Online Appendix

The Impact of Trade Credit Provision on Retail Inventory: An Empirical Investigation Using Synthetic Controls

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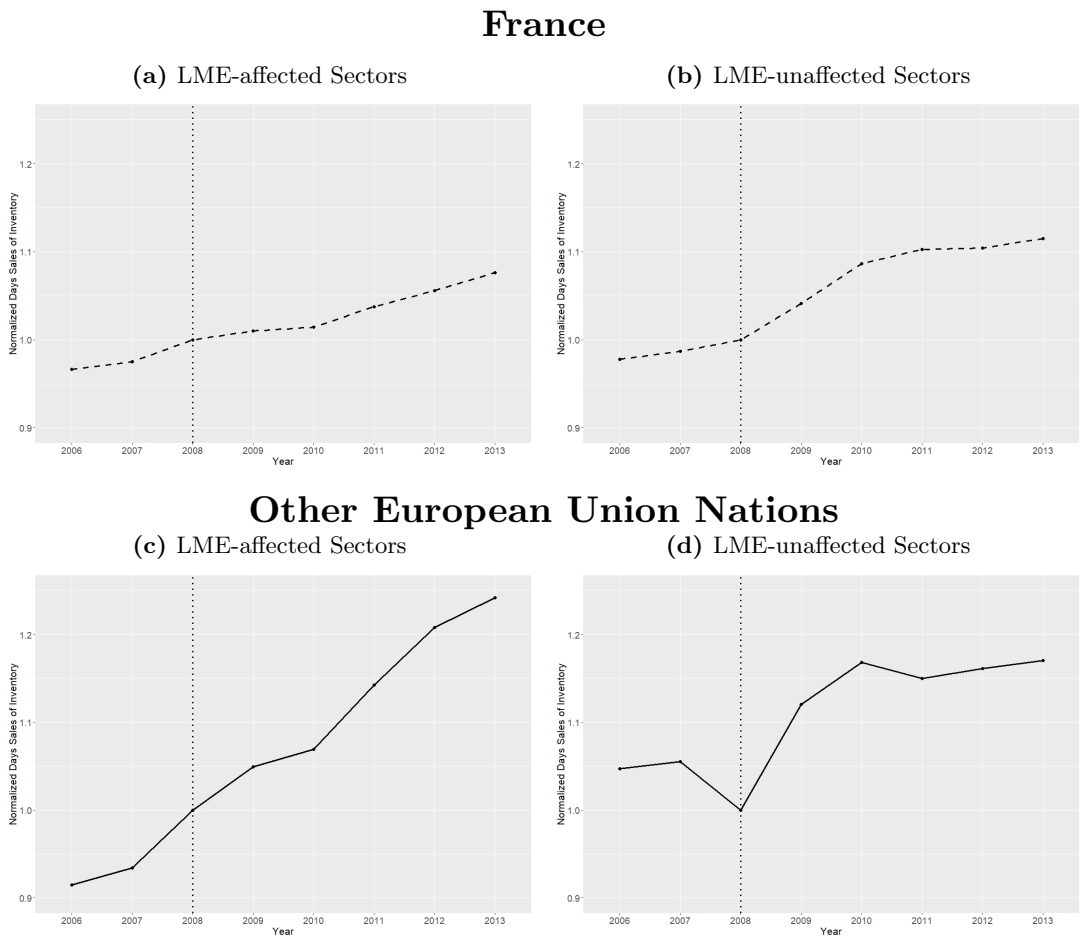
Appendix A: Model-Free Evidence: Trends in Inventory Levels in Pre-and Post-LME Periods

Similar to Figure 1, Figure A1 presents the model-free evidence of the trends in inventory levels, measured as $\text{DSI}_{kt} = \frac{\text{STOK}_{kt}}{\text{MATE}_{kt}} \times 365$. As shown, the model-free data supports a lessor proportional increase in the LME-Affected (LA) sectors in France relative to their European counterparts (8% vs. 25%) while the LME-Unafftected (LU) sectors had more comparable proportional changes in France and non-French countries (12% vs. 17%).

Figure A1 Trends in Inventory Levels: Pre and Post LME

This figure shows trends in average DSI received by the retailers in the LME-affected and LME-unaffected sectors over an eight-year period between 2006 and 2013. Panels (a) and (b) present these trends for France. Panels (c) and (d) present these trends averaged across six European nations. The vertical axis shows the average DSI after normalizing each firm's DSI usage by its 2008 value. In the LME-affected sectors, compared to the European firms, we find a muted increase in the French firms' DSI usage in post 2008 period. In contrast, the increasing trends are much comparable between French and European firms in LME-unaffected sectors.



Appendix B: Synthetic Control: Method Overview with Single Treatment Unit

We illustrate the Synthetic Control (SC) method using the following policy-intervention example. Suppose we observe $k=1,\ldots,K$ firms with only one firm (without the loss of generality, $k=1$) that has experienced the policy intervention. We observe $t=1,\ldots,T$ periods of data with the policy coming into force in $t=T_o+1>1$ period. We denote firm k's outcome during the non-intervention period by Y_{kt}^N and during the intervention period by Y_{kt}^I. Further, let D_{kt} and $\tau_{kt}=Y_{kt}^I-Y_{kt}^N$ denote respectively whether firm k experiences the intervention in period t and the corresponding impact of that intervention. Based on these notations, we can define the observed outcomes as

$$Y_{kt}=Y_{kt}^N+\tau_{kt}D_{kt}. \tag{1}$$

Note that, for firms $k=2,\ldots,K$ that never experience the policy intervention, $D_{kt}=0$ for all t's and thus, $Y_{kt}=Y_{kt}^N$.[1] For firm $k=1$, $D_{kt}=1$ for $t>T_o$ and 0 otherwise. The goal is to estimate $(\tau_{1T_o+1},\ldots,\tau_{1T})$. For $t>T_o$, we have

$$\tau_{1t}=Y_{1t}^I-Y_{1t}^N=Y_{1t}-Y_{1t}^N. \tag{2}$$

Here, note that for $t>T_o$ while Y_{1t}^I is observed, Y_{1t}^N is never observed and has to be estimated using the pool of available control entities. Let Y_{kt}^N be defined by the following linear model

$$Y_{kt}^N=\theta_t\mathrm{Z}_k+\lambda_t\mu_k+\delta_t+\epsilon_{kt}, \tag{3}$$

where Z_k denotes a vector of observed pre-intervention covariates with time-varying coefficients θ_t, μ_k denotes a vector of unobserved covariates with time-varying coefficients λ_t, δ_t denotes the time-fixed effect, and ϵ_{it} is the idiosyncratic error term with mean zero. Here, note that the simple linear DiD model can be recovered from Eq. (3) by setting $\lambda_t=\lambda$. In other words, in comparison to the SC method, which permits time-varying coefficients of the unobservable confounders, the linear difference-in-difference (DiD) model restricts the coefficients of unobservable confounders to be time-invariant, which is also known as the parallel trends assumption.

A potential SC can be constructed by assigning relative weights to each of the available control entities. Consider a $(K-1)\times 1$ vector $\mathrm{W}=(w_2,\ldots,w_K)$, where $w_k\geq 0$ for $k=2,\ldots,K$, and $\sum_{k=2}^K w_k=1$. These restrictions on weights ensure that interpolation of an SC is within the convex hull of available control entities.[2] The value of the outcome variable for an SC with weights W is given by

$$\sum_{k=2}^K Y_{kt}=\delta_t+\theta_t\sum_{k=2}^K w_k\mathrm{Z}_k+\lambda_t\sum_{k=2}^K w_k\mu_k+\sum_{k=2}^K w_k\epsilon_{kt}. \tag{4}$$

Abadie et al. (2010) show that if there exists W^* such that

$$\sum_{k=2}^K w_k^*Y_{kt}=Y_{kt}\text{ for }t=1,\ldots,T_o,\qquad\text{and}\qquad\sum_{k=2}^K w_j^*\mathrm{Z}_k=\mathrm{Z}_1. \tag{5}$$

[1] Following Rosenbaum (2007), we assume that no interference is made, that is, the treated entity outcomes do not interfere with the control entities' outcomes, or, the Stable Unit Treatment Value Assumption (SUTVA).

