Why do mergers and acquisitions lead to underperformance in the long-run?

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Abstract

We investigate the long-run performance of firms that went through mergers or acquisitions (M&A). We propose "synthetic-matching", a new matching procedure to create high-quality controls for each M&A firm. We show how this method augments already used practices from the matching and differences-in-differences literature. Our empirical results show a positive 0.7% immediate effect during the announcement's month and negative 0.6% excess returns for 3 years after the announcement. Our matching procedure allows for heterogeneity analysis, where we find differences in excess returns through the channels of firm size, momentum, leverage, sales over price, and whether the target firm is from the same industry. We also capture non-linear variation in excess returns with a local linear forest that accounts for more than 15% of the variation.

JEL: C33, G14, G34

Keywords: Corporate events, M&A, synthetic control, matching

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1 Introduction

Merger and acquisition (M&A) are some of the most important events in a company's life and have a significant impact on the firm's operations and activities. These transactions are fundamental to the interests of the leadership, board of directors, employees, investment bankers, and government regulators. An extensive empirical literature in finance has been motivated by answering the basic questions of why and when M&A transactions occur, what are the processes used, and what are the economic effects of the transactions. (Mulherin et al., 2017) These are complex questions as the answers vary across many fundamental factors including the transaction type, the time period, and the specific characteristics of the firms involved.

In this paper, we propose a new matching method to create a better control firm. As the firm characteristics of each M&A firm differ in multiple dimensions we use a set of candidate firms for each event firm and weight them such that they match the event firm's characteristics before the event. We show that the created "synthetic" firms have statistically indistinguishable firm characteristics, which is the core of our method's internal validity. As we match each M&A event individually, we can assess the heterogeneity in M&As and show how different types of M&A transactions have different channels and effects on the firm's performance.

There is a rich collection of academic studies investigating firm performance around and after a merger. The assessment of whether average returns after M&As are abnormal is one of the most frequently encountered empirical exercises in this field of finance. Such assessments require that researchers specify normal or benchmark returns (see e.g. Bessembinder et al., 2018). As Kothari and Warner (2007) notes this is a first-order issue when one compares firms' performance in the long run as potential errors cumulative over the compared time horizon. This leads the long-run event study literature to face the "bad-model" problem, which produces conflicting results for the same type of corporate event based on different samples and different approaches to modeling long-run stock returns.[1]

Renneboog and Vansteenkiste (2019) classifies papers investigating long-run effects of M&As into two broad categories: (i) studies that compare returns for event firms to those of a set of control firms based on matching firm characteristics such as size, industry, or market-to-book ratio. Table A2 presents different matching methods used for corporate events and shows that there is more or less an agreement on using market capitalization (as firm size) and market-to-book ratio. Our paper contributes to this branch of literature by providing a flexible method to match multiple firm characteristics. The second category (ii) consists of papers, which obtain alpha coefficients from regressing event firm returns on market-wide factor models such as the capital asset pricing model (Sharpe 1964, Lintner 1965), Fama-French three/five-factor models (Fama 1998, Fama and French 2015), the four-factor model proposed by Hou et al. (2015) or other portfolio constructions such as Daniel et al. (1997) or Eckbo et al. (2000). From this branch of research we would like to highlight a paper by Bessembinder et al. (2018), which proposes a characteristic-based benchmark return approach. The authors specifically incorporate firm characteristics to control for pre-

[1] See e.g. Fama (1998), Brav et al. (2000), Eckbo et al. (2000), Eckbo et al. (2007), Loughran and Ritter (2000), Yan Liu and Zhang (2023)

event characteristics and to analyse post-event performance of the (event) firms. The paper introduces two sets of firm characteristics: 'C5' contains the firm size, book-to-market ratio, momentum, ROA, and asset growth. The second, broader set of characteristics 'C14', includes C5 variables and market beta, accrual, dividend, cumulative 2-year returns, idiosyncratic risk, illiquidity, turnover, leverage, and sales over price (see the detailed description of the variables in Table A1). The paper points out that these variables with the frequently used matching methods are poorly matched before M&A events[2] in general.[3] Instead of matching, Bessembinder et al. (2018) construct benchmark returns using C5 and C14 variables to control for differences in firm characteristics, by subtracting the benchmark return from the realized return. They employ a Fama-MacBeth regression (Fama and MacBeth, 1973) along with pooled OLS to regress on event dummies and the results are interpreted as abnormal stock returns after specific events.

We build on their contribution, but see two potential threats to their identification strategy, when the goal is to assess the (causal) impact of M&As. The first concern is the use of bad controls.[4] The aforementioned C5 and C14 variables (or other factor model loadings) are indeed relevant variables before the event happens, however, after the event these variables are changing along with the performance measure (returns). M&A by construction will change the size of the firm and controlling for this change will reduce or eliminate the effect of M&A. For long-run assessment, lagged variables will show up after the event (the number of lags will determine the exact period) and push the coefficient(s) of interest toward zero. In contrast, we take an agnostic approach to the causal chains and control for variables only before the event.[5] The second concern became more visible due to recent econometric developments in panel estimation (differences-in-differences methods). De Chaisemartin and d'Haultfoeuille (2020) shows that panel estimation with heterogeneous treatment effect will result in a biased estimate of the average treatment effect (ATE) or average treatment effect for the treated (ATT). Wooldridge (2021) and Callaway and Sant'Anna (2021) show that if the treatment effect takes place at a different point in time, the identification of the causal effect is even more troublesome and requires multiple modifications in the estimation procedure. Roth et al. (2023) gives a nice overview of recent developments in the field and collects the potential solutions to estimate consistently the parameter of interest. Although, it is still future research to show under which conditions can heterogeneous treatment effects with multiple time periods with controls be identified and estimated, that would be the case in our question. When we replicate Fama-MacBeth and other panel estimates for M&As we find parameter of interest is varying through different methods. We see these signs as an indication of the econometric concerns.

To get a credible estimate on the long-run effects of M&As, we propose a new matching

[2]In their paper they examine multiple different corporate events

[3]The first paper to show poor matching quality was Bessembinder and Zhang (2013), which highlights this miss-match for market beta, firm size, book-to-market ratio, momentum, idiosyncratic risk, illiquidity, and investment variables. Bessembinder and Zhang (2013) and Kolari et al. (2021) argues on how to control for such differences in a regression framework.

[4]Cinelli et al. (2023, forthcoming) gives a nice overview on bad controls in general.

[5]Note that the usual concern with identification for our approach is present: if there are other (fundamental) variables that we have not matched on (or have a poor matching quality) and has a confounding effect, then it may invalidate our results.

method that we call "synthetic-matching". We use the well-established literature on synthetic control methodology (see e.g. Abadie et al., 2010, Abadie et al., 2015, Abadie, 2021, Arkhangelsky et al., 2021) and extend it to match over multiple variables. To be more specific, for each event firm we create a "synthetic-event firm" that is similar in the pre-specified firm characteristics. Synthetic event firms are weighted by a pool of candidate firms that have not gone through M&A around the event. An example would be the acquisition of Merrill Lynch Wealth Management by Bank of America. To investigate how this acquisition affected Bank of America's performance, we create a "synthetic Bank of America" by using JPMorgan Chase, Citigroup, Wells Fargo, U.S. Bancorp. etc. We assign for each of the candidate banks a weight that sums up to one. Weights are chosen such that it matches the variation (and level) in multiple firm characteristics such as book-to-market ratio, market capitalization, momentum, ROA, etc. We also weight the pre-event periods to get a better quality match closer to the event: we put more weight on one month before the event than three years before. If the matching created a valid synthetic event firm (same or close to firm characteristic), we will interpret the differences after the event as the causal effect of M&A. We may control for other external factors during our matching procedure, but it is important to distinguish variables that we match on and may have a role in the causal mechanism and other confounder factors. After doing the matching for all M&A events we have a distribution of excess returns that we can analyze. To check the robustness of our method we use different sets of firm characteristics to match: size and book-to-market ratio, C5 and C14 variables proposed by Bessembinder et al. (2018). Results are stable and show 0.6-0.7% point lower returns on the three-year horizon.

As the last part of our paper, we carry out heterogeneity analysis on the excess returns to find drivers of success or failures in M&As. We found that (lagged) size and momentum are two important and significant driving factors explaining excess returns. Linear models suggest that with 1% larger size, we can associate on average -0.023pp excess return, with 1pp larger momentum we see on average 3pp larger excess returns. Sales over price and leverage are also significant at 5 and 10% levels. A unit larger sales over price show a 0.2pp larger excess returns on average, while a unit larger leverage is associated with 0.4pp point smaller excess returns on average. We also use different random forest methods to assess nonlinearity. We achieve 15% R^2 out-of-sample for the local-linear forest, which adopts to breaks in functional forms better than simple random forest and boosted forest. We show the nonlinear associations between firm characteristics and excess returns based on a local-linear forest model revealing interesting patterns in explaining excess returns.

The structure of the paper is as follows: section 2 describes the data that we are using. Section 3 explains the benchmark matching procedures and introduces our method. We show summary statistics on the matching quality for the synthetic-matching method. Section 4 shows the results on the point estimates for the excess returns using different matching methods as well as benchmark panel methods. This section also reports our results on heterogeneity analysis. Sections 5 concludes.

2 Data and Samples

We focus on acquirer firms that are located in the US and the event happened between 1980 and 2018. In order to evaluate the long-run performance of these firms, we used returns and other market-based variables from the Center for Research in Security Prices (CRSP), and quarterly accounting data[6] for firms from Compustat fundamentals. We extend the time window by 36 months, thus firms have records between 1977 and 2021. This extension is due to two reasons: i) extending 36 extensions backward allows our matching methods to find a good quality match up to 36 months before the event happens; ii) extending time period forwards helps to study post-event return horizons in 36 months that broadly match the existing empirical practice (see e.g. Bessembinder and Zhang, 2013, Bessembinder et al., 2018).

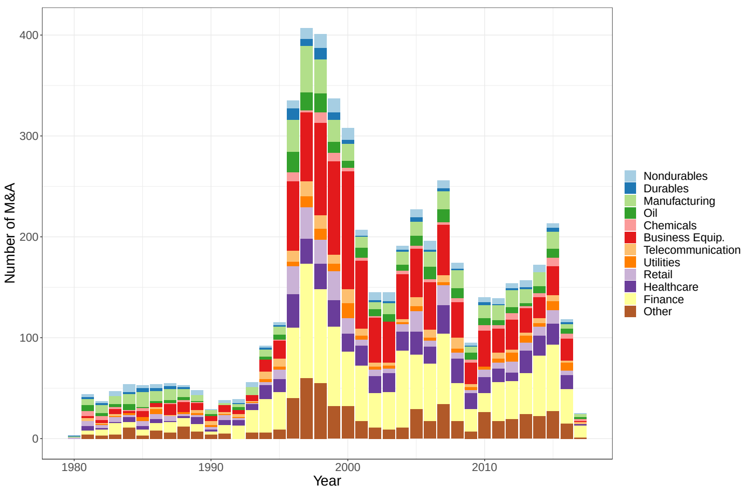
2.1 Mergers and Acquisitions

We consider mergers and acquisitions (M&As) from SDC Platinum database. We follow Netter et al. (2011), Phillips and Zhdanov (2013), Ewens et al. (2018) and Bessembinder et al. (2018) to select the pool of mergers and acquisitions. We filter for disclosed and undisclosed deals where the deal is completed and the percentage of shares acquired in the transaction grants a majority in the firm (percentage of shares acquired in transaction is more than 50% and percentage of shares held by the acquirer six months prior to the announcement are less than 49%). The number of unique events that satisfies these criteria is 77,098. Following Bessembinder et al. (2018), we select deals with types of a merger (SDC form "M"), acquisition of majority interest ("AM"), acquisition of remaining interest ("AR"), or acquisition of partial interest ("AP"). In addition, we also exclude small transactions that have no material impact on the acquirer: the transaction value must be more than $5 million and more than 5% of the acquirer's market capitalization before the deal announcement. This restricted sample contains 8,083 such mergers and acquisitions. To avoid overlapping event bias, we require that the event firm has not done a merger or acquisition in the past 36 months, resulting in 5,378 events. We also filter out events, where between the date of announcement and the transaction date there have been more than 24 months. This affected 19 events. Finally, we require that the acquirer firms have records in CRSP and Compustat. After merging the events with the CRSP+Compustat data[7], we have 5,235 events. Figure 1. shows the number of M&As for each years, with the Fama-French 12 industry categorization.

