Synthetic portfolio for causal event studies in finance

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Outline

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- Traditional event study methodology.
- Contribution: Synthetic portfolio method.
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- Applications.
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Event Studies

- *Analysis of whether there was a statistically significant reaction in financial markets to past occurrences of a given type of event that is hypothesized to affect public firms' market values*, D. Cram (MIT).
- Literature goes back to the 30's.
- Popularity late 60's (Corrado, 2011): CAPM, CRSP data, statistical software.
- Continues to be popular: long list of accounting and finance applications: M&A, earnings announcements, issuing new debt or equity, macroeconomic and regulatory announcements, name changes,.....
- Also used in certain legal proceedings (securities fraud).
- Data intensive and methodologically simple.
- Traditional method has not changes a lot apart from better tools for statistical inference (Corrado, 2011).

Causal inference

Research questions (using applied statistics) that are causal rather than descriptive (beyond correlation). Cross over many disciplines.

- Structural and graphical models (computer science), Pearl (2000), Pearl et al. (2016)
- Potential outcomes (social and biomedical sciences), Imbens and Rubin (2015), Murphy (2005).
- Economics (credibility revolution Angrist and Pischke, 2010), Marketing and Finance.

Research tools

- Randomized experiments (design of experiments), biomedical sciences mainly but also feasible in other disciplines, experimental economics, quantitative marketing.
- Natural experiments, social sciences (economics, public policy, political sciences).
- Observational studies; the data is there, how do we identify causal effects? approximate a random experiment.

Potential outcomes, Imbens and Rubin (2015)

- Causation ties to an action (treatment or intervention) applied to a unit.
- Set up is an experiment where units are grouped into: control and treatment.
- Potential outcome is an associated realization to a action-unit pair.
- If some potential outcomes are not observable they can be considered as missing data.
- Conditions under which we can learn about causal effects (stable unit treatment value assumptions).

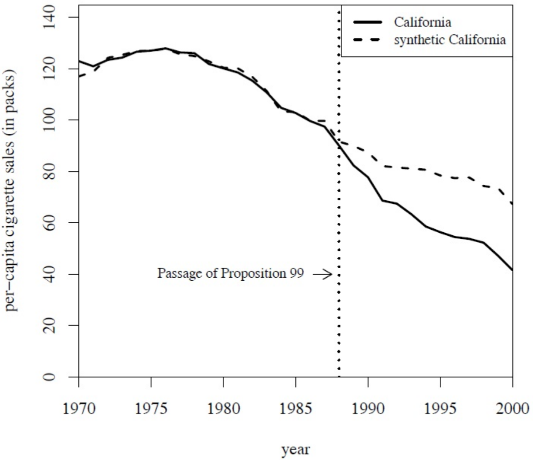
Potential outcomes for observational studies

In observational studies is not possible to observe all instances of the variable of interest, for example the non-treated unit after an event takes place: A missing variable problem.

1. Model base imputation.
2. Weighting and blocking (with control units).
3. Matching (with control units).
4. Combine 2 and 3.

Weighting and matching: Synthetic Control Method, Abadie, Diamond and Hainmueller (2010)

Comparative case studies compare the evolution of a variable of interest from a unit (1) affected by an intervention to the evolution of the variable of interest for a control group. synthetic control return



Traditional event studies

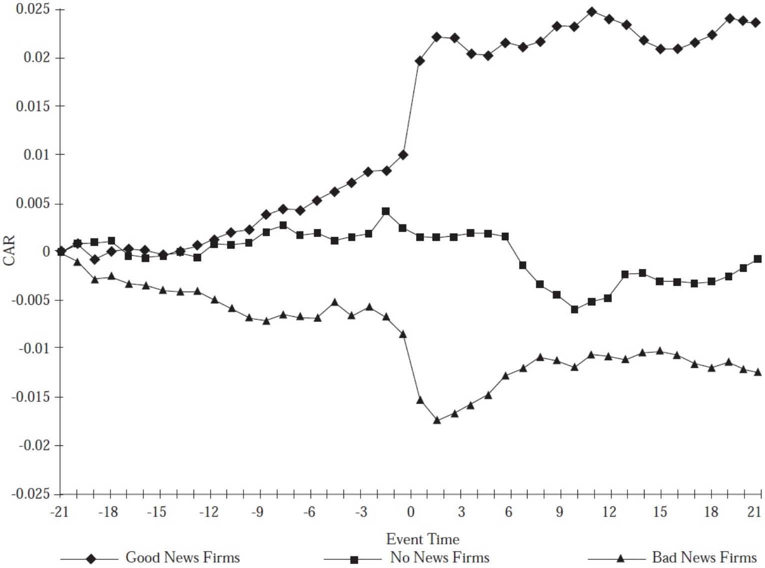
In traditional event studies (model based imputation) the potential outcome are the "normal" returns, $R^N_{1,t} := E[R_{1,t} \mid R_{m,t}]$,