[2] A limitation of non-negative weights is that it may fail to generate a good-fit SC for a treated unit with characteristics not representative of the available control units. In a recent paper, Ben-Michael et al. (2018) present an extension of SC methodology that relaxes this restriction on weights.

then under general conditions, as the number of pre-intervention periods increase, we have:

$$\left| Y_{1t}^{N} - \sum_{k=2}^{K} w_k^* Y_{kt} \right| \longrightarrow 0. \tag{6}$$

This enables the construction of an unbiased estimator. Here, it is important to note that, depending on the structure of Y_{kt}^N model, the number of pre-intervention periods required for an unbiased estimator varies. For example, if Y_{kt}^N follows an AR(1) model, the SC method can yield unbiased estimates with just one pre-intervention data point. Building on Eq. (6), the treatment effect τ_{1t} for $t = T_o + 1, \ldots, T$ can be estimated using the following estimator

$$\widehat{\tau}_{1t} = Y_{1t} - \sum_{k=2}^{K} w_k^* Y_{kt}. \tag{7}$$

With real data, finding W^* that satisfies conditions Eq. (5) is not always possible. Instead, the SC method searches for optimal weights that best approximate these two conditions, or equivalently, minimizes the distance between the pre-intervention period values for the outcome variable and observed covariates of the treated unit. We refer readers to Abadie et al. (2010) for the implementation details of the SC method to compute optimal weights.

Appendix C: Synthetic Control Implementation: A Sampling Approach

In this section, we first present details of a sampling approach to SC estimation. We adapt this approach to manage the towering computational challenge due to large sample size in our setting. Next, we elaborate on our approach that extends the SC methodology to implement a DDD identification strategy.

We tailor the SC estimation procedure for multiple treatment settings (Acemoglu et al., 2016; Kreif et al., 2016) to meet the large sample-size challenge of our empirical setting. Although multiple packages have been developed over the past 15 years for SC estimation, most applications have been on samples with a small number of treated and control entities. To the best of our knowledge, in the extant literature, SC studies have examined settings where the number of treated entities is in a range of 22 to 100, and control entities is between 31 to 500. Table A1 provides a review of these papers. In contrast, in our sample, the four LME-affected sectors include between 555 and 2,419 treated entities, and between 203 and 474 control entities. As the complexity of the search for the optimal weights in the construction of a good-fit SC increases in the size of available control entities, applying the conventional SC estimation on such a large sample imposes a prohibitively high demand on computational time. We find a steep non-linear increase in computational time with the increase in the sample size of control entities. For instance, computing one SC for one of the 956 treated firms in sector 47.52 using all 459 control firms takes 95 minutes in R using the synth package on a dual E5-2650v3 CPU totalling 20 cores/40 threads for one dependent variable. In contrast, computing an SC using a random sample of 100 control firms require only 1.5 minutes.

Table A1 Multiple Treatment Literature. Literature review of studies with multiple treatment settings using the Synthetic Control (SC) methodology.

	Paper	Description	#Trt	# Ctrl	# Obs
1	Cavallo et al. (2013)	Natural disasters on GDP growth	∼27	∼192	7,644
2	Dube and Zipperer (2015)	Minimum wage on employment	29	31	7,344
3	Acemoglu et al. (2016)	Firm connections on stock performance	22	70	∼24,000
4	Kreif et al. (2016)	P4P payment scheme on mortality	24	132	1,872
5	Powell (2017)	Minimum wage on employment	29	31	7,344
6	Steffen (2017)	Construction ban on real estate prices	∼100	∼500	10,496
7	Jones (2018)‡	Invasive species on birth-weight	790 combined		13,430

‡ Jones (2018) analyzes a combined sample of 790 entities that are classified as a treated and/or control entity based on temporal rollout of treatment intervention.

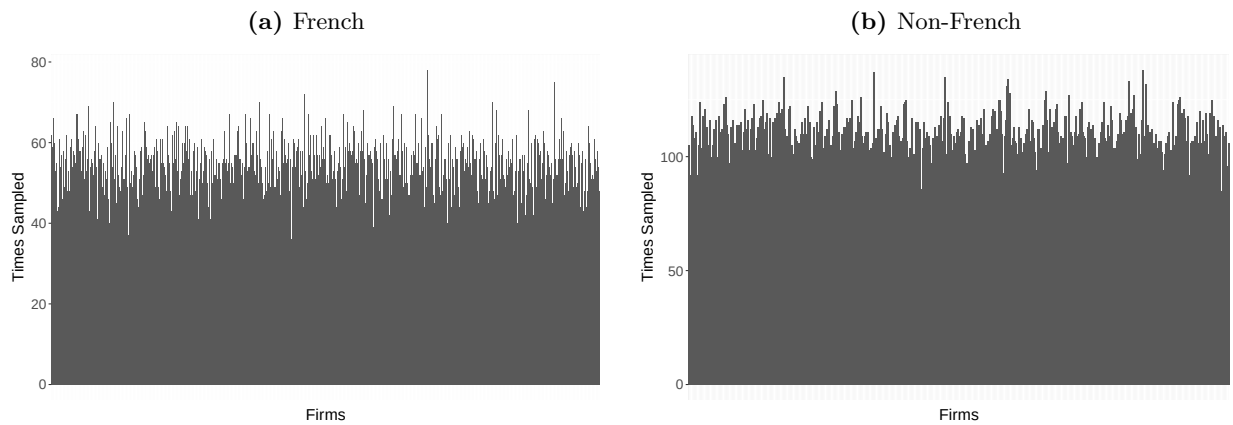
To overcome this computational challenge, we adopt a sampling approach for the SC estimation, which is based on the principle of deriving empirical findings through representative random sub-samples. Specifically, we apply SC estimation to study random sub-samples of up to 100 treated entities using a random sub-sample of up to 100 control units.[3]

[3] We note that computational time increases linearly with treated entities. Therefore, an alternate sampling approach could be to sample only control units for each treated entity. However, unlike our proposed sampling on both the treated and control entities that generates a one-to-one mapping between a treated entity and its SC, this approach would generate multiple SCs for each treated entity. Consequently, one faces an additional challenge of aggregating the multiple SCs into a single SC per treated entity. An intuitive choice is to pick the best-fitting SC; we find our results are robust to this alternate approach.

One concern about such a sampling approach could be that the findings are driven by a small subset of treated entities. To alleviate this concern, we draw our findings based on 500 iterations of such sub-sample analysis; this enables a fair representation of all treated and control entities, as detailed in Figure A2.

Figure A2 Sampling Frequency of Treated and Control Entities

This figure illustrates the fair representation of available treated and control entities in computing average treatment effect using the adapted SC sampling procedure in this study. The figure shows sampling frequency of firms in sector 47.52. Panels (a) and (b) respectively present sampling frequency of these firms for the French or Non-French nations.



A second potential concern could be the construction of poorly fitted SCs as, in each sampling iteration, the SC construction is restricted to a limited pool of control entities. A larger pool of control entities could enable construction of a better fitted SC. We test for this concern by studying the distribution of the goodness-of-fit of constructed SCs with an increasing number of control units where goodness-of-fit is measured using RMSPE, $\widehat{\sigma}_k$, as defined in Eq. (5). Below, in Section C.3 we show the distribution of the goodness-of-fit of constructed SCs with 100, 200, and 300 control entities. Using the Kolmogorov-Smirnov (KS) test (Gibbons and Chakraborti, 2011) for distribution comparison, we find no significant differences across the three distributions. This analysis suggests that, in our setting, a random sample of 100 control entities sufficiently represents the available heterogeneity across all the control entities and, thus, there is no significant improvement in the quality of the SCs with the increase in sampling size.