[6]Using quarterly data instead of annual allows us to have more variation in accounting variables.

[7]We used Michael Ewens's mapping for M&A between SDC and Compustat from his github page.

Figure 1: Number of Mergers and Acquisition with Fama-French 12 industry categorization for the acquirer firm



To highlight the heterogeneity in mergers and acquisitions, Table 1. shows descriptive statistics on the characteristics of the M&As. One can see i) the imposed restrictions (e.g. shares owned before are capped at 49% and shares owned after has a minimum of 50%, moreover minimum transaction value is 5.05 million dollars); ii) there is a significant amount of heterogeneity in the events captured by the standard deviation. It might be interesting to note that the average time between M&A announcement and transaction done is 112 days and in 65% of the cases acquirer and target firm were in the same Fama-French 48 industry.

Table 1: Descriptive statistics for Mergers and Acquisitions related variables

	N	Mean	Median	SD	Min	P25	P75	Max
Shares owned before (%)	5235	0.89	0.00	5.18	0.00	0.00	0.00	49.00
Shares owned after (%)	5235	98.67	100.00	6.78	50.00	100.00	100.00	100.00
Shares acquired during transaction (%)	5235	97.78	100.00	8.46	50.00	100.00	100.00	100.00
Transaction Value (Million $)	5235	895.47	101.20	4257.59	5.05	31.18	388.01	164746.86
Log of transaction value in Million Dollar	5235	4.82	4.62	1.81	1.62	3.44	5.96	12.01
Equity Value (Million $)	5356	970.84	98.59	9260.28	0.00	30.68	362.41	602632.88
Log of equity value	5356	4.81	4.60	1.78	0.00	3.46	5.90	13.31
Time spent between announcement and transaction (days)	5235	111.78	95.00	97.07	0.00	40.00	160.00	723.00
Percentage of Stock as method of payment (%)	2894	76.95	100.00	29.39	0.49	53.69	100.00	100.00
Probability: Acquirer and Target firm from same industry (FF12)	5235	75.13	-	43.23	-	-	-	-
Probability: Acquirer and Target firm from same industry (FF48)	5235	64.69	-	47.80	-	-	-	-

2.2 Firms characteristics and other variables

We re-create firm characteristic variables defined by (Bessembinder et al., 2018, Table A1.) to use them as matching variables. We report the summary statistics of these firm characteristics in Table 2.

Table 2: Summary statistics of firm characteristics

	N	Mean	Median	SD	Min	P25	P75	Max
Return (%)	3332742	1.0939	0.0000	16.5115	-100	-5.3691	6.0465	300
C5 characteristics								
Log Size	3272851	4.9121	4.8186	2.1869	-4.5504	3.3490	6.3880	11.2670
Log BM	2508444	-0.5788	-0.4860	0.9632	-3.5780	-1.1078	0.0374	1.7270
Momentum	3119967	0.0008	0.0504	0.5200	-12.1786	-0.1837	0.2566	4.6701
ROA	3249966	-0.0124	0.0045	0.0580	-0.1960	-0.0115	0.0171	0.0459
Asset growth	3021465	0.0903	0.0581	0.3845	-1.1860	-0.0431	0.1844	1.7205
Additional 9 characteristics for the C14 model								
Beta	3226108	0.9482	0.9081	0.7342	-0.9137	0.4471	1.3631	3.2528
Accrual	3182541	-0.0091	-0.0043	0.1555	-0.8119	-0.0403	0.0352	0.5240
Dividend	3039706	0.0211	0.0031	0.0330	0.0000	0.0000	0.0309	0.1780
Log LR Return	2854837	0.0332	0.1219	0.7397	-12.9260	-0.2336	0.4250	4.9836
Idio. risk	3098100	0.0240	0.0208	0.0148	0.0000	0.0130	0.0322	0.0922
Illiquidity	2494854	0.6128	0.0346	1.6556	0.0000	0.0037	0.3510	51.3476
Trunover	2874219	0.1352	0.0681	0.2084	0.0000	0.0304	0.1529	1.4605
Leverage	3130801	0.7300	0.1476	1.7091	0.0000	0.0000	0.6594	11.8318
Sales/Price	2621610	2.1195	0.9165	3.5860	0.0000	0.3647	2.2281	23.9728

We use quarterly Compustat data and monthly CRSP variables. We have winsorized returns at -100 and 300 percent replacing 0.0001% of the observations. We have winsorized the ROA at 5% and 95% and winsorized log size, log BM, asset growth, beta, accrual, turnover, leverage and sales/price at 1% and 99%

To compare our results with other models/papers, we use the Fama-French 5 factors (Fama and French, 2015) from Kenneth's R. French's website[8], and we use the characteristic-based benchmark returns: CBBR5 and CBBR14 (Bessembinder et al., 2018) from contributed data at WRDS.

3 Matching

3.1 Matching Methods

To find or create valid control firms the literature uses some kind of matching procedure. Table A2. in the Appendix lists some of the different matching methods used for evaluating long-run performance after corporate events. Here, we focus on two commonly used methods and propose our new "synthetic-matching" procedure.

Classical Matching

The most commonly used matching method for a corporate events is to find a firm that has similar market capitalization and the closest, but larger book-to-market ratio one period before the event. See e.g. Loughran and Ritter (1995), Eckbo et al. (2007), Bessembinder

[8] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

and Zhang (2013), Bessembinder et al. (2018), or Yan Liu and Zhang (2023).[9] This method picks only one firm and if the picked firm is delisted the second-best candidate is placed from the time of delisting and so on. This matching method has a critique that it fails to produce good matching quality in terms of firm characteristics (see e.g. Bessembinder and Zhang 2013 or Bessembinder et al. 2018). We will call this method "classical matching" and use it as our benchmark to show improvements in our proposed matching method. For our implemented "classical matching" method, we require that the matching firm has to have a log of market capitalization between 50% and 150% of the event firm and to be in the same FF48 industry, proposed by Fama and French (1997).[10]

TSCS-Matching

As a second method, we use a method more commonly used in the economic literature. We follow Imai et al. (2019), who proposes matching methods for time-series cross-sectional data. The main advantage of this method compared to the "classical matching" method is it allows multiple candidate firms to be used and weighted instead of picking one firm. This also means that the control firm's trajectories can be averaged out, thus will be more robust to individual firm's life cycles. It also allows matching on multiple time periods before the event. After defining the number of pre-periods before the event, one can match on multiple firm characteristics and choose/weight those firms which are the closest to the event firm defined by these characteristics. There are two caveats to this method. First, it requires that the number of pre-periods is defined before the analysis. In some cases, there is a theory that helps to select the number of pre-periods, but in our case, there is no direct evidence on how many pre-periods should be selected.[11] In our case it is problematic as we would like to weight firm characteristics that are closer to the event more and put less weight on periods that are further away. Equal weighting can result in fair matching on past characteristics and poor matches on more recent characteristics. Secondly, this method matches the levels and thus favors candidate firms which has a more volatile variable but around the event firm in contrast to a firm that has the same pre-trend, but with a slight level shift.

To be more specific in our empirical strategy, we use 12 months of data before the event and match on the log of market capitalization, and log of book-to-market ratio and require that firms are in the same FF48 industry. We use the Mahalanobis distance measure to evaluate the distance from the event firm and choose a maximum of 50 firms that are closest to the event firm.[12] We will call this method "TSCS-matching" standing for Time-Series Cross-Sectional matching.

[9]Note, that the actually implemented method in the cited paper differs to some degree. E.g. Loughran and Ritter (1995) does not match on book-to-market and matches on the following December 31. Eckbo et al. (2007), Bessembinder and Zhang (2013) also matches on December 31 values.

[10]Note that e.g. Bessembinder and Zhang (2013) or Bessembinder et al. (2018) do not use industry matching and require market capitalization to be in the threshold of 70% and 150%.

[11]Furthermore, as Imai et al. (2019) notes, the more pre-periods are taken into account the more credible the analysis in terms of similarity, however, the fewer the candidate matching firms and the quality of the match tend to decrease.

[12]The number of matched firms can be smaller if the number of firms with exactly the same treatment pattern before the event differs. Note that we may use propensity score matching or propensity score weighting as well to difine closeness/weights.

Synthetic Matching

Finally, we introduce a new matching method that we call "synthetic-matching". This method builds on the literature of the synthetic difference-in-differences method proposed by Arkhangelsky et al. (2021). We extend their methodology to multiple outcomes with unified firm weight and time weight vectors. The main advantage of this method compared to the previous ones is that i) it allows multiple firm characteristics to match ii) does not require specifying the exact number of pre-event periods, but estimates in a data-driven way iii) it (sparsely) weights candidate firms such that it matches the variation in the event firm allowing for individual and time fixed effects differences. The limitation of this method is that it assumes an underlying latent factor structure[13] that is captured by the optimization task outlined in Equation 1,

$$\underset{\delta,\gamma,\tau,\beta}{\arg\min}\left\{\sum_{j,t,i}\left(Y_{itj}-\delta_{ij}-\gamma_{tj}-W_{itj}\tau_j-X_{itj}\beta_j\right)^2\omega_i\,\lambda_t\,\eta_j\right\}\ . \tag{1}$$

Here, Y_{itj} is the firm characteristic j at time t for firm i. δ_{ij},γ_{tj} are individual and time-fixed effects for each firm characteristics j, W_{itj} is one if the event takes place and afterward, otherwise it is zero (unified for all j), X_{itj} are potential additional controls. ω_i and λ_t are the individual and time weights respectively. η_j is the variable j weights given by the researcher. We propose to use equal weights while standardizing variable j, thus all variables will have an equal role in finding the weights.[14] We are going to estimate λ_t and ω_i given by Equation 2. and 3. similarly to Arkhangelsky et al. (2021), and take η_j as given when summing over the firm characteristics.

$$\begin{gathered}
(\hat{\omega}_0,\hat{\omega})=\underset{\omega_0\in\mathbb{R},\omega\in\Omega}{\arg\min}\sum_{j=1}^{J}\sum_{t=1}^{T_{pre}}\left(\omega_0+\sum_{i=1}^{N_{co}}\omega_iY_{itj}-\frac{1}{N_{tr}}\sum_{i=N_{co}+1}^{N}Y_{itj}\right)^2+\zeta^2T_{pre}||\omega||_2^2 \\
\Omega=\left\{\omega\in\mathbb{R}_+^N:\sum_{i=1}^{N_co}\omega_i=1,\omega_i=N_{tr}^{-1}\text{ for all }i=N_{co}+1,\dots,N\right\},
\end{gathered} \tag{2}$$

where T_{pre} stands for the number of pre-event periods, N_{co} for the number of candidate control firms, N_{tr} is for the number of event firms. The regularization parameter ζ is set similarly as in Arkhangelsky et al. (2021), but summarised overall variable $j=1,\dots,J$. The time weights are given by

$$\begin{gathered}
\left(\hat{\lambda}_0,\hat{\lambda}\right)=\underset{\lambda_0\in\mathbb{R},\lambda\in\Lambda}{\arg\min}\sum_{j=1}^{J}\sum_{i=1}^{N_{co}}\left(\lambda_0+\sum_{t=1}^{T_pre}\lambda_tY_{itj}-\frac{1}{T_{post}}\sum_{t=T_{pre}+1}^{T}Y_{itj}\right)^2 \\
\Lambda=\left\{\lambda\in\mathbb{R}_+^T:\sum_{i=1}^{N_co}\lambda_t=1,\lambda_t=T_{post}^{-1}\text{ for all }t=T_{pre}+1,\dots,T\right\},
\end{gathered} \tag{3}$$

[13]More on this latent structure model see: Arkhangelsky et al. (2021).

