Abnormal returns and Dow Jones Sustainability Index listing: A generalised synthetic control approach

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Abstract

Listing on the Dow Jones Sustainability Index is seen as a gold-standard, verifying to the market that a firm is fully engaged with a corporate social responsibility agenda. Quantifying the impact of listing through a generalised synthetic control approach delivers a robustness to any industry level shocks as well as evolution in the competitive relationship between firms within the industry absent in existing works. Consistent with the pre-announcement hypothesis it is shown that cumulative abnormal returns on stocks added to the index are significantly positive in the three trading weeks prior to the official announcement. The post-listing correction result posited to date is also demonstrated to hold; for the three trading weeks subsequent cumulative abnormal returns are significantly negative. Considering periods straddling the listing date no significant abnormal returns are found. Whilst there are considerable gains to be made, they come pre-announcement date with only a very short term correction seen in the days post announcement. Investors may gain from shorting announced new members.

Keywords: Listing effects, synthetic control, abnormal returns, corporate social responsibility.

1 Introduction

Corporate social responsibility (CSR) has been demonstrated to impact corporate financial performance; typically it is assumed that the outcome stems from consumer preference for goods from CSR practitioners outweighing costs of implementing responsible practice. Improved profitability, and hence stronger future cash flows, have been disputed, but those who obtain higher CSR recognition are found to have lower volatility, positing an argument for lower returns. Evaluating the balance between stronger future cash flows and reduced volatility, this paper asks whether there are any positive impacts on stock returns and, if so, where they occur relative to the public announcement day. Generating results from two-sample comparisons and dummy variable regression approaches we verify that our dataset

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produces the same ambiguity of conclusions that characterise other studies on CSR and returns. Employing the generalised synthetic control approach delivers robustness to industry, or economy wide level shocks as the reference for abnormal returns is not the past performance of the share but the present performance of a portfolio of shares weighted to match the performance of the share over a long pre-treatment period. This paper thus contributes deeper understanding of the impact of CSR behaviour recognition on stock returns in a framework attentive to wider conditions, competition and the relative performance within the sector.

Although there is disagreement on measuring CSR a listing on the Dow Jones Sustainability Index (DJSI) North America signals clearly to the market that a firm is meeting critical Corporate Social Responsibility (CSR) standards[1]. As a measure of CSR it is binary, making interpretation simple Studying DJSI listing, or continued membership, becomes simpler than discerning the marginal effects of indexes that are reported only for subsets of firms[2]. Such binary delineation also facilitates event studies and regression approaches of the type performed here. From an investor behaviour perspective it is implicitly assumed that listing conveys information more effectively than discerning marginal effects amongst metrics of CSR activity.

Event studies have advantage where timings are known and exogenous to the units being considered MacKinlay (1997). Oberndorfer et al. (2013) discusses how listing on a social responsibility index, such as the DJSI, can be seen as completely exogenous from the share price of a particular firm. Likewise although the inclusion of a firm into the index is a result of the firms efforts it is timed at a point dictated by the listing agency. It is this that offers the requisite exogeneity. The financial literature expanding upon CSR events focuses on either company specific events, or exogenous occurrences that impact a subset of stocks[3]. Index listing, or de-listing, fits firmly into this second class[4].

Evaluations of the effect of joining the DJSI have applied event studies on listing announcements (Cheung, 2011; Robinson et al., 2011; Lourenço et al., 2014; Joshi et al., 2017; Hawn et al., 2018). Consistent through all of these works is the belief that there needs to be consideration of the time before, and after, the announcement rather than a focus purely on the announcement week itself. Motivation comes from the imperfect information in the markets and the ability of some traders to form meaningful expectations of any upcoming listing. There is evidence of a number of abnormal movements presented here which is consistent with this approach. Evaluation of the abnormal returns therefore begins three weeks before the actual announcement, with most pre-announcement changes occurring around two weeks ahead of the official release of the DJSI constituent list. A further consistency

[1]Disagreement about CSR measurement is charted in Scalet and Kelly (2010) and subsequently Venturelli et al. (2017).

[2]Continuous measures are often born from research carried out by teams at large agencies such as MSCI KLD. From here emerges either a scale reading or a series of binary evaluations of strengths and concerns that then form the measure using net strengths. Whilst not continuous there are advantages over the low level of splitting offered by the DJSI dummy. However, as Mattingly (2017) notes in reviewing the dataset there are challenges of subjectivity in measure construction and problems of data coverage outside the biggest firms.

[3]Clacher and Hagendorff (2012) and Cai and He (2014) fall into the category of single company events

[4]Wider consideration of listing as an event drives Denis et al. (2003) evaluation of learning expectations following inclusion in the S&P 500 index. A large literature on listing effects follows in this mould.

lies in the creation of abnormal returns in the short term, but that all shares revert to their expected levels within a few weeks of the announcements[5].

Other studies consider alternative indices such as the Newsweek Green Rankings[6] (Cordeiro and Tewari, 2015) and the World's Most Ethical Companies list (Karim et al., 2016). As public facing measures these have garnered greater media coverage. Cordeiro and Tewari (2015) hypothesised higher rankings in the 2009 listing would correspond to stronger favourable reactions, and that this would continue both short-term and long-term; evidence of such effects is found. For works dependent on such single-year orderings there is an inevitable problem of repeatability; we demonstrate subsequently the impact of DJSI listing is significantly different during the period studied by Cordeiro and Tewari (2015).

Oberndorfer et al. (2013) posit two competing hypotheses for the short term impact of DJSI listing, a revisionist and a traditionalist perspective. Revisionists argue that inclusion represents a commitment to stakeholders that boosts sales, increases employee happiness and hence productivity, is hard for rivals to compete against and sets an upward trend of financial performance. Consequently the revisionist argument is summarised by Oberndorfer et al. (2013) as leading to positive short term listing effects. Contrary to this the traditionalist approach contends that focus on CSR diverts resources from productive endeavours, reducing productivity and hence lowering profitability. Ziegler and Schröder (2010) and Oberndorfer et al. (2013) both question the extent to which inclusion in a DJSI listing is truly representative of leading CSR performance. Though arguments for the impacts of non-sustainability related motivations for inclusion are compelling, listing remains a market recognised indicator and hence applied here.

Synthetic control approaches offer natural synergies in finance, where their allocations of weightings to a series of assets to create a portfolio that recreates the asset of interest is synonymous with exchange traded funds. This motivates work on the effect of political connections to the Trump administration following the 2016 presidential election (Acemoglu et al., 2016), the impact of the Arab Spring on Egyptian markets relative to others (Acemoglu et al., 2017), and Chamon et al. (2017) work on currency interventions in Brazil. In each case comparison with a portfolio of assets is championed as effective in capturing the change from the treatment, be that political connections, the position of the Egyptian market, or the Brazilian currency. This paper preserves the benefits exposited in these papers, whilst simultaneously introducing an ability to cope with multiple listings from the same asset group in the same period.

Existing literature guides expectations of pre-announcement effects, post-announcement corrections, and for these to be evidenced through a control approach which captures movements in the overall market. Abadie et al. (2010) is the facilitator for this robustness but it has subsequently been shown to struggle with multiple treatment groups simultaneously, and to be computationally intensive for confidence interval calculation. This paper responds

[5]International studies likewise find evidence of short-term effects (Oberndorfer et al., 2013; Orsato et al., 2015; Nakai et al., 2013).

[6]The Newsweek Green Rankings were first released in 2009 and gained wide interest in the USA. Scores are constructed as a combination of an environmental impact score (45%) using emissions data, green policies (45%) which are obtained in part from the KLD database, and a green reputation score (10%) based on a survey of relevant stakeholders and academics (Cordeiro and Tewari, 2015). These are thus more environmentally focused than the DJSI index which captures more of the social responsibility range.

using the generalised synthetic control (Xu, 2017) in finance for the first time[7]. Primary advantages of so doing are the ability to produce treatments that recognised the simultaneity derived from a single potential listing date per year. Further the software implementation of the generalised synthetic control, *gsynth* (Xu and Liu, 2018), generates all necessary confidence intervals meaning there is no need to follow the bootstrapping approach of placebo treatments used in Acemoglu et al. (2016).

Three key contributions are made to the literature. A primary contribution comes in the formalisation of the effect of pre-announcement leakage of news about DJSI membership. We evidence some post-listing correction, as rationality may expect. Results here point to such corrections as being much more rapid than the drip of pre-announcement longing return opportunities. By implementing a new approach which facilitates unobserved factors, and multiple treatments simultaneously, is brought to finance for the first time. Here it meets the challenges laid down in the recent work on the synthetic control method by Abadie et al. (2015); Acemoglu et al. (2016) and others. Thirdly, the toolkit developed here can be readily ported out of these listing effects studies and into the wider event study framework. Across these three we are demonstrating how econometric advances from other areas can usefully inform in important finance debates. In this instance data selection comes from the desire to better appreciate the role of social responsibility. In this regard the paper advances understanding.

The remainder of the paper is organised as follows. Data, abnormal return construction and financial controls are introduced in Section 2 in preparation for the analysis of cumulative abnormal returns in Section 3. Section 4 details the generalised synthetic control method and gives results from the comparisons between listed shares and counterfactual alternatives constructed on the assumption those firms did not join the DJSI. Section 5 reviews the information gained from this robust analysis before Section 6 reinforces the value of the work and the ways in which useful extensions may be made.

2 Data and Descriptive Statistics

2.1 Full Sample

Data on constituents of the DJSI is constructed using listings from RobeccoSam, with entries recorded for each year[8]. For each listing the North American Industry Classification System (NAICS) code is obtained at the two-digit level, this facilitates the formation of a control sample from the same industry. Share price data comes from CRSP and is gathered daily for the period beginning the first of November in the year prior to the listing, to a date 15 days after the listing announcement. This results in up to 250 observations for each firm. In order to be included in the samples the firms must have sufficient numbers of observations throughout the studied period. Data on firms accounting fundamentals is taken from Compustat. Data is merged such that the accounting data from the financial year

[7]This development from sythntic to generalised synthetic has been kept up with in the political economy literature. Interested readers are direct to Abadie et al. (2015).

[8]An introduction to the index, containing details of how to construct an entrants list, is provided in RobecoSAM (2013).

Figure 1: Listing Timeline

Notes: Control refers to the period over which models are trained, beginning at time T_{start} and ending 16 days prior to the announcement at time T_{end}. The length of the control period is defined as T_c and represents the difference in trading days between T_{start} and T_{end} The subsequent day,$T_{end} + 1$, is the first in the treatment period over which models are assessed. This treatment period ends after T_0 periods at time $T_{end} + T_0$. Announcement periods vary by year, but in all cases T_{start} is the 1st November in the year prior to the announcement being studied.

previous to the announcement being studied is used as controls in the listing effect analysis.

Figure 1 depicts the periods discussed in the exposition that follows. In all cases the specific time (trading day) being considered is referred to as t. A control period, $t \in [T_{start}, T_{end}]$ is defined as the period over which all models are trained. Model performance is then evaluated in the treatment period which begins on day $T_{end}+1$ and ends on day $T_{end}+T_0$, T_0 days later. Following past works the treatment period extends 15 trading days before, and after, the listing announcement. Henceforth we can think of the treatment period as capturing $t \in [-15, 15]$ as the time frame for which we are evaluating listing effects, with $T_0 = 31$. In this way announcement day becomes day 0. As announcements are in late September or early October the control period for the subsequent year does not begin until 1st November. In this way the impact of any past membership announcements do not influence the modelling for the listing in the year being evaluated. This pattern repeats for each listing year between the formation of the DJSI North America in 2005 to 2017, being the final year for which we have the data completed. Our share data thus runs from 1st November 2004 to 15 trading days after the 2017 membership announcement on 6th October 2017[9].

In any given year the number of treated observations can vary, and many industries will not feature amongst the newly listed set. Two digit NAICS codes, and the number of entering firms there from, are reported in Table 1. For the univariate and regression approaches these numbers do not present a challenge, but for the generation of counterfactual versions of listed shares the numbers in L are important. The original synthetic control method of Abadie et al. (2010) allows for only one treated unit but it is clear from the numbers that many year-industry pairs have more than one entrant. In this case we can not ignore the potential impact that the other newly listed firm(s) might have upon any other DJSI joining firm. Hence there is a call for a methodology that is robust to such diversity of treated unit profiles; Xu (2017) employed in Section 4.2 meets this call.

[9]Note that in 2017 the announcement of membership was made on the 11th September, significantly earlier than previous years.

Table 1: Treatment and Control Numbers

		NAICS 2-Digit Industry Code																				
Year		0	2	3	21	22	23	31	32	33	42	44	45	48	51	52	53	54	56	62	71	72
2005	L	6	2	1	1	1	1	3	6	7		4	1	1	4	7		2				1
	C	87	32	21	121	37	30	82	305	648		88	53	84	484	534		111				55
2006	L	1	2		2	1		1	3	1	1				1	3						
	C	95	32		133	39		85	311	667	48				301	539						
2007	L				1	1				2			1		1	3		1		1		
	C				153	40				677			49		318	517		113		52		
2008	L	2	1					1	1	2			1		1	2	2		1			
	C	98	31					78	267	556			34		256	440	153		49			
2009	L		2		1			1	4	2	2		1	1	1	3		1				
	C		30		115			64	210	416	57		59	78	204	353		85				
2010	L	1	1		3				4	3					1			1	1			
	C	102	34		134				258	553					248			110	45			
2011	L		1	1					1	4		1	1	2		3	1		1		1	1
	C		37	15					260	558		77	33	84		462	175		48		10	47
2012	L					1		2	2	2			1		3	1		1	1			
	C					37		86	261	554			36		263	499		104	47			
2013	L	2			2			1	4	3		2			2	2	3	1				
	C	107			145			92	279	568		79			287	542	187	97				
2014	L	1	1			1	1		1	3				1	2	2	1					1
	C	117	28			42	41		335	613				110	322	590	216					58
2015	L	1					1	1	3	1					1	1	2					1
	C	113					40	86	378	576					333	591	213					60
2016	L			1				2	1	1		1			1	3	2		1			
	C			18				85	368	538		76			329	562	219		53			
2017	L	3			1			2	2	3				1	2	2	2	1				2
	C	121			135			92	417	596				114	358	653	235	96				64

Notes: Numbers represent the number of firms included in the full sample for the estimation of cumulative abnormal returns. L is used to denote the number of firms joining the DJSI in the given year, whilst C denotes the numbers of controls. These numbers reflect those for which there is sufficient share price data and assets for the preceding financial year.