Implementation Steps. We compute the treatment effect, that is, the impact of the LME, at the sector level. In particular, we implement an iteration i of the above-described sampling approach in four steps. First, for a given sector, we draw a random sample of up to 100 firms from the pool of French firms (resulting in a sub-sample of treated entities) and from the collective pool of non-French firms (resulting in a sub-sample of control entities). Second, for each drawn treated entity, we generate an SC unit using the drawn pool of control entities. Next, following Acemoglu et al. (2016), we drop poorly fitted treated entities. We define a treated entity k as having a poor fit if $\widehat{\sigma}_k \geq \widehat{\sigma}\sqrt{3}$ where $\widehat{\sigma} = \sum_{k=1}^{K} \widehat{\sigma}_k / K$ is the average goodness-of-fit across all treated entities, and K is the number of firms in the treatment group of iteration i. Finally, using

the remaining well-fitted treated entities, we compute an estimate of the average treatment effect $\bar{\tau}_i$ for iteration i as the quality-adjusted weighted-average of treatment effects, $\widehat{\tau}_{kt}$. We repeat the above steps for 500 iterations to generate an empirical distribution of $\bar{\tau}_i$ and calculate the LME's average treatment effect $\bar{\tau}$ as the average of this empirical distribution.

C.1. Synthetic Control: Inference Procedure for Significance Testing.

A commonly preferred inference procedure in the SC estimation literature tests the significance of the average treatment effect against the distribution of the no-treatment effect (Abadie et al., 2010; Acemoglu et al., 2016; Kreif et al., 2016).[4] Intuitively, the no-treatment distribution emulates the distribution of change in treated entities in the absence of treatment, that is, the counterfactual. If the estimated treatment effect is within the $1-\alpha\%$ Confidence Interval (CI) of the no-treatment distribution then one cannot reject the hypothesis that the change in treated entities equals that in the control entities at $\alpha\%$ significance level.

We construct an empirical no-treatment effect distribution in three steps, which retains the country-level treatment characteristic of our empirical setting (akin to the French Government's LME legislation). First, we select a *placebo-treated* nation through a random draw from the set of non-French nations. The remaining non-French nations constitute the pool of *placebo-control* entities. Second, we apply the sampling approach described in Section C to construct an estimate of the no-treatment effect in the selected placebo-treated nation. Finally, we perform 500 iterations of the preceding two steps to construct the empirical distribution of the no-treatment effect.

C.2. SC Sampling Approach: DDD Extension

We apply two extensions to the iteration step for implementing the DDD identification strategy (as discussed in Section 3.2 of the main paper). First, in each iteration i, we draw additional random sub-samples of up to 100 entities from the pool of firms in French and non-French nations' LME-unaffected sectors. By applying the SC estimation on these sub-samples, we obtain an estimate of only the GFC-related impact on the focal outcome variable. Next, we subtract the estimate from the SC estimate, computed using random sub-samples of the LME-affected sectors, to construct iteration i's revised DDD estimate for the treatment effect $\bar{\tau}_i$. Applying this modified iteration step, we construct our empirical distributions for the treatment and no-treatment effect.

C.3. Synthetic Control with Sampling: Supplementary Analyses

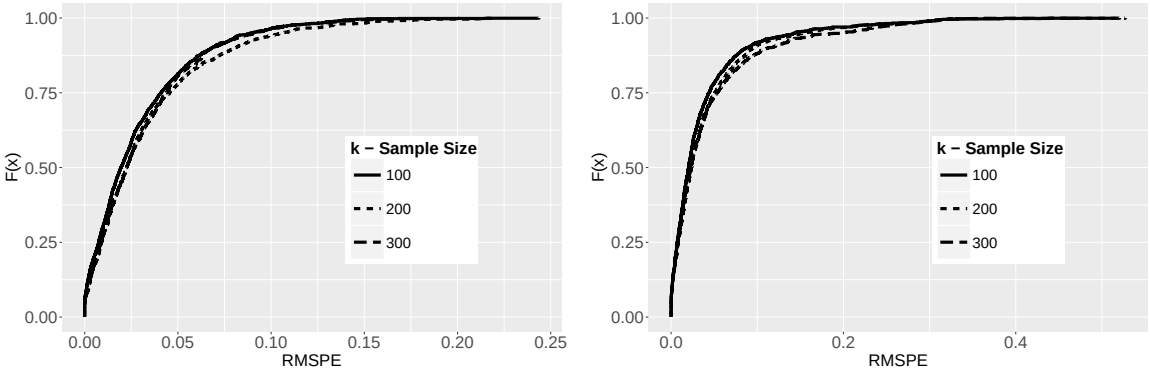
In a single iteration of the sampling approach used in our main analysis, we draw random sub-samples (with replacement) of up to 100 treated and control entities. It is conceivable that the higher the number of control entities, the better the quality of constructed SCs. Here, we examine whether restricting size of control entities' random sub-samples to 100 materially impacts the quality of constructed SCs. We implement the following three-step test. First, we draw a random sub-sample of 100 treated entities from the sample of firms' in Sector 47.52. Next, we draw 30 random sub-samples of size $k \in \{100, 200, 300\}$ control entities from the pool of all available non-French firms. Using each of these random sub-samples of control entities (120 in

[4] Alternatively, Campos et al. (2014) implement a DD regression framework using the actual data and its synthetic counterfactual to carry out statistical inference.

all), we construct SCs for the drawn sub-sample of 100 treated entities. Figure A3 shows three cumulative distribution plots of treated entities' (that satisfy the good-fit criterion) Root Mean Squared Prediction Error (RMSPE) (σ_k)–a plot each for three focal outcomes variables. We find that RMSPE distribution varies little by k. For all three variables, the Kolmogorov-Smirnov test fails to reject that the distribution with $K > 100$ is significantly different from the distribution with $k = 100$.

Figure A3 **Root Mean Squared Prediction Error (RMSPE) by Sample Size.** Empirical CDFs of the average RMSPE of 100 French firms matched against 100/200/300 randomly drawn control firms for accounts payable and inventory.

(a) Account Payables **(b)** Inventory



Appendix D: Results on Sectors 45.32, 47.59, and 47.71

In the main body of the paper, among the four retail sectors that satisfy the original selection criterion (sectors with at least five non-French European countries that have at least 10 firms in this sector), we focus on Sector 47.52, which generates the best SC-fit. For the remaining three LME-affected sectors, we find mixed evidence towards the impact of the LME on trade credit provision. Tables A2, A3, and A4 provide summary statistics for these sectors.

Compared to the pool of control entities, the constructed SCs continue to exhibit characteristics that are more comparable to that of the treated French firms in all dimensions. Figures A5 to A7 illustrate the SC estimation for these sectors. For firms in sector 47.71 (specialized clothing retailers), we find a significant decline in average trade credit level in the post-LME period: the average DDD treatment effect estimate is -6.2 days, with the 99% CI of the no-treatment effect being $[3.7, 22.2]$. Similarly, we find a significant reduction in average inventory level, the triple-difference estimate is -17.4 days (90% CI $[-17.3, -1.7]$). In Sectors 45.32 and 47.59, we find that the LME did not significantly impact firms' trade credit level: the average treatment coefficients for these sectors are not significantly different compared to the average no-treatment effect at 10% level.

We conjecture that the insignificant impact of the LME in these sectors is driven by a large number of firms that were likely to already comply with the LME (i.e., those repaying trade credit within the imposed 60-day ceiling). We find that the compliance rate (the fraction of firms whose DPO is less than 60 days before the LME) for these two sectors are 35% and 46% respectively, while the compliance rate of 47.52 is only 31%. Further, as illustrated in Figure A4, the quality of the SC-fit among firms in Sectors 45.32, 47.59, and 47.71 is considerably poorer than that in Sector 47.52. This low SC-fit quality also affects the quality of our treatment effect estimates as it impairs construction of counterfactual change in the treated entities in the absence of treatment.

Next, we test if the LME affects non-compliant firms in these sectors. Table A6 shows the results based on a sub-sample of non-compliant firms. Panels A, B, and C respectively report results with firms that had in 2008 DPO greater than or equal to 60, 75, and 90 days in 2008 respectively. We find that as the criterion of non-compliance becomes more stringent, the support for our finding — LME leads to both trade credit and inventory decline — becomes stronger in the remaining three sectors.

We also find consistent support for our finding across these sectors using the alternate econometric model, presented in the main paper, that models a non-linear change in the outcome variable. Specifically, we replicate Tsoutsoura (2015) methodology (for details see page 7.2 of the main paper) with proportional outcome variables pDPO and pDSI. Table A7 reports results of this analysis.

