export Value	Domestic Sales
Crisis Dummy = 1	-0.0602***	-0.00268	1.457***	-0.789	3.412
	(0.00934)	(0.0181)	(0.476)	(5.800)	(2.449)
Post-Crisis Dummy = 1	-0.0512***	0.117***	3.756***	-0.401	-2.251***
	(0.0145)	(0.0280)	(0.423)	(5.104)	(0.857)
ln(Credit Score)	0.739***	0.581***	1.152***	1.721*	-0.721***
	(0.0282)	(0.0528)	(0.0945)	(0.950)	(0.178)
ln(Credit Score)$\cdot CrisisDummy$			-0.331***	0.306	-0.724
			(0.107)	(1.285)	(0.525)
ln(Credit Score)$\cdot Post-CrisisDummy$			-0.822***	0.128	0.543***
			(0.0956)	(1.110)	(0.201)
ln(TFP$_{ACF}$)	-0.123***	0.199***	0.196***	0.719	1.034***
	(0.00449)	(0.0164)	(0.0164)	(0.468)	(0.0987)
ln(Number of Employees)	0.199***	0.0245	0.0241	0.539	0.239***
	(0.00584)	(0.0160)	(0.0159)	(0.372)	(0.0493)
ln(Age)	0.0120	0.0439***	0.0374**	0.118	0.378***
	(0.00807)	(0.0154)	(0.0155)	(0.142)	(0.0423)
Foreign = 1	0.288***	0.267***	0.263***	-0.667**	-0.179*
	(0.0155)	(0.0286)	(0.0286)	(0.295)	(0.106)
ln(Fixed Assets)	-0.106***	0.0196**	0.0185**	0.585***	0.338***
	(0.00311)	(0.00847)	(0.00846)	(0.131)	(0.0198)
Trend	0.0392***	0.0405***	0.0432***	-0.0525	-0.0441
	(0.00241)	(0.00458)	(0.00462)	(0.0437)	(0.0273)
Constant	-3.662***	-5.399***	-7.883***	-12.90***	1.234
	(0.115)	(0.245)	(0.412)	(4.264)	(1.056)
Observations	198,739	198,739	198,739	198,739	198,737
R-squared				0.587	0.215
Method	probit	logit	logit	PPML	PPML

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Probit model with and Logit model fitted that accounts for sector fixed effect. The table presents the effect of credit constraints and the global crisis on the probability of exporting (coefficients). The Poisson Pseudo Maximum Likelihood, PPML, reports the effect on export values and on domestic sales. We account for TFP, size and firm's age, sector and year dummies as additional control variables.

Column (3) introduces an interaction term for credit score with the Crisis and PostCrisis dummies, indicating that the indicate that the marginal impact of changing credit status on export probability is less compared to the pre-crisis period. We note that the combined coefficient on ln(Credit Score) and the interaction term is always positive, although reduced, particularly in the post-crisis period. When we take the mean of ln(Credit Score) as about

[5]We should note that this contrasts with a negative estimated sign on UK SMEs for all firms above five years old in a survey by Love et al. (2015).

Table 3: Marginal Effects: Export Behaviour

VARIABLES	(1) Export	(2) Export	(3) Export
Crisis Dummy = 1	-0.0602***	-0.00268	1.457***
	(0.00934)	(0.0181)	(0.476)
Post-Crisis Dummy = 1	-0.0512***	0.117***	3.756***
	(0.0145)	(0.0280)	(0.423)
ln(Credit Score)	0.739***	0.581***	1.152***
	(0.0282)	(0.0528)	(0.0945)
ln(Credit Score)$\cdot CrisisDummy$			-0.331***
			(0.107)
ln(Credit Score)$\cdot Post - CrisisDummy$			-0.822***
			(0.0956)
ln(TFP$_{ACF}$)	-0.123***	0.199***	0.196***
	(0.00449)	(0.0164)	(0.0164)
ln(Number of Employees)	0.199***	0.0245	0.0241
	(0.00584)	(0.0160)	(0.0159)
ln(Age)	0.0120	0.0439***	0.0374**
	(0.00807)	(0.0154)	(0.0155)
Foreign = 1	0.288***	0.267***	0.263***
	(0.0155)	(0.0286)	(0.0286)
ln(Fixed Assets)	-0.106***	0.0196**	0.0185**
	(0.00311)	(0.00847)	(0.00846)
Observations	198,739	198,739	198,739
Method	Probit	logit	logit

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Probit model with and Logit model fitted that accounts for sector fixed effect. The table presents the effect of credit constraints and the global crisis on the probability of exporting (marginal effects). We account for TFP, size and firm's age, sector and year dummies as additional control variables.