2.2 Reduced Sample

Amongst the full sample are a number of firms who are significantly smaller than any of those who are listed on the DJSI. This creates a potential bias in the comparison due to the well studied size anomaly[10]. Consequently a further control is placed upon firms that ensures the control set is more directly comparable with the listed set. Here a reduced sample is constructed using only those firms who have assets of at least 80% of those of the smallest firm that joins the DJSI in that year. By imposing this restriction we significantly reduce the number of shares available to serve as comparators for the listed set, but are able to minimise the impact of size. Alternative thresholds could be considered, but with the contribution of this paper stemming from an approach that does not require sample size reduction robustness of the results in Section 3 to minimum size is taken as given from the papers advocating those approaches. Details of the number of treated firms, and controls, are provided in the supplementary material analysing CARs.

In the discussion of established modelling methodologies we present both the base sample and full sample, but do not use the base sample for the generalised synthetic control approach.

2.3 Cumulative Abnormal Returns

Evaluation of the DJSI listing effect is based upon the ability of membership to generate returns which differ from those that might have been expected in the event of non-membership. This may be achieved by comparing new entrants with similar firms that are not joining the DJSI that year. However, it is more usefully considered as the difference between the ob-

[10]See (Keim, 1983) for a review of the work that established this anomaly within the asset pricing literature.

served returns and those that would have been realised had that shares pricing behaviour continued in the same way as it had been doing during the control period.

Simplest of the models to study the cross section of stock returns is the capital asset pricing model (CAPM) as introduced through the works of Lintner (1965); Sharpe (1964) and Treynor (1962). Although subsequent advancements of the CAPM are able to generate better fit for future returns predictions it is widely accepted that the CAPM is the most parsimonious solution (Acemoglu et al., 2016). Before proceeding note that in all that follows we could add an additional y subscript to recognise that all estimation and prediction applies to a specific year and that there are multiple years in the dataset. For the control period, $t \in [T_{start}, T_{end}]$, we estimate equation (1) using ordinary least squares (OLS) regression. This is done for all firms in the sample individually.

$$R_{it} = \alpha_i + \beta_i MKT_t \tag{1}$$

In which R_{it} is the excess return on share i at time t, MKT_t is the Fama-French excess return for the market at time t, and α_i and β_i are the coefficients of interest. Estimated values $\hat{\alpha}_i$ and $\hat{\beta}_i$ are then used to compute the fitted excess returns for share i, $\hat{R}_{it}$ with the abnormal return then defined as the difference between fitted and observed values. That is:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta} MKT_t \tag{2}$$

A subperiod $t \in [\underline{t}, \bar{t}]$ has cumulative abnormal returns (CAR)s of:

$$CAR_i[\underline{t}, \bar{t}] = \sum_{t=\underline{t}}^{\bar{t}} AR_{it} \tag{3}$$

Investors have natural interest in obtaining abnormal returns, with higher absolute values being most attention grabbing. If correctly priced the CAR would be zero and hence the relationship between CARs and listing on the DJSI becomes of interest.

This paper contrasts these simple abnormal returns with those generated by the synthetic control family. For this purpose we employ the mean square predicted error (MSPE) within the control period as a measure of model fit. For any given share i the MSPE over the interval $[T_{start}, T_{end}]$ is given by equation (4).

$$MSPE_i = \frac{1}{T_c} \sum_{t=T_{start}}^{T_{end}} AR_{it}^2 \tag{4}$$

T_c is the total number of trading days within the control period. Construction of the abnormal returns for the generalised synthetic control involves taking the difference between observed returns and those of the counterfactual version of that share. Consequently comparison can only be done on those shares considered "treated" by listing to the DJSI. In the subsequent sections we report the CAPM CARs at an aggregate level and broken down by industry-year for those joining firms[11]. Note further that because those announced as gaining listing on the DJSI are included in both the full and base samples there is no distinction between samples in the later reporting.

[11] A full set of CARs is provided in the supplementary material.

Table 2: Descriptive Statistics

Panel A: Summary Statistics for Full Panel									
		Mean	Min	25th pctile	Median	75th pctile	Max	St. dev.	*N*
(1)	DJSI	0.008	0.000	0.000	0.000	0.000	1	0.090	29443
(2)	Size	7.306	1.179	5.957	7.201	8.456	14.761	1.867	22419
(3)	Profitability	0.078	-21.62	0.040	0.097	0.162	0.162	7.003	21759
(4)	Leverage	0.433	-46.57	0.153	0.395	0.660	22.55	0.536	22124
(5)	CAR[-15,1]	0.013	-81.84	-4.077	-0.227	3.704	133.8	8.541	21467
(6)	CAR[-15,15]	0.124	-117.1	-6.100	0.181	6.217	180.45	12.93	21467
(7)	CAR[-1,1]	0.169	-43.56	-1.532	0.122	1.829	90.79	3.777	21467
(8)	CAR[0]	-0.174	-36.45	-1.032	-0.055	0.815	73.36	2.483	21467
(9)	CAR[0,10]	0.287	-81.85	-3.200	0.234	3.771	83.55	7.768	21467
Panel B: Large firm summary statistics:									
(10)	DJSI	0.041	0.000	0.000	0.000	0.000	1	0.197	5982
(11)	Size	9.669	6.617	8.613	9.462	10.47	14.76	1.441	3708
(12)	Profitability	0.138	-1.984	0.066	0.121	0.197	5.279	0.224	3595
(13)	Leverage	0.537	-13.38	0.351	0.504	0.721	8.672	0.396	3640
Panel C: Univariate sample comparisons:									
		Full Sample					Large Firms		
		List	Other	Diff.			List	Other	Diff.
(14)	Size	10.05	7.264	2.786***		Size	10.05	9.649	0.400***
(15)	Profitability	0.176	0.077	0.099***		Profitability	0.176	0.137	0.039***
(16)	Leverage	0.494	0.415	0.079***		Leverage	0.494	0.517	-0.023
Panel D: Correlations									
		Full Sample				Large Firms			
		DJSI	Size	Profit	Leverage	DJSI	Size	Profit	Leverage
(17)	DJSI	1				1			
(18)	Size	0.140	1			0.063	1		
(19)	Profit	0.027	0.154	1		0.039	0.030	1	
(20)	Leverage	0.025	0.505	0.053	1	-0.021	0.265	0.024	1

Notes: Descriptive statistics for variables used in main analyses. Samples are restricted by two digit NAICS code to those industries with one or more firm joining the DJSI within a given year. Full sample includes all firms listed on the major American stock exchanges with sufficient data, with the base sample considering only those with assets at least 80% as large as the smallest joining firm in their industry. All stock data is sourced from CRSP. DJSI listing data is taken from Robecco SAM. Size (log assets), profitability(return on equity) and leverage (ratio of total debt to total capital) are sourced from Compustat. Significance given by * = 10%, ** = 5%, *** = 1%.

2.4 Descriptive Statistics

Descriptive statistics in Table 2 remind just how few firms obtain listing within any given year, 0.8% of all observations represent listings. Focusing only on larger firms in Panel B that figure rises to 4.1%, but this is still low relative to the overall volume of data. A full breakdown of the entrants by NAICS2 code is provided in Table 1. Rows (2) to (4) provide some statistics for three key firm characteristics. Size, measured as the log of total assets, shows that firms within the full sample are drawn from a wide ranging distribution. This diversity is the motivation for the reduction in the sample. The base sample has a much higher average and a minimum value close to the median of the full sample. Profitability, captured as the return on equity, in rows (3) and (12), is also wide ranging with a number of firms reporting losses in both samples. Once the minimum size requirement is imposed the minimum ROE is much larger. Leverage also has a smaller range amongst the largest firms. Comparison of means on rows (4) and (13) verify this pattern.

Focus in this paper is on the abnormal returns, if any, gained when entering the DJSI. For this purpose CAR are used, calculated using (3). For the full sample, rows (5) to (9) give values for five periods of interest. From the start of the treatment period, day -15, to the day before listing we note a small positive average return of 1.3% amongst the whole sample. Across the whole treatment period row (10) reports a mean CAR of 12.4%, with much of this then coming in the period around the announcement date; 16.9% in the three trading days that include the day prior to announcement and the day immediately subsequent. On the announcement day the mean AR is highly negative but the percentiles show that much is the result of big losses at the bottom end of the abnormal returns distribution. Finally looking at the two trading weeks following the announcement a strong positive CAR of 28.7% is recorded on average. As these figures contain all firms they remind that there will be many more stories behind the results, and that it is not possible to attribute all of these changes to the DJSI listings.

Univariate tests in Panel C inform on the differences between those firms who join the DJSI and the control groups for that given year. These are aggregated into a large list and tested for equality of mean between the joining and non-joining samples. In both the full sample and the base sample the firms joining the list are significantly larger, this result remains even when the restriction based on size has been imposed. Looking at profitability the joining firms have a significantly higher ROE than the non-joiners; this would be consistent with the broad observation that improving CSR is costly and therefore typically only practiced by firms who have the profitability to support such measures. After reducing the sample to the base, the average ROE for control firms rises but the gap remains significant. Finally, we see that amongst the whole sample firms joining the DJSI have a higher debt to capital ratio, but in the base sample it is the non-joining firms who have the higher leverage. The latter difference is not significant however. It is therefore the largest firms with the greater profitability and ability to raise their leverage to fund investment who are most likely to join.

Panel D addresses the correlations between the data. Leverage and size are the most correlated, but fall short of the 0.7 threshold usually assumed to be a concern for multicollinearity. For the base sample the correlations between the three financial variables drop significantly. Correlations between DJSI listing and all three controls are low in both the full, and base, samples. Thus in any regression contexts where these variables feature we can have confidence in the inference gained.

3 DJSI Listing and Stock Returns

Identification of listing effects to date has relied on the comparison of samples or a dummy variable regression approach. Our preliminary discussion thus considers these two approaches, presenting univariate tests of equality in returns and CAR for periods surrounding the DJSI listing announcement date. Event studies proceed in this way, but may opt to perform matching between samples prior to conducting the univariate tests. For this reference case we maintain the maximal set of data and do not exclude firms for which sufficient data is available. Second we consider common company financial variables that have been linked to stock returns. Thus, in the spirit of Acemoglu et al. (2016) we identify a measure of the listing effect which controls for these typically considered determinants. Both approaches corroborate the inconclusiveness identified within the literature.

3.1 Two-Sample Approach

Identifying listing effects by comparing samples of firms entering the DJSI with their peers reveals many of the already identified phenomenon. First we consider the posted excess returns for the share sample. Whilst not accounting for past performance these do deliver the most direct outward impression of the performance of the shares of the new entrants to the DJSI. Compared to larger firms new entrants deliver significantly lower returns eight trading days prior to the announcement, but for the week before there is a significant out-performance of that same group of large-asset firms. When comparing with all firms the effect is weakened slightly, of the positive differentials in returns only the trading day one week before maintains statistical significance. Event studies have spoken of the positive pre-announcement effect and we do see evidence of such here, although many of the positive differences are not significant.

CARs recognise the trend in the stocks performance prior to the listing, they offer a measure of how listing creates deviation from that pre-announcement path. For this purpose in the pre-announcement period the CAR is reported from the day given in the row label up to, and including, the announcement date. For post-announcement days CARs begin on announcement day and include all values up to the day listed in the first column. Significant positive CARs are seen as evidence of sustained performance above expectation during the relevant assessed period. Table 3 contains a second set of columns testing for equality of CARs between the DJSI entry sample and the two reference sets. Compared to the full industry sample significant positive CARs exist for periods beginning 7 trading days prior to the announcement. With the large firm only sample there is an additional period between the first day of the evaluation period and day -11 where there are significant differentials of more than 0.5%. This is then most analogous to the results of other event studies. Post-announcement there are many negative differentials between DJSI entrants and the control groups but these are seldom significant

3.2 OLS Regressions

To understand better the extent to which factors lie behind the observed CAR patterns we regress the CARs observed over five sub-periods from Table 2 on the listing dummy, size, profitability and leverage. We study $CAR_i[from, to]$ as the dependent variable, where this is either $CAR_i[-15, 1]$, $CAR_i[-15, 15]$, $CAR_i[-1, 1]$, $CAR_i[0]$ and $CAR_i[0, 10]$. Regression is performed following equation (5):

$$CAR_i[from, to] = \alpha + \beta_{DJSI} DJSI_{iy} + \boldsymbol{\theta} X_{iy} + \gamma_j + \psi_y + \epsilon_{iy} \tag{5}$$

Here X_{iy} is the set of firm level covariates, $DJSI_{iy}$ is a dummy equal to 1 if firm i joins the DJSI in year y. $\boldsymbol{\beta}$ is a vector of coefficients on the firm controls. γ_j introduces fixed effects for industries where firm i is in industry j. These fixed effects are incorporated to capture unobserved heterogeneity between industries, enabling the model to include any factors which act solely upon that sector. ψ_y is the year fixed effect that is added to represent the variation in conditions over time, this includes those which would have been brought about during the GFC. Remaining error terms, ϵ_{iy}, are assumed to have constant variance and an expected value of 0. To address questions about the best choice of covariates, or whether they should enter linearly, quadratically or otherwise, we follow Acemoglu et al. (2016) to allow each of the three controls to enter as linear, squared and cubic. Robustness checks have been performed using just the linear, and then the linear with quadratic effects.