Finally, we also find support for our finding across these sectors with the alternate approach to constructing SCs using the non-French LME-affected firms, except those in the focal sector (for details, see description of this test on page 23 of the main paper). Table A5 reports results of this test. The DDD estimates, except for those of sector 47.59, are consistent with our main treatment estimates. Though these results provide a positive support to our finding, we would like to note that the estimated DPO effect is relatively small compared to our main finding based on Sector 47.52 (DPO: -14.1^{***} and DSI: 15.9^{***}). Exclusion of the

most comparable set of firms—those belonging to the same focal sector in non-French nations—seems to have driven these differences in treatment estimates. Not surprisingly, we find that this exclusion results in a drop in SC-fit quality.

Table A2 Summary Statistics: Treated versus Synthetic Controls for Sector 47.71

	French (# of Firms: 2,419)					Non-French (# of Firms: 473)				
47.71	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	85.7	53.7	42.5	75.6	119.8	113.3	75.2	46.1	102.9	167.9
Inventory (DSI)	178.4	113.1	92.4	153.2	233.5	213.3	152.8	105.1	171.5	274.4
Cash to assets	0.18	0.17	0.03	0.12	0.28	0.13	0.14	0.02	0.07	0.21
Fixed assets to assets	0.35	0.21	0.17	0.34	0.52	0.20	0.18	0.05	0.14	0.31
Debt to assets	0.59	0.23	0.41	0.60	0.77	0.73	0.23	0.58	0.77	0.90
Gross profit to assets	0.72	0.29	0.5	0.67	0.89	0.66	0.40	0.36	0.57	0.86
COGS to assets	0.88	0.37	0.60	0.81	1.11	1.10	0.51	0.70	1.01	1.40
log(Total assets)	12.61	1.02	11.93	12.50	13.17	13.94	1.71	12.68	13.66	14.91
	Synthetic Controls: DPO					Synthetic Controls: DSI				
	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	77.9	22.3	63.8	75.5	89.8	-	-	-	-	-
Inventory (DSI)	-	-	-	-	-	208.6	71.2	163.8	198.7	244.5
Cash to assets	0.18	0.16	0.09	0.15	0.27	0.13	0.09	0.07	0.10	0.18
Fixed assets to assets	0.32	0.14	0.21	0.31	0.43	0.30	0.14	0.20	0.31	0.41
Debt to assets	0.59	0.15	0.47	0.59	0.72	0.63	0.15	0.51	0.63	0.76
Gross profit to assets	0.74	0.20	0.60	0.74	0.86	0.73	0.22	0.58	0.68	0.87
COGS to assets	1.02	0.26	0.84	0.99	1.20	0.98	0.28	0.79	0.95	1.16
log(Total assets)	14.00	0.97	13.22	13.90	14.58	13.74	0.95	13.11	13.71	14.41

Table A3 Summary Statistics: Treated versus Synthetic Controls for Sector 47.59

	French (# of Firms: 1,564)					Non-French (# of Firms: 474)				
47.59	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	76.7	42.1	43.0	69.3	102.3	96.8	66.9	41.8	81.6	140.2
Inventory (DSI)	154.7	104.8	74.4	134.8	207.4	216.9	170.3	104.5	166.8	272.0
Cash to assets	0.23	0.19	0.06	0.19	0.37	0.12	0.12	0.02	0.07	0.17
Fixed assets to assets	0.23	0.17	0.09	0.19	0.34	0.20	0.19	0.04	0.13	0.30
Debt to assets	0.62	0.21	0.47	0.63	0.79	0.67	0.24	0.49	0.73	0.87
Gross profit to assets	0.92	0.38	0.62	0.86	1.16	0.65	0.4	0.35	0.56	0.89
COGS to assets	0.99	0.40	0.68	0.95	1.26	1.12	0.59	0.67	1.02	1.48
log(Total assets)	12.88	0.95	12.22	12.86	13.49	14.06	1.54	12.88	13.94	15.11
	Synthetic Controls: DPO					Synthetic Controls: DSI				
	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	79.6	19.8	67.1	78.1	89.1	-	-	-	-	-
Inventory (DSI)	-	-	-	-	-	196.0	72.4	145.2	191.5	237.7
Cash to assets	0.19	0.10	0.10	0.18	0.26	0.15	0.09	0.08	0.13	0.21
Fixed assets to assets	0.23	0.11	0.14	0.21	0.30	0.20	0.11	0.12	0.16	0.26
Debt to assets	0.61	0.16	0.49	0.63	0.75	0.61	0.15	0.49	0.60	0.74
Gross profit to assets	0.81	0.24	0.61	0.80	0.98	0.80	0.23	0.63	0.82	0.95
COGS to assets	1.12	0.90	1.09	1.31	1.56	1.12	0.29	0.92	1.13	1.27
log(Total assets)	13.85	0.88	13.22	13.73	14.50	13.41	0.74	12.96	13.26	13.91

Table A4 Summary Statistics: Treated versus Synthetic Controls for Sector 45.32

	French (# of Firms: 555)					Non-French (# of Firms: 203)				
45.32	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	86.2	36.4	57.3	84.7	111.3	102.4	69.6	45.0	89.5	149.1
Inventory (DSI)	102.3	61.6	57.9	89.7	128.1	156.8	115.3	73.6	128.9	199.7
Cash to assets	0.23	0.19	0.06	0.19	0.37	0.12	0.12	0.02	0.07	0.18
Fixed assets to assets	0.22	0.16	0.08	0.17	0.32	0.16	0.16	0.04	0.09	0.23
Debt to assets	0.62	0.21	0.46	0.63	0.78	0.66	0.23	0.48	0.72	0.85
Gross profit to assets	1.02	0.40	0.72	0.94	1.26	0.57	0.32	0.33	0.47	0.78
COGS to assets	1.24	0.53	0.83	1.17	1.56	1.21	0.64	0.82	1.12	1.48
log(Total assets)	12.79	0.95	12.06	12.77	13.43	13.86	1.46	12.73	13.6	14.82
	Synthetic Controls: DPO					Synthetic Controls: DSI				
	Mean	SD	25th	50th	75th	Mean	SD	25th	50th	75th
Trade Credit (DPO)	78.7	22.0	64.6	76.5	90.9	-	-	-	-	-
Inventory (DSI)	-	-	-	-	-	133.8	45.0	108.3	127.4	154.3
Cash to assets	0.21	0.12	0.09	0.19	0.32	0.19	0.11	0.10	0.18	0.28
Fixed assets to assets	0.20	0.12	0.10	0.16	0.30	0.18	0.10	0.11	0.14	0.22
Debt to assets	0.57	0.15	0.45	0.58	0.69	0.60	0.14	0.46	0.63	0.72
Gross profit to assets	0.91	0.25	0.74	0.88	1.09	0.92	0.21	0.76	0.91	1.05
COGS to assets	1.37	0.48	1.02	1.31	1.72	1.35	0.45	1.03	1.22	1.56
log(Total assets)	13.48	0.78	12.95	13.44	13.93	13.46	0.61	13.05	13.50	13.88

Figure A4 Synthetic Controls Fit Quality: Sector-wise Comparison

This figure shows the relative fit of constructed SCs across the four sectors. The quality of constructed SCs is largely determined by the convex-hull characteristics of the available control units and available covariates. Figures (a) and (b) respectively compare the CDFs of the pre-LME period gaps Δ in the DPO and DSI outcome variables between the treated firms and corresponding SCs.