$$R_{1,t} = \hat{\alpha}_i - \hat{\beta}_i R_{m,t}, t \in [T_1, T_3]$$

where $R_{m,t}$ denotes the market return and $R_{1,t}$ the stock return of firm 1 affected by the event. The parameters of the market model (1 factor model) are estimated using the information from the estimation window. The treatment effect (abnormal returns) is:

$$AR_{1,t} = R_{1,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}, t \in [T_4, T_5]$$

Traditional event studies: Earning announcements, MacKinlay (1997)



Contribution

Provide a causal inference method to perform event studies in finance.

- The approach is based on synthetic control methods. synthetic control
- Provide a set of estimators that can handle high-dimensional problems. The method provides automatic pruning of the control group.
- Contributes to growing tools of causal inference in finance: alternative to propensity score matching. propensity score
- To the best of our knowledge we are the second paper to apply a synthetic matching (Acemoglu et al, 2016) and the first to document the methodology.

Synthetic Portfolio Method

Simple extension of Synthetic Control Method is to perform index tracking, that is, we estimate w^* by minimizing the tracking error in the estimation window $t \in [T_1, T_3]$ and then we predict the synthetic portfolio in the event window $t \in [T_4, T_5)$.

$$\underset{w}{\text{minimize}} \sum_{t=T_1}^{T_3} \left(R_{1,t} - \sum_{j=2}^{J} w_j R_{j,t} \right)^2$$

where $(R_{2,t}, \ldots, R_{J,t})$ are the set of stock that make up the control group (firms that have not been affected by the event). A portfolio optimization problem it is possible to include additional restrictions: non-negative weights $(w_j \geq 0)$, $\sum_{j=2}^{J} w_j = 1$.

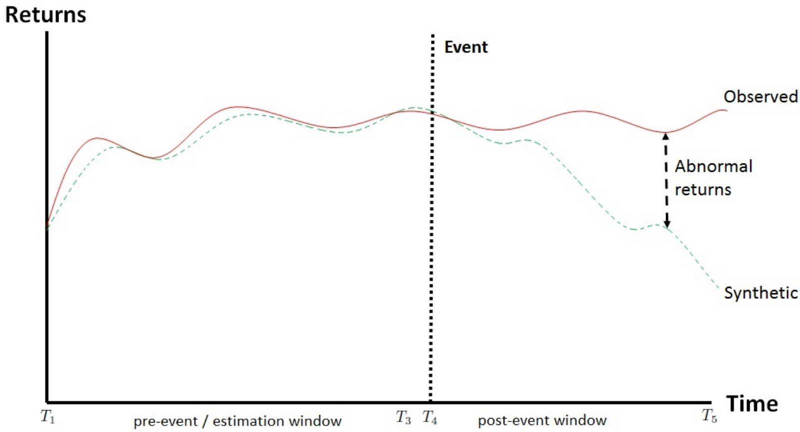
Synthetic Portfolio Method

The effect of the intervention is equivalent to the abnormal returns of the asset of interest,

$$\hat{\alpha}_{1,t} = AR_{1,t} = R_{1,t} - R^N_{1,t} = R_{1,t} - \sum_{j=2}^{J} w_j^* R_{j,t}, t \in [T_4, T_5]$$

- Finding the potential outcome is equivalent to portfolio optimization problem.
- The potential outcome is a cross-sectional weighted average over (all) available stock not affected by intervention. These asset are traded at the same time.