4.4, from Table A2, the net direct plus interaction impact of the Crisis on export probability is -0.08, and in the PostCrisis period it is +0.11, both net effects being small and insignificant.

The evidence for a dynamic search process, as shown in the effects of age upon exporting, suggest that we should investigate firm dynamics. Column (4) includes the previous year's exports, which have a strong and significant positive effect upon export probability; this has important implication for the export decision, since it helps account for potential self-selection into trading activity (Girma et al., 2005): i.e. sunk costs play an important role in the export decision, and only firms that are able to overcome these costs are able to export in the future. Greenaway et al. (2007); Temouri et al. (2013) argue that previous export activity is a well-established measure of sunk cost, suggesting that Column (4) provides evidence for the sunk costs hypothesis.

Moreover, once existing export presence is incorporated in the regressions, we find that the direct effects of both the crisis and postcrisis periods become smaller and in the former case insignificant. Also, the interaction terms with credit score are no longer significant. In other words, changes over the period are explained by the indirect effects of the crisis and postcrisis period upon the other variables (primarily credit score, TFP and foreign ownership), combined with what has now become a slight negative time trend, perhaps reflecting the more stagnant nature of global trade after the crisis.

The final two columns cover the effects of our causal variables upon export value and domestic sales per firm. Both have been deflated by appropriate sectoral producer price indices. We utilise a poisson pseudo maximum likelihood (PPML) estimator, to eliminate bias due to some firms not exporting.

4.2 Matching analysis of export propensity.

While the results in the previous subsection provide interesting and broadly plausible results for firm export participation and sales, we acknowledge that a potentially important issue is the possible endogeneity of many of the variables in Table (A2) - not just the lagged dependent variable, but also the various explanatory variables. For example, we have noted that there is a degree of endogeneity in the credit scores which we are using - notably, there seems to be a selection effect leading to an improvement in credit scores of surviving firms during and after the crisis compared to the pre-crisis period. This could create some collinearity between the credit scores and the crisis/postcrisis dummy variables in Table (2).

This suggests the use of an alternative approach based upon differences-in-differences, hereafter Diff-in-Diff, whereby the two later periods - crisis and post-crisis - are seen as treatments compared to pre-crisis.

In addition, as a natural application of this Diff-in-Diff approach, we utilise a pairwise matching approach of firms, based on propensity scores, hereafter DID-PSM, in which firms in the treated period are compared with firms closely matched in terms of the other explanatory variables (credit score, size, TFP etc.) in the untreated period. This approach allows us to carry out the DID-PSM analysis while relaxing the assumption that the ways in which the treatments work through other variables are linear.

We use the following propensity score matching specification (Caliendo and Kopeinig, 2008) for the average treatment effect τ_{ATT}:

$$\tau_{ATT} = E_{p(X)|Crisis=1}[E(EXP_1)|Crisis = 1, p(X)) - E(EXP_0|Crisis = 0, p(X))] \quad (4)$$

where EXP is the probability that a firm is an exporter of export (export=0/1), also defined as the extensive margin of trade.[6] Equation (4) estimates the difference in EXP, the probability of export, between the treated group (during the crisis) or the control group (pre-crisis), while holding the probability that an observation with a particular set of characteristics is treated is held constant (Caliendo and Kopeinig, 2008).

Table (4), below, reports the results of the DID-PSM analysis using a number of key firm level characteristics to match firms.[7] We selected a caliper of 0.0000001 which has passed a sensitivity test reported in Panel B.