Table 3: Univariate Tests of Return Equality

Period	Returns					Cumulative Abnormal Returns				
Period	DJSI	All firms		Large firms		DJSI	All firms		Large firms	
-15	-0.257	-0.298	0.04	-0.368	0.111	0.267	0.004	0.263	-0.314	0.581*
-14	0.174	0.286	-0.112	0.259	-0.086	0.269	-0.036	0.305	-0.302	0.571*
-13	0.219	0.289	-0.07	0.318	-0.099	0.341	-0.066	0.407	-0.247	0.588*
-12	0.422	0.397	0.025	0.403	0.019	0.353	-0.008	0.361	-0.189	0.542*
-11	0.019	-0.043	0.061	-0.095	0.114	0.219	0.03	0.189	-0.233	0.452
-10	0.535	0.499	0.036	0.474	0.061	0.167	0.037	0.13	-0.277	0.444
-9	-0.477	-0.293	-0.185	-0.532	0.055	0.073	-0.079	0.152	-0.264	0.337
-8	0.256	0.62	-0.364**	0.764	-0.508***	0.226	-0.055	0.281	-0.165	0.391
-7	-0.183	0.202	-0.384**	0.211	-0.394**	0.321	-0.137	0.458*	-0.215	0.536**
-6	-0.511	-0.648	0.138	-0.658	0.148	0.509	-0.064	0.573**	-0.068	0.577**
-5	0.214	-0.076	0.29***	-0.123	0.337***	0.481	-0.104	0.585**	-0.117	0.598**
-4	0.185	0.141	0.044	-0.072	0.257**	0.208	-0.085	0.294	-0.099	0.307
-3	0.465	0.417	0.048	0.444	0.021	0.259	0.028	0.231	0.053	0.206
-2	0.21	0.063	0.147	0.225	-0.015	0.132	0.059	0.073	-0.023	0.155
-1	-0.43	-0.384	-0.045	-0.766	0.336*	0.03	0.175	-0.145	0.048	-0.017
0	0.051	-0.006	0.058	0.17	-0.118	-0.014	-0.122	0.108	-0.025	0.011
1	-0.697	-0.64	-0.057	-0.578	-0.119	-0.15	-0.177	0.027	-0.025	-0.125
2	-0.281	-0.074	-0.207	-0.491	0.21	-0.176	-0.074	-0.102	-0.181	0.005
3	0.013	0.104	-0.091	0.047	-0.034	-0.234	-0.168	-0.067	-0.274	0.04
4	-0.247	-0.122	-0.125	-0.243	-0.004	-0.384	-0.205	-0.179	-0.32	-0.064
5	-0.664	-0.669	0.005	-0.715	0.051	-0.523	-0.179	-0.344	-0.335	-0.188
6	0.191	0.208	-0.016	0.265	-0.074	-0.603	-0.297	-0.306	-0.32	-0.284
7	-0.456	-0.401	-0.055	-0.58	0.123	-0.7	-0.35	-0.35	-0.336	-0.363
8	-0.125	0.05	-0.175	-0.172	0.047	-0.633	-0.135	-0.498	-0.3	-0.333
9	0.999	1.232	-0.232	1.366	-0.366	-0.651	-0.236	-0.415	-0.389	-0.262
10	0.216	0.327	-0.112	0.104	0.112	-0.767	-0.205	-0.562	-0.462	-0.305
11	-0.941	-1.188	0.247	-1.442	0.501**	-0.744	-0.195	-0.549	-0.525	-0.219
12	0.212	0.726	-0.514***	0.362	-0.15	-0.903	-0.061	-0.841*	-0.738	-0.164
13	0.391	-0.005	0.396**	0.051	0.34**	-0.752	-0.162	-0.589	-0.797	0.045
14	0.1	0.089	0.011	0.102	-0.002	-0.709	-0.259	-0.45	-0.904	0.195
15	-0.203	-0.133	-0.07	-0.432	0.229*	-0.807	-0.177	-0.63	-0.965	0.158

Notes: Join refers to firms which join the DJSI. All firms include any share listed on the major US exchanges from the same industry as a joining firm, with large firms including only those with assets 80% of those of the smallest new entrant to the DJSI. Evaluation processes are repeated anually such that reported figures represent the average effect across the period. In the returns case period represents the trading day for which the returns are reported. Cumulative abnormal returns are calculated for the period bounded on one end by the stated date and has 0 as its' other end.For example -15 provides the cumulative abnormal return over [-15,0]. Asterisks denote significance levels of a two-tailed t-test (*** - 1%, ** - 5% and * - 1%).

Table 4: OLS Regressions for Cumulative Abnormal Returns and Firm Controls

	Full sample					Base sample				
From	-15	-15	-1	0	0	-15	-15	-1	0	0
To	0	15	1	0	10	1	15	1	0	10
DJSI	0.822	1.278	-0.007	-0.043	-0.083	0.534	1.136	-0.046	-0.012	0.183
	(0.628)	(0.950)	(0.277)	(0.180)	(0.551)	(0.463)	(0.711)	(0.201)	(0.128)	(0.423)
Size	2.540***	4.688***	0.005	-0.669***	1.402**	-9.173*	-12.367	-2.009	-1.088	10.27**
	(0.679)	(1.027)	(0.299)	(0.194)	(0.596)	(5.566)	(8.556)	(2.414)	(1.538)	(5.085)
$Size^2$	-0.327***	-0.59***	-0.008	0.081***	-0.166**	0.885*	1.051	0.154	0.103	-1.06**
	(0.087)	(0.132)	(0.038)	(0.025)	(0.076)	(0.534)	(0.821)	(0.232)	(0.147)	(0.488)
$Size^3$	0.013***	0.023***	0.000	-0.003***	0.007**	-0.027	-0.027	-0.004	-0.003	0.036**
	(0.004)	(0.005)	(0.002)	(0.001)	(0.003)	(0.017)	(0.026)	(0.0070	(0.005)	(0.015)
Profitability	-2.293***	-1.385***	-0.058	0.199***	0.699***	-1.335**	1.844**	0.332	0.273	2.501***
	(0.200)	(0.302)	(0.088)	(0.057)	(0.175)	(0.601)	(0.925)	(0.261)	(0.166)	(0.549)
$Profitability^2$	0.004	-0.026	-0.055**	-0.020	-0.029	-0.416	-1.907**	-1.016***	-0.080	-1.202**
	(0.058)	(0.087)	(0.025)	(0.017)	(0.051)	(0.622)	(0.957)	(0.270)	(0.172)	(0.569)
$Profitability^3$	0.006**	0.005	-0.002	-0.001*	-0.001	0.094	0.329*	0.196***	0.006	0.196*
	(0.003)	(0.004)	(0.001)	(0.0010	(0.002)	(0.125)	(0.193)	(0.054)	(0.035)	(0.115)
Leverage	-3.797*	0.284	1.189	0.527	2.744	2.377	-0.194	4.265**	-2.025	-0.438
	(1.952)	(2.953)	(0.860)	(0.559)	(1.712)	(4.490)	(6.902)	(1.948)	(1.241)	(4.102)
$Leverage^2$	-0.207	-14.80*	-3.849*	-0.295	-8.958**	-13.25	-9.679	-7.685*	4.348	-0.743
	(5.186)	(7.843)	(2.284)	(1.485)	(4.549)	(10.50)	(16.14)	(4.553)	(2.900)	(9.590)
$Leverage^3$	4.105	16.08***	3.122*	-0.365	7.021**	11.819*	8.557	4.067	-3.108	0.184
	(3.744)	(5.663)	(1.649)	(1.072)	(3.284)	(7.111)	(10.93)	(3.085)	(1.965)	(6.497)
R-squared	0.03	0.03	0.04	0.06	0.04	0.03	0.08	0.06	0.06	0.07

Notes: Coefficients are reported for the base sample (All), and for the reduced sample with just firms with a size at least 80% of the size of the smallest firm gaining listing (Large). Selected pairings of from and to dates are shown. Coefficients from regression $CAR_i[from, to] = \alpha + \beta_{DJSI} DJSI_{iy} + \boldsymbol{\theta} X_{iy} + \gamma_j + \psi_y + \epsilon_{iy}$ for cumulative abnormal returns between the from and to dates stated at the top of the column, $CAR_i[from, to]$. $DJSI_y$ is a dummy taking the value 1 if firm i joins the DJSI in year y. X_{iy} is a vector of common firm characteristics associated with stock returns, being size (log assets), return on equity and leverage (ratio of debt to capital). All characteristics are included as linear, quadratic and cubic. γ_j is an industry fixed effect where firm i is in industry j as defined by the North American Industry Classification System at the two-digit level. ψ_y are year fixed effects. Figures in parentheses report robust standard errors. Significance denoted by * = 1%, ** = 5%, and ***=1%.

Table 5: Estimated Listing Effect from Cumulative Abnormal Returns OLS Regressions

From	1	1	1	1	1	1	1	6	6
To	15	16	17	18	21	26	31	15	16
Full	0.864	0.822	0.779	0.917	0.718	0.781	1.278	0.821	0.778
	(0.622)	(0.628)	(0.652)	(0.691)	(0.764)	(0.842)	(0.950)	(0.517)	(0.529)
Base	0.547	0.534	0.533	0.66	0.528	0.73	1.136	0.485	0.473
	(0.455)	(0.463)	(0.475)	(0.515)	(0.567)	(0.634)	(0.711)	(0.374)	(0.388)
From	6	6	6	6	11	11	11	11	11
To	17	18	21	26	15	16	17	18	21
Full	0.735	0.874	0.675	0.738	1.235	0.659*	0.617	0.574	0.712
	(0.555)	(0.594)	(0.669)	(0.751)	(0.869)	(0.369)	(0.391)	(0.419)	(0.467)
Base	0.472	0.599	0.467	0.669	1.075*	0.404	0.392	0.39	0.518
	(0.410)	(0.451)	(0.499)	(0.569)	(0.650)	(0.273)	(0.289)	(0.316)	(0.367)
From	11	11	15	15	15	15	15	15	16
To	26	31	16	17	18	21	26	31	16
Full	0.513	0.576	1.074	0.035	-0.007	0.131	-0.068	-0.005	0.492
	(0.555)	(0.651)	(0.779)	(0.236)	(0.277)	(0.338)	(0.456)	(0.573)	(0.712)
Base	0.385	0.587	0.994*	-0.044	-0.046	0.082	-0.051	0.151	0.558
	(0.427)	(0.501)	(0.591)	(0.163)	(0.201)	(0.262)	(0.342)	(0.436)	(0.534)
From	16	16	16	16	16	17	17	17	17
To	17	18	21	26	31	18	21	26	31
Full	-0.085	0.053	-0.146	-0.083	0.414	0.095	-0.104	-0.041	0.457
	(0.236)	(0.295)	(0.420)	(0.551)	(0.691)	(0.239)	(0.384)	(0.517)	(0.659)
Base	-0.014	0.114	-0.019	0.183	0.59	0.126	-0.006	0.196	0.602
	(0.171)	(0.231)	(0.310)	(0.423)	(0.526)	(0.196)	(0.298)	(0.407)	(0.506)

Notes: Coefficients on gaining DJSI listing are reported for the base sample (Full), and for the reduced sample with just firms with a size at least 80% of the size of the smallest firm gaining listing (Base). Coefficients from regression $CAR_i[from, to] = \alpha + \beta_{DJSI} DJSI_{iy} + \boldsymbol{\theta} X_{iy} + \gamma_j + \psi_y + \epsilon_{iy}$ for cumulative abnormal returns between the stated from and to dates, $CAR_i[from, to]$. $DJSI_{iy}$ is a dummy taking the value 1 if firm i joins the DJSI in year y. X_{iy} is a vector of common firm characteristics associated with stock returns, being size (log assets), return on equity and leverage (ratio of debt to capital). All characteristics are included as linear, quadratic and cubic. γ_j is an industry fixed effect where firm i is in industry j as defined by the North American Industry Classification System at the two-digit level. ψ_y are year fixed effects. Figures in parentheses report robust standard errors. Significance denoted by * = 1%, ** = 5%, and ***=1%.

Across all five periods, and for both samples, the main consistency observed is that the DJSI joining dummy is not significant in any of the ten equations. Such a result is opposite to the univariate tests of the previous section, but is entirely in line with the ambiguity of conclusions on listing effects in the current literature. Firm size is used to split the sample and for the full sample log assets has significant coefficients on the linear, quadratic and cubic terms. Only for the full 31 day period is no significance really seen. By contrast in the base sample very few of these size coefficients are significant. Profitability is significant in the linear term, but not for the quadratic or cubic. Leverage in these equations is also significant in the full sample, this can be linked to the correlations observed in Table 2. When reducing to the base sample much of the significance of leverage disappears.

Table 5 reports a wider set of ranges for the CAR, providing coefficients on the DJSI joining dummy. These models maintain the full set of controls and fixed effects from Table 4, but the full details are not reported for brevity. There are now some significant coefficients at the 10% level, but these account for less than 5% of all the coefficients reported. As such this extended set does little to reverse the conclusions from Table 4.

Regressions presented here suggest that much of the difference assigned to a new DJSI listing by the two-sample tests may actually be a consequence of other characteristics, this highlights one of the many challenges of using a testing approach.

4 Generalised Synthetic Control Approach

Synthetic control methodologies (Abadie and Gardeazabal, 2003; Abadie et al., 2010) seek to construct a counterfactual for a treated unit under the assumption that the treatment was not administered. Inherently unobservable this is useful for identifying the treatment effect as the difference between the observed unit and its counterfactual. In the assessment of excess stock returns from DJSI listing the unit is the firm that gains listing and the treatment is the listing. This paper departs from the Abadie and Gardeazabal (2003) family of models by introducing the generalised approach of Xu (2017). Departure here owes to the fact that in many instances there are multiple firms gaining listing within the same industry and there is a strong likelihood of co-integrating relationships amongst stocks. Before presenting the results an outline of the Xu (2017) approach is provided.

4.1 Methodology

Following Acemoglu et al. (2016) we construct a portfolio from the other stocks within the firms industry, selected using the two digit NAICS code. As discussed the portfolio is assembled using observations from the first trading date in November of the previous year, to 16 trading days ahead of the formal listing announcement. This typically provides a training set of 230 days[12]. The synthetic control is then analysed for the period between three weeks in advance of the listing announcement and three weeks after the announcement. In total this gives a 31 trading day long period. This period coincides with the observations of past event studies that impacts die out soon after listing but allows for the discovery of new effects in the post-listing that mirror identified time spans from pre-listing.

Following Xu (2017) we define the set of N_{tr} units in the treatment group as $\mathcal{T}$ and the set of N_{co} control firms as $\mathcal{C}$. Such that $N_{co} + N_{tr} = N$. Units are observed for T periods, covering the $T_{o,i}$ control periods prior to listing, and the $q_i = T - T_{0,i}$ evaluation periods following the listing. Y_{tr}. The Xu (2017) approach offers the possibility of differing numbers of observations for each firm, i, however for simplicity this exposition has $T_{0,i} = T_0$ and $q_i = q$. It is thus assumed that the outcome of interest, excess returns for firm i at time t, R_{it}, are given by a linear factor model of equation (6).

$$R_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \epsilon_{it} \tag{6}$$

The treatment dummy, D_{it}, takes the value 1 for firms obtaining listing on the DJSI, that is $i \in \mathcal{T}$ and $t > T_0$. For our purposes there are no controls and so we can simplify the exposition to remove $x'_{it}\beta$. Innovation in Xu (2017) draws on the $\lambda'_i f_t$ factor model which expands to (7):

$$\lambda'_i f_t = \lambda_{i1} f_{1t} + \lambda_{i2} f_{2t} + ... + \lambda_{ir} f_{rt} \tag{7}$$

This takes a linear additive form that covers conventional additive unit and time fixed effects as special cases. Many further common financial models are also permissable, including autoregressive components[13].