Synthetic Portfolio Method



Regularized Synthetic Portfolio Method

Synthetic portfolio method is only feasible if the the number of stocks in the control group are of moderate size with respect to the size of the estimation window (the number of pre-treatment outcomes) $J << T_3 - T_1$. In other words, we need sufficient time series observations to be able to estimate the J-dimensional vector of portfolio weights.
Explore regularization techniques in portfolio optimization (ill-posed problem).

Regularized Synthetic Portfolio Method

- LASSO regression
- Elastic net (linear combination of LASSO and Ridge regression)
- Naive synthetic portfolio
- Portfolio policy function (introduce co-variates), Brand et al (2009).

A recent generalization of synthetic control methods, Doudchenko and Imbens (2017) also borrows these techniques to deal with a mid-size-dimensional space of features, explanatory variables and/or control units.

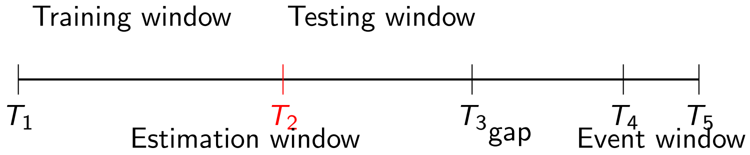
Regularized Synthetic Portfolio Method

LASSO regression

$$\underset{w}{\text{minimize}} \sum_{t=T_1}^{T_3} \left(R_{1,t} - \sum_{j=2}^{J} w_j R_{j,t} \right)^2 + \tau \sum_{j=2}^{J} |w_j|$$

Elastic net (linear combination of LASSO and Ridge regression)

$$\underset{w}{\text{minimize}} \sum_{t=T_1}^{T_3} \left(R_{1,t} - \sum_{j=2}^{J} w_j R_{j,t} \right)^2 + \tau \left(\frac{1-\alpha}{2} \sum_{j=2}^{J} w_j^2 + \alpha \sum_{j=2}^{J} |w_j| \right)$$



Regularized Synthetic Portfolio Method

Naive synthetic portfolio (equal weights, no estimation)

$$\hat{\alpha}^{\bar{w}}_{1,t} = AR_{1,t} = R_{1,t} - R^{\bar{w}}_{1,t} = R_{1,t} - \frac{1}{J-1}\sum_{j=2}^{J} R_{j,t},\ t \in [T_4, T_5]$$

Regularized Synthetic Portfolio Method

Portfolio policy function (introduce co-variates), Brand et al (2009).

$$\underset{\theta}{\text{minimize}} \sum_{t=T_1}^{T_3} \left(R_{1,t} - \sum_{j=2}^{J} \left(\bar{w}_j + \theta X_j \right) R_{j,t} \right)^2$$

- $\bar{w}_j$ is the weight of benchmark (value weighted or naive) portfolio weight for stock j.
- X_j standardized cross-sectionally characteristics (size, value and momentum) of the stock j.
- θ parameters, whose role is to modify the benchmark portfolio in (or away) the direction from an specific anomaly.

Simulation: traditional vs regularized synthetic portfolio

- Perform simulation (1000) over asset space of 500 assets using two different data generating process (for all of the assets):
  - $R_{i,t} = \alpha + \beta R_{m,t} + \gamma \mathbf{1}_{t=T_E} + \varepsilon_{i,t}$
  - $R_{i,t} = \alpha + \phi R_{i,t-1} + \gamma \mathbf{1}_{t=T_E} + \varepsilon_{i,t}$.
- We design the asset of interest with a β of a particular value or change the value of the parameter of the AR(1) process.
- Treatment is created as a structural change in the intercept at the event date.
- We look at the performance of the estimators using the mean square error in the testing window and the average treatment effect.