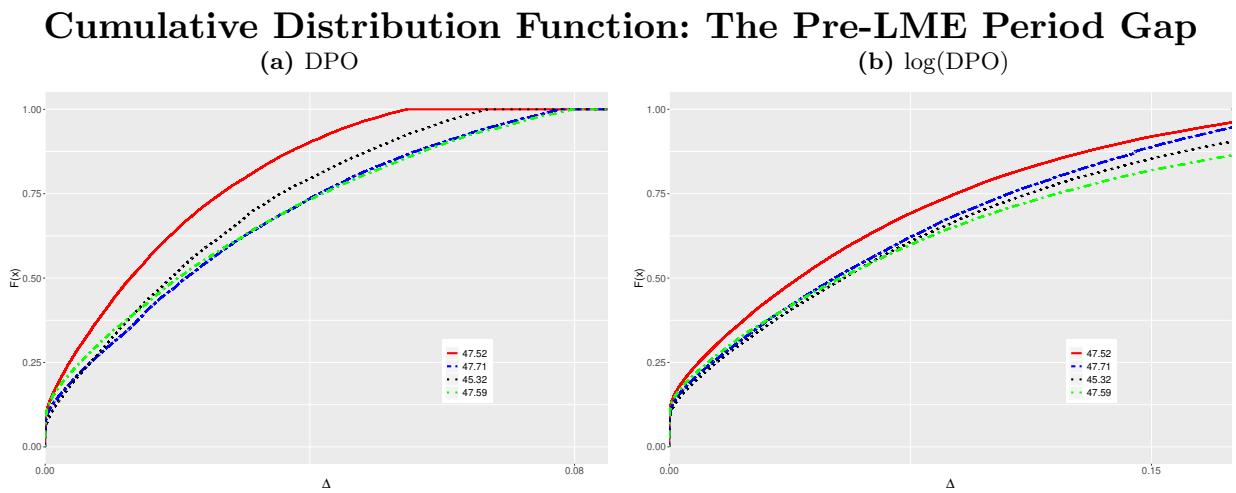


Figure A5 Triple Difference-in-Differences SC Estimation: Sector 47.71

Trade-Credit (DPO)

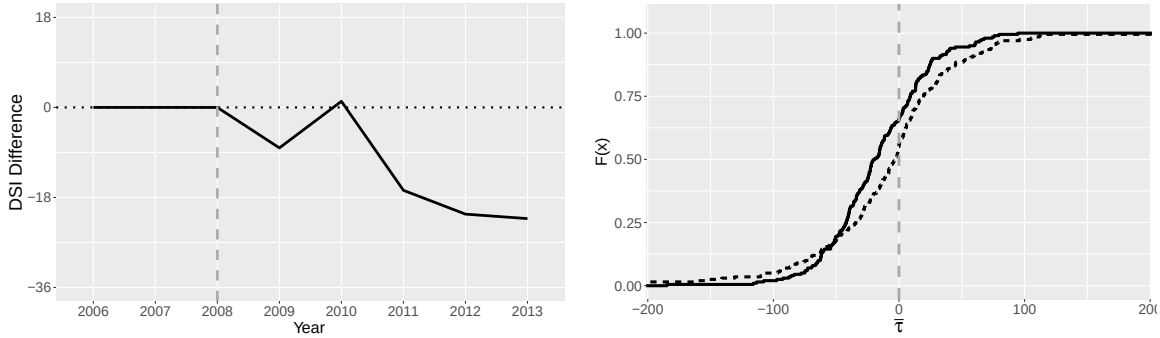
The average treatment effect is −6.2 and 99% CI is [3.7, 22.2]†.

(a) Average Treatment Effect **(b)** Empirical Distribution

Inventory (DSI)

The average treatment effect is −17.4 and 90% CI is [−17.3, −1.7]†.

(c) The average treatment effect **(d)** Empirical Distribution

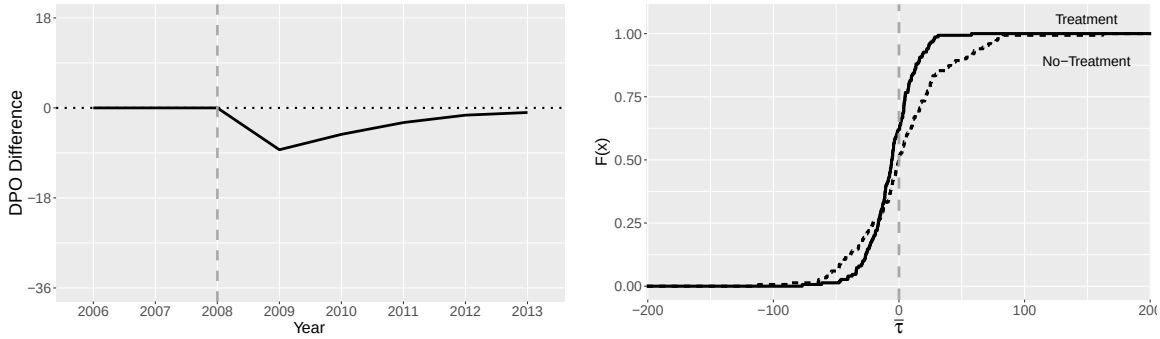


†CI is based on no-treatment effect distribution, see discussion on page 7.

Figure A6 Triple Difference-in-Differences SC Estimation for Trade Credit (DPO): Sector 45.32

The average treatment effect is −5.8 and 90% CI is [−5.8, 3.9]†.

(a) Average Treatment Effect **(b)** Empirical Distribution

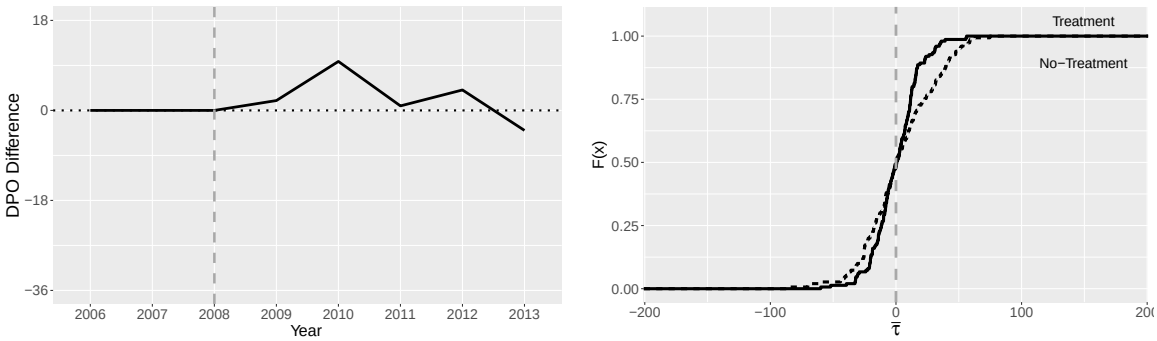


† CI is based on no-treatment effect distribution, see discussion on page 7.

Figure A7 Triple Difference-in-Differences SC Estimation for Trade Credit (DPO): Sector 47.59

The average treatment effect is 0.2 and 90% CI is [−0.9, 6.4]†.

(a) Average Treatment Effect **(b)** Empirical Distribution



† CI is based on no-treatment effect distribution, see discussion on page 7.

Table A5 SUTVA Analysis. The 99% no-treatment confident intervals are reported

	Dependent Variable	
	DPO	DSI
47.71	-1.0^{***} [−0.6, 9.6]	-16.2^{***} [−13.7, 4.0]
47.59	-3.0^{***} [−2.1, 8.0]	−6.2 [−13.3, 9.2]
45.32	-4.2^{***} [−0.1, 9.5]	-28.7^{***} [−10.2, 9.8]
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A6 Synthetic control triple differences estimates of the LME-effect on DPO and DSI by sector over a range of non-compliance cutoffs at the firm level. The 99% no-treatment confident intervals are reported in the brackets.