The initial sample of treated firms is divided by the matching process into 3,543 firms which found an appropriate match, as opposed to 31,239 which did not (as shown in Panel C). We term these the matched and unmatched samples. Although the matched sample is not a high proportion of the initial sample, it is easily large enough to provide good statistical results. In Panel B, while the unmatched sample shows statistically significant differences in key variables compared to the matched sample, these are greatly reduced in the matched sample: the extremely low Pseudo-R^2 and the rejection of likelihood ratio support the high quality of the matching.

Comparing the unmatched and matched samples in panel A, both show a small but significant positive difference in exports between the treated group (firms experiencing the crisis)

[6]We later repeat the exercise for export values: the intensive margin of trade.

[7]Note: we also include time and sector fixed effect as additional control variables.

and the control group (no crisis).[8] Specifically, before doing the matching, firms were 0.68% more likely to be exporters during the crisis, and while this difference is slightly increased, to 1.04% once we carry out the matching, the t-statistic is no longer significant. We can conclude that the direct effect of the crisis on export probability compared to the pre-crisis period is small and insignificant. We should however note that we have not included a time trend or dynamics here.

Panel B considers the various confounding variables: in the unmatched samples TFP was lower during the crisis, and firms were older and with higher average credit score and fixed assets but fewer employees. The net result of these indirect effects was to roughly cancel each other out. [9]

4.2.1 Export probability propensity scores: comparison of the post-crisis period with pre-crisis

We now repeat the analysis for the post-crisis period, as shown in Table 5. In this case, Panel C shows that 13,500 observations find a match: again, while 97,909 do not. This is, again, easily a large enough sample to obtain statistically significant results: Panel B confirms that this has a very good pseudo R^2.

Comparing Panel A, export probability among the untreated firms is 3.7% higher after the crisis than before, and this is slightly reduced by the treatment to 2.93% (although t-stat is still significant). It follows that, even after the treatment, export participation in this recovery period is therefore higher than pre-crisis. There are a number of possible interpretations of this (such as a long-run trend growth) but one possibility is that selection effects during the crisis favoured exporting firms.

As Panel B indicates, the unmatched sample showed higher TFP, larger size, increased age, increased probability of being foreign and better credit scores than before the crisis: despite this, Panel A shows that the matching has only a small effect in reducing the rise in

[8]Of course, this is based upon a comparison with the average of the period 2005-8, not on 2008 itself, the year just before the crisis.

[9]Although the previous section found evidence of a time trend and/or firm export dynamics, incorporation of time dummies or lagged export values in a PSM framework can be problematic. We investigate dynamics by a different method - analysis of export behaviour by cohorts - in a subsequent section.

Table 4: DID-PSM: Probability of Export Crisis vs Pre-Crisis

Variables	Panel A: Selection					
	Sample	Treated	Controls	Difference	S.E.	T-stat
Export	Unmatched	0.4443	0.4376	0.0067	0.0034	1.96
	ATT	0.4981	0.4877	0.0104	0.0121	0.86

Variables	Unmatched Matched	Mean			t-test	
		Treated	Control	%bias	t	p>|t|
ln(TFP$_{ACF}$)	U	3.7974	3.8556	-3.0	-4.29	0.000
	M	3.6752	3.7145	-2.0	-0.91	0.363
ln(Number of Employees)	U	4.2	4.2467	-2.8	-3.98	0
	M	4.2814	4.3166	-2.1	-1.00	0.318
ln(age)	U	2.757	2.7346	2.2	3.11	0.002
	M	2.8243	2.8409	-1.6	-0.69	0.488
Foreign	U	0.46107	0.45333	1.6	2.24	0.025
	M	0.46954	0.49704	-5.5	-2.26	0.024
ln(Credit Score)	U	4.4297	4.407	10.3	14.63	0
	M	4.4688	4.4598	4.0	4.89	0.000
ln(Fixed Assets)	U	4.0196	3.8961	3.9	8.67	0.000
	M	3.9096	3.892	0.6	0.48	0.632

Panel B: Sensitivity Test

Sample	Pseudo-R2	LR-χ^2	p>χ^2	Mean Bias	Med. Bias
Unmatched	0.004	1127.58	0.000	6.3	5.4
Matched	0.001	38.57	0.000	1.5	1.2

Panel C: Propensity Score Matching Common Support

	Off Support	On Support
Untreated	0	51,550
Treated	31,239	3,543
Total	31,239	55,093

Note: This table reports the results of the propensity score matching, where the treatment effect is given by the global financial crisis. Furthermore, it reports a number of tests that supports the quality of matched sample.

export propensity.