[14]Defining η_j allows a large variety of different scaling. E.g. an alternative to our method is to use means and var-covar matrix instead of individual standardization. Another possibility is to use orthogonalization procedure to transform Y_{itj} for the optimization. The differences in optimization are beyond the scope of this paper.

where T_{post} stands for time periods at and after the event. The main difference between our method and Arkhangelsky et al. (2021) is that we summarise over all variables J, thus the weights are selected such that we match on all J variable's pretreatment trends.

One can see our method as an extension of the "classical matching" and "TSCS-matching" in the following ways:

- "Classical matching": $\delta_{ij} = \gamma_{tj} = 0$ (no fixed effects), $\lambda_{T_{pre}} = 1$ otherwise it is zero and we use a special regularization parameter such that we select only one firm. (Note: this comparison neglects delisting.)

- "TSCS-matching": $\delta_{ij} = \gamma_{tj} = 0$ (no fixed effects), $\lambda_t = 1/T_{pre}$ (equal weight for all selected pre-periods, ω_i and η_j is dependent on the method used with TSCS-matching. One advantage of TSCS-matching compared to our method is that it can flexibly estimate $\hat{\omega}_i$ and η_j: e.g. for Mahalanobis measure η_j is similar to our method but scaled with the var-covar matrix instead of individual standardization.

Our empirical strategy for "synthetic-matching" method is the following. First, we use a pre-filter, similar to the "classical method": restrict our attention to firms that are in the same FF48 industry and their log market capitalization and log of book-to-market ratio is between 50% and 150% of the event firm before one month of the announcement. We allow a maximum of 100 candidate matches, however, we require that each candidate firm has return values for 36 months after the event (no delisting). If there are more than 100 candidates, we select the closest 100 in terms of the euclidean norm. In the second step, we use our synthetic-matching method for each event one by one. This generates for each event firm a synthetic firm. We allow for 36 months before the event, thus $T_{pre} = 36$, but require that the number of candidate firms is more or equal to 3. We carry out synthetic matching with three sets of variables:

1. SM-SBM: using only log of size and log of book-to-market ratio.

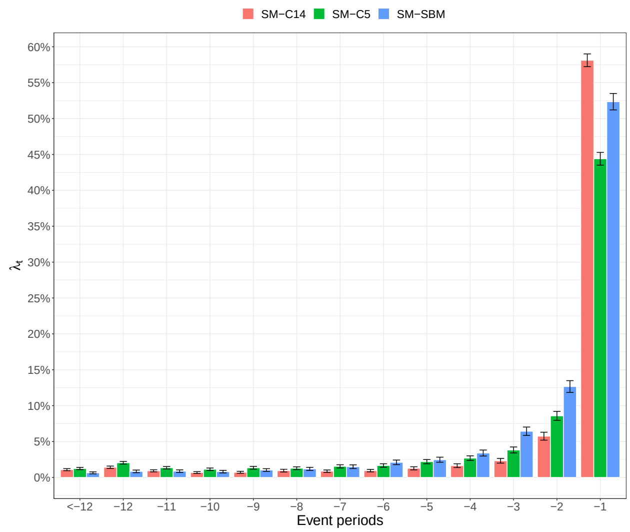
2. SM-C5: using C5 variables: log of size, log of book-to-market ratio, momentum, ROA and asset growth (non-lagged values)[15]

3. SM-C14: using C14 variables. In addition to C5 variables, market beta, accrual, dividend, log of long-run return, idiosyncratic risk, illiquidity, turnover, leverage and sales over price (non-lagged values).

3.2 Weights of synthetic matching

To assess matching quality we report the average of time-weights in Figure 2. We report the averaged pre-event period weights: $\overline{\hat{\lambda}_t} = \frac{1}{E}\sum_{e=1}^{E}\hat{\lambda}_{t,e}$, where $e = 1, \ldots, E$, are the distinct events. We can see that the trajectory of time weights are similar for all variable set: they

Figure 2: Average of time weights



Each bar represents the average $\hat{\lambda}_t$ across events for each time-period up to -12 (one year). After one year, bars with the tick '¡-12' shows the average weights between -13 and -36 periods. Error bars are added to each bar to show variations in weights.

put around 50% of the weights on one period before the announcement and then the weights exponentially decay.

Table 3. shows the summary statistics for the firm weights $\hat{\omega}_{i,e}$ across events. The first row shows the distribution for the number of candidate firms before synthetic matching. On average each event firm has 46 candidate firms. After estimating the weights we report the number of non-null weighted firms, which is naturally shifted towards zero. We see that the distribution is quite stable across the different matching variable sets with 18-19 weighted firms on average. The weight distribution is skewed to the right and truncated at 100.[16]

3.3 Matching quality on firm characteristics variables

To understand the matching quality of the different matching methods, we provide visual and quantitative evidence. Figure 3. and Figure 4 shows C5 and C14 variables with Classical Matching, TSCS-Matching and SM-C5 method. In the Appendix we provide further figures, showing SM-SBM and SM-C14 methods, however, these are not too much different from SM-C5 method. Figure 3. shows how matching methods capture the pre-trend variation in the control vs treated firms for C5 variables. Note that Classical Matching and TSCS-Matching have been matched only on book-to-market ratio and size, while SM-C5 method has used all five of the variables. Although, the pool of variables is different (SM-SBM method is used to

[15] Bessembinder et al. (2018) proposes to lag C5 or C14 variables, when creating CBBR5 or CBBR14. This is essential if one wants to create a benchmark return based on market information. However, we would like to create a good quality match before the event that allows us to use contemporaneous variables before the event.

[16] Figure A1 shows the distribution of non-null weighted firms.

Table 3: Descriptive statistics for the number of firms used during synthetic matching methods

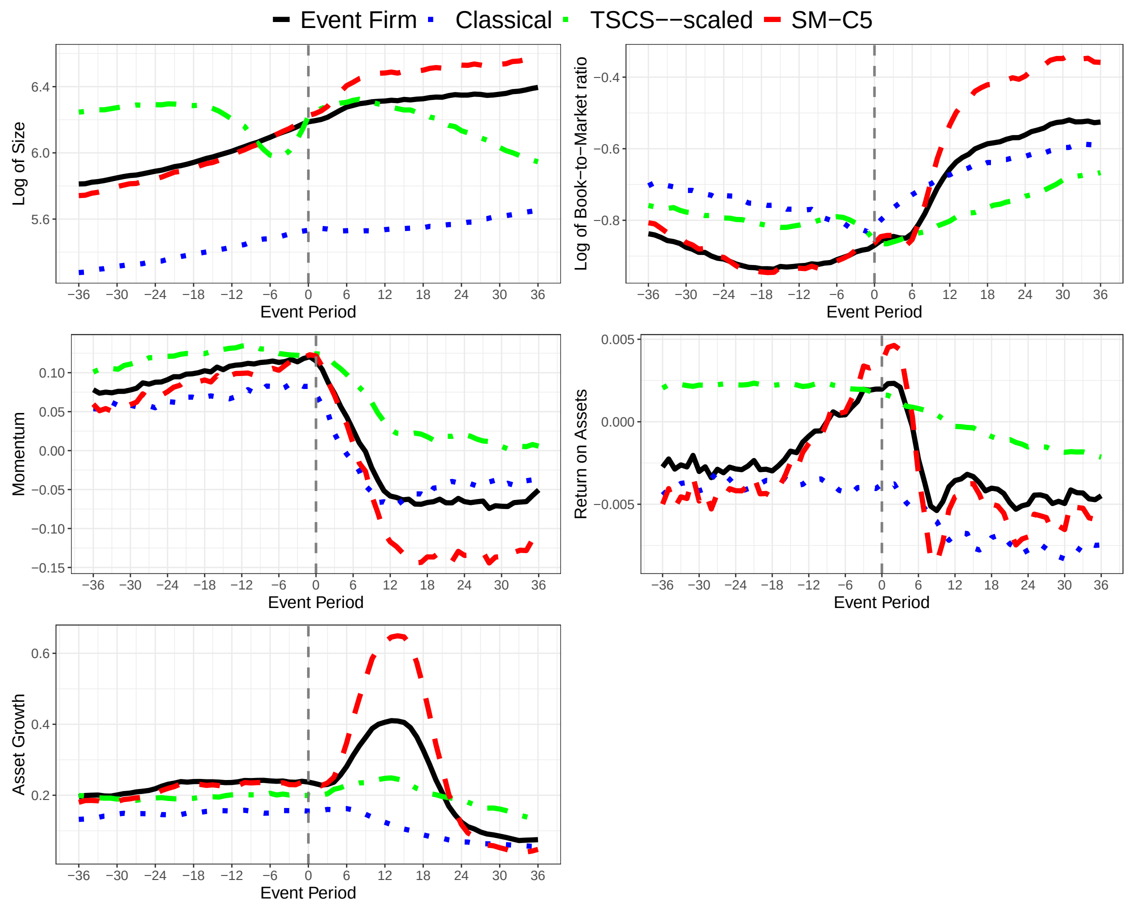
		N	Mean	Median	SD	Min	P25	P75	Max
No. candidate firms		4,655	46.24	35	35.74	3	14.00	86.00	100
	SM-SBM	4,655	18.27	13	17.89	1	7.00	23.00	100
No. non-null weight firms	SM-C5	4,655	19.84	15	17.81	2	9.00	24.00	100
	SM-C14	4,655	19.21	14	18.53	1	9.00	23.00	100

Descriptive statistics for the distribution of firm-specific weights. Each event firm can have a maximum of 100 candidate firms, but the number of actual candidate firms varies as we require to have log of size and log of book-to-market ratio within the 50% and 150% range and to be in the same industry. The No. candidate firms are the same regardless of the matching variables. No. non-null weight firms are showing the distribution of the estimated non-zero weights over each event firm.

have the same pool of variables and has similar results to SM-C5), SM-C5 outperforms the competing methods. Figure 4. shows the remaining 9 variables of C14. None of the methods have used these variables to match, however, they are fairly similar in their trends. SM-C5 provides in every variable a closer fit in terms of level, trend, and variation. In the appendix, we show pre-trend results for all methods together and for synthetic matching separately.