Simulation: traditional vs regularized synthetic portfolio

Estimator	DGP:1-factor model $\beta = 0.5$	$\beta = 1$	DGP:Autoregressive model $\phi = 0$	$\phi = 0.5$
Market	25.019	**25.275**	25.162	**33.616**
Syn.Lasso	26.960	27.682	27.051	38.518
Syn.Elastic-Net	31.211	31.869	31.356	43.187
Syn.naive	**24.895**	25.338	**25.041**	33.144
$w_j \geq 0$				
Syn.Lasso	26.222	26.317	26.249	34.433
Syn.Elastic-Net	25.555	25.893	25.521	33.997

Table 1: Mean square error (testing window)

Simulation: traditional vs regularized synthetic portfolio

	DGP:1-factor model		DGP:Autoregressive model	
Estimator	$\beta = 0.5$	$\beta = 1$	$\phi = 0$	$\phi = 0.5$
Market	-0.098	-0.098	0.000	-0.082
Syn.Lasso	-0.060	-0.061	0.006	-0.042
Syn.Elastic-Net	-0.060	-0.098	0.029	-0.044
Syn.naive	-0.105	-0.096	-0.004	**-0.035**
$w_j \geq 0$				
Syn.Lasso	**-0.031**	-0.074	**-0.044**	-0.047
Syn.Elastic-Net	-0.027	**-0.060**	-0.049	-0.052

Table 2: Average Treatment Effect, $\gamma = -0.035$

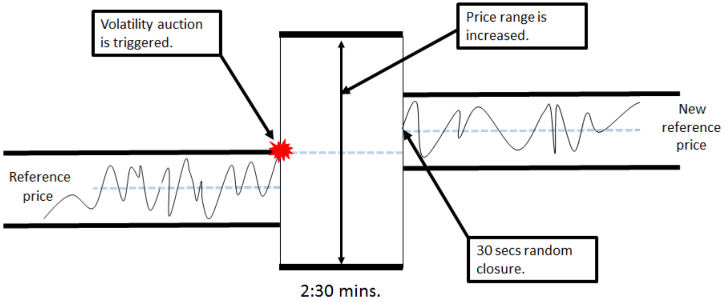
Empirical applications

- No-Regularization ($J < T_3 - T_1$), $J < 10$ and 5 minutes data, 50 data points.
  - **Measuring the effectiveness of volatility auctions**, joint work with Agudelo (EAFIT) and Preciado, R&R: *International Review of Finance*. volatility auctions
- Regularization ($J >> T_3 - T_1$), $J > 5000$ and daily data, 250 data points.
  joint work with Cristian Pinto (UCONN).
  - **Merger announcements**: re-examine market reaction for the bidder and target. m&a
  - Seasoned equity offerings (new equity issue by an already publicly traded company): re-examine short run under performance that is documented in the literature.

Volatility auctions, volatility interruptions, reservation period

- Intraday market, circuit breakers and trading halts. intraday market
- They are present in many European markets (Deutsche Borse, Euronext, Bolsa de Madrid); in the US there is a similar mechanism known as Limit Up-Limit Down, proposed in 2011.
- Strong debate on market crash scenarios based on malfunctioning algorithms or investor overreaction.
- Auctions are already present to open and close the market (mid day auctions), in between there is continuous trading (for the more liquid stocks).
- General idea and design of these interruptions is more or less uniform in all trading venues (Gomber et al, 2011)

Volatility auctions



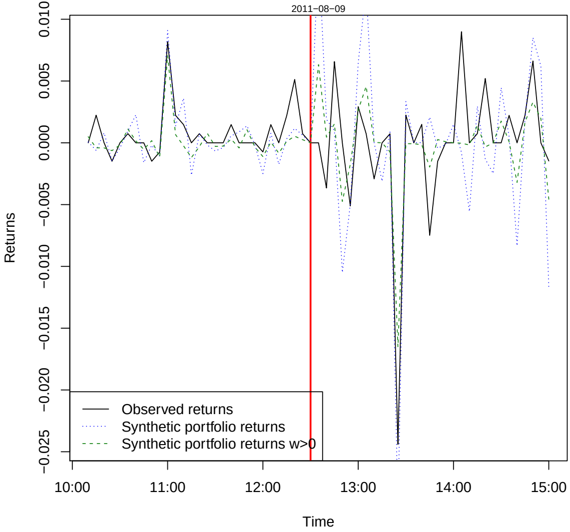
Volatility call auctions and data

- In 2009 the Bolsa de Valores de Colombia (BVC), the Colombian Stock Exchange, changed the stock trading platform. The new platform incorporated features such as volatility call auctions.
- In the Colombian case stocks have price limits defined using deviations of the closing price of the previous day of trading, according to the volatility there are three price intervals (6.5%, 5.5%, and 4%).
- The auction last for two and a half minutes and has a 30 seconds random closure.