Table 5: DID-PSM: Probability of Export Post-Crisis vs Pre-Crisis

Variables	Panel A: Selection					
	Sample	Treated	Controls	Difference	S.E.	T-stat
Export	Unmatched	0.477235282	0.440358152	0.03687713	0.002260229	16.32
	ATT	0.501899407	0.472648534	0.029250874	0.006452141	4.53

Note: This table reports the results of the propensity score matching, where the treatment effect is given by the global financial crisis. Furthermore, it reports a number of tests that supports the quality of matched sample.

4.3 The Intensive Margin of Exports

We now look at the value of exports per firm, or intensive margin of exports, as well as domestic sales per firm, for comparison.[10] These were covered in columns (5) and (6) of Table (2) in Section 4.1 above.

To summarise the implications of these columns: higher TFP has the expected positive sign on both exports and domestic sales, as does a higher value of fixed assets and (though not significantly for exports) higher employment. Foreign ownership has a slight negative effect upon sales: possibly this indicates lower fixed costs of exporting for firms who have a foreign owner.

The time trend is not significant for exports, and only marginally so (and negative) for domestic sales. The crisis dummy does not have a significant effect. For exports, the higher postcrisis dummy must be weighed against a negative interaction term with ln(Credit Score): at the mean value of the latter, the net effect of the postcrisis period is -1.01. While higher credit scores have a positive effect on export in the pre-crisis period, this is almost exactly cancelled by the interaction term in the postcrisis period.

It follows that we have a bit of a mixed message on credit scores. Prior to the crisis, firms with better credit scores export more on average, as we would expect from Manova et al. (2009),[11] and that continues during the crisis. However, this seems to break down after the crisis. Nevertheless, we do need to investigate issues of potential endogeneity of the credit scores in this case: hence we move on to propensity score matching.

[10]Note, we use deflated values throughout, to exclude effects of general inflation.
[11]These results are in line with Muûls (2015)'s study of Belgian firms.

Table 6: DID-PSM: Intensive Margins of Trade Crisis vs Pre-Crisis

Variables	Panel A: Selection					
	Sample	Treated	Controls	Difference	S.E.	T-stat
Export Value	Unmatched	3000.7477	2505.4322	495.3155	795.69081	0.62
	ATT	2556.80891	1473.0967	1083.7122	690.7815	1.57

Note: This table reports the results of the propensity score matching, where the treatment effect is given by the global financial crisis. Furthermore, it reports a number of tests that supports the quality of matched sample. The caliper has been increased to 0.000012, due to difficulty in getting a large enough match with the original caliper.

Table 7: DID-PSM: Intensive Margins of Trade Post-Crisis vs Pre-Crisis

Variables	Panel A: Selection					
	Sample	Treated	Controls	Difference	S.E.	T-stat
Export Value	Unmatched	3634.4964	2707.1212	927.3752	676.7731	1.37
	ATT	3197.3093	2248.9012	948.4080	648.0877	1.46

Note: This table reports the results of the propensity score matching, where the treatment effect is given by the global financial crisis. Furthermore, it reports a number of tests that supports the quality of matched sample. The caliper has been increased to 0.000012, due to difficulty in getting a large enough match with the original caliper.

4.4 DID-PSM: Export Value

Following our analysis on the extensive margins, Table (6) reports the use of propensity score matching of firms before and during the crisis.

Examining the results in Table (6), Panel C shows that we were able to find matches for 16,758 firms, although we needed to use a somewhat relaxed caliper of 0.000012 to achieve this.

In Panel A, both the unmatched and matched samples show somewhat higher values of exports per firm: however, neither is statistically significant. Panel B supports the quality of this matching as there are no statistically significant differences between firms in the matched sample. Furthermore, the statistical test -i.e. likelihood ratio as well as the Pseudo-R^2 supports the good quality of the matching.

Looking at the unmatched sample: during the crisis, TFP and number of employees were lower (which would tend to reduce exports), but credit scores were improved, presumably implying selection effects. This works in the opposite direction.