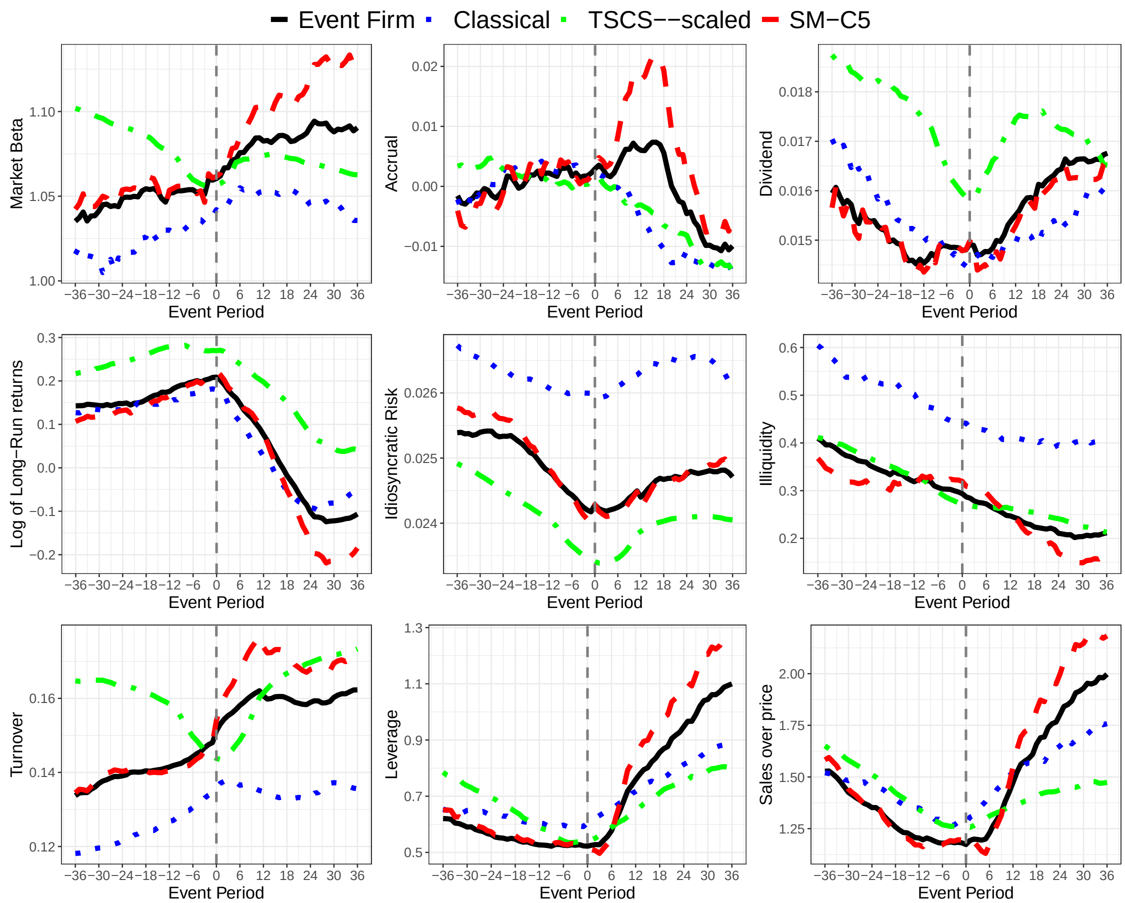
To quantify the match quality we check the *differences* between the event firms and created matched/synthetic firms. We carried out three different tests that are reported in Table 4. The first test compares the weighted differences in the variables and is shown by columns 'Weighted'. This test shows that if the assumed number of pre-periods is correctly chosen what is the average differences between the control and treated firms. For "Classical" we take only one period before the event. For TSCS we take 12 months before the event and weigh equally. For synthetic matching we use the time weights $\hat{\lambda}_{t,e}$. Results show that while Classical and TSCS methods are rejecting the H_0 that the means are the same for almost all cases, with synthetic methods we can not reject the null in any of the cases. The second and third blocks of columns are showing the unweighted differences for 12 months or 36 months before the event. The general pattern is similar: for Classical and TSCS we reject the H_0 at a lower significance level.

Figure 3: C5 variables for treated and different control firms by methods



Averaged firm characteristics before and after the event for 36 months. Classical stands for "classical matching", TSCS–scaled is a re-scaled (adjust event period -1 to match with treated and adjusted with treated pre-event standard deviation) to fit to plot using "TSCS-matching" with Mahalanobis distance measure. SM-C5 stands for the "synthetic-matching" method using C5 variables.

Figure 4: Remaining C14 variables for treated and different control firms by methods



Averaged firm characteristics before and after the event for 36 months. Classical stands for "classical matching", TSCS–scaled is a re-scaled (adjust event period -1 to match with treated and adjusted with treated pre-event standard deviation) to fit to plot using "TSCS-matching" with Mahalanobis distance measure. SM-C5 stands for the "synthetic-matching" method using C5 variables.

Table 4: Differences in the means for pretrend

Variable	Weighted					12 months					36 months				
	Classical	TSCS	SM-SBM	SM-C5	SM-C14	Classical	TSCS	SM-SBM	SM-C5	SM-C14	Classical	TSCS	SM-SBM	SM-C5	SM-C14
C5 variables															
Log BM	−0.0031*	−0.487***	-2e-19	-5.3e-19	-2.14e-18	−0.0131*	−0.487***	0.0046	0.0033	0.0061	0.0046	−0.4341***	0.0023	-0.0021	-0.0017
Log Size	0.6097***	2.9142***	-3.8e-19	1.6e-18	2.59e-18	0.5951***	2.9142***	0.0139***	0.0048	0.0094**	0.5831***	2.7852***	0.0305***	0.0317***	0.0423***
Momentum	0.046***	0.0676***	1.4e-19	8.4e-19	-6.7e-19	0.0445***	0.0676***	0.0137***	0.0072*	0.0043	0.0352***	0.0576***	0.0154***	0.0126***	0.0114**
ROA	0.0058***	-9e-04	0.0000	1.3e-19	-2e-20	0.0052***	-9e-04	0.0007*	-0.0004	0.0001	0.004***	−0.0015**	0.0021***	0.0008**	0.0014***
Asset growth	0.0397***	0.1125***	1.1e-19	8.8e-19	9e-19	0.0236***	0.1125***	0.0065*	0.0068**	0.0042	0.0053	0.0906***	0.0109**	0.0109***	0.0079**
Additional 9 variables for C14															
Market beta	0.018	0.5822***	-2.4e-18	8.1e-19	2.4e-19	0.0164	0.5822***	-0.0029	-0.0013	-0.0036	0.0234	0.5596***	-0.0051	-0.0035	-0.0035
Accrual	-0.0004	0.0029*	-1.7e-19	9e-20	-1.2e-19	-0.0008	0.0029*	5e-04	-0.0001	-0.0002	-0.0016	0.0012	0.0017	0.0004	0.0002
Dividend	0.0013**	0.0063***	-2e-20	5e-20	4e-20	0.0013**	0.0063***	-0.0001	0.0000	0.0003	0.0011**	0.0066***	0.0000	0.0001	0.0003
Log LR return	0.0924***	0.1557***	5e-19	2.7e-19	-1.45e-18	0.0868***	0.1557***	0.01**	0.0032	0.0024	0.0591***	0.1223***	0.0095	0.0146***	0.0175***
I. risk	−0.0023***	0.0132***	3e-20	0.0000	-1e-20	−0.0023***	0.0132***	0.0000	0.0000	0.0000	−0.002***	0.0128***	−0.0002**	−0.0001**	−0.0001**
Illiquidity	−0.181***	0.0707***	1.11e-18	-1.3e-19	-7.7e-19	−0.1984***	0.0707***	-0.0054	-0.0096	-0.0022	−0.1994***	0.0857***	0.0375***	0.0229***	0.0247***
Turnover	0.0127***	0.0878***	3e-20	3.3e-19	1.3e-19	0.0124***	0.0878***	0.001	0.0011	0.0019**	0.0129***	0.0798***	-0.0011	0.0000	0.0017*
Leverage	−0.052**	0.2501***	1.51e-18	-1.53e-18	-1.97e-18	−0.0513*	0.2501***	-0.003	-0.0031	-0.0064	-0.0303	0.2708***	0.0038	-0.0103	−0.0186**
Sales/price	-0.0042	0.6307***	-6.9e-19	-1.9e-18	-3.11e-18	-0.0243	0.6307***	0.0192	0.0082	0.0095	0.0117	0.6951***	0.0433**	0.0003	-0.008

Differences in the variables for event and control firms pre-trend. Different matching methods are reported along different time horizons. Weighted stands for the assumed/pre-set pre-periods. For classical it is one period before the event. TSCS uses 12 months prior to the event with equal weights. SM methods use the estimated weights $\hat{\lambda}_{t,e}$. Stars are corresponding Bonferroni-adjusted p-values for having the same means pooled over all events. *** stands for 0.1%, ** stands for 1% and * for 5%. Standard errors are clustered at firm and calendar time levels.

4 Results

To evaluate the long-run performance of each firm we calculate the excess returns for each event firm using the matched/synthetic firms created. We use raw monthly excess returns r_{it} (instead of log returns[17]). We follow Petersen (2008) and cluster the standard errors at the firm level and across calendar time. Table 5. shows the main aggregated results on the long-run excess returns for M&A. We regress excess returns on pre-event ($e = -36, \ldots, -1$) and post-event ($e = 0, \ldots, 36$) step indicator variables that covers 36 months before and after the event. Results show that Classical Matching and TSCS Matching have a significant pre-event excess return, thus the matched/compared firms have on average 0.23pp – 1.17pp higher returns before the event. We claim that this is due to poor matching quality. In contrast, synthetic matching methods have insignificant pre-event values, only SM-SBM method has significantly lower excess returns at 10%. More interestingly, the post-event coefficients are non-significant for Classical and TSCS Matching methods, indicating on average zero excess returns. However, with synthetic matching, we have a rather stable -0.54pp to -0.72pp monthly excess return on average.

Table 5: Average excess returns after announcement up to 36 months

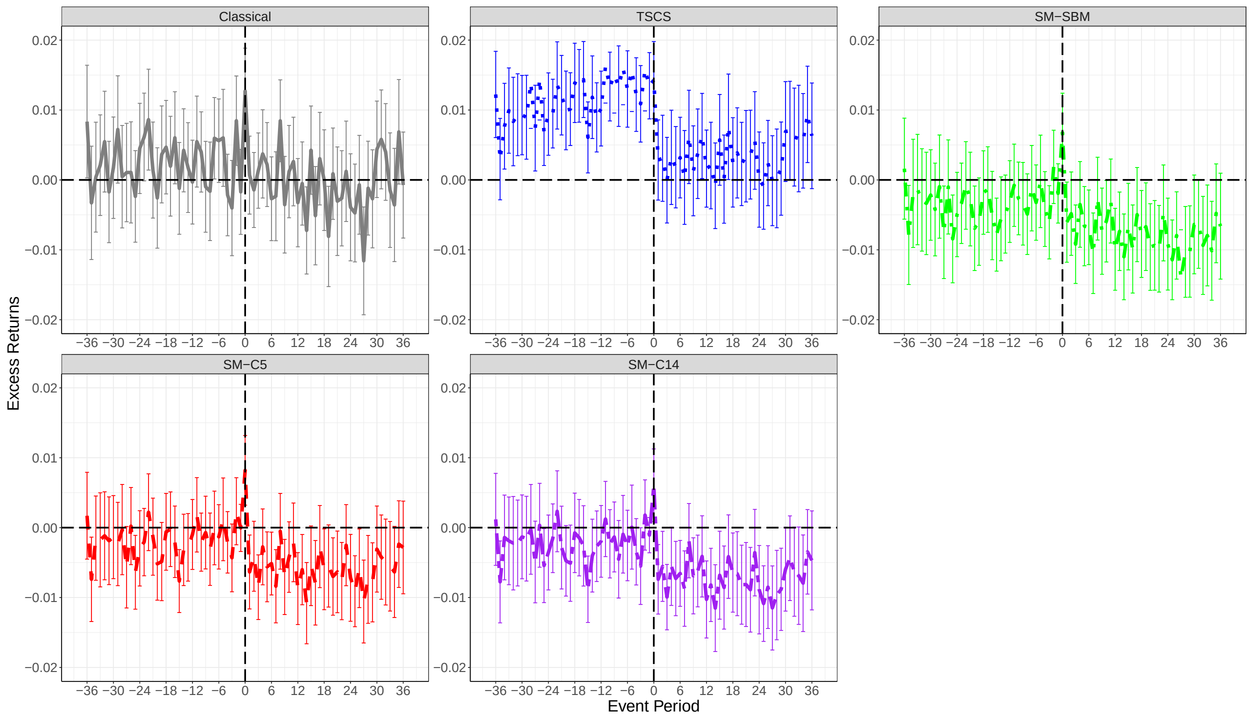
Model:	Classical Mathcing	TSCS Matching	SM-SBM	SM-C5	SM-C14
Variables					
pre-event	0.0023***	0.0117***	-0.0033*	-0.0018	-0.0023
	(0.0007)	(0.0017)	(0.0019)	(0.0014)	(0.0015)
post-event	-0.0001	0.0036	-0.0072***	-0.0054***	-0.0068***
	(0.0007)	(0.0022)	(0.0019)	(0.0015)	(0.0017)
Fit statistics					
Observations	270,810	270,810	270,810	270,810	270,810
R^2	0.000032	0.00079	0.00011	0.00011	0.00016

Clustered standard-errors at firm level and calendar time
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 5. shows the same results with plotting the excess returns between 36 months before and after the event. We estimate the effect of each event time, which allows time variation in our results. The figure shows that there is no unique driver of the pooled results in Table 5. but there is an ongoing trend in excess returns. Classical matching method varies around zero, while TSCS matching produces significantly higher excess returns before the event. Synthetic methods show that the pooled average is a good approximation of the excess returns after the event. One important insight that Figure 5 adds is at the time of the announcement there is a significant positive excess return documented with synthetic matching and classical matching. During the heterogeneity analysis, we get back to this point.