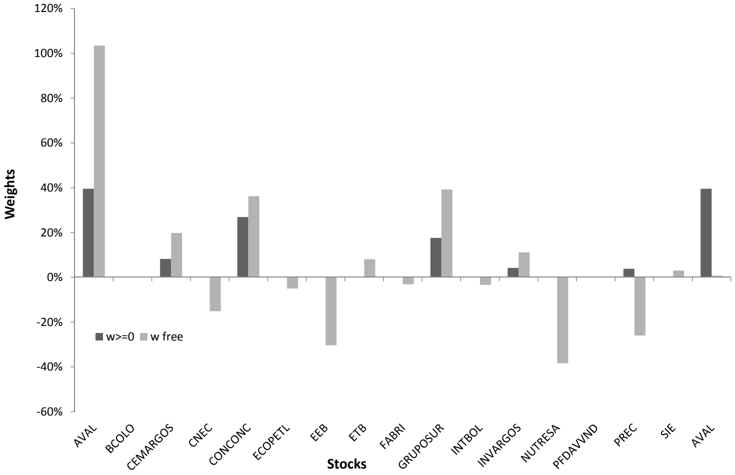
Trade and Quote data (TAQ)

- 45 listed stocks.
- Intra-day data (less incidence of confounding effects) from August 2010 to August 2012.
- Total number of volatility auctions 1062, perform analysis on 184(transactions) to 442(mid price).