[12]Because of the annual cycle of the DJSI listings we do not include a full year of training data.

[13]See discussion in Xu (2017) and Gobillon and Magnac (2016).

Define $R_{it}(1)$ as the excess stock return for firm i at time $t > T_0$ and $R_{it}(0)$ as the pre-treatment excess returns for firm i at time $t \leq T_0$. $\delta_{it} = R_{it}(1) - R_{it}(0)$ for any $i \in \mathcal{T}$, $t > T_0$. It may be written that:

$$R_i = D_i \odot \delta_i + F\lambda_i + \epsilon_i, i \in 1, 2, ..., N_{co}, N_{co} + 1, N \tag{8}$$

in which $R_i = |R_{i1}, R_{i2}, ..., R_{iT}|$;$D_i = |D_{i1}, D_{i2}, ..., D_{iT}|'$, $\delta_i = |\delta_{i1}, \delta_{i2}, ..., \delta_{iT}|$, and $\epsilon_i = |\epsilon_{i1}, \epsilon_{i2}, ..., \epsilon_{iT}|'$ are $T \times 1$ vectors. The factors $F = |f_1, f_2, ..., f_T|'$ is a $(T \times r)$ matrix. Determination of r is discussed subsequently.

Stacking all N_{co} control units together produces $R_{co} = [R_1, R_2, ..., R_{N_{co}}]$ and $\epsilon_{co} = [\epsilon_1, \epsilon_2, ..., \epsilon_{N_co}]$, the factor matrix, $\Lambda_{co} = [\lambda_1, \lambda_2, ..., \lambda_{N_{co}}]$, is $(N_{co} \times r)$, whilst R_{co} and ϵ_{co} are both $(T \times N_{co})$. The stacked model is stated as equation (9):

$$R_{co} = F\Lambda'_{co} + \epsilon_{co} \tag{9}$$

Identification of the parameters is constrained by a requirement that $F'F/T = I_r$ and $\Lambda'_{co}\Lambda_{co}$ =diagonal. Average listing effects for those who are listed on the DJSI, are then the average effects of treatment on the treated (ATT). At time t, $t > T_0$ the ATT, $ATT_{t,t>T_0}$ is estimated as per equation (10)[14].

$$ATT_{t,t>T_0} = 1/N_{tr} \sum_{i \in \tau} [Y_{it}(1) - Y_{it}(0)] = \frac{1}{N_{tr}} \sum_{i \in \tau} \delta_{it} \tag{10}$$

Xu (2017), like Abadie et al. (2010), treat the treatment effects δ_{it} as conditional on the sample data. Identification of these necessitates an appropriate measure of $R_{it}(0)$ when $t > T_0$ and $i \in \mathcal{T}$[15]. Estimation of the parameters of the model proceeds using three steps. Firstly estimates for $\hat{F}\hat{\lambda}_c o$ are obtained through:

$$(\hat{F}, \hat{\Lambda_{co}}) = \underset{\tilde{\beta}, \tilde{F}\tilde{\Lambda}_c o}{argmin} \sum_{i \in \mathcal{C}} (R_i - \tilde{F}\tilde{\Lambda}_i)'(R_i - \tilde{F}\tilde{\Lambda}_i) \tag{11}$$

Recalling that this minimisation is performed subject to the twin constraints that $\tilde{F}'\tilde{F}/T = I_r$ and that $\tilde{\Lambda}'_{co}\tilde{\Lambda}_{co}$ is a diagonal matrix.

Following Xu (2017) the factor loadings are calculated. Values restricted to the pre-announcement period gain subscript "0"'s. Hats denote estimates from (11). Step 2 is thus:

$$\begin{aligned} \hat{\lambda}_i &= \underset{\hat{\lambda}_i}{argmin} (R_i^0 - \hat{F}^0 \tilde{\lambda}_i)'(R_i^0 - \hat{F}^0 \tilde{\lambda}_i) \\ &= (\hat{F}^{0\prime}\hat{F}^0)^{-1} \hat{F}^{0\prime} R_i^0, i \in \mathcal{T} \end{aligned} \tag{12}$$

Step 3 calculates treated counterfactuals based on the estimated $\hat{F}$ and $\hat{\lambda_{co}}$:

$$\hat{R}_{it}(0) = \hat{\lambda_i}' \hat{f}_t, i \in \mathcal{T}, t > T_0 \tag{13}$$

[14]For more on the social economic interpretation of this see Blackwell and Glynn (2018).

[15]A discussion of the requirements for causal inference in the generalised synthetic control framework is provided as a supplementary appendix to Xu (2017).

Estimates for the average treatment effect on the treated, ATT_t are provided as:

$$A\hat{T}T_t = (1/N_{tr}) \sum_{i \in \mathcal{T}} [R_{it}(1) - \hat{R}_{it}(0)] \text{ for } t > T_0 \tag{14}$$

In order to obtain convergence in the estimated factor loadings it is required that there be sufficiently large numbers of controls and a sufficiently long control period. As we have more than 200 days of data, and a large number of firms in each two digit NAICS code, there would not be expected to be any concerns about convergence. Indeed in every case the reported tests of convergence reveal that the model does converge.

Within the Xu (2017) the number of factors to be included is determined using a five step procedure. Firstly a given r is selected and an interactive fixed effects (IFE) model is estimated for the control group data to obtain an estimate of F, $\hat{F}$. A cross-validation loop is run at step 2 which first works systematically through the control period omitting one period and obtaining factor loadings for each treated unit, i, according to the formula:

$$\hat{\lambda}_{i,-s} == \left(F^{0\prime}_{-s} F^{0}_{-s}\right)^{-1} F^{0\prime}_{-s} R^{0}_{i-s}, i \in \mathcal{T} \tag{15}$$

where the use of $-s$ in the subscripts denotes the ommision of period s from the estimation. Predicted outcomes for the missing period are saved and compared with the observed period s return to construct a prediction error $e_{is} = R_{is}(0) - \hat{R}_{is}(0)$. Step 3 sees the calculation of the mean square predicted error (MSPE) given the selected number of factors. Given r the MSPE is:

$$MSPE(r) = \sum_{s=1}^{T_0} \sum_{i \in \mathcal{T}} e_{is}^2 / T_0 \tag{16}$$

Repeating the process over further possible r enables the identification of r^* as that number of factors which minimises the MSPE from equation (16). Xu (2017) demonstrate through Monte Carlo simulation that this simplistic procedure performs well in factor number selection[16].

In order to obtain inference from the estimated ATT we need a conditional variance of the ATT estimator, i.e. $Var_{\epsilon}(A\hat{T}T_t | D_t, \Lambda F)$. Although ϵ should be the only random variable not being conditioned upon it may be correlated with $\hat{\lambda}_i$ from the estimation loop above, it remains a measurement of the variations in returns that we cannot explain and which is unrelated to treatment assignment.

In an approach similar to Acemoglu et al. (2016), Xu (2017) proposes a four step algorithm for determining the uncertainty estimates of, and hence confidence intervals for, $A\hat{T}T_t$. Treated counterfactuals are simulated for control units, that is firms whose DJSI membership status does not change in the given year. For this purpose the resampling scheme is given as:

$$\begin{aligned} \tilde{R}_i(0) &= \hat{F}\hat{\lambda}_i + \tilde{\epsilon}_i, && \forall i \in \mathcal{C}; \\ \tilde{R}_i(0) &= \hat{F}\hat{\lambda}_i + \tilde{\epsilon}_i^p, && \forall i \in \mathcal{T}; \end{aligned}$$

[16] It is also shown to perform well in small datasets, but this is not a concern for our daily financial data (Xu, 2017).

where simulated outcomes from the event of the treatment not occurring are collected in $\tilde{R}_i(0)$, the estimated conditional mean is captured through the estimated factors, $\hat{F}\hat{\lambda}_i$ and the resampled residuals are incorporated through $\tilde{\epsilon}_i$ and $\tilde{\epsilon}_i^p$. The variance of the latter is liable to be bigger than the former since $\hat{F}\hat{\lambda}_i$ is estimated from the control units and will therefore be expected to fit better on those firms that did not gain listing.

Step one is to start a loop that will run a specified number of times to generate a sufficiently large number of comparison observations for the confidence intervals. Within this element of the process it is necessary take a control unit, i, and act as if it has been treated in the time $t > T_0$. The rest of the control units are resampled with replacement to form a new sample which contains that new "treated" unit and a full set of N_{co} controls. The generalized synthetic control method is applied to obtain a vector of residuals, $\hat{\epsilon}^p_{(m)} = R_i - \hat{R}_i(0)$. Collecting these residuals from every loop then creates a vector e^p. Step two applies the generalised synthetic control method to the original data to obtain the fitted average treatment effects, $A\hat{T}T_t$ for all time periods. Estimate coefficients and obtain fitted values and residuals for the control units, $\hat{\mathbf{R}}_{\mathbf{co}} = \{\hat{R}_1(0), \hat{R}_2(0), ...\hat{R}_{N_{co}}(0)\}$ and $\hat{\mathbf{e}} = \{\hat{\epsilon}_1, \hat{\epsilon}_2, \epsilon_{\hat{N_{co}}}\}$

Step three of the process then involves another bootstrap loop, operating for B_2 repetitions. For each repetition a bootstrapped sample, $S^{(k)}$ is used. In this case in round $k \in \{1, ..., B_2$ the previous estimates of $\tilde{\epsilon}_i$ and $\tilde{\epsilon}_j^p$ are randomly selected from the sets and $\mathbf{e^p}$. We fit $\hat{R}_i = \hat{F}\hat{\lambda}_i$ and hence construct a sample by:

$$\tilde{R_i}^{(k)}(0) = \hat{R}_i(0) + \tilde{\epsilon}_i 1 \in \mathcal{C}$$
$$\tilde{R_i}^{(k)}(0) = \hat{R}_j(0) + \tilde{\epsilon}_i^p \mathrm{J} \in \mathcal{T}$$

In this case Xu (2017) notes that the simulated treatment counterfactuals do not contain the treatment effect. From here the generalised synthetic control is applied to the bootstrapped sampled $S^{(k)}$ new estimates for the average treatment effects, $A\hat{T}T_{t,t>T_0}$. Adding this estimate to the others creates a set of stored estimates allowing the final obtaining of the bootstrap estimator $A\hat{T}T^k_{t,t>T_0}$. Finally the variance of all of these collected average treatment effects may be calculated and the confidence intervals constructed accordingly.

4.2 Results

Cumulative abnormal returns are constructed for periods of two trading days, or longer, resulting in a set of 465 potential time spans. Brevity dictates that only a selection of these may be reported, full results being provided in a supplementary appendix. This papers main contribution lies in its application of a novel method to event studies within finance. Building on the precedent in Acemoglu et al. (2016, 2017) and Chamon et al. (2017), we extend into the generalised framework of Xu (2017) because there are too often more than one company obtaining listing on the DJSI from any given industry. As a first stage in confirming the need for this paper Table 6 reports the number of treated units by industry-year within the sample. It can be seen that whilst there are a number of ones within the Tr (treated) column there are also many many industries with two or more. Table 6 also confirms that the number of control units is always significantly higher than the number of treated.

Table 6 provides a summary of the fitted models resulting from the package. MSPE are reported at the two digit NAICS code level to indicate the quality of the fit through the training period. In the majority of cases these values are below 2, with high values appearing only where the number of controls is low. There are many occasions near the GFC where the synthetic control model has an MSPE well below that associated with the CAPM, sometimes being less than half that of the original approach. Industry 45 in 2008 is a good example of this. In more recent years the number of times where the CAPM delivers a better fit is almost identical, though often the margin is very small. Overall there are 55 cases where the CAPM can be considered better fitting during the control period, compared to 76 for the generalised synthetic control approach.

Of particular interest to the study of net listing effects are the abnormal returns of periods that involve the announcement date. Hence Table 7 only reports a subset of the possible time combinations. A full set of abnormal returns over periods of one day, or longer, is included within the appendix. Significance on periods starting three weeks ahead of the announcement and ending around, or after, the listing details become public is seen. This includes an abnormal monthly return of greater than 5% per annum equivalent in the period ending the day before announcement day. Across the whole thirty one day period there is a cumulative abnormal return of 0.479, or 6% across the whole year.

Evidence is provided that much of the uptick from DJSI listing occurs prior to the change date, a result which appears in Oberndorfer et al. (2013). There is also evidence in the synthetic control cumulative abnormal returns of the correction that Oberndorfer et al. (2013) argues takes place after the announcement date. Such reversion effects manifest as significant negative abnormal returns in the windows starting at date 0 and ending the next trading day or two weeks afterwards. By the three week point none of the reduced set of periods show significant cumulative abnormal returns. For all time frames starting before the announcement date there are positive cumulative abnormal returns but their magnitude diminishes and their significance is lost post announcement.

Within the results there is thus support for the twin hypotheses derived from the literature. Firstly the benefit of higher expected profitability causes a rise in the price of the share over and above any effects happening to the control shares. Secondly there is a correction as the lower risk associated with CSR activities takes over; such is consistent with the risk/return relationship. Our confirmation from this approach lends weight to the theories and results of Oberndorfer et al. (2013) and others.