[17] Chen and Roth (2023) shows that $log(1 + y)$ type of transformation with zero-valued outcomes are resulting ATE to be arbitrarily scale-dependent.

Figure 5: Time-varying excess returns with different matching methods



Error bars are showing 95% CI based on clustered standard errors at firm level and calendar time.

Finally, we compare our matching results with different benchmarks and methods proposed in Bessembinder et al. (2018). We follow their description and use an (unbalanced) panel approach to estimate the average treatment effect for the treated based on the following equation,

$$r_{it} - E\left[r_{it}|f(x_{it})\right] = \alpha + \tau D_{it} + \epsilon_{it}\,. \tag{4}$$

$E\left[r_{it}|f(x_{it})\right]$ stands for different benchmark returns. We will use four types of benchmark returns. "None" stands for raw returns, where we do not adjust with any benchmarks. CBBR-5 and CBBR-14 use the characteristic-based benchmark returns with 5 variables and 14 variables respectively, proposed by Bessembinder et al. (2018). Finally, we use the Fama-French 5 (FF5) factor model's benchmark returns as well. We regress these excess returns on a "treatment" variable D_{it}, that takes the value of 1 if M&A is announced up to 36 months after the announcement for firm i along t, otherwise, it is 0. The last dimension is the estimation method. The first column for each benchmark estimation is the Fama and MacBeth (1973) type of estimation that weights each time period equally. The second uses pooled OLS that weights each observation similarly. "W-TWFE" method uses the two-way-fixed effect estimator for event studies proposed by Wooldridge (2021).

Table 6: Average excess returns calculated with panel calendar-time methods

	None			CBBR-5			CBBR-14			FF5		
	Fama-MacBeth	Pooled	W-TWFE	Fama-MacBeth	Pooled	W-TWFE	Fama-MacBeth	Pooled	W-TWFE	Fama-MacBeth	Pooled	W-TWFE
Intercept	1.3249***	0.0133***	-	0.0475	−0.0004	-	0.0482	−0.0004	-	0.2223	0.0024	-
SE	(0.0026)	(0.0025)	-	(0.0029)	(0.0026)	-	(0.0029)	(0.0026)	-	(0.0024)	(0.0022)	-
t-stat	[5.0725]	[5.3978]	-	[0.1612]	[-0.14]	-	[0.1636]	[-0.1407]	-	[0.9308]	[1.0652]	-
$\hat{\tau}$	−0.0659	−0.0039	-0.178	−0.1676	0.0005	-0.2510	−0.1564	0.0005	-0.224	−0.0659	−0.0038	-0.2150
SE	(0.0008)	(0.0024)	(0.399)	(0.0009)	(0.0026)	(0.420)	(0.0009)	(0.0026)	(0.428)	(0.0008)	(0.0022)	0.3790
t-stat	[-0.8086]	[-1.6182]	[-0.0004]	[-1.8689]	[0.1941]	[-0.006]	[-1.7536]	[0.1945]	[-0.0005]	[-0.8086]	[-1.7679]	[-0.0006]
Observations: 2,227,161												

*Standard errors for pooled OLS and W-TWFE are clustered at firm level and calendar time. Fama-MacBeth standard errors are incorporating Newey-West correction with four lags. *** stands for 0.1%, ** stands for 0.5% and * stands for 1% significance levels. For W-TWFE method due to computation reasons, this paper reports results using a 25% random sample.*

Table 7: Average of excess returns at and after M&A announcement

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Announcement month	0.0075***	0.0080***	0.0082***	0.0020	0.0025
	(0.0026)	(0.0026)	(0.0026)	(0.0706)	(0.4845)
3 year average	-0.0062***	-0.0015	-0.0009	-0.0042	-0.0038
	(0.0015)	(0.0015)	(0.0015)	(0.0705)	(0.4844)
Controls					
C5		Yes	Yes	Yes	Yes
C14			Yes	Yes	Yes
M&A characteristics				Yes	Yes
Industry FE					Yes
Fit statistics					
Observations	164,249	164,212	164,212	88,165	88,165
R^2	0.00016	0.00903	0.01049	0.01111	0.02065
Within R^2					0.01091

Clustered firm & calendar time standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The main takeaway of Table 6. is the sign of the average excess return is similar to our matching methods, but they are all insignificant and the magnitude of the coefficient is changing over different methods and techniques. From the theoretical point, this variation may be a result of violation of the identification assumptions.

4.1 Heterogeneity analysis

We investigate heterogeneity in excess returns based on the synthetic matching method with C5 variables. First, we consider linear models to better understand the possible differences or channels in high/low excess returns. As a second stage, we will employ non-linear models in the form of random forests to account for flexible forms of non-linearities. As we will show these methods can account for significantly higher explained variation in the data.
First, we investigate the differences along the event-time horizon. We have seen in Figure 5. that there is a spike in the month of the intervention. Multiple papers document a similar increase in short-run returns ranging from 1% - 24% (see for overview in Renneboog and Vansteenkiste, 2019, p. 653). We document in our sample a 0.75pp increase in excess return in the month of the announcement. Table 7. shows the effect of the announcement month and the 3-year average of the excess returns after the announcement. Model (1) shows the coefficients without any controls. Model (2) and (3) controls for (lagged) C5 and C14 variables. The coefficient of 3 year average becomes insignificant showing that variation in excess returns after the announcement can be explained by these sets of variables. However, the month of the announcement remains significant. Model (4) and (5) controls for M&A characteristics (type of M&A, share acquired, equity value, transaction value, percent stock used) and for industries. We see that in this case both coefficients become insignificant, showing that these controls will explain the variation in excess returns.

As a second exercise, we investigate the variation explained in excess returns by C5

Table 8: Average of excess returns by differences in CBBR variables after M&A announcement

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Constant	-0.0011					-0.0005				
	(0.0015)					(0.0015)				
Log of BM	0.0018	0.0016	0.0019	0.0007	0.0013	0.0019	0.0017	0.0020	0.0005	0.0009
	(0.0032)	(0.0033)	(0.0032)	(0.0040)	(0.0040)	(0.0032)	(0.0033)	(0.0032)	(0.0040)	(0.0039)
Log of Size	-0.0219***	-0.0221***	-0.0219***	-0.0229***	-0.0235***	-0.0231***	-0.0234***	-0.0232***	-0.0239***	-0.0245***
	(0.0033)	(0.0033)	(0.0034)	(0.0046)	(0.0046)	(0.0037)	(0.0038)	(0.0038)	(0.0053)	(0.0052)
Momentum	0.0307***	0.0308***	0.0307***	0.0281***	0.0279***	0.0317***	0.0317***	0.0317***	0.0294***	0.0291***
	(0.0039)	(0.0039)	(0.0038)	(0.0047)	(0.0046)	(0.0040)	(0.0040)	(0.0040)	(0.0050)	(0.0049)
ROA	-0.0316	-0.0307	-0.0310	-0.0145	-0.0068	-0.0361	-0.0353	-0.0354	-0.0144	-0.0083
	(0.0420)	(0.0420)	(0.0420)	(0.0515)	(0.0504)	(0.0407)	(0.0407)	(0.0407)	(0.0501)	(0.0493)
Asset Growth	-0.0024	-0.0023	-0.0024	-0.00009	0.0004	-0.0015	-0.0013	-0.0014	0.0001	0.0006
	(0.0036)	(0.0037)	(0.0037)	(0.0050)	(0.0050)	(0.0036)	(0.0038)	(0.0038)	(0.0050)	(0.0050)
Beta						0.0009	0.0009	0.0009	0.0018	0.0012
						(0.0027)	(0.0027)	(0.0027)	(0.0037)	(0.0037)
Accrual						-0.0144	-0.0143	-0.0143	-0.0142	-0.0127
						(0.0111)	(0.0111)	(0.0111)	(0.0158)	(0.0153)
Dividend						0.0893*	0.0898*	0.0909*	0.0759	0.0886
						(0.0488)	(0.0488)	(0.0489)	(0.0863)	(0.0858)
Log LR return						0.0084**	0.0086**	0.0086**	0.0083*	0.0080*
						(0.0035)	(0.0035)	(0.0036)	(0.0048)	(0.0047)
Idio.risk						0.2932	0.2914	0.3000	0.2313	0.1407
						(0.2458)	(0.2459)	(0.2470)	(0.3134)	(0.3109)
Illiquidity						-0.0033*	-0.0033*	-0.0033*	-0.0028	-0.0028
						(0.0020)	(0.0020)	(0.0020)	(0.0022)	(0.0021)
Turnover						-0.0219*	-0.0217*	-0.0225*	-0.0031	-0.0044
						(0.0128)	(0.0128)	(0.0129)	(0.0170)	(0.0169)
Leverage						-0.0041***	-0.0041***	-0.0041***	-0.0041*	-0.0037*
						(0.0015)	(0.0015)	(0.0015)	(0.0022)	(0.0021)
Sales/price						0.0021**	0.0020**	0.0020**	0.0028**	0.0027**
						(0.0009)	(0.0009)	(0.0009)	(0.0013)	(0.0013)
Controls										
Event time FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Calendar time FE			Yes	Yes	Yes			Yes	Yes	Yes
M&A characteristics				Yes	Yes				Yes	Yes
Industry FE					Yes					Yes
Fit statistics										
Observations	164,212	164,212	164,212	88,165	88,165	164,212	164,212	164,212	88,165	88,165
R^2	0.00896	0.00927	0.01361	0.01748	0.02710	0.01043	0.01075	0.01510	0.01875	0.02821
Within R^2		0.00893	0.00882	0.00964	0.00952		0.01041	0.01032	0.01092	0.01065

Clustered firm & calendar time standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

and C14 variables. This helps to understand how excess return varies with these variables indicating potential channels. Note that the C5 and C14 variables are lagged according to Bessembinder et al. (2018), thus it accounts only for publicly available knowledge. Models (1)-(5) use only C5 variables with a different set of controls and models (6)-(10) for C14 variables. We see log of size and momentum to be significant across all specifications. For size, we see that with one percent larger size we observe 0.023pp lower excess returns. In contrast with a unit higher momentum value, we see 3pp higher excess returns. With C14 variables leverage and sales over price seem to be (marginally) significant. With leverage, there is a negative relation while with sales over price, the relationship is positive. In general, the sign and magnitude remain the same in most of the variables while adding more controls.

Next, we check the relation between the characteristics of the M&A and excess return. We find that percent of stocks used for the transaction is significant if there are no controls.