Figure 7 makes a similar comparison for export value by firm for the post-crisis period compared to pre-crisis. Again, with a more relaxed caliper, we get a large matched sample, and the pseudo-R^2 indicates a good match. Several factors (greater TFP, larger number of employees, greater probability of being foreign and more fixed assets) would all tend to have boosted exports in the post-crisis period. Credit scores are also significantly better. Despite correcting for all of these, not all of the increase in export value per firm is eliminated (it is higher, but with low statistical significance).

It is clear that foreign firms were hit by the recent crisis, especially in the manufacturing sector. The combination of lower credit scores as well as TFP highlights potential difficulties in accessing credit, which have affected the export probability. This supports the hypothesis that exports are vulnerable to credit imperfections. This is because tight credit conditions in the aftermath of the financial crisis has affected firms' ability to invest but also their ability to grow (i.e. Bernanke and Gertler (1990) and Clementi and Hopenhayn (2006)). This argument is particularly significant in the last financial turmoil where banks have reduced drastically the amount of lending to business and consumers. Indeed, after controlling for all covariates between the matched groups any mean-difference that is left is mainly due to the treatment.

5 Matching comparisons of firm export behaviour before, during and after the crisis: by age and sector

5.1 Export propensity: matching of firms by age cohort and sector

There are a number of important theoretical and empirical reasons why we should consider firm export behaviour to be a dynamic phenomenon. In particular, if entering an export market involves costs which are not just fixed, but sunken, then firms which are already exporting are more likely to continue doing so. At the same time, as firms generally tend to increase in productivity and size in the initial few years, there is likely to be a point at which they enter export markets, dependent upon how fast their growth is, and upon macroeconomic conditions at the time (Sedláček and Sterk, 2017).

Firm age appears as a significant variable in several, but not all the regressions in 2, with older firms generally being more likely to export thank younger ones, even after correcting for firm size and TFP. This may partly reflect exporting history (interestingly, age drops out when lagged exporting is included in column (4)), but it is also possible that younger firms may find it harder to obtain credit, simply through not having a credit history.[12] However, the effect of a firm's age also reflects cohort effects: a young firm at a time of recession will have a qualitatively different history to one set up in boom times. This may include differences in pre-selection (firms which enter may do so in different fields - for example, Sedláček and Sterk (2017) argue that firms set up in a recession are more likely to be in niche areas, with lower long-run growth potential), selection(different closure rates at different times of the cycle) and different behaviour by lenders. Hence, we seek to carry out analysis identifying cohort from the combination of age variables and date. hence, we seek to compare firms by age group in our three periods: pre-crisis, crisis and post-crisis. The results the crisis period are confined in Appendix B.

Pre-2009 vs Post-2010 Comparison

Looking now at the period after the crisis: one would expect firms that have survived the financial crisis to have undergone tough selection. Hence, we compare firms active during the 2011-2016 to firms active in the pre-crisis period.

Table (8) reports the results for both young and old firms. As we would expect, young firms have a lower probability of being an exporter than older firms both before and after the crisis. However, looking at the treatment effect (the change within firms of similar ages between the two periods), we find an increase in export probability after the crisis, and while this is reduced by correcting for the other causal factors in the matching, this difference remains positive and significant for younger firms, while being positive but smaller and borderline significant for older firm cohorts. Hence it seems that there has been a greater increase in likelihood of exporting among younger firms than older ones.

[12]This may actually reflect not just perceived risk, as reflected in the credit score, but also a real options value on the part of lenders: wait until the firm has a better history before deciding whether or not to lend.

To understand the difference in export behaviour among younger firms, we seek further evidence by utilising a sectoral breakdown. Tables (9) and (10) break down manufacturing, services and construction sectors. There are, of course, significant differences in export propensity between these sectors: manufacturing firms are much likelier to export than services firms, while construction firms are least likely to export. Interestingly, comparing the two tables, while export propensity has generally risen, the largest and most significant increases are among younger firms in the services sector. Indeed, the rises in export propensity in the treated sample in manufacturing are not generally statistically significant, except perhaps among the oldest firms, whereas for services the difference for younger firms is quite significant.