4.3 Comparison

Three approaches to identifying the listing effects of joining the DJSI have been presented in this paper and we have seen variations in the predictions made. Two-sample tests revealed significant positive CARs for periods that began either three weeks before the announcement, or one week ahead of the new member details becoming public. Generalised synthetic control modelling obtains this result too, with a magnitude similar to the differences in the mean cumulative abnormal returns of the two stock samples. Relative to the two-sample approach the synthetic control does not require any similarities amongst control group members to be interpreted cleanly as a listing effect. We can take the CAR from the DJSI members versus their respective CAPM predictions, the values of these are not as large as those generated for the synthetic control for the periods starting three weeks ahead of the listing (day -15), but are larger for the periods that begin a week ahead (day -6). The negative CAR identified

Table 6: Fit Statistics by Industry

Year	NAICS2	MSPE		V.	Co.	Tr	Ctrl	Year	NAICS2	MSPE		V.	Co.	Tr	Ctrl
		CAPM	Synth							CAPM	Synth				
2005	0	0.983	0.985	0	5	6	87	2011	2	0.442	0.314	0	2	1	37
	2	0.871	0.543	0	4	2	32		3	0.751	0.792	0	3	1	15
	3	0.913	1.030	0	5	1	21		32	0.948	0.992	0	4	1	260
	21	3.434	1.385	0	3	1	121		33	1.462	1.480	0	3	4	558
	22	1.508	1.481	0	1	1	37		44	3.400	3.420	0	1	1	77
	23	2.654	2.589	0	3	1	30		45	1.601	1.354	0	5	1	33
	31	0.769	0.824	0	1	3	82		48	3.309	2.546	0	4	2	84
	32	1.034	0.995	0	5	6	305		52	1.296	0.955	0	4	3	462
	33	1.582	1.491	0	3	7	648		53	1.932	1.153	0	5	1	175
	44	1.641	1.608	0	1	4	88		56	1.908	1.676	0	1	1	48
	45	1.145	1.015	0	2	1	53		71	2.661	2.734	0	1	1	10
	48	0.903	0.809	0	5	1	84		72	0.939	0.995	0	1	1	47
	51	0.863	0.955	0	1	4	284	2012	22	0.878	0.671	0	4	1	37
	52	0.708	0.715	0	2	7	534		31	0.602	0.596	0	4	2	86
	54	1.790	1.804	0	5	2	111		32	0.519	0.627	0	1	2	261
	56	0.854	0.891	0	4	1	55		33	1.399	1.388	0	2	2	554
	72	1.250	1.105	0	2	1	61		45	7.568	7.654	0	1	1	36
2006	0	0.756	0.572	0	5	1	95		51	2.266	2.137	0	3	3	263
	2	1.553	1.391	0	4	2	32		52	2.377	1.933	0	3	1	499
	21	4.492	1.617	0	5	2	133		54	1.843	1.934	0	3	1	104
	22	0.772	0.598	0	4	1	39		56	0.730	0.776	0	1	1	47
	31	0.400	0.412	0	2	1	85	2013	0	1.887	1.992	0	1	2	107
	32	2.229	1.719	0	3	3	311		21	1.573	1.382	0	2	2	145
	33	1.736	1.792	0	1	1	667		31	0.575	0.513	0	4	1	92
	42	0.835	0.873	0	5	1	78		32	1.393	1.420	0	4	4	279
	51	4.300	4.265	0	1	1	301		33	0.727	0.763	0	1	3	568
	52	0.863	0.832	0	3	3	539		44	0.848	0.880	0	5	2	79
2007	21	1.597	0.932	0	3	1	153		51	3.043	3.002	0	1	2	287
	22	1.125	1.068	0	4	1	40		52	1.206	1.0336	0	3	2	542
	33	3.022	2.752	0	4	2	677		53	1.477	1.140	0	5	3	187
	45	2.584	2.464	0	4	1	49		54	4.442	4.451	0	1	1	97
	51	2.390	2.417	0	4	1	318	2014	0	0.563	0.561	0	4	1	117
	52	1.038	1.027	0	4	3	517		2	1.280	1.099	0	1	1	28
	54	1.687	1.715	0	1	1	113		22	0.715	0.531	0	5	1	42
	62	3.334	3.172	0	3	1	52		23	0.672	0.781	0	4	1	41
2008	0	5.716	3.449	0	4	2	98		32	1.952	2.144	0	4	1	335
	2	2.238	1.236	0	5	1	31		33	1.324	1.392	0	3	3	613
	31	1.805	1.858	0	5	1	78		48	0.714	0.708	0	3	1	110
	32	3.646	3.536	0	4	1	267		51	2.241	2.178	0	4	2	322
	33	5.702	3.687	0	4	2	556		52	0.832	0.814	0	4	2	590
	45	5.073	2.497	0	2	1	34		53	1.317	1.313	0	3	1	216
	51	4.649	4.593	0	1	1	256		72	2.989	3.043	0	1	1	58
	52	5.020	3.594	0	3	2	440	2015	0	2.191	2.015	0	4	1	113
	53	3.532	2.779	0	2	2	153		23	2.222	0.898	0	4	1	40
	56	1.622	1.638	0	2	1	49		31	0.465	0.440	0	4	1	86
2009	2	2.356	1.475	0	4	2	30		32	0.810	0.881	0	2	3	378
	21	9.809	5.633	0	1	1	115		33	0.854	0.927	0	5	1	576
	31	2.328	2.082	0	5	1	64		51	0.715	0.737	0	5	1	333
	32	4.554	4.535	0	5	4	210		52	0.428	0.426	0	5	1	591
	33	3.312	3.348	0	5	2	416		53	1.488	0.985	0	4	2	213
	42	4.389	4.599	0	1	2	57		72	3.045	0.998	0	5	1	60
	44	4.531	4.478	0	4	1	59	2016	3	3.438	3.830	0	1	1	16
	45	8.880	5.395	0	5	1	26		31	1.021	1.072	0	4	2	85
	48	3.044	2.485	0	4	1	78		32	1.102	1.322	0	2	1	368
	51	2.093	2.115	0	5	1	204		33	0.731	0.793	0	3	1	538
	52	9.025	7.191	0	5	3	353		44	1.763	1.421	0	2	1	76
	54	4.442	4.463	0	1	1	85		51	2.330	2.364	0	5	1	329
2010	0	0.563	0.599	0	1	1	102		52	2.022	1.403	0	5	3	562
	2	1.058	0.778	0	5	1	34		53	2.986	2.485	0	5	2	219
	21	4.191	1.891	0	4	3	134		56	0.572	0.607	0	3	1	53
	32	1.308	1.329	0	1	4	258	2017	0	3.753	3.669	0	2	3	121
	33	1.350	1.252	0	5	3	553		21	11.40	2.101	0	3	1	135
	51	0.583	0.650	0	5	1	248		31	1.689	0.554	0	3	2	92
	54	2.245	2.181	0	5	1	110		32	3.065	3.902	0	3	2	417
	56	2.170	2.301	0	1	1	45		33	2.335	2.969	0	1	3	596
									48	2.301	1.693	0	5	1	114
									51	1.162	1.179	0	3	2	358
									52	2.254	2.836	0	3	2	653
									53	4.095	2.465	0	2	2	235
									54	1.980	2.712	0	1	1	96
									72	1.179	1.486	0	2	2	64

Notes: Models are fitted using the generalised synthetic control method of Xu (2017). NAICS2 reports the two-digit North American Industry Classification System (NAICS) code for the considered industry. MSPE is the Mean Squared Prediction Error when fitting the synthetic versions of the fitted shares to the training data. CAPM reports the MSPE for the CAPM based CARs from Section 2.3, whilst Synth reports the MSPE for the generalised synthetic control methodology. V. reports a test for the cointegration of the error matrix with 0 implying rejection. Co. gives the number of cointegrating relationships used in the construction of the unobserved parameter. Tr is the number of firms who joined the DJSI for that two digit NAICS code. Ctrl is the number of control firms used to construct the couterfactual model for entering firms. All firms with missing data are eliminated, including some new listings to the DJSI. All estimations performed using *gsynth* (Xu and Liu, 2018)

Table 7: Average Cumulative Abnormal Returns 2005-2017

Start	Window End						
	-1	0	1	2	5	10	15
-15	0.784*	0.638	0.626	0.503	0.397	0.334	0.479
-10	0.525	0.379	0.367	0.244	0.138	0.075	0.22
-5	0.519*	0.373	0.361	0.238	0.132	0.068	0.214
-1	0	0.012	-0.001	-0.123	-0.23	-0.293	-0.148
0	0	0	-0.158	-0.281	-0.387*	-0.45*	-0.305
1	0	0	0	-0.135	-0.242	-0.305	-0.159

Notes: Average cumulative abnormal returns are reported for the period starting on the row label and ending according to the column label. These are averaged over time and industry. A t-test across the time-industry space results in a report of their difference from zero. Significant returns are denoted by * - 5%, ** - 1% and *** - 0.1%. A full set of results are reported in the supplementary material.

for the CAPM in Table 3 are much larger than those seen in Table 7. Smaller CAR would be expected for a model which fits better and as such there is more evidence here in support for the synthetic control.

In the OLS regressions there were no significant impacts of listing for any of the considered periods. Identified CARs were absorbed by the strength of the role of other firm characteristics that are linked to returns; size leverage and profitability were all shown to have significance in Table 4. Critically gaining DJSI status was not. Such significance shows the importance of the controls when comparing two samples and reminds of the need to take care when using differences in sample means as measures of impact.

Utilising the generalised synthetic control approach means there is only one variable being considered, the returns of the share for which the synthetic control is being generated. What is important for generating the counterfactual is not the levels of financial performance in the control set, but the way their share price contributes to a portfolio which matches the behaviour of the firm to be listed. Like the CAPM we have only to consider the firms at an individual level, but the presence of the controls is allowing the performance of others to affect CARs. Across a single year there will be few changes in a firms financial performance, meaning that the relationships between shares would not be expected to change by much between the control and treatment periods. Hence what we see is a significance in the results of a similar nature to the two-sample approach but is now encapsulating many of the benefits that come from understanding the relative properties of the control firms.

5 Discussion

This paper seeks to understand more of the impact of firm CSR performance on their stock returns. It achieves this goal using a binary rating of whether a firm receives their listing, or not. There are many reasons to call into question such an arbitrary measure, but as outlined there is much to be said for a simple measure. Ability to interpret is critical and the binary approach does permit a clear communication with investors and the public alike. Such appeal has led to a wealth of literature capturing CSR in this binary way. Event studies become a viable method as the listing is fixed externally and is not related to the level of returns a share is experiencing at the time of the listing, or de-listing.

Through the construction of a synthetic control potential post-evaluation period impacts on non-treated shares are accounted for in a way existing event studies have failed to do. By comparing a listed share to the performance of a portfolio of its' peers a greater understanding of the listing impact is gained. It is seen that there is an impact three weeks ahead of the effective date. Confirmation is found of a positive listing effect in the pre-change period, and a small correction in the days following the announcement. The latter is shorter in duration than has been found from past works. However, in all cases the size of the abnormal return is much larger in the synthetic control. There is a definite argument for incorporating relative performance to avoid such effects being masked by linear models.

Synthetic controls can offer potential new insights for a series of treatments in finance, such as the impact of cross-listing, option availability and changes to trading rules. All of these would represent interesting applications to complement this study and the connection study of Acemoglu et al. (2016). Here assets are used as a time-invariant control because of the comparatively large size of DJSI listed firms compared to the majority of non-DJSI listed firms. Extending the set of controls, including introducing time-variant controls, becomes increasingly possible. However, the low error within the simple fit lends a tractability to the work presented here. Likewise the approach may be fitted to intra-day data, although appropriate account for noise would be beneficial if making such an extension. This paper highlights such potential and the value of controlling for post-treatment events.

Listing on the DJSI sends an important signal to the market that a firm has achieved the highest standards of CSR. However, the effect on investors has long been considered ambiguous. Increased demand from consumers has potential to raise profitability, but in turn this delivers a stability that means lower returns are required to compensate for risk in the share price. Over and above any other impacts upon the returns of newly-listed DJSI members it is shown that abnormal returns fall when the market becomes aware of the listing. Negative effects quickly dissipate leaving an insignificant impact of DJSI listing on stock-returns.

6 Summary

Being listed to the DJSI sends a clear signal to the market that a firm has obtained a high level of CSR performance, and that it will be treated as such by the market. There have been numerous attempts to capture this effect but they either fail to account for important control variables, such as the two-sample approach, or they require careful matching to focus on the true listing effect. By exploring the generalised synthetic control (Xu, 2017) as a useful multi-treatment version of the Abadie et al. (2010) method this paper has demonstrated strong abnormal returns for stocks which list on the DJSI North America. These returns far out-rated those suggested by CAPM and produced listing effects greater than those from comparing new joiners CAPM CAR with the CAR of the controls. By contrast the correction effect that sees joiners work through periods of negative CARs these are not as large as those in other methods. We conclude that there are higher returns initially, but that as the news goes public the response reverses to bring stocks back to their usual return levels.

There is scope to introduce more control variables to hone the match of the portfolio, and models beyond the CAPM could be useful. Splitting the time period may be fruitful, as the financial crisis is well known from the literature for creating an important role for socially responsible investment. Further extension could be made to winzorise the returns data, or to relax the assumption that stocks must have all of their data present. Although computationally intensive that remains an option for further work. Notwithstanding these questions the results produce cast important light on a positive benefit of listing which appears over and above the returns the treated stock would have obtained having not been listed.

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A Simple Cumulative Abnormal Returns

In the main paper we use the cumulative abnormal returns (CAR) generated from the capital asset pricing model (CAPM). The process for generating these is described in Section 2.3 of the main paper. In essence we estimate the CAPM during the control period and use the estimated coefficients to fit values through the control period. These fitted values are compared with the observed values to obtain the prediction error. Implicitly shares that have more volatility are likely to produce larger errors, we expect to see lower control MSPE from the base sample. That is, excluding small firms should reduce the errors noticeably.

Tables 8 to 12 provide the full break down of the industry year combinations for which there are DJSI entries. For the full sample it is clear that there are abundant control stocks for each listing, but for the base sample there are many cases where there are none. For the estimation of listing effects such low numbers pose problems for the simple models because there is very little to compare the firm joining the DJSI against. Of interest here are the prediction errors which are typically at their highest for the controls in the full sample. This is entirely in line with the theoretical prediction that smaller stocks will be harder to fit. Firms joining the DJSI have a much lower MSPE than those which do not in almost every case, this relationship still holds even when the smaller firms are removed from the sample. This follows since we have already seen in the main paper that the joiners are on average much larger (measure in terms of log assets) than the control set.