Table 9: Average of excess returns by M&A related variables after M&A announcement

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	0.0229					
	(0.0475)					
M&A Type: AR	0.0027	0.0028	-0.0002	0.0041	0.0020	0.0019
	(0.0300)	(0.0300)	(0.0308)	(0.0293)	(0.0296)	(0.0322)
M&A Type: M	-0.0236	-0.0236	-0.0224	-0.0210	-0.0228	-0.0267
	(0.0295)	(0.0295)	(0.0299)	(0.0290)	(0.0296)	(0.0284)
Share Acquired (%)	0.00005	0.00005	-0.00002	-0.00001	-0.00002	0.0001
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Share Owned Before (%)	-0.0001	-0.0001	-0.0002	-0.0002	-0.0001	0.00002
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Log of Equity Value	-0.00002	-0.00002	-0.0005	-0.0013	-0.0013	-0.0019
	(0.0059)	(0.0059)	(0.0060)	(0.0059)	(0.0058)	(0.0055)
Percent of Stocks used for transaction	-0.0002**	-0.0002**	-0.0001*	-0.0001	-0.0001	-0.0001
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00008)
Log of Transaction Value	-0.0016	-0.0016	-0.0012	0.0001	0.0003	0.0008
	(0.0059)	(0.0059)	(0.0059)	(0.0058)	(0.0057)	(0.0055)
Target firm from same FF48 industry	0.0096**	0.0096**	0.0096**	0.0085*	0.0088*	0.0101*
	(0.0046)	(0.0046)	(0.0047)	(0.0047)	(0.0046)	(0.0056)
Controls						
Event time FE		Yes	Yes	Yes	Yes	Yes
Calendar time FE			Yes	Yes	Yes	Yes
C5				Yes	Yes	Yes
C14					Yes	Yes
Industry FE						Yes
Fit statistics						
Observations	88,091	88,091	88,091	88,091	88,091	88,091
R^2	0.00167	0.00207	0.00944	0.01743	0.01872	0.02809
Within R^2		0.00167	0.00150	0.00955	0.01086	0.01070

Clustered firm & calendar time standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The magnitude is rather small, it is around -0.2pp of the excess return, however, the sign is the same as documented in Bhagat et al. (2005) or Savor and Lu (2009). We also find a significant coefficient on the variable that counts for the target firm being from the same FF48 industry and the acquirer firm. Not surprisingly excess returns are 1pp higher if they are from the same industry.

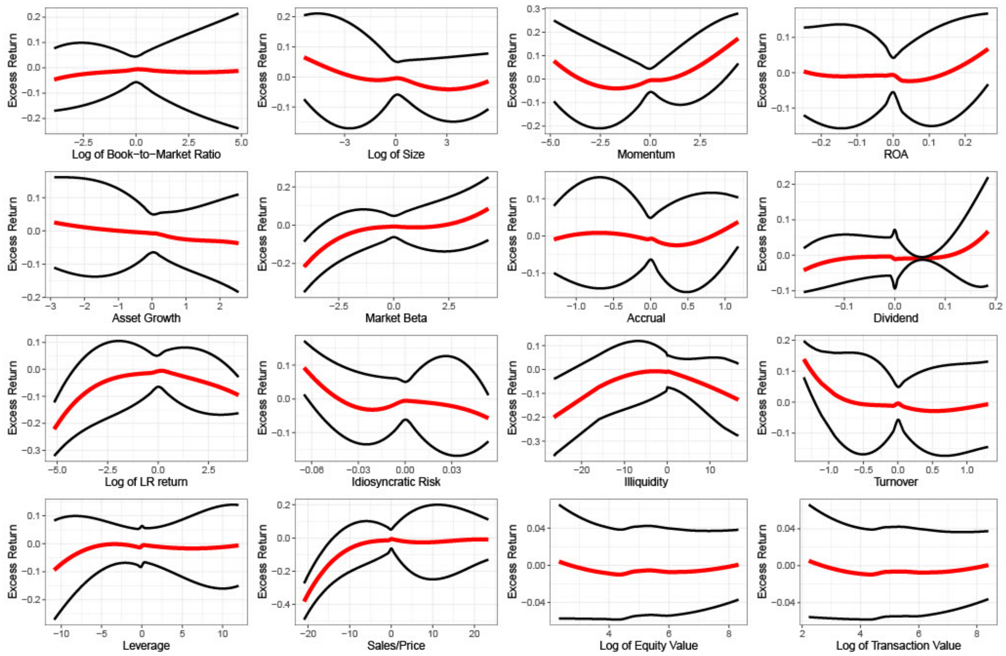
As a final exercise, we use all of the previous variables and employ different random forests to explore non-linear patterns. We use three different random forests: regression forest (Athey et al., 2019), boosted regression forest (Ghosal and Hooker, 2020), and local linear forest (Friedberg et al., 2020). Regression forest is the same as random forests using the MSE criterion. Boosted regression forest is adaptive to errors taken by previously built trees, while local random forest has larger flexibility in sharp changes in the estimated expectation functions through using local linear regressions. These methods explain a considerably larger proportion of the variation than the linear models. We achieve 7-15% R2 in the test sample, which is much larger than the compared 1% R2 (training sample) for the linear models. Table 10. shows the variable importance (VI) along with the rankings for each forest. Both measures are quite stable through the methods showing a reliable ranking in the importance of the used variables. We see that size and momentum are the two leading variables. The log of equity value in the transaction has the third rank, but it's VI measure is considerably lower than the first two. Acquirer firm's industry using FF48 categorization also seems to be important. Next, we take the Local Linear Forest model as it performed the best in terms of test MSE. To show the non-linear relation between excess return and variables we estimate

Table 10: Variable Importance for different Random Forests

	Regression Forest		Boosted Regression Forest		Local Linear Forest	
	VI	Rank	VI	Rank	VI	Rank
Log of Size	0.54042	1	0.54147	1	0.54429	1
Momentum	0.28777	2	0.28868	2	0.28127	2
Log of Equity Value	0.0241	3	0.02473	3	0.02382	3
Sales/Price	0.01409	5	0.01337	5	0.01675	4
Acquirer Firm's Industry (FF48)	0.01708	4	0.01827	4	0.01629	5
ROA	0.01321	6	0.01286	7	0.01367	6
Log of Transaction Value	0.01173	8	0.0114	8	0.01285	7
Idiosyncratic Risk	0.01239	7	0.01322	6	0.01238	8
Asset Growth	0.01092	9	0.01016	9	0.01078	9
Accrual	0.00857	11	0.00845	11	0.00921	10
Date	0.00912	10	0.00965	10	0.00899	11
Turnover	0.00831	12	0.00714	12	0.00785	12
Log of BM	0.0074	13	0.00665	13	0.00664	13
Pctg of Stock used in Transaction	0.00549	15	0.0057	15	0.00598	14
Illiquidity	0.00554	14	0.00573	14	0.00564	15
Target Firm's Industry (FF48)	0.00466	18	0.00427	17	0.00479	16
Event Period	0.00515	16	0.00481	16	0.00475	17
Log of LR return	0.00486	17	0.00412	18	0.00465	18
Market Beta	0.00327	19	0.00294	20	0.00309	19
Dividend	0.00282	20	0.00306	19	0.00294	20
Leverage	0.00252	21	0.00268	21	0.00267	21
Acquirer and Targer firms are in same Industry (FF48)	0.00032	22	0.00043	22	0.00048	22
Share Acquired (%)	6e-05	24	6e-05	24	1e-04	23
MA Type	0.00016	23	0.00012	23	8e-05	24
Share Owned Before (%)	3e-05	25	2e-05	25	3e-05	25
	Train	Test	Train	Test	Train	Test
MSE	0.02956	0.03421	0.02376	0.03263	0.01455	0.0314
R2	0.22665	0.07844	0.37847	0.1208	0.61941	0.15419

the expected excess returns based on the model and plot against different variables. Figure 6. shows the non-linear patterns in the variables along with 95% confidence intervals.

Figure 6: Association between excess return and firm characteristics with Local Linear Forest Predictions



5 Conclusion

In this paper, we propose a new matching method to create a better control for firms went through M&As. As the firm characteristics of each M&A firm differ in multiple dimensions we use a set of candidate firms for each event firm and weight them such that they match the event firm's characteristics before the event. We use the synthetic control approach and extend its methodology to match on multiple dimensions. We use three sets of variables: i) market capitalization as size and book-to-market ratio; ii) C5 variables: size, book-to-market ratio, momentum ROA, and asset growth; and iii) C14 variables: in addition to C5 variables, market beta, accrual, dividend, log of long-run returns, idiosyncratic risk, illiquidity, turnover, leverage and sales over price. We show that by matching these characteristics with our synthetic matching method, control firms have statistically indistinguishable firm characteristics before multiple time periods of the announcement of M&As. We show that our method is superior in multiple dimensions compared to the most commonly used matching methods in finance and economics. We also replicate frequently used panel methods to evaluate long-run returns. We raise recently emerged concerns with these methods as current development in econometrics theory shows identification problems of the causal effects. Empirically, we find unstable parameter estimates for these methods that indicate that the underlying assumptions of these models are violated in our setup.

With our synthetic matching method, we find on average 0.7pp larger excess return in the month of announcement and a constant -0.6pp lower excess returns over 36 months after the announcement for M&As. We also carry out heterogeneity analysis where we investigate potential channels and differences in types of M&As. In terms of channels, we find that size is negatively correlated with excess returns and momentum has a large effect on higher excess returns. Leverage and sales over price have been found marginally significant as well with negative and positive coefficients respectively. For heterogeneity in types of M&As we find that percent of stocks used for the transaction has a negative marginally significant difference in excess returns, whereas if the target firm is in the same (FF48) industry, we find on average higher excess returns. Non-linear analysis with random forest methods also shows that the relation between excess return and the investigated variables is highly nonlinear. We achieve 15% out of sample R2 with local linear forest instead of 1% of in-sample R2 with linear models. For random forest methods, apart from the size, momentum, and sales over price, we find the log of equity value, log of transaction value and acquirer firms' industry along with the date of M&A important.

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Appendix

Table A1: Definition of the C5 and C14 firm characteristics as in bcz2019cbbr

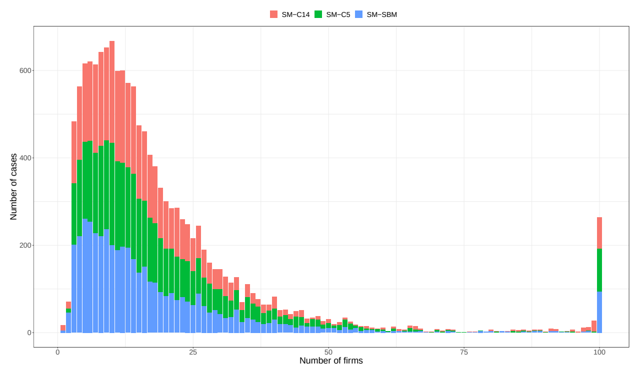
Characteristics in the C5 model	
log size	Natural log of market capitalization, which is stock price (prc in CRSP monthly stock file) times number of shares outstanding (shrout), at the end of the prior month
log book-to-market ratio	Natural log of the book-to-market ratio at the end of the prior month. Book value is the firm's common equity (Compustat item ceq) in the latest annual report. Market value is the firm's market capitalization (prc times shrout) at the end of the prior month reported in CRSP.
Momentum	Buy-and-hold stock returns over months (-12, -2) before the month of interest
ROA	Income before extraordinary items (ib) divided by average total assets (at) in the year
Asset growth	Natural log of the ratio of total assets (at) at the end of the year to total assets at the beginning of the year, following Cooper et al. (2008)
Additional nine characteristics in the C14 model	
Beta	Market beta is estimated using monthly excess stock returns and market risk premiums over the preceding 60 months. We require a minimum of six data points for the accuracy of the estimation
Accrual	Change in working capital from the last year minus depreciation and amortization (dp), divided by average total assets (at) in the year, following Sloan (1996). Working capital equals current assets (act) minus cash and short-term investment (che) minus current liabilities (lct) plus debt in current liabilities (dlc) plus income taxes payable (txp). Missing act, che, lct, dlc, txp, and dp are replaced with zero
Dividend	Dividends per share over the prior 12 months divided by the price at the end of the prior month
Log LR return	Natural log of buy-and-hold stock returns over months $(-13, -36)$ before the month of interest
Idiosyncratic risk	In each month, we compute the standard deviation of the residual daily stock returns in the Fama and French (1993) three-factor regression, following Ang et al. (2006). Idiosyncratic risk is the average standard deviation over the prior 12 months
Illiquidity	The average daily ratio of absolute stock return to dollar trading volume during the prior 12 months, as defined by Amihud (2002)
Turnover	Average monthly turnover (shares traded divided by shares outstanding) during the prior 12 months
Leverage	Debt in current liabilities (dlc) plus long-term debt (dltt), divided by market capitalization (prc times shrout in CRSP) at the end of the last month. Missing dlc and dltt are replaced with zero
Sales/price	Sales (sale) divided by market capitalization (prc times shrout in CRSP) at the end of the last month.