Looking more closely at the services sector the results show that young firms are more likely to be a trader that in the pre-crisis period. Indeed, the estimated τ_{ATT} ranges from 0.072 to 0.092 among firms less than 5 years old (ones set up during or after the crisis).However, the mean difference in the probability to export is smaller and not statistically significant between pre-post-crisis for the old cohort (except the very oldest) . This suggest not direct effect of the 2011-2016 period on the likelihood to be an exporter for both groups.

Results for the construction sector are a bit mixed, but are more significantly positive for younger firms than older.

From this section, we can conclude that exports by all cohorts in all sectors recovered as TFP and credit scores recovered, but that the one group of firms which shows a strong and significant upturn in export probability in the postcrisis period is younger firms in the services sector.

Table 8: Comparison of Probability of Export by Age Thresholds: 2011-2016 vs Pre-Crisis Period

	Sample	Treated	Controls	Difference	S.E.	T-stat
Dependent Var.: Export (0/1)	Panel A: Young Firms					
Compare 5 years old (or younger) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.3962	0.3516	0.0446	0.0153	2.91
Compare 4 years old (or younger) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.3941	0.3575	0.0365	0.0175	2.08
Compare 3 years old (or younger) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.4002	0.3458	0.0543	0.0135	4.00
Compare 2 years old (or younger) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.3853	0.3543	0.0310	0.0169	1.83
Panel B: Old Firms						
Compare 10 years old (or older) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.5225	0.5110	0.0115	0.0243	0.48
Compare 15 years old (or older) firms during 2011-2016 with similar firms in Pre-Crisis Periods						
	ATT	0.5550	0.4838	0.0711	0.0286	2.49
Compare 20 years old (or older) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.5468	0.5142	0.0326	0.0270	1.21
Compare 25 years old (or older) firms during 2011-2016 with similar firms in Pre-Crisis Period						
	ATT	0.5848	0.5282	0.0565	0.0274	2.06

Note: This table shows a number of alternative matching between old-old firms and young-young firms. The treatment is the crisis (2009-2010) period.

Table 9: Comparison of Firms by Age: Pre-2009 vs 2011-2016: Young Firms

	Manufacturing	Services	Construction
Dependent Var.: Export (0/1)		Treated	
	9 years old (or younger) firms		
ATT	0.746	0.319	0.107
T-Stat	[1.12]	[5.10]	[2.42]
	5 years old (or younger) firms		
ATT	0.732	0.336	0.09
T-Stat	[1.05]	[5.21]	[1.01]
	4 years old (or younger) firms		
ATT	0.736	0.321	0.074
T-Stat	[0.80]	[3.73]	[0.70]
	3 years old (or younger) firms		
ATT	0.732	0.317	0.075
T-Stat	[1.39]	[3.01]	[0.55]
	2 years old (or younger) firms		
ATT	0.732	0.322	0.09
T-Stat	[0.42]	[2.13]	[1.74]

Note: This table shows a number of alternative matching between young firms. The treatment is the 2011-2016 period. That is this table compares the 2011-2016 period with firms in the pre-crisis period.

Table 10: Comparison of Firms by Age: Pre-2009 vs 2011-2016: Old Firms

	Manufacturing	Services	Construction
Dependent Var.: Export (0/1)		Treated	
	10 years old (or younger) firms		
ATT	0.812	0.396	0.129
T-Stat	[1.93]	[1.14]	[3.29]
	15 years old (or younger) firms		
ATT	0.809	0.411	0.14
T-Stat	[1.97]	[0.39]	[1.58]
	20 years old (or younger) firms		
ATT	0.798	0.4211	0.135
T-Stat	[-1.48]	[0.66]	[2.89]
	25 years old (or younger) firms		
ATT	0.821	0.444	0.132
T-Stat	[2.43]	[2.88]	[1.72]

Note: This table shows a number of alternative matching between old-old firms. The treatment is the 2011-2016 period.

6 Concluding remarks

This paper is a novel contribution to understanding the effects of the aftermath of the Great Trade Collapse upon UK firms' extensive and intensive margins of trade. By analysing a large panel of firms across the period 2005-16 inclusive, we can examine the key relationships underlying export behaviour. By applying propensity score matching, we are then able to investigate whether, and how, these relationships may have changed across different time windows.