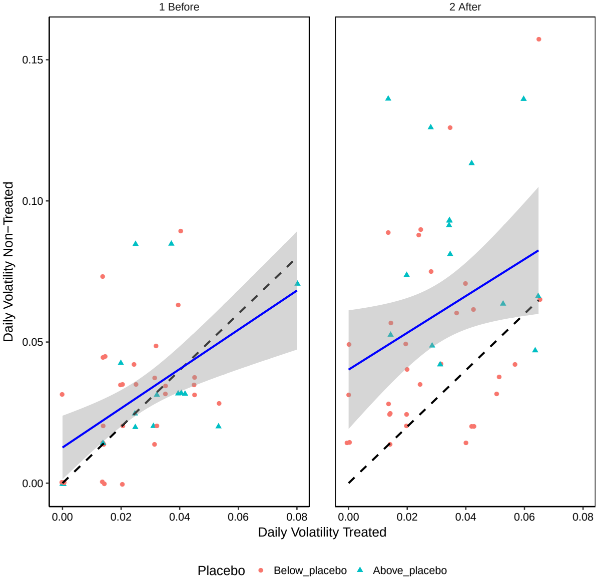
Synthetic portfolio performance



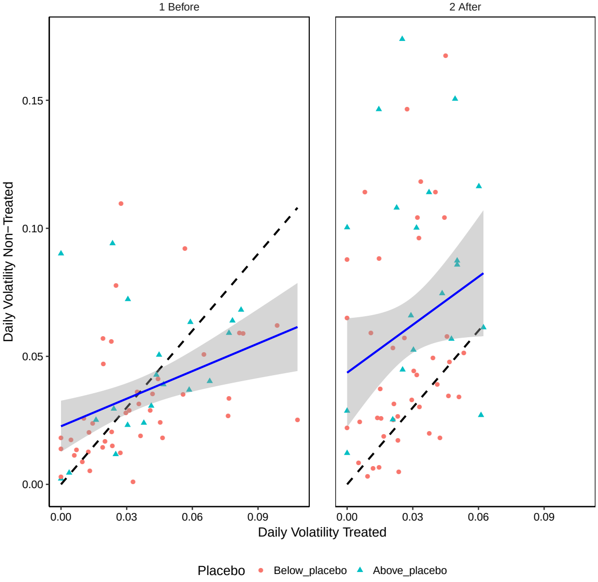
Synthetic portfolio performance



Are volatility call actions working?, trades



Are volatility call actions working?, trades, 1h



Impact on market quality of the volatility auction

	End of the trading day		1h before and after	
Difference (After- Before)	Treated	Non-Treated	Treated	Non-Treated
Trades -observed	1.02%*	2.20%***	-0.21%	1.98%***
Mid Price -fundamental	0.00%	7.90%***	-0.28%	3.8%***
Quote Bid-Ask Spread	-0.70%***	-1.00%***	0.09%	-0.30%***
Efective Spread	-0.20%	-0.30%***	0.04%	-0.17%***
Bid Depth	-11.37***	23.38***	-7.43***	17.56***
Ask Depth	0.70	-2.08	2.58	9.82
Spread Depth	-0.01%*	-0.02%***	0.00%**	0.00%**
Turnover	3.60	0.66	-4.44	-6.74

M&A announcements: Short review of the literature, large sample ($N > 1000$)

Study	ACAR %	sample and results		
M&A Announcement-induced ACAR to U.S. Bidders, large sample (1980-2002)				
		total sample	target public	target private
Fuller, Netter, and Stegemoller (2002)	(-2,2)	1.80	-1.00	2.10
Bradley and Sundaram (2006)	(-2,2)	1.40	-0.70	1.90
Betton, Eckbo, and Thorburn (2009)	(-1,1)	-1.20		
			sic related	sic unrelated
Akbulut and Matsusaka (2003)	(-2,1)		1.20	1.10
			all stock	all cash
Savor (2006)	(-1,1)		-3.50	1.00
			public all-stock	private all-stock
Moeller, Shlingemann and Stultz (2007)	(-1,1)	0.80	-2.30	3.40
M&A Announcement-induced ACAR to U.S. Bidders, large sample (1985-2009), Propensity Score				
			all-stock	all-cash
Golubov, Petmezas, Travlos (2015)	(-2,-2)	-1.31	-2.29	0.50
with propensity score and accounting for SEO		0.91		
			No PSM	PSM
difference all-stock, all-cash			2.79	1.53
Petrova and Shafer (2010)	BHAR	-0.01		
M&A Announcement-induced ACAR to U.S. Target, large sample (1980-2002), Propensity Score				
			bidder public	bidder private
Svetina (2012)	(-1,1)		27.79	17.69

M&A announcements: Regularized Synthetic Portfolio

	ACAR (-1,1) %			Absolute Difference wrt Market (individual events)	
Bidders	Market	Lasso	Naive	Lasso	Naive
Total sample	0.64	0.61	0.69	1.93***	0.81***
Public target	-0.57	-0.61	-0.58	2.01***	0.78***
Private target	0.90	0.88	0.97	1.90***	0.82***
All-cash	0.62	0.57	0.67	1.89***	0.79***
All-stock	0.37	0.24	0.35	1.95***	0.96***
Undiversified	0.58	0.58	0.66	1.99***	0.85***
Diversified	0.63	0.58	0.67	1.88***	0.78***
1 bidder	0.61	0.57	0.66	1.92***	0.81***
$>$ 1 bidder	0.95	1.65	0.97	2.13**	1.05**
Target					
total sample	19.86	19.95	19.89	2.52**	0.99**

Table 3: M&A Announcement-induced ACAR to U.S., large sample (2003-2014)

Example: MSFT-YHOO, 2008

Conclusions, synthetic portfolio method

Method

- Synthetic portfolio provides a simple tool to build potential outcomes in a data rich environment, financial event studies using market data.
- Regularized synthetic control estimates are less biased than traditional method even when the true data generating process is the one-factor model.
- **To do:** Still need to asses the introduction of exogenous variables (is the role equivalent to regularization or complementary). Portfolio policy function. Does it provide useful conditional interchangeability of the units?

Limitations, synthetic portfolio method

Limitations.

- No calendar based events (earning announcements), not so feasible to build a control group.
- Causal inference for observational studies is still in its infancy, some statistical inference has not been fully developed.
- How convincing is the argument that there is no need for exogenous variables, tracking portfolio argument?

Conclusions, Applications

Application: Volatility auctions.