We measure these characteristics following Lewellen (2015). All variables are created using data from the CRSP stock price files and the Compustat annual data. Accounting data are assumed to be available 4 months after the fiscal year-end.

Table A2: Different matching methods for event firms

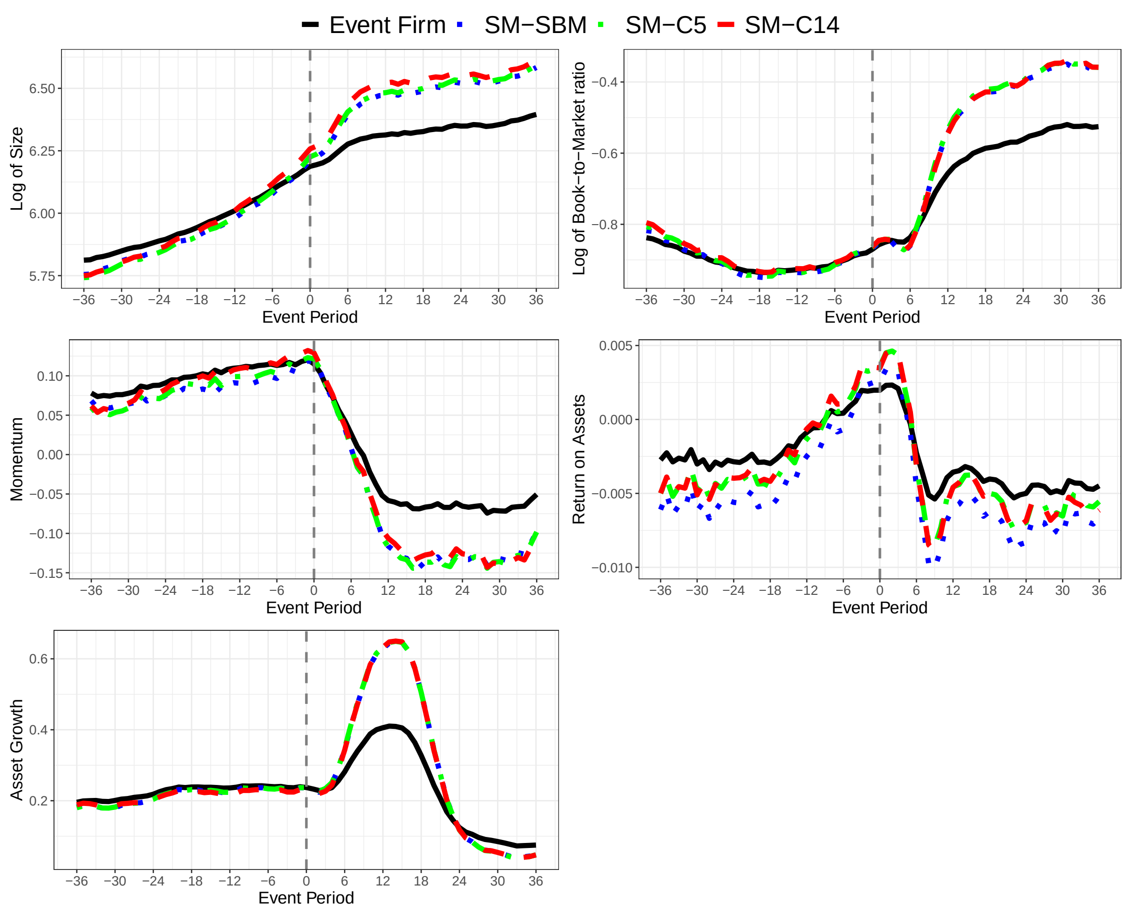
Matching method	Corporate Event	Replace if delisted	Further constraint	Papers introducing or using the method
Closest market capitalization on December 31	M&A, SEO, dividends	Y	-	Loughran and Ritter (1995)
Closest market capitalization on December 31	IPO	Y	For IPO matching firm must have been traded publicly for 5 years	Loughran and Ritter (1995), Bessembinder and Zhang (2013), Kolari et al. (2021)
Closest market capitalization and filter to Book-to-Market Ratio (BMR) on proceeding December 31	M&A, SEO, dividends	Y	Market capitalization between 70%-130%.	Bessembinder and Zhang (2013), Kolari et al. (2021)[18]
Market Capitalization and Book-to-Market Ratio (BMR) on one period before event time	M&A, SEO, dividends	Y	Market capitalization between 70%-130%.	Eckbo et al. (2007), Bessembinder et al. (2018), Yan Liu and Zhang (2023)
Closest Book-to-Market Ratio after the event time is first available, the filter for the market capitalization (MC)	IPO	Y	MC is larger than the event firm's MC and less than 20 times. Matching firm is publicly traded for more than 3 years	Lyandres et al. (2007)[19], Bessembinder et al. (2018), Yan Liu and Zhang (2023)
Closest operating income before depreciation and amortization (OIBD) relative to assets, with same industry	SEO	N	Not issued equity during the five years prior to the offering date. Same industry (2-digit SIC codes), with asset size as of the end of year 0 between 25 percent and 200 percent of the issuer are ranked by their year 0 OIBD relative to assets. The firm with the closest OIBD/assets ratio among these non issuing firms is picked as the matching firm. If no matching firm, neglect industry restriction and asset size within 90 percent to 110 percent of the issuer are ranked by OIBD/assets, and the firm with the closest, but higher, the ratio is chosen as the matching firm	Barber and Lyon (1996), Loughran and Ritter (1997)
Market capitalization in June and book-to-market ratio in December (t-1), using multiple firms	SEO (and other stock-related events)	N	order multiple times to decide and/or quantiles. Event firms are compared to firms in the same bracket.	Lyon et al. (1999)
Market capitalization and book-to-market ratio via (yearly) regressions	M&A	N	Estimate regressions of market capitalization and book-to-market ratio on cumulative returns. Get the F-value and rank firms. Closest to the event firm will be the matching firm.	Loughran and Vijh (1997)
Propensity score matching with market capitalization, book-to-market ratio, and cumulative returns	SEO	N	Matching firm has not initiated SEO in the past 3 years	Li and Zhao (2006)
Industry, sales, and EBITDA grid	IPO	N	Matching firm is in the same industry (FF48) and a 3x3 grid by sales and EBITDA is created to categorize. The closest in sales is chosen.	Purnanandam and Swaminathan (2004)

Figure A1: Number of cases for the number non-null weighted firms



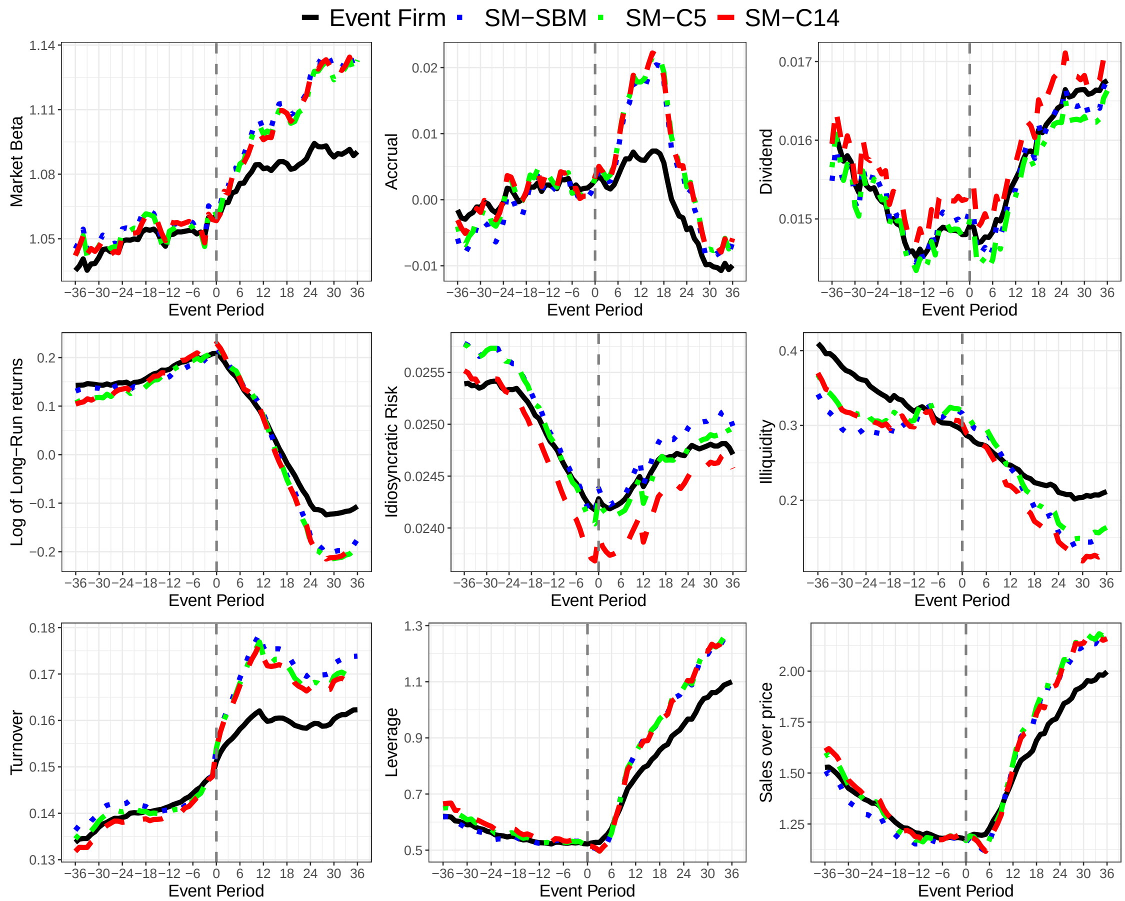
Each bar represents the number of cases for the number of non-null weighted firms by each method.

Figure A2: C5 variables and synthetic matching methods



Averaged firm characteristics before and after the event for 36 months. SM-SBM stands for synthetic matching with size and book-to-market variables. SM-C5 stands for the synthetic-matching method using C5 variables, whereas SM-C14 uses the C14 variables.

Figure A3: Remaining C14 variables and synthetic matching methods



Averaged firm characteristics before and after the event for 36 months. SM-SBM stands for synthetic matching with size and book-to-market variables. SM-C5 stands for the synthetic-matching method using C5 variables, whereas SM-C14 uses the C14 variables.