The first thing to note is that most of the relationships known in the existing literature are shown to hold true for UK firms in this period. Larger firms, and firms with higher TFP are more likely to export (and to export more) than smaller or less productive ones. Foreign owned firms are more likely still to export. Older firms are more prone to export than younger ones, indicating the role of search and development of trading relationships over time.

On finance, we are the first to use firms' credit scores directly in the study of export propensities, but our conclusions are again in line with the previous literature addressing financial constraints on the likelihood to export (Chaney, 2013; Manova et al., 2009; Manova, 2013; Muûls, 2015): financially stronger companies are considerably more likely to export (and export more).

We consider these relationships to be the fundamental descriptors of firm-level export behaviour. However, importantly, these relationships change relatively little between the pre- and post-crisis periods. First of all, even though the trend growth of export participation may have slowed, it has by no means stopped following the crisis, at least when other factors are taken into account. Importantly, while the crisis itself may have involved a credit crunch, firms' credit scores have generally improved a little over the whole period, suggesting that selection effects and market discipline have had positive effects. The relationship between credit score and export propensity has perhaps weakened over the period - certainly not strengthened.

In terms of export propensity (the extensive margin), once we carry out matching, there seems to have been relatively little change over the period. The only group of firms to have significantly changed export propensity seem to be younger firms in the services industry, who are now more likely to export than before.

Similar results hold in terms of intensive margins, the total value of domestic sales and total exports.

Our overall view is that, while trade has performed less impressively after the crisis than before, the drivers of this effect probably do not come from the trade sector itself, and neither do they come directly from worsened access to finance. Note that our analysis basically predates the Brexit vote effect, let alone the rise of President Trump and trade wars.

Our tentative conclusion is that trade performance has been poor, at least in part, due to poor productivity performance (not finance), combined with slower growth of export markets.

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Appendix

Figure A1: This graph shows total exports values for all firms in our UK sample since 2005 and emphasises that the financial crisis of 2009 led to a sharp contraction in export activity.

Table A1: **Summary Statistics**

variable	**mean**	**sd**	**min**	**max**	**N**
Export propensity	0.4611173	0.4984871	0	1	198739
Export value	3209.182	148658.6	0	2.33e+07	198739
Domestic sales	17614.73	239164.1	0	3.11e+07	198737
ln(Fixed Assets)	3.962064	3.136412	-4.642466	12.99816	198739
ln(Turnover)	6.186343	2.530754	-5.769615	13.65417	198739
ln(Age)	2.806712	.9965658	0	5.075174	198739
ln(Employment)	4.253141	1.617202	0	8.546364	198739
ln(Credit score)	4.429394	.2239887	1.791759	4.59512	198739
ln(TFP$_{ACF}$)	3.855878	1.944546	-7.321015	12.146	198739
lnTFP$_{LP}$	5.461103	2.212903	-6.479221	12.98897	198739
lnTFP$_{OP}$	5.430525	2.211642	-6.5036	12.98203	198739

Note: this Table reports summary statistics of the main variables of interest. ln(.) represents the natural logarithm. Values are expressed in thousands.

A Exogeneity of credit scores

Table (A2), in the Appendix, reports the correlation of the score with the key firm-level financial variables. All regressions include firm size and year and firm fixed effects, and foreign and domestic firms are separated. The coefficient on number of employees is larger for domestic firms, perhaps because few foreign firms are perceived as being small, even if they only have a few local employees.

The regressions treat other variables one at a time. While there are significant positive correlations, all regressions have low R-squared values, suggesting that no one of these variables plays a large role in explaining credit scores. Looking at columns (4) and (8), this is true of TFP, even though it has more effect with domestic than foreign firms, probably for similar reasons to firm size.

On the other hand, the efficiency of capital management, in columns (1)-(3) and (5)-(7), is strongly significant in the score for both groups. Firms which can employ their capital efficiently have higher average scores. Moreover, the return on total assets turns out to be strongly significant: those firms which have a higher score are more profitable. In terms of firms' structure, the liquidity ratio, which assesses firms' ability to meet their short-term obligations, shows that more liquid firms have higher scores. However, while the point estimate is positive for both groups, it turns out to be more important for foreign firms.