- Average effect of the volatility auction is between 1.2% and 8% less volatility after continues trading resumes. Using the data just one hour before and after the auction the effect is between 2.2% and 4%.
- Mixed results with before and after data (increases with trade, decreases with mid-price).
- No effect on other dimensions of market quality.

Conclusions, Applications

Application: Mergers and Acquisitions.

- The average cumulative abnormal returns from synthetic portfolio are not different from the results based on traditional methods. There is no change in the direction of the effects (public/private targets, bidder/target, cash/stocks,...).
- However, the absolute difference do indicate that CAR measured using synthetic portfolio show a larger effect on each event, on average $1\% - 2\%$ above or below the estimated treatment effect by traditional methods.
- Large cross-sectional variation in CAR does not seem to be exploited by researchers, quantile regression?
- Still we need to compare the historical sample (1985-2002).

Synthetic Control Method, Abadie, Diamond and Hainmueller (2010)

1. $J+1$ units. Unit 1 exposed to intervention from $T_0+1,\ldots,T$.
2. $Y_{i,t}^{I}$ outcome with the intervention.
3. $Y_{i,t}^{N}$ outcome absent the intervention (not observable).
4. Suppose that $Y_{i,t}^{N}$ is given by a factor model.

$$Y_{i,t}^{N}=\gamma_t+\theta_t\mathbf{Z}_i+\lambda_t\mu_i+\varepsilon_{i,t}$$

5. Effect of the intervention, $\hat{\alpha}_{1,t}=Y_{1,t}-\sum_{j=2}^{J}w_j^*Y_{j,t}$
6. w_j^* is estimated by finding a synthetic control unit that best matches the behavior of unit 1 before the intervention.
7. Minimum distance estimator on, $\sum_{j=2}^{J+1}w_j^*Y_{j,1}=Y_{1,1},\ldots,\sum_{j=2}^{J+1}w_j^*Y_{j,T_0}=Y_{1,T_0}$ and $\sum_{j=2}^{J+1}w_j^*Z_j=Z_1$

return

Propensity score matching: method

Match treated and control observations on the estimated probability of being treated. The scores can be used to reduce or eliminate selection bias in observational studies by balancing covariates (the characteristics of participants) between treated and control groups. When the covariates are balanced, it become much easier to match participants with multiple characteristics. Key assumption is that participation in treatment is unrelated to the characteristics. Involves various steps.

1. Data on treated and control units
2. Logistic regression to estimate treatment participation as a function of characteristics.
3. Estimated propensity score of each unit.
4. Match pairs
5. Calculate treatment effects by comparing the means of outcomes across participants and their matched pairs.

There is a recent debate the risk of using propensity score matching, King and Nielsen (2016). return

How do we buy and sell liquid securities in organized exchanges?

Auctions

Call Auctions (open, close the market, mid day, volatility)

- Coordinated orders (batched together)
- Multi-lateral.
- Simultaneous execution
- Single price (sharpen the accuracy of price discovery process).
- BVC: close $(14:55-15:00)$ $(15:55-16:00)$.

Continuous trading

- Orders are matched according to sequence of arrival.
- Bi-lateral
- Transaction prices distributed over wide range of prices (in brief time intervals). Prices more likely to reflect transitory noise.
- BVC: $(8:30-14:55)$ $(9:30-15:55)$.

Circuit breakers

- Circuit breakers are mechanisms implemented in trading platforms at stock exchanges to provide time for agents to assimilate new information in a continuous trading environment in order to enhance the price discovery process.
- There is no consensus with respect to the need and the effectiveness of circuit breakers (in efficient markets there is no need of them). Cooling off period vs undesirable intrusion in the market.
- Regulatory interest in a mechanism to prevent market turmoil due to overreaction from investors or malfunctioning trading algorithms.
- EURO SEC called for further empirical evidence (European Commission, 2010)
- Circuit breakers can have different designs (rule base vs discretionary) that may be used simultaneously.

Trading Halts

- Discretionary, firm specific or market wide.
- Empirical evidence provides mixed results (US and other markets).
- US markets (NYSE, NASDAQ): increased trading activity and volatility after halts, trader are able to revise their trading intentions, clearing price is informative on future prices.
- Spanish market: trading activity increases, narrower spreads but volatility remains the same.

return