	Dependent Variable	
	DPO	DSI
Panel A. Days Payable Outstanding > 60 Days (2008)		
47.52	-11.3^{***} [−2.7, 9.5]	-13.0^{***} [−12.1, 9.5]
47.71	-7.0^{***} [−2.9, 7.7]	-15.8^{***} [−9.5, 11.0]
Panel B. Days Payable Outstanding > 75 Days (2008)		
47.52	-12.7^{***} [−2.7, 9.5]	-13.0^{***} [−12.1, 9.6]
47.71	-10.1^{***} [−2.9, 7.7]	-19.4^{***} [−9.5, 11.0]
45.32	-8.8^{**} [−8.9, 1.6]	-8.4^{**} [−9.8, 14.7]
Panel C. Days Payable Outstanding > 90 Days (2008)		
47.52	-15.0^{***} [−2.7, 9.5]	-12.5^{***} [−12.1, 9.6]
47.71	-10.4^{***} [−2.9, 7.7]	-22.0^{***} [−9.5, 11.0]
45.32	-10.4^{***} [−8.9, 1.6]	-10.8^{***} [−9.7, 14.6]
47.59	-3.4^{*} [−5.2, 5.9]	-19.6^{***} [−12.4, 13.0]
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A7

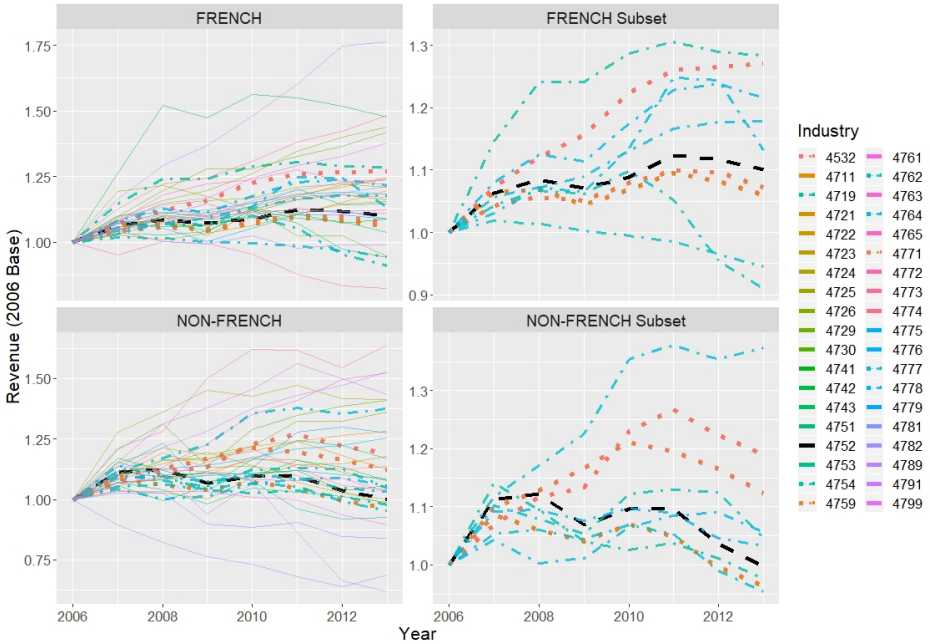
	Affected				Unaffected				Differences
	All (1)	French (2)	Non-French (3)	Mean DD (4)	All (5)	French (6)	Non-French (7)	Mean DD (8)	Mean DDD (9)
No. of Firms	1415	956	459		2517	2125	392		
Panel A. Annual Controls (47.52)									
Proportion in DPO	-0.096	-0.120	-0.046	-0.073***	0.054	0.068	-0.024	0.092	-0.166***
	(0.007)	(0.008)	(0.014)	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.000)
Proportion in DSI	0.032	0.005	0.088	-0.082***	-0.018	-0.002	-0.103	0.100	-0.183***
	(0.007)	(0.007)	(0.016)	(0.000)	(0.008)	(0.008)	(0.024)	(0.000)	(0.000)
Panel B. Annual Controls (47.71)									
Proportion in DPO	-0.030	-0.020	-0.078	0.058***	0.034	0.049	-0.045	0.094***	-0.036***
	(0.007)	(0.008)	(0.017)	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.000)
Proportion in DSI	0.009	-0.001	0.056	-0.057***	-0.010	0.008	-0.105	0.113***	-0.170***
	(0.005)	(0.005)	(0.013)	(0.000)	(0.008)	(0.008)	(0.025)	(0.000)	(0.000)
Panel C. Annual Controls (45.32)									
Proportion in DPO	-0.087	-0.080	-0.105	0.025***	0.026	0.040	-0.047	0.086***	-0.061***
	(0.010)	(0.011)	(0.024)	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.000)
Proportion in DSI	0.001	-0.020	0.057	-0.076***	0.000	0.014	-0.080	0.094***	-0.170***
	(0.010)	(0.011)	(0.021)	(0.000)	(0.007)	(0.008)	(0.024)	(0.000)	(0.000)
Panel D. Annual Controls (47.59)									
Proportion in DPO	-0.049	-0.041	-0.077	0.037***	0.040	0.054	-0.038	0.092***	-0.056***
	(0.007)	(0.008)	(0.016)	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.000)
Proportion in DSI	0.012	-0.009	0.081	-0.090***	-0.010	0.006	-0.097	0.103***	-0.193***
	(0.006)	(0.006)	(0.014)	(0.000)	(0.008)	(0.008)	(0.025)	(0.000)	(0.000)

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix E: Did the GFC uniquely impact the hardware retail sector?

Figure A8 show temporal trends in revenue for various sectors in France and non-French nations. The x-axis covers the entire study period: 2006-2013. The y-axis shows the corresponding year's sector-wide average of revenue, measured as the ratio of 2006 revenue, across firms. The dash lines denote the four sectors in our main sample, with black color representing the 47.52 sector. The dot-and-dash lines represent the additional six sectors present in the extended sample obtained by relaxing the required number of non-French nations, for SC construction, to four from five. The solid lines denote all the other remaining sectors. The top and bottom panel respectively present sectors in France and non-French nations. Collectively, these graphs indicate that the hardware retail sector is among the sectors with lower revenue growth in the post-GFC period but is not the one that is extremely affected.

Figure A8 Temporal Trend in Revenues: 47.52 vs other sectors.



Next, we formally test for the relative change in revenues at the sector level to examine if the hardware retail sector is uniquely affected by the GFC crisis. Specifically, we test if the average proportional revenue change for 47.52 firms is significantly different from the that observed for firms in the remaining sectors. For a firm i, we measure the average proportional change in its revenue by $\Delta Rev_i = (Rev_{i,2006} + Rev_{i,2007})/(Rev_{i,2008} + Rev_{i,2009})$. We note that for French firms in the affected sectors, Rev_i reflects both the LME and GFC impact. In contrast, for non-French firms Rev_i only reflects GFC impact. Thus, we run separate tests for the sample of French and non-French firms. Table A8 shows mean comparison t-test results.

Row 1 of Table A8 shows results of test that compares mean of French firms in the 47.52 sector with that of the firms in the remaining three sectors of our main sample (i.e., 47.71/47.59/45.32). Row 2 shows comparison results with the nine sectors of our expanded sample that applies minimum four non-French

nations criterion for SC construction.[5] Rows 3 and 4 respectively present analogous results of Rows 1 and 2 tests with non-French firms. Except for Row 1 in which mean difference is positive at p-value 0.09, all other tests report insignificant differences in Rev_i mean levels between 47.52 firms and the other remaining sectors. In summary, in each of the above described four tests, we fail to reject that the change in revenue for the firms in the hardware sector is comparable to other sectors.

Table A8 Revenue Comparison: Hardware Retail Sector (47.52) versus other sectors. p-value is reported in the parenthesis.

#	Test Description	Mean Difference	Comment
1	France: 47.52 vs Remaining 3 main sample sectors	0.012* (0.09)	Within France comparison
2	France: 47.52 vs Remaining 9 extended sample sectors	−0.002 (0.79)	Within France comparison
3	Non-French Nations: 47.52 vs Remaining 3 main sample sectors	−0.012 (0.40)	Across EU comparison
4	Non-French Nations: 47.52 vs Remaining 9 extended sample sectors	−0.002 (0.88)	Across EU comparison

Note: *p<0.1

[5] 47.71/47.59/45.32/47.19/47.54/47.62/47.64/47.77/47.78

Appendix F: Supplementary Tables and Figures

Table A9 **Country Count by Industry.** Number of countries with at least 10 firms in a given industry.

NACE Code	# Countries	NACE Code	# Countries	NACE Code	# Countries
45.32	6	47.19	5	47.24	2
47.25	2	47.42	3	47.43	2
47.51	3	**47.52**	6	47.53	2
47.54	5	**47.59**	7	47.61	3
47.62	4	47.63	1	47.64	4
47.65	3	**47.71**	7	47.72	3
47.74	3	47.75	3	47.77	5
47.78	5	47.82	1	47.89	1
47.91	3	47.99	2		

Table A10 **Placebo Results.** This table shows the results of the placebo analysis with non-French nations individually designated as pseudo-LME treated. Coefficient estimates are given along with the 90% confidence intervals of the no-treatment distribution.