Working through the tables the largest values can be found in 2009, which was a highly uncertain period coming off the back of the main financial crisis hit. By 2010 although there are still MSPE of around 5 there are very few of the 10's seen during the GFC. Highest in the post crisis period are found in industry 32, a subdivision of manufacturing concerned with natural resources and chemicals. However, for those that do list onto the DJSI the MSPE are much lower. Compared to 10.22 for industry 32 overall in 2016, the firm that does join has an MSPE of just 1.102, almost ten times smaller. After exclusion of the small firms the MSPE of the remainder is 1.874 with 1.929 for the base sample control set. Similar patterns are seen with the same industry in 2014 and 2015. The gap in 2013 was more reasonable, and likewise 2012.

B Gap Plots

Abnormal returns in the generalised synthetic control approach are calculated as the "gap" between the observed return and that which would be estimated using a portfolio of the control shares. Weights for shares within the portfolio are derived from the learning period to minimised the mean squared percentage error (MSPE). Confidence intervals are estimated by calculating the error that emerges for the non-listed shares and determining the range in which 95% of observations are centred. Only 2005 is reported here to show the time variance of the results, with the full set of results available upon request. An immediate observation from Figure 2 is that the majority of the returns are not significantly different from zero. This pattern repeats through all other plots (Figures 3 to 3). Such reflects the nature of stock returns, the expectation they will be close to zero on average, but that there will be volatility above that which would emerge from a normal distribution.

Table 8: Listing and Control Numbers plus Model Fit 2005-2007

Year	Industry	Full Sample Total No.	Full Sample Total MSPE	Join DJSI No.	Join DJSI MSPE	Controls No.	Controls MSPE	Base Sample Total No.	Base Sample Total MSPE	Base Sample Controls No.	Base Sample Controls MSPE
2005	0	99	2.197	6	0.983	93	2.28	49	1.333	43	1.382
2005	2	37	1.188	2	0.871	35	1.21	14	1.026	12	1.052
2005	3	23	3.297	1	0.913	22	3.41	8	1.678	7	1.788
2005	21	132	4.807	1	3.436	131	4.82	3	2.797	2	2.477
2005	22	41	2.476	1	1.508	40	2.50	2	1.039	1	0.571
2005	23	32	3.859	1	2.654	31	3.90	8	3.040	7	3.095
2005	31	86	3.287	3	0.769	83	3.38	11	1.385	8	1.616
2005	32	332	5.267	6	1.034	326	5.34	118	3.101	112	3.212
2005	33	697	5.649	7	1.582	690	5.69	194	2.833	187	2.880
2005	44	96	3.834	4	1.641	92	3.93	46	2.769	42	2.876
2005	45	57	4.676	1	1.145	56	4.74	2	0.897	1	0.648
2005	48	90	3.726	1	0.903	89	3.76	10	1.635	9	1.716
2005	51	312	4.781	4	0.863	308	4.83	90	2.063	86	2.118
2005	52	583	2.292	7	0.708	576	2.31	43	1.059	36	1.128
2005	54	123	5.123	2	1.790	121	5.18	9	1.570	7	1.507
2005	56	60	4.185	1	0.854	59	4.24	1	0.854	NA	NA
2005	72	65	3.798	1	1.250	64	3.84	1	1.250	NA	NA
2006	0	99	2.922	1	0.756	98	2.944	25	1.481	24	1.511
2006	2	36	1.611	2	1.553	34	1.615	21	1.171	19	1.131
2006	21	141	5.939	2	4.492	139	5.960	16	3.775	14	3.672
2006	22	45	2.813	1	0.772	44	2.859	2	1.030	1	1.288
2006	31	94	4.599	1	0.400	93	4.644	4	0.647	3	0.729
2006	32	331	5.376	3	2.229	328	5.405	82	2.340	79	2.344
2006	33	712	5.942	1	1.736	711	5.948	34	1.983	33	1.991
2006	42	86	4.521	1	0.835	85	4.564	2	1.031	1	1.228
2006	51	324	4.842	1	4.299	323	4.843	56	1.944	55	1.902
2006	52	599	2.410	3	0.863	596	2.418	84	1.376	81	1.395
2007	21	158	4.225	1	1.597	157	4.242	1	1.597	NA	NA
2007	22	44	2.589	1	1.125	43	2.623	2	1.312	1	1.499
2007	33	713	5.182	2	3.022	711	5.188	76	2.124	74	2.100
2007	45	51	4.779	1	2.584	50	4.823	4	1.672	3	1.368
2007	51	327	4.781	1	2.390	326	4.788	47	1.740	46	1.726
2007	52	556	3.045	3	1.038	553	3.055	260	2.125	257	2.138
2007	54	123	4.451	1	1.687	122	4.474	9	1.493	8	1.469
2007	62	57	5.015	1	3.334	56	5.045	2	2.359	1	1.385

Notes: Full sample contains all shares listed on major US exchanges with sufficient data and at least one DJSI joining firm within their 2 digit NAICS code group. Base sample includes only those firms whose total assets are at least 80% of those of the smallest firm that gains DJSI listing from their industry. NA in the controls indicates there were no controls available satisfying the criteria in that year-industry pair. No. gives the number of firms. MSPE provides the mean squared predicted error for the control period.

Table 9: Listing and Control Numbers plus Model Fit 2008-2010

Year	Industry	Full Sample						Base Sample			
		Total		Join DJSI		Controls		Total		Controls	
		No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE
2008	0	102	5.458	2	5.716	100	5.453	34	3.409	32	3.265
2008	2	35	2.361	1	2.238	34	2.365	10	1.936	9	1.902
2008	11	7	7.525	1	2.632	6	8.340	1	2.632	NA	NA
2008	31	85	6.204	1	1.805	84	6.256	11	2.340	10	2.394
2008	32	277	8.900	1	3.646	276	8.919	38	3.527	37	3.523
2008	33	575	7.881	2	5.702	573	7.888	154	4.969	152	4.959
2008	45	36	9.155	1	5.073	35	9.272	8	4.453	7	4.364
2008	51	265	7.120	1	4.649	264	7.129	113	4.758	112	4.759
2008	52	481	6.902	2	5.020	479	6.910	38	4.154	36	4.106
2008	53	162	5.488	2	3.533	160	5.513	100	4.539	98	4.560
2008	56	52	7.415	1	1.622	51	7.528	18	3.613	17	3.730
2009	2	36	4.701	2	2.356	34	4.839	9	4.316	7	4.876
2009	21	124	13.658	1	9.809	123	13.689	17	7.948	16	7.832
2009	31	76	8.706	1	2.328	75	8.791	28	5.838	27	5.968
2009	32	235	10.485	4	4.554	231	10.587	62	6.651	58	6.795
2009	33	467	10.185	2	3.312	465	10.214	152	7.388	150	7.443
2009	42	67	8.999	2	4.389	65	9.141	6	5.158	4	5.543
2009	44	67	12.489	1	4.531	66	12.610	9	4.575	8	4.580
2009	45	30	9.086	1	8.880	29	9.093	7	7.936	6	7.779
2009	48	85	9.618	1	3.044	84	9.697	12	6.228	11	6.517
2009	49	5	8.438	1	5.117	4	9.268	2	3.622	1	2.126
2009	51	226	9.460	1	2.093	225	9.492	3	2.990	2	3.439
2009	52	407	11.669	3	9.025	404	11.689	172	12.168	169	12.223
2009	54	93	10.396	1	4.442	92	10.460	27	6.133	26	6.198
2010	0	108	3.091	1	0.563	107	3.114	25	1.850	24	1.903
2010	2	36	1.572	1	1.058	35	1.587	5	1.176	4	1.205
2010	5	2	2.919	1	2.226	1	3.612	2	2.919	1	3.612
2010	21	142	4.586	3	4.191	139	4.594	61	3.167	58	3.114
2010	32	276	5.456	4	1.308	272	5.517	81	2.094	77	2.135
2010	33	585	4.591	3	1.350	582	4.608	135	2.638	132	2.668
2010	51	261	4.055	1	0.583	260	4.068	3	0.930	2	1.104
2010	54	113	4.668	1	2.245	112	4.690	18	2.280	17	2.282
2010	56	49	4.014	1	2.170	48	4.053	5	1.714	4	1.600

Notes: Full sample contains all shares listed on major US exchanges with sufficient data and at least one DJSI joining firm within their 2 digit NAICS code group. Base sample includes only those firms whose total assets are at least 80% of those of the smallest firm that gains DJSI listing from their industry. NA in the controls indicates there were no controls available satisfying the criteria in that year-industry pair. No. gives the number of firms. MSPE provides the mean squared predicted error for the control period.

Table 10: Listing and Control Numbers plus Model Fit 2011-2013

Year	Industry	Full Sample						Base Sample			
		Total		Join DJSI		Controls		Total		Controls	
		No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE
2011	2	38	2.133	1	0.442	37	2.179	11	0.817	10	0.854
2011	3	17	2.988	1	0.751	16	3.128	7	1.652	6	1.802
2011	32	273	4.451	1	0.948	272	4.464	63	1.816	62	1.830
2011	33	584	4.622	4	1.462	580	4.643	58	1.954	54	1.990
2011	44	81	4.052	1	3.400	80	4.060	10	1.897	9	1.730
2011	45	35	4.357	1	1.601	34	4.438	9	2.215	8	2.292
2011	48	89	2.584	2	3.309	87	2.567	12	2.122	10	1.884
2011	52	486	2.532	3	1.296	483	2.540	58	2.036	55	2.077
2011	53	183	2.440	1	1.932	182	2.443	33	1.739	32	1.733
2011	56	51	4.022	1	1.908	50	4.064	5	2.026	4	2.056
2011	71	11	2.255	1	2.661	10	2.214	3	2.628	2	2.611
2011	72	51	4.518	1	0.939	50	4.590	15	2.683	14	2.807
2012	22	39	1.990	1	0.878	38	2.019	3	0.853	2	0.841
2012	31	92	4.200	2	0.602	90	4.280	34	1.782	32	1.856
2012	32	279	5.117	2	0.519	277	5.150	43	1.504	41	1.553
2012	33	573	4.382	2	1.399	571	4.392	151	2.584	149	2.600
2012	45	37	4.860	1	7.568	36	4.784	10	3.658	9	3.224
2012	51	275	4.868	3	2.266	272	4.897	164	3.556	161	3.580
2012	52	532	2.572	1	2.377	531	2.573	33	2.422	32	2.424
2012	54	106	4.684	1	1.843	105	4.711	21	3.805	20	3.903
2012	56	49	4.219	1	0.730	48	4.292	2	1.135	1	1.540
2013	0	112	2.771	2	1.887	110	2.787	39	1.548	37	1.529
2013	21	149	3.946	2	1.573	147	3.979	52	2.940	50	2.995
2013	31	95	3.016	1	0.575	94	3.042	10	0.974	9	1.019
2013	32	293	4.453	4	1.393	289	4.495	108	1.893	104	1.913
2013	33	597	3.543	3	0.727	594	3.557	133	1.953	130	1.982
2013	44	82	3.160	2	0.848	80	3.218	8	1.371	6	1.545
2013	51	299	4.561	2	3.043	297	4.571	116	2.974	114	2.973
2013	52	570	2.079	2	1.206	568	2.082	34	1.502	32	1.521
2013	53	197	2.125	3	1.477	194	2.135	108	1.716	105	1.723
2013	54	104	3.525	1	4.442	103	3.516	10	2.527	9	2.314

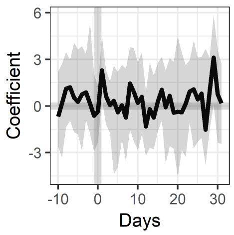
Notes: Full sample contains all shares listed on major US exchanges with sufficient data and at least one DJSI joining firm within their 2 digit NAICS code group. Base sample includes only those firms whose total assets are at least 80% of those of the smallest firm that gains DJSI listing from their industry. NA in the controls indicates there were no controls available satisfying the criteria in that year-industry pair. No. gives the number of firms. MSPE provides the mean squared predicted error for the control period.

Table 11: Listing and Control Numbers plus Model Fit 2014-2016

Year	Industry	Full Sample						Base Sample			
		Total		Join DJSI		Controls		Total		Controls	
		No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE
2014	0	121	3.267	1	0.563	120	3.290	8	1.753	7	1.923
2014	2	30	1.274	1	1.280	29	1.274	11	1.061	10	1.039
2014	22	43	2.584	1	0.715	42	2.628	3	0.625	2	0.580
2014	23	43	3.006	1	0.672	42	3.061	8	1.798	7	1.959
2014	32	344	9.934	1	1.952	343	9.957	88	1.797	87	1.795
2014	33	632	3.992	3	1.324	629	4.004	166	1.741	163	1.749
2014	48	112	2.932	1	0.714	111	2.952	7	1.283	6	1.378
2014	51	331	5.222	2	2.241	329	5.240	193	3.230	191	3.240
2014	52	612	1.956	2	0.832	610	1.960	58	1.040	56	1.047
2014	53	222	1.720	1	1.318	221	1.722	30	1.167	29	1.162
2014	72	61	3.275	1	2.989	60	3.280	22	2.553	21	2.532
2015	0	117	3.506	1	2.191	116	3.517	43	1.977	42	1.972
2015	23	42	4.186	1	2.222	41	4.234	8	2.543	7	2.589
2015	31	89	3.124	1	0.465	88	3.154	2	0.814	1	1.164
2015	32	400	8.352	3	0.810	397	8.409	53	2.221	50	2.306
2015	33	595	4.162	1	0.854	594	4.168	34	1.770	33	1.798
2015	51	342	4.983	1	0.715	341	4.995	43	1.745	42	1.769
2015	52	618	2.250	1	0.428	617	2.253	21	1.359	20	1.406
2015	53	218	2.260	2	1.488	216	2.267	61	1.488	59	1.488
2015	72	62	4.134	1	3.045	61	4.152	5	6.715	4	7.633
2016	3	17	3.347	1	3.438	16	3.342	4	1.860	3	1.333
2016	31	88	4.275	2	1.021	86	4.350	44	2.183	42	2.238
2016	32	384	10.217	1	1.102	383	10.241	15	1.874	14	1.929
2016	33	554	5.201	1	0.731	553	5.209	41	2.140	40	2.175
2016	44	77	5.728	1	1.763	76	5.780	27	2.965	26	3.012
2016	51	336	5.410	1	2.330	335	5.419	129	2.978	128	2.983
2016	52	600	2.525	3	2.022	597	2.527	201	1.842	198	1.839
2016	53	228	3.410	2	2.986	226	3.414	68	2.433	66	2.416
2016	56	55	4.576	1	0.572	54	4.650	3	1.872	2	2.522

Notes: Full sample contains all shares listed on major US exchanges with sufficient data and at least one DJSI joining firm within their 2 digit NAICS code group. Base sample includes only those firms whose total assets are at least 80% of those of the smallest firm that gains DJSI listing from their industry. NA in the controls indicates there were no controls available satisfying the criteria in that year-industry pair. No. gives the number of firms. MSPE provides the mean squared predicted error for the control period.