Table A3: Differences in pretrend variables

Weighted

	Classical				TSCS				SM-SBM				SM-C5				SM-C15			
Variable	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val
Log of BM	-0.0031	0.0015	-2.0880	0.0374	-0.4870	0.0139	-34.9258	0.0000	-2.00e-19	6.366e-04	-3.1376e-16	0.9999	-5.30e-19	1.2532e-03	-4.2006e-16	0.9999	-2.14e-18	1.0523e-03	-2.0301e-15	0.9999
Log of Size	0.6097	0.0243	25.0923	0.0000	2.9142	0.0451	64.6109	0.0000	-3.80e-19	2.5528e-04	-1.4907e-15	0.9999	1.60e-18	7.4107e-04	2.1612e-15	0.9999	2.59e-18	5.5591e-04	4.6652e-15	0.9999
Momentum	0.0460	0.0077	5.9740	0.0000	0.0676	0.0074	9.1567	0.0000	1.40e-19	7.3951e-04	1.9149e-16	0.9999	8.40e-19	8.5864e-04	9.8128e-16	0.9999	-6.70e-19	8.1170e-04	-8.3098e-16	0.9999
ROA	0.0058	0.0008	7.5153	0.0000	-0.0009	0.0006	-1.5521	0.1213	0.00e+00	5.9191e-05	9.4400e-18	0.9999	1.30e-19	8.4383e-05	1.4889e-15	0.9999	-2.00e-20	4.5964e-05	-4.0774e-16	0.9999
Asset growth	0.0397	0.0077	5.1867	0.0000	0.1125	0.0050	22.6003	0.0000	1.10e-19	1.2062e-04	9.4690e-16	0.9999	8.80e-19	3.2753e-04	2.6777e-15	0.9999	9.00e-19	4.0352e-04	2.2246e-15	0.9999
Beta	0.0180	0.0160	1.1258	0.2609	0.5822	0.0115	50.7015	0.0000	-2.40e-18	4.6468e-04	-5.1725e-15	0.9999	8.10e-19	6.8652e-04	1.1729e-15	0.9999	2.40e-19	1.0000e-05	2.4492e-14	0.9999
Accrual	-0.0004	0.0022	-0.1831	0.8548	0.0029	0.0011	2.5061	0.0126	-1.70e-19	1.0000e-05	-1.7198e-14	0.9999	9.00e-20	1.0000e-05	9.0967e-15	0.9999	-1.20e-19	7.9114e-05	-1.5024e-15	0.9999
Dividend	0.0013	0.0004	3.0128	0.0027	0.0063	0.0004	15.6846	0.0000	-2.00e-20	2.8161e-05	-7.6668e-16	0.9999	5.00e-20	1.0934e-05	4.7328e-15	0.9999	4.00e-20	2.6846e-05	1.6069e-15	0.9999
Log of LR ret.	0.0924	0.0115	8.0080	0.0000	0.1557	0.0107	14.5548	0.0000	5.00e-19	1.0000e-05	5.0159e-14	0.9999	2.70e-19	5.6941e-04	4.7141e-16	0.9999	-1.45e-18	1.0000e-05	-1.4470e-13	0.9999
Idio. Risk	-0.0023	0.0002	-12.0838	0.0000	0.0132	0.0002	56.6680	0.0000	3.00e-20	1.0665e-05	3.1566e-15	0.9999	0.00e+00	1.3493e-05	-9.9300e-17	0.9999	-1.00e-20	7.9636e-06	-1.6651e-15	0.9999
Illiquidity	-0.1810	0.0209	-8.6659	0.0000	0.0707	0.0148	4.7805	0.0000	1.11e-18	7.3686e-04	1.5115e-15	0.9999	-1.30e-19	2.1680e-04	-5.9994e-16	0.9999	-7.70e-19	7.6686e-04	-1.0029e-15	0.9999
Turnover	0.0127	0.0031	4.0630	0.0001	0.0878	0.0026	33.1548	0.0000	3.00e-20	1.6133e-04	1.5707e-16	0.9999	3.30e-19	1.7422e-04	1.9002e-15	0.9999	1.30e-19	1.0150e-04	1.2634e-15	0.9999
Leverage	-0.0520	0.0193	-2.6970	0.0073	0.2501	0.0176	14.1984	0.0000	1.51e-18	1.0000e-05	1.5122e-13	0.9999	-1.53e-18	1.0000e-05	-1.53004e-13	0.9999	-1.97e-18	1.0000e-05	-1.9720e-13	0.9999
Sales/price	-0.0042	0.0302	-0.1383	0.8901	0.6307	0.0323	19.5555	0.0000	-6.90e-19	7.1363e-04	-9.6711e-16	0.9999	-1.90e-18	1.0000e-05	-1.8968e-13	0.9999	-3.11e-18	1.5545e-03	-1.9977e-15	0.9999

12 months

	Classical				TSCS				SM-SBM				SM-C5				SM-C15			
Variable	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val
Log of BM	-0.0131	0.0063	-2.0849	0.0376	-0.4870	0.0139	-34.9258	0.0000	0.0046	0.0036	1.2854	0.1993	0.0033	0.0034	0.9697	0.3327	0.0061	0.0038	1.5970	0.1110
Log of Size	0.5951	0.0263	22.5860	0.0000	2.9142	0.0451	64.6109	0.0000	0.0139	0.0028	4.9855	0.0000	0.0048	0.0026	1.8922	0.0591	0.0094	0.0030	3.1194	0.0019
Momentum	0.0445	0.0064	6.9297	0.0000	0.0676	0.0074	9.1567	0.0000	0.0137	0.0037	3.6906	0.0003	0.0072	0.0030	2.4443	0.0149	0.0043	0.0034	1.2797	0.2013
ROA	0.0052	0.0007	7.8828	0.0000	-0.0009	0.0006	-1.5521	0.1213	0.0007	0.0003	2.3917	0.0172	-0.0004	0.0002	-1.8415	0.0662	0.0001	0.0003	0.3033	0.7618
Asset growth	0.0236	0.0059	4.0391	0.0001	0.1125	0.0050	22.6003	0.0000	0.0065	0.0030	2.1365	0.0332	0.0068	0.0022	3.1332	0.0018	0.0042	0.0026	1.6247	0.1049
Beta	0.0164	0.0140	1.1715	0.2420	0.5822	0.0115	50.7015	0.0000	-0.0029	0.0036	-0.8252	0.4097	-0.0013	0.0031	-0.4307	0.6669	-0.0036	0.0032	-1.1210	0.2629
Accrual	-0.0008	0.0016	-0.4833	0.6291	0.0029	0.0011	2.5061	0.0126	0.0005	0.0010	0.4630	0.6436	-0.0001	0.0009	-0.0629	0.9499	-0.0002	0.0009	-0.2046	0.8380
Dividend	0.0013	0.0004	2.7993	0.0053	0.0063	0.0004	15.6846	0.0000	-0.0001	0.0001	-0.6638	0.5072	0.0000	0.0001	0.1819	0.8557	0.0003	0.0001	1.9129	0.0564
Log of LR ret.	0.0868	0.0113	7.6751	0.0000	0.1557	0.0107	14.5548	0.0000	0.0100	0.0037	2.7117	0.0069	0.0032	0.0032	0.9997	0.3180	0.0024	0.0033	0.7397	0.4599
Idio. Risk	-0.0023	0.0002	-11.9531	0.0000	0.0132	0.0002	56.6680	0.0000	0.0000	0.0000	-0.4974	0.6191	0.0000	0.0000	1.4079	0.1599	0.0000	0.0000	0.5633	0.5735
Illiquidity	-0.1984	0.0204	-9.7481	0.0000	0.0707	0.0148	4.7805	0.0000	-0.0054	0.0058	-0.9390	0.3482	-0.0096	0.0057	-1.6985	0.0901	-0.0022	0.0044	-0.5007	0.6168
Turnover	0.0124	0.0030	4.1690	0.0000	0.0878	0.0026	33.1548	0.0000	0.0010	0.0007	1.4712	0.1419	0.0011	0.0006	1.8774	0.0611	0.0019	0.0006	3.2760	0.0011
Leverage	-0.0513	0.0215	-2.3831	0.0176	0.2501	0.0176	14.1984	0.0000	-0.0030	0.0051	-0.5952	0.5520	-0.0031	0.0047	-0.6555	0.5124	-0.0064	0.0050	-1.2975	0.1951
Sales/price	-0.0243	0.0323	-0.7542	0.4511	0.6307	0.0323	19.5555	0.0000	0.0192	0.0105	1.8241	0.0688	0.0082	0.0085	0.9708	0.3321	0.0095	0.0093	1.0250	0.3059

36 months

	Classical				TSCS				SM-SBM				SM-C5				SM-C15			
Variable	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val	Diff in Mean	SE	t-val	p-val
Log of BM	0.0046	0.0084	0.5508	0.5821	-0.4341	0.0129	-33.5949	0.0000	0.0023	0.0042	0.5513	0.5817	-0.0021	0.0039	-0.5475	0.5843	-0.0017	0.0046	-0.3623	0.7173
Log of Size	0.5831	0.0288	20.2550	0.0000	2.7852	0.0437	63.7844	0.0000	0.0305	0.0036	8.3680	0.0000	0.0317	0.0034	9.4572	0.0000	0.0423	0.0039	10.7953	0.0000
Momentum	0.0352	0.0045	7.8682	0.0000	0.0576	0.0063	9.1111	0.0000	0.0154	0.0044	3.5286	0.0005	0.0126	0.0032	3.9885	0.0001	0.0114	0.0037	3.1101	0.0020
ROA	0.0040	0.0006	6.4601	0.0000	-0.0015	0.0005	-2.9289	0.0036	0.0021	0.0004	5.6387	0.0000	0.0008	0.0002	3.2446	0.0013	0.0014	0.0003	4.9779	0.0000
Asset growth	0.0053	0.0044	1.2044	0.2290	0.0906	0.0038	23.8618	0.0000	0.0109	0.0039	2.7884	0.0055	0.0109	0.0026	4.2644	0.0000	0.0079	0.0030	2.6292	0.0088
Beta	0.0234	0.0135	1.7295	0.0844	0.5596	0.0108	51.7643	0.0000	-0.0051	0.0057	-0.9089	0.3639	-0.0035	0.0043	-0.8218	0.4116	-0.0035	0.0041	-0.8520	0.3946
Accrual	-0.0016	0.0012	-1.3743	0.1700	0.0012	0.0008	1.4931	0.1361	0.0017	0.0013	1.3301	0.1841	0.0004	0.0010	0.3790	0.7048	0.0002	0.0010	0.1627	0.8708
Dividend	0.0011	0.0004	2.5903	0.0099	0.0066	0.0004	17.1850	0.0000	0.0000	0.0002	-0.0897	0.9285	0.0001	0.0001	0.3780	0.7056	0.0003	0.0002	1.8838	0.0602
Log of LR ret.	0.0591	0.0093	6.3335	0.0000	0.1223	0.0097	12.6542	0.0000	0.0095	0.0052	1.8224	0.0690	0.0146	0.0037	3.9584	0.0001	0.0175	0.0041	4.2156	0.0000
Idio. Risk	-0.0020	0.0002	-10.1988	0.0000	0.0128	0.0002	60.0597	0.0000	-0.0002	0.0001	-2.7446	0.0063	-0.0001	0.0000	-2.9416	0.0034	-0.0001	0.0000	-2.9825	0.0030
Illiquidity	-0.1994	0.0202	-9.8899	0.0000	0.0857	0.0137	6.2438	0.0000	0.0375	0.0082	4.5661	0.0000	0.0229	0.0065	3.5363	0.0004	0.0247	0.0061	4.0304	0.0001
Turnover	0.0129	0.0029	4.4754	0.0000	0.0798	0.0026	30.1572	0.0000	-0.0011	0.0010	-1.0397	0.2990	0.0000	0.0008	-0.0581	0.9537	0.0017	0.0008	2.2567	0.0245
Leverage	-0.0303	0.0219	-1.3794	0.1684	0.2708	0.0183	14.7670	0.0000	0.0038	0.0076	0.4948	0.6210	-0.0103	0.0059	-1.7393	0.0826	-0.0186	0.0058	-3.1959	0.0015
Sales/price	0.0117	0.0363	0.3212	0.7482	0.6951	0.0357	19.4606	0.0000	0.0433	0.0133	3.2523	0.0012	0.0003	0.0100	0.0342	0.9727	-0.0080	0.0111	-0.7212	0.4711

Differences in the variables for event and control firms pre-trend. Different matching methods are reported along different time horizons. Weighted stands for the assumed/pre-set pre-periods. For classical it is one period before the event. TSCS uses 12 months prior to the event with equal weights. SM methods use the estimated weights $\hat{\lambda}_{t,e}$. p-values are Bonferroni-adjusted p-values for having the same means pooled over all events.