Country	DPO	DSI
Finland	−5.6 [−8.9, −0.2]	17.0*** [−14.4, −3.6]
Germany	1.4 [−2.9, 2.7]	−7.5 [−7.7, 6.5]
Italy	23.0*** [−7.6, −0.7]	−3.2 [−12.8, −3.1]
Portugal	−2.9 [−4.2, 2.8]	114.0*** [−26.1, −5.9]
Spain	−7.2 [−9.5, −2.2]	8.5 [−10.5, 9.8]
Sweden	−4.1 [−6.7, −0.2]	−4.9 [−13.5, −3.4]
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A11 **Robustness Test: Sensitivity of Estimates to Inclusion/Exclusion of Covariates.** Numbers in bracket report the 99% no-treatment confidence intervals.

(1) Variable	(2) DPO	(3) DSI
1) Cash-to-Assets	−9.0*** [1.2, 9.9]	−18.0*** [-10.3, 8.3]
2) Debt-to-Assets	−6.8*** [3.2, 13.2]	−12.3*** [-10.1, 4.6]
3) Fixed Assets-to-Assets	−7.6*** [2.8, 12.2]	−15.1*** [-11.5, 4.3]
4) Gross Profits-to-Assets	−9.6*** [2.5, 11.0]	−11.5*** [-8.3, 3.7]
5) log(Assets)	−9.2*** [−1.1, 9.3]	−12.6*** [-9.2, 9.5]
6) log(GDP)	−7.7*** [2.0, 10.9]	−18.0*** [-9.0, 6.3]
7) Debt-to-GDP	−9.1*** [3.6, 12.9]	−13.2*** [-5.6, 6.7]
8) log(5yr CDS)	−15.4*** [5.8, 13.9]	−14.7*** [-3.1, 13.2]

Figure A9 Relative Sampling Frequency of Treated and Control Entities

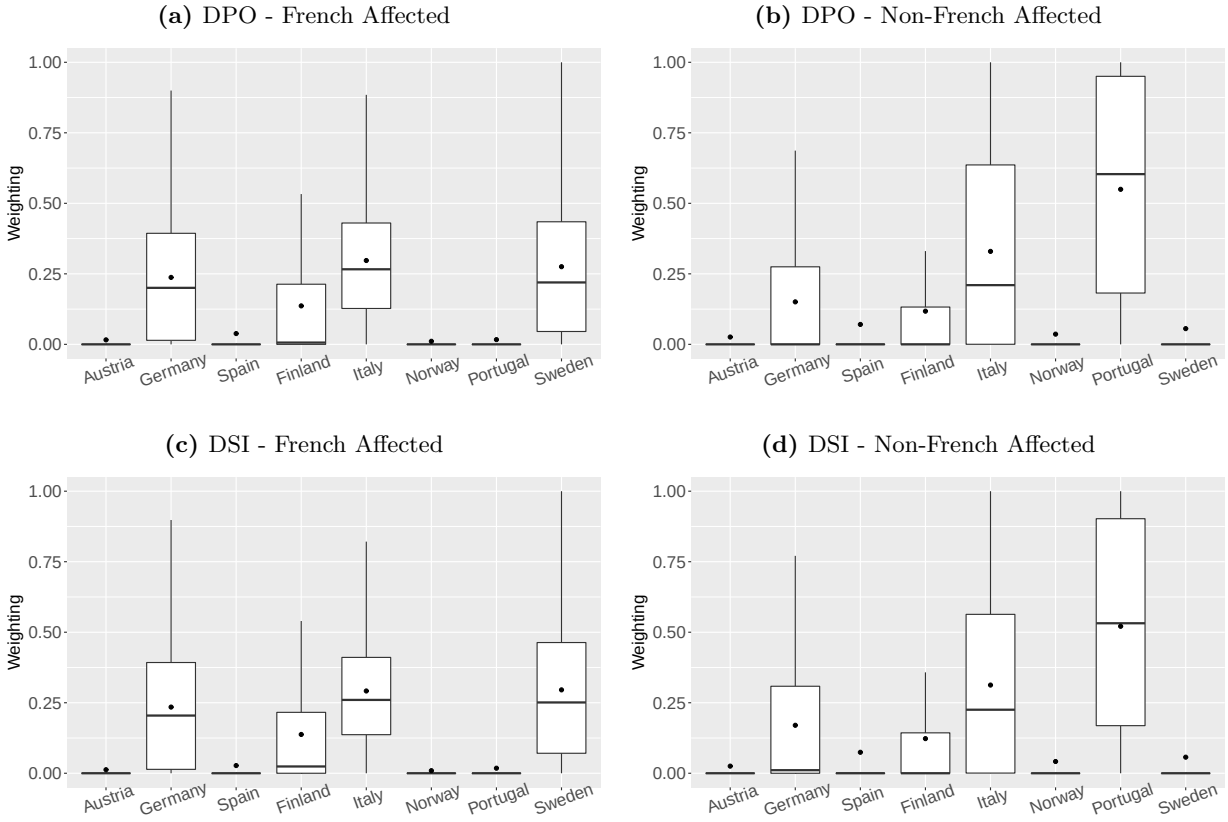


Table A12 GFC Placebo analysis (Sample period: 2005–2008, Placebo-LME Year: 2007). The 90% no-treatment confident intervals are reported in brackets.

	Dependent Variable	
	DPO	DSI
47.52	−9.0 [−34.8, 34.4]	10.9 [−52.4, 48.4]
47.71	18.8 [−34.4, 33.6]	4.5 [−52.4, 48.4]
45.32	10.8 [−34.9, 33.6]	15.9 [−52.4, 48.4]
47.59	−6.7 [−34.5, 34.3]	4.4 [−51.1, 48.4]
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A13 Financial Metrics Results: Using SC Methodology. Outcome variables normalized by Total Assets. The 99% no-treatment confident intervals are reported in the bracket.

	Revenue	Gross Profit
47.52	-0.32^{***} [−0.07, 0.17]	-0.03^{***} [−0.02, 0.03]
45.32 with DPO > 90 days	-0.50^{***} [−0.06, 0.19]	-0.05^{***} [−0.03, 0.04]
47.59 with DPO > 90 days	-0.34^{***} [−0.09, 0.18]	-0.05^{***} [0.01, 0.09]
47.71 with DPO > 90 days	-0.43^{***} [−0.15, 0.10]	-0.08^{***} [−0.00, 0.07]
6-sector pooled	-0.43^{***} [−0.14, 0.11]	-0.07^{***} [−0.03, 0.04]

Appendix G: Linear Triple Difference-in-Differences (DDD) with Parallel Trends Assumption

In Tables A16 and A17, we present results of the linear DiD analysis, along with that of parallel trend validation tests, of the LME impact on trade credit (DPO) and inventory level (DSI) respectively. In line with the main analysis, we identify the impact of the LME using the DDD identification strategy with firms in sector 47.52 as those that are LME-affected and firms in Sectors 47.21, 47.22, 47.23, 47.30 as those that are LME-Unaffected. Formally, we estimate the following specification (at the firm × year level)

$$\begin{aligned} DV_{it} = & \beta_1 Post_t \times France_i + \beta_2 Post_t \times Affected_i \\ & + \beta_3 Post_t \times France_i \times Affected_i \\ & + \gamma X + \delta_i + \eta_t + \epsilon_{it}, \end{aligned} \tag{8}$$

where $DV \in \{DPO, DSI\}$ is the outcome variable of interest, $Post$ is an indicator variable that is set to 1 for the post-LME period (from 2009 to 2013) and 0 otherwise, $France$ is an indicator variable that is set to 1 for French firms and 0 otherwise, $Affected$ is an indicator variable that is set to 1 for firms in the LME-affected sector and 0 otherwise, and X is a vector of control variables. In addition, we include firm- and time-fixed effects (δ and η, respectively). We allow error terms (ϵ_{it}) to be correlated for French and non-French observations and thus cluster standard errors for inference. The coefficient of interest is β_3, which captures the DDD estimate of the LME on the outcome variable.