For the purpose of this paper the score does not include export performance in its derivation. However, through productivity, size and profitability etc., exports might affect the score indirectly leading to a potential problem of endogeneity. Exporters are typically more productive and able to organize their activity more efficiently than non-traders. Hence, the score might reflect firms' export performance indirectly through other channels.

On the basis of the above analysis, we acknowledge that there may be some endogeneity of credit scores, which we handle by including firm-specific variables - i.e. age and capital- in any model which utilises credit scores. However, the great proportion of variation in credit scores is not explained by the other causal variables.

Table A2: Correlation between the score and key firm-level variables

Dependent: score	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Foreign				Domestic			
Return on Capital Employed	0.0133***				0.0140***			
	(0.000632)				(0.000637)			
Return on Total Assets		0.0660***				0.0616***		
		(0.00123)				(0.00112)		
Liquidity Ratio			0.144***				0.0592***	
			(0.0162)				(0.0159)	
TFP				4.15e-05***				9.48e-05***
				(5.95e-06)				(7.78e-06)
ln(Number of Employees)	2.062***	2.087***	2.088***	1.942***	2.819***	2.758***	2.818***	2.657***
	(0.0780)	(0.0769)	(0.0788)	(0.0792)	(0.0809)	(0.0798)	(0.0818)	(0.0819)
Observations	94,045	94,277	94,101	94,345	103,116	103,664	103,609	104,025
R-squared	0.029	0.058	0.024	0.024	0.026	0.055	0.020	0.022
Number of id	16,034	16,070	16,061	16,082	22,115	22,290	22,283	22,370
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The table presents a simple correlation between credit score and key control variable. We include a measure of profitability, firm's structure and productivity. Moreover, this table reports the results for both domestic and foreign firms, respectively.

B Appendix

Table B1, below, compares firms by age group during the crisis with those before the crisis, using propensity score matching. Panel A makes a comparison for young firms, while Panel B does the same for older firm cohorts.

While firms were reported in previous sections as having a higher export propensity during the crisis than before (albeit maybe below the long-run trend increase), the matching analysis shows that this difference becomes small and insignificant for younger firm cohorts once matching is carried out. For older firm cohorts, probabilities of being an exporter are higher, but the change compared to pre-crisis is again insignificant, except for firms over 20 years once treated.

A tentative conclusion regarding the crisis period is that firms' export propensities remained remarkably similar to the pre-crisis period for all cohorts, once correction is made for decreased firm size and TFP but increased creditworthiness (which work in opposite directions).

Table B1: Comparison of Probability of Export by Age Thresholds: Crisis Period

Variable	Sample	Trated	Controls	Difference	S.E.	T-stat
Panel A: Young Firms						
Compare 5 years old (or younger) firms during the crisis with similar firms pre-2008						
	ATT	0.3250	0.3250	0	0.0720	0.00
Compare 4 years old (or younger) firms during the crisis with similar firms pre-2008						
	ATT	0.3360	0.3320	0.0040	0.0130	0.29
Compare 3 years old (or younger) firms during the crisis with similar firms pre-2008						
	ATT	0.3270	0.3260	0.0010	0.0150	0.07
Compare 2 years old (or younger) firms during the crisis with similar firms pre-2008						
	ATT	0.3400	0.3360	0.0040	0.0250	0.15
Panel B: Old Firms						
Compare 10 years old (or older) firms during the crisis with similar firms pre-2008						
	ATT	0.4470	0.4390	0.0080	0.0090	0.91
Compare 15 years old (or older) firms during the crisis with similar firms pre-2008						
	ATT	0.4680	0.4690	−0.0010	0.0100	−0.09
Compare 20 years old (or older) firms during the crisis with similar firms pre-2008						
	ATT	0.4980	0.4000	0.0970	0.0135	7.21
Compare 25 years old (or older) firms during the crisis with similar firms pre-2008						
	ATT	0.5000	0.5750	−0.0750	0.1120	−0.67

Note: This table shows a number of alternative matching between old-old firms and young-young firms. The treatment is the crisis (2009-2010) period.