Figure 2: Gap plots 2005



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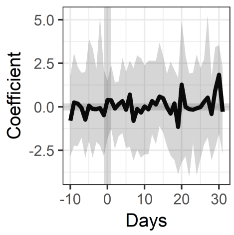

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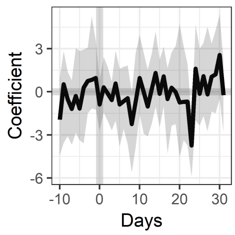

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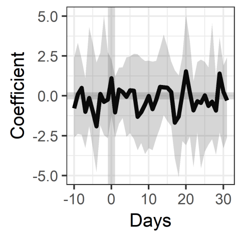

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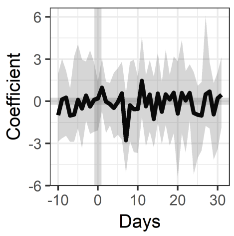

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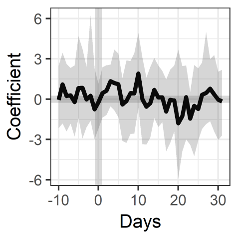

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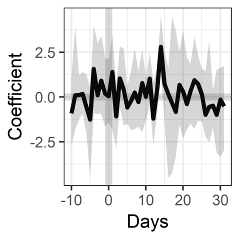

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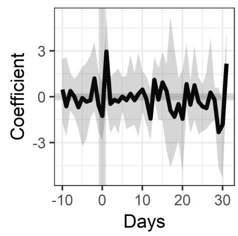

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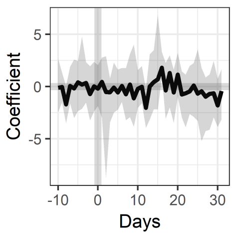

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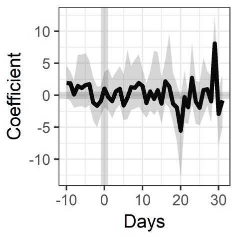

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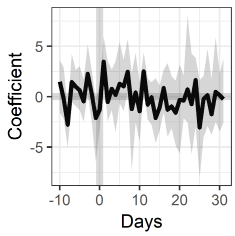

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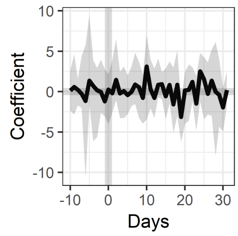

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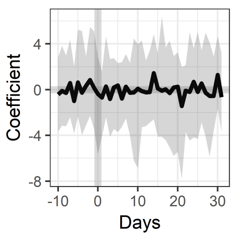

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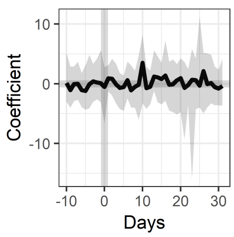

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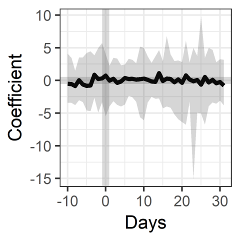

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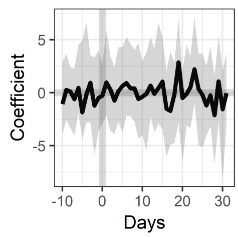

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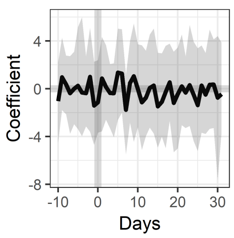

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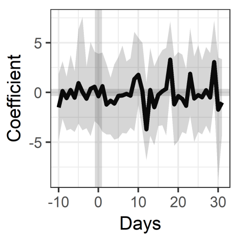

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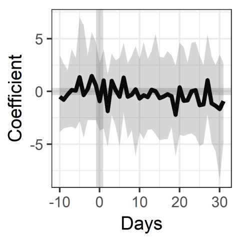
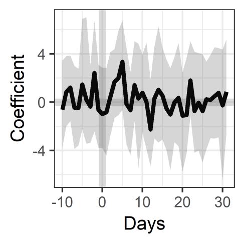


19393 (32)



23915 (32)

Notes: Lines plot abnormal returns on the share for whom the CRSP PERMNO is provided below. Grey polygons provide 95% confidence intervals for the test that the true abnormal return is zero. Labels below also feature the firm's NAICS2 code in parentheses.

Table 12: Listing and Control Numbers plus Model Fit 2017

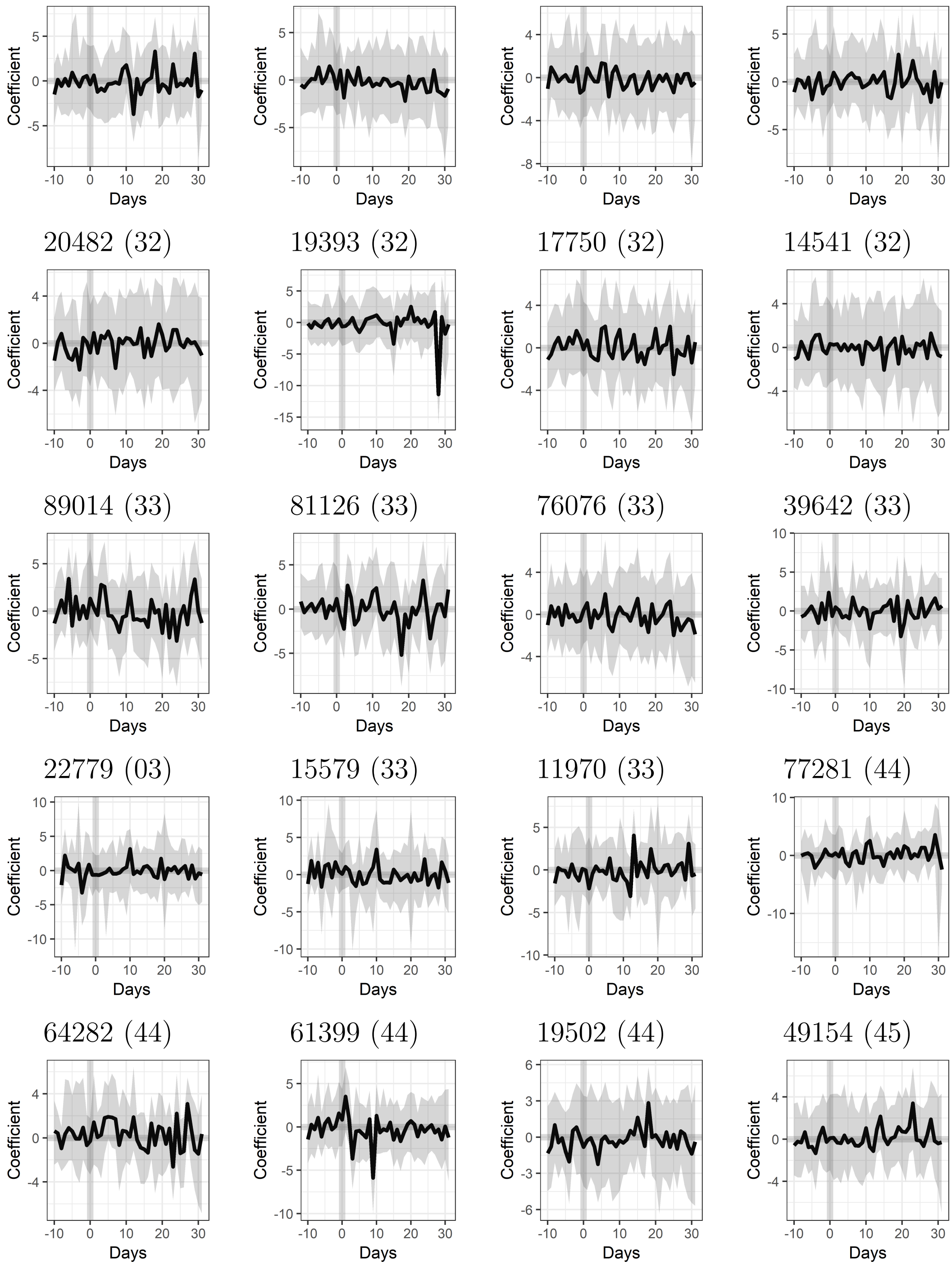
Year	Industry	Full Sample						Base Sample			
		Total		Join DJSI		Controls		Total		Controls	
		No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE	No.	MSPE
2017	0	119	5.701	3	3.753	116	5.751	65	3.904	62	3.912
2017	21	120	14.240	1	11.396	119	14.264	8	5.761	7	4.956
2017	31	88	5.199	2	1.689	86	5.281	18	3.384	16	3.596
2017	32	395	12.049	2	3.065	393	12.095	63	4.762	61	4.818
2017	33	574	6.818	3	2.335	571	6.842	168	4.034	165	4.065
2017	48	107	6.749	1	2.301	106	6.791	36	3.701	35	3.740
2017	51	341	6.434	2	1.162	339	6.465	9	1.466	7	1.553
2017	52	642	4.258	2	2.254	640	4.264	92	3.126	90	3.145
2017	53	225	3.914	2	4.095	223	3.912	38	3.790	36	3.773
2017	54	89	5.209	1	1.980	88	5.245	9	3.546	8	3.741
2017	72	63	4.109	2	1.179	61	4.205	15	3.870	13	4.284

Notes: Full sample contains all shares listed on major US exchanges with sufficient data and at least one DJSI joining firm within their 2 digit NAICS code group. Base sample includes only those firms whose total assets are at least 80% of those of the smallest firm that gains DJSI listing from their industry. NA in the controls indicates there were no controls available satisfying the criteria in that year-industry pair. No. gives the number of firms. MSPE provides the mean squared predicted error for the control period.

2005 is a year in which there were a large number of listings because it was the year when the DJSI North America was born from the DJSI Global. As such there are far more listings than in other years. These are, nonetheless, listings in the same sense as every other flagging to the US markets that the firms concerned are achieving the standard of social responsibility that will be required of the future entrants. In the results significant positive returns were found for the first 15 days, on the plots these are days 0 to 15 and inspection would concurr that this is the range over which many of the interesting jumps occur. Recall listing takes place on day 16. Firm 23915 at the bottom right of Figure 2 shows this initial positive reaction very clearly, as does 21979 in the top left. On listing day there are fewer movements than might have been expected, this is consistent with the lack of significance identified in the main paper. Firm 27991 shows most movement just after the listing, whilst 20482 shows significant negative abnormal returns following day 10 but then positive around day 17, the day after listing.

Figure 3 adds a few more interesting cases to the discussion, including a few large significant negative impacts. Firm 81126 is an example of this spiked pattern. More generally there is a similarity between the two groups. In the final set of plots, Figure 4, there are some more pronounced effects, with a big spike close to listing seen for 79323 in industry 52. Firm 43449 shows a great deal of volatility within the evaluation period, particularly before the announcement date. Individually these plots have some interest, but the real take-away message comes from the tests of average coefficients.

Figure 3: Gap plots 2005



20482 (32) 19393 (32) 17750 (32) 14541 (32)

89014 (33) 81126 (33) 76076 (33) 39642 (33)

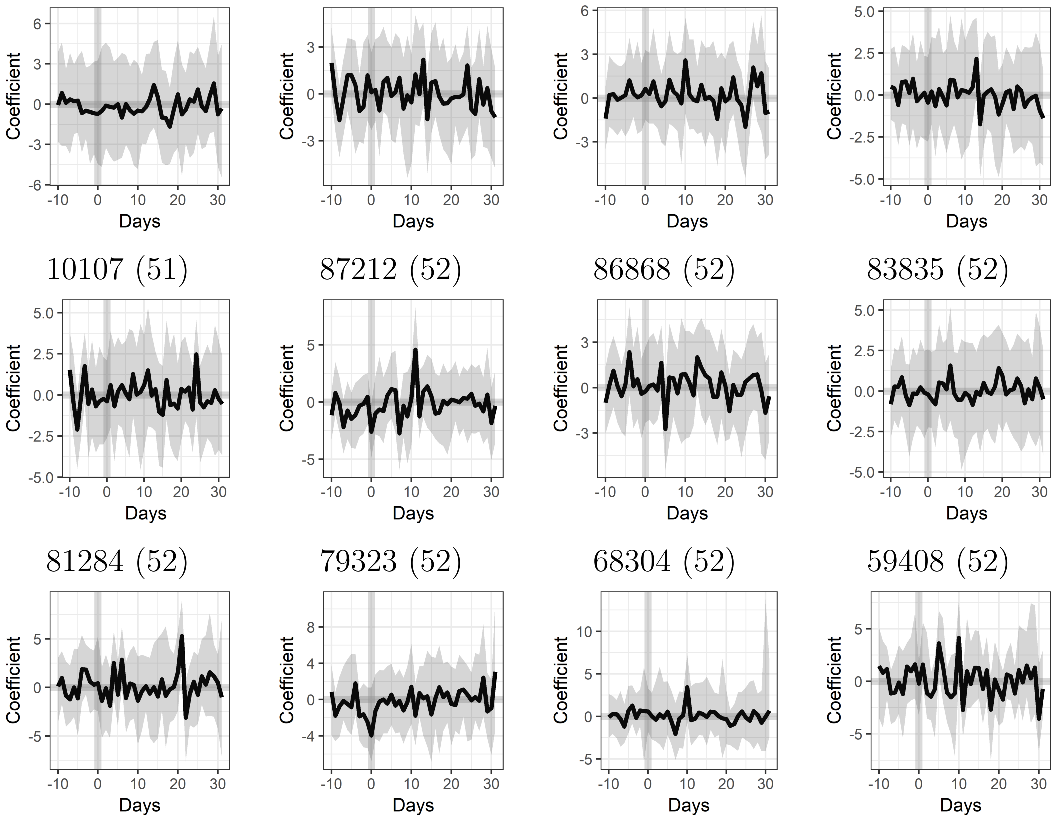
22779 (03) 15579 (33) 11970 (33) 77281 (44)

64282 (44) 61399 (44) 19502 (44) 49154 (45)

67774 (48) 47466 (51) 26403 (51) 12490 (51)

Notes: Lines plot abnormal returns on the share for whom the CRSP PERMNO is provided below. Grey polygons provide 95% confidence intervals for the test that the true abnormal return is zero. Labels below also feature the firm's NAICS2 code in parentheses.