Columns 1 and 2 (in both Tables A16 and A17) show the results estimated using matched samples constructed using the Propensity Score Matching (PSM) (Dhanorkar, 2017) and Coarsened and Exact Matching (CEM) (Iacus et al., 2012) methods respectively. PSM uses a specified model to compute propensity scores of an entity being treated. The estimated scores are then used to create matched pairs. For our analysis, we estimate the PSM-based model using all the covariates included in the main analysis and we implement the nearest neighbor algorithm for creating matched pairs (Campello et al., 2010). Statistics for the PSM matched sample are shown in Table A14.

In comparison to PSM, CEM excludes treated and control entities that do not meet the ex-ante specified matching criteria, with the benefit of bounding the imbalance between treated and control groups prior to matching. Consequently, the size of the matched sample is quite sensitive to the strictness of the matching criteria and the underlying heterogeneity of firm characteristics across the treated and control entities. For instance, in our context, CEM matching based on the complete list of covariates Z used in SC estimation yields a small sample of only six entities. Thus, we adopt a restricted list of matching variables comprised of the two outcome variables (DPO, DSI) and the total assets (TA) variable as a measure of firm size. We implement many-to-many matching and estimate the model using weighted OLS. Table A15 presents the sample statistics of the CEM-based sample.

Columns 3 to 6 (in both Tables A16 and A17) provide the results of tests validating the parallel trends assumption. In particular, we test whether outcome variables $DV \in \{DPO, DSI\}$ show any difference in trends between the LME-affected firms in France and non-French nations during the pre-LME period. We use two alternate specifications to test for the presence of such a difference.

Table A14 Summary Statistics of the Propensity Score Matching (PSM) Sample for Sector 47.52

	LME-affected Sector				LME-unaffected Sector			
	French ($N = 956$)		Non-French ($N = 221$)		French ($N = 2{,}125$)		Non-French ($N = 210$)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Trade credit (DPO)	77.8	36.1	80.1	55.8	42.2	25.8	43.3	35.9
Inventory (DSI)	148.4	83.1	135.0	131.6	18.5	23.0	28.5	31.8
Cash to assets	0.17	0.18	0.16	0.15	0.31	0.22	0.29	0.23
Fixed assets to assets	0.20	0.14	0.17	0.17	0.41	0.26	0.30	0.22
COGS to assets	0.61	0.21	0.62	0.23	0.64	0.24	0.68	0.28
Gross profit to assets	0.84	0.36	0.83	0.54	1.31	0.62	1.35	0.87
Long-term debt to assets	1.16	0.45	1.29	0.72	2.32	1.69	2.60	1.57
log(Total assets)	13.07	1.07	13.14	1.37	12.22	0.82	12.45	1.21

Table A15 Summary Statistics of the Coarsened Exact Matching (CEM) Sample for Sector 47.52

	LME-affected Sector				LME-unaffected Sector			
	French ($N = 770$)		Non-French ($N = 243$)		French ($N = 1{,}787$)		Non-French ($N = 249$)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Trade credit (DPO)	80.3	36.5	94.9	51.1	40.2	21.9	36.5	32.9
Inventory (DSI)	142.4	80.3	157.0	116.8	14.6	18.3	21.9	21.9
Cash to assets	0.18	0.18	0.12	0.13	0.31	0.22	0.22	0.23
Fixed assets to assets	0.20	0.14	0.15	0.15	0.42	0.25	0.29	0.24
COGS to assets	0.61	0.21	0.64	0.21	0.63	0.23	0.69	0.27
Gross profit to assets	0.85	0.36	0.54	0.36	1.30	0.61	0.82	0.56
Long-term debt to assets	1.18	0.45	1.17	0.60	2.42	1.73	4.17	2.37
log(Total assets)	13.15	1.00	13.49	0.96	12.2	0.79	13.13	0.87

First, following Gallino et al. (2016), we adopt a continuous time-indexed specification. Formally, we estimate the following specification using observations from the pre-LME period of the LME-affected firms:

$$DV_{it} = \alpha_1 t_{index} \times France_i + \gamma X + \delta_i + \eta_t + \epsilon_{it}, \tag{9}$$

where t_{index} denotes the order of the year in the pre-LME period (i.e, $t_{index} = 1$ for 2006 and $t_{index} = 3$ for 2008). The coefficient α_1 captures any trend in the differences between outcome variable DV of LME-affected firms in France and non-French nations. Columns 3 and 4 present the results using the PSM and CEM matched samples respectively.

The second test adapts the approach from Barrot (2016), which discretizes the short pre-treatment period and tests whether the differences in outcome variables between the treated and control entities differ significantly in pre-treatment sub-periods. Compared to the Gallino et al. (2016) approach, this approach avoids

the over-fitting concerns of estimating a time-indexed linear trend with a short pre-treatment period. We execute this test by estimating a modified version of the full triple-difference specification (Eq. (8)) which is presented below in a concise manner for brevity:

$$DV_{it} = \alpha_1' Year_{2008} \times France_i \times Affected_i + \alpha_2' Year_{2009} \times France_i \times Affected_i + \alpha_3' Year_{2010-13} \times France_i \times Affected_i + \gamma' X' + \delta_i + \eta_t + \epsilon_{it}, \tag{10}$$

where $Year_{2008}$, $Year_{2009}$ and $Year_{2010-13}$ are dummy variables indicating year 2008, 2009, and the four-year span of 2010 to 2013, respectively. The covariate vector X' includes all the $Year_{\{\cdot\}}$ interaction terms not shown in the above abbreviated specification. The coefficient α_1' tests whether the difference in outcome variables of treated and control entities differs in the pre-LME sub-period (specifically, in 2008) compared to the base pre-LME period of 2006–07. A significant value of α_1' indicates the presence of a non-constant difference in the outcome variables in the pre-LME period. In Columns 5 and 6, we present results of this specification with the PSM and CEM matched samples, respectively.

Table A16 Linear DDD estimate for the impact of LME on Trade Credit Provisioning

	Dependent variable: DPO					
	LME Impact		Parallel Trends Tests			
	(1)	(2)	(3)	(4)	(5)	(6)
Post × France × Affected	−13.361***	−15.993***				
	(0.018)	(2.328)				
t_{index} × Affected			−7.429***	−5.261***		
			(0.000)	(0.000)		
France × $Year_{2008}$ × Affected					−2.588***	−2.882**
					(0.000)	(1.250)
France × $Year_{2009}$ × Affected					−11.241***	−14.663***
					(0.018)	(1.590)
France × $Year_{2010-13}$ × Affected					−14.970***	−17.527***
					(0.018)	(2.951)
Post × Initial Controls	Yes	Yes	No	No	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,096	24,392	3,531	3,039	28,096	24,392
Adjusted R^2	0.775	0.777	0.774	0.778	0.776	0.778

Note: *p<0.1; **p<0.05; ***p<0.01

The results shown in the columns 1 and 2 of Tables A16 and A17 continue to support our main findings that the LME significantly reduced the average trade credit usage and the average inventory stocked by

Table A17 Linear DDD estimate for the impact of LME on Inventory Levels

	Dependent variable: DSI					
	LME Impact		Parallel Trends Tests			
	(1)	(2)	(3)	(4)	(5)	(6)
Post × France × Affected	-22.933^{***}	-26.459^{***}				
	(0.195)	(2.288)				
t_{index} × Affected			-4.753^{***}	-0.406^{***}		
			(0.000)	(0.000)		
France × $Year_{2008}$ × Affected					-7.829^{***}	-4.783^{***}
					(0.000)	(0.241)
France × $Year_{2009}$ × Affected					-6.269^{***}	-13.391^{***}
					(0.195)	(0.272)
France × $Year_{2010-13}$ × Affected					-30.361^{***}	-31.719^{***}
					(0.195)	(2.906)
Post × Initial Controls	Yes	Yes	No	No	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,096	24,392	3,531	3,039	28,096	24,392
Adjusted R^2	0.937	0.933	0.906	0.896	0.937	0.934

Note: *p<0.1; **p<0.05; ***p<0.01

the retailers in the sector 47.52. We note that these results, however, are subject to bias as we find strong evidence towards violation of the parallel trends assumption in our setting. Both the trend coefficient α_1 (in columns 3 and 4) and the marginal difference coefficient α_1' (in columns 5 and 6) are significant.

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