Figure 4: Gap plots 2005



10107 (51) | 87212 (52) | 86868 (52) | 83835 (52)

81284 (52) | 79323 (52) | 68304 (52) | 59408 (52)

89071 (54) | 49373 (54) | 11955 (56) | 43449 (72)

Notes: Lines plot abnormal returns on the share for whom the CRSP PERMNO is provided below. Grey polygons provide 95% confidence intervals for the test that the true abnormal return is zero. Labels below also feature the firm's NAICS2 code in parentheses.

C Full Cumulative Abnormal Return Results

In this final appendix we provide full tables of the cumulative abnormal returns tests. Because of space considerations the set is divided into three key subsets. First is a pre-change periods that start from the opening evaluation block and end around the time of the announcement.Such are reported in Table 13. Secondly, we have periods that begin around the time of the listing announcement and end within the remaining fifteen days; these are the post listing data provided in Table 14. Finally the periods beginning before the announcement and extending post announcement are presented in Table 15.

Table 13: Average Cumulative Abnormal Returns 2005-2017: Pre-announcement

Start	Window End															
	-14	-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-15	0.176	0.108	0.106	0.259	0.398	0.527*	0.466	0.348	0.265	0.268	0.456	0.472	0.627	0.784*	0.638	0.626
-14	0	0.022	0.019	0.173	0.312	0.441	0.38	0.262	0.179	0.182	0.369	0.386	0.541	0.698	0.552	0.54
-13	0	0	-0.07	0.083	0.223	0.352	0.29	0.172	0.09	0.092	0.28	0.297	0.451	0.609	0.463	0.451
-12	0	0	0	0.151	0.29	0.419*	0.358	0.24	0.157	0.16	0.348	0.364	0.519	0.676*	0.53	0.518
-11	0	0	0	0	0.293	0.422*	0.36	0.242	0.159	0.162	0.35	0.367	0.521	0.678*	0.533	0.521
-10	0	0	0	0	0	0.268	0.207	0.089	0.006	0.009	0.197	0.213	0.368	0.525	0.379	0.367
-9	0	0	0	0	0	0	0.068	-0.05	-0.133	-0.13	0.057	0.074	0.229	0.386	0.24	0.228
-8	0	0	0	0	0	0	0	-0.179	-0.262*	-0.259*	-0.072	-0.055	0.099	0.257	0.111	0.099
-7	0	0	0	0	0	0	0	0	-0.201	-0.198	-0.01	0.006	0.161	0.318	0.173	0.16
-6	0	0	0	0	0	0	0	0	0	-0.08	0.108	0.124	0.279	0.436	0.291	0.278
-5	0	0	0	0	0	0	0	0	0	0	0.19	0.207	0.362	0.519*	0.373	0.361
-4	0	0	0	0	0	0	0	0	0	0	0	0.204	0.359	0.516*	0.37	0.358
-3	0	0	0	0	0	0	0	0	0	0	0	0	0.171	0.328	0.183	0.171
-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0.312	0.166	0.154
-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.012	-0.001

Notes: Start indicates the start date of calculation of the cumulative abnormal returns. End gives the end date of the CAR calculation. Figures reported are the average CAR across all firms joining the index in the full sample. Significance based on t-test that true mean CAR for the period is equal to 0. * - 10%, ** - 5%, *** less than 5%.

Table 14: Average Cumulative Abnormal Returns 2005-2017: Post-announcement

Start	Window End															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-1	0.012	-0.001	-0.123	-0.189	-0.134	-0.23	-0.289	-0.247	-0.231	-0.279	-0.293	-0.403	-0.37	-0.416	-0.154	-0.148
0	0	-0.158	-0.281	-0.346*	-0.291	-0.387*	-0.447*	-0.404*	-0.389	-0.436*	-0.45*	-0.56**	-0.528*	-0.574**	-0.311	-0.305
1	0	0	-0.135	-0.201	-0.146	-0.242	-0.301	-0.259	-0.243	-0.29	-0.305	-0.415*	-0.382*	-0.428*	-0.165	-0.159
2	0	0	0	-0.189	-0.134	-0.229	-0.289	-0.246	-0.231	-0.278	-0.293	-0.402*	-0.37	-0.416*	-0.153	-0.147
3	0	0	0	0	-0.011	-0.107	-0.166	-0.124	-0.108	-0.155	-0.17	-0.28	-0.247	-0.293	-0.03	-0.024
4	0	0	0	0	0	-0.041	-0.1	-0.058	-0.042	-0.09	-0.104	-0.214	-0.181	-0.227	0.035	0.042
5	0	0	0	0	0	0	-0.155	-0.113	-0.097	-0.145	-0.159	-0.269	-0.236	-0.282	-0.02	-0.013
6	0	0	0	0	0	0	0	-0.017	-0.001	-0.049	-0.063	-0.173	-0.14	-0.186	0.076	0.082
7	0	0	0	0	0	0	0	0	0.058	0.011	-0.004	-0.114	-0.081	-0.127	0.135	0.142
8	0	0	0	0	0	0	0	0	0	-0.032	-0.046	-0.156	-0.123	-0.169	0.093	0.1
9	0	0	0	0	0	0	0	0	0	0	-0.062	-0.172	-0.139	-0.185	0.078	0.084
10	0	0	0	0	0	0	0	0	0	0	0	-0.124	-0.092	-0.137	0.125	0.131
11	0	0	0	0	0	0	0	0	0	0	0	0	-0.077	-0.123	0.139	0.146
12	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.013	0.249	0.255
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.216	0.223
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.269

Notes: Start indicates the start date of calculation of the cumulative abnormal returns. End gives the end date of the CAR calculation. Figures reported are the average CAR across all firms joining the index in the full sample. Significance based on t-test that true mean CAR for the period is equal to 0. * - 10%, ** - 5%, *** less than 5%.

Table 15: Average Cumulative Abnormal Returns 2005-2017: Cross-announcement

Start	Window End															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-15	0.638	0.626	0.503	0.438	0.493	0.397	0.337	0.38	0.395	0.348	0.334	0.224	0.256	0.211	0.473	0.479
-14	0.552	0.54	0.417	0.351	0.406	0.311	0.251	0.293	0.309	0.262	0.247	0.138	0.17	0.124	0.387	0.393
-13	0.463	0.451	0.328	0.262	0.317	0.221	0.162	0.204	0.22	0.172	0.158	0.048	0.081	0.035	0.297	0.304
-12	0.53	0.518	0.395	0.33	0.385	0.289	0.229	0.272	0.287	0.24	0.226	0.116	0.148	0.103	0.365	0.371
-11	0.533	0.521	0.398	0.332	0.387	0.291	0.232	0.274	0.29	0.242	0.228	0.118	0.151	0.105	0.367	0.374
-10	0.379	0.367	0.244	0.179	0.234	0.138	0.078	0.121	0.136	0.089	0.075	-0.035	-0.003	-0.048	0.214	0.22
-9	0.24	0.228	0.105	0.039	0.094	-0.001	-0.061	-0.019	-0.003	-0.05	-0.065	-0.174	-0.142	-0.188	0.075	0.081
-8	0.111	0.099	-0.024	-0.09	-0.035	-0.13	-0.19	-0.148	-0.132	-0.179	-0.194	-0.304	-0.271	-0.317	-0.054	-0.048
-7	0.173	0.16	0.038	-0.028	0.027	-0.069	-0.128	-0.086	-0.07	-0.118	-0.132	-0.242	-0.209	-0.255	0.007	0.013
-6	0.291	0.278	0.155	0.09	0.145	0.049	-0.01	0.032	0.048	0	-0.014	-0.124	-0.091	-0.137	0.125	0.131
-5	0.373	0.361	0.238	0.173	0.227	0.132	0.072	0.115	0.13	0.083	0.068	-0.041	-0.009	-0.055	0.208	0.214
-4	0.37	0.358	0.235	0.17	0.225	0.129	0.07	0.112	0.127	0.08	0.066	-0.044	-0.012	-0.057	0.205	0.211
-3	0.183	0.171	0.048	-0.018	0.037	-0.059	-0.118	-0.076	-0.06	-0.108	-0.122	-0.232	-0.199	-0.245	0.017	0.024
-2	0.166	0.154	0.031	-0.035	0.02	-0.075	-0.135	-0.093	-0.077	-0.124	-0.139	-0.248	-0.216	-0.262	0.001	0.007
-1	0.012	-0.001	-0.123	-0.189	-0.134	-0.23	-0.289	-0.247	-0.231	-0.279	-0.293	-0.403	-0.37	-0.416	-0.154	-0.148
0	0	-0.158	-0.281	-0.346*	-0.291	-0.387*	-0.447*	-0.404*	-0.389	-0.436*	-0.45*	-0.56**	-0.528*	-0.574**	-0.311	-0.305

Notes: Start indicates the start date of calculation of the cumulative abnormal returns. End gives the end date of the CAR calculation. Figures reported are the average CAR across all firms joining the index in the full sample. Significance based on t-test that true mean CAR for the period is equal to 0. * - 10%, ** - 5%, *** less than 5%.

Table 16: Average Cumulative Abnormal Returns 2005-2017: Pre-announcement

Start	Window End														
	-14	-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-15	-0.039	-0.007	0.06	0.072*	0.052	0.033	-0.001	-0.006	-0.001	0.022	0.029	0.04	0.051**	0.029	0.033	0.023
-14	0	-0.01	0.08	0.09*	0.062	0.038	-0.002	-0.006	-0.001	0.025	0.032	0.043	0.055**	0.031	0.035	0.025
-13	0	0	0.158**	0.146***	0.097**	0.061	0.011	0.004	0.009	0.036	0.043	0.054*	0.066**	0.039	0.043*	0.032
-12	0	0	0	0.189***	0.11**	0.062	0.002	-0.005	0.002	0.033	0.041	0.054*	0.067**	0.037	0.042	0.03
-11	0	0	0	0	0.036	-0.003	-0.062	-0.058	-0.041	0.001	0.014	0.031	0.048	0.017	0.024	0.012
-10	0	0	0	0	0	-0.065	-0.123**	-0.103**	-0.074	-0.019	-0.001	0.02	0.04	0.007	0.015	0.003
-9	0	0	0	0	0	0	-0.161**	-0.12**	-0.08	-0.013	0.007	0.029	0.051	0.013	0.022	0.008
-8	0	0	0	0	0	0	0	-0.14*	-0.079	0.004	0.025	0.048	0.069*	0.025	0.033	0.017
-7	0	0	0	0	0	0	0	0	0.001	0.085	0.091*	0.105**	0.121***	0.063*	0.067*	0.045
-6	0	0	0	0	0	0	0	0	0	0.148**	0.135***	0.142***	0.153***	0.08**	0.082**	0.056
-5	0	0	0	0	0	0	0	0	0	0	0.181***	0.175***	0.181***	0.088**	0.089**	0.058
-4	0	0	0	0	0	0	0	0	0	0	0	0.135**	0.157***	0.046	0.056	0.025
-3	0	0	0	0	0	0	0	0	0	0	0	0	0.181***	0.026	0.043	0.009
-2	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.043	0.003	-0.03
-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.095	-0.107*
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.017

Notes: Start indicates the start date of calculation of the cumulative abnormal returns. End gives the end date of the CAR calculation. Figures reported are the average CAR across all firms joining the index in the full sample. Significance based on t-test that true mean CAR for the period is equal to 0. * - 10%, ** - 5%, *** less than 5%.

Table 17: Average Cumulative Abnormal Returns 2005-2017: Post-announcement

Start	Window End															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
-1	-0.095	-0.107*	-0.09	-0.06	-0.062	-0.08*	-0.058	-0.053	-0.072**	-0.043	-0.051	-0.042	-0.05	-0.027	-0.016	-0.024
0	0	-0.017	-0.024	-0.003	-0.017	-0.045	-0.025	-0.024	-0.048	-0.019	-0.03	-0.022	-0.032	-0.008	0.002	-0.008
1	0	0	-0.084	-0.036	-0.045	-0.074	-0.045	-0.041	-0.066	-0.032	-0.043	-0.032	-0.042	-0.016	-0.005	-0.015
2	0	0	0	0.011	-0.017	-0.06	-0.028	-0.026	-0.057	-0.019	-0.033	-0.022	-0.034	-0.007	0.005	-0.007
3	0	0	0	0	-0.006	-0.066	-0.026	-0.023	-0.06	-0.017	-0.032	-0.021	-0.034	-0.004	0.008	-0.004
4	0	0	0	0	0	-0.13*	-0.055	-0.044	-0.084	-0.029	-0.045	-0.031	-0.044	-0.01	0.004	-0.01
5	0	0	0	0	0	0	-0.046	-0.034	-0.087	-0.021	-0.041	-0.025	-0.041	-0.003	0.011	-0.004
6	0	0	0	0	0	0	0	0.042	-0.054	0.021	-0.012	0.002	-0.02	0.02	0.033	0.015
7	0	0	0	0	0	0	0	0	-0.129	-0.004	-0.038	-0.016	-0.039	0.009	0.026	0.006
8	0	0	0	0	0	0	0	0	0	0	-0.047	-0.017	-0.044	0.013	0.031	0.008
9	0	0	0	0	0	0	0	0	0	0	0.052	0.059	0.006	0.064	0.077	0.045
10	0	0	0	0	0	0	0	0	0	0	0	-0.035	-0.074	0.019	0.043	0.011
11	0	0	0	0	0	0	0	0	0	0	0	0	-0.04	0.073	0.09	0.041
12	0	0	0	0	0	0	0	0	0 0	0	0	0	0.073	0.095	0.034	
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.22**	0.098
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.007

Notes: Start indicates the start date of calculation of the cumulative abnormal returns. End gives the end date of the CAR calculation. Figures reported are the average CAR across all firms joining the index in the full sample. Significance based on t-test that true mean CAR for the period is equal to 0. * - 10%, ** - 5%, *** less than 5%.