Synthetic portfolio for causal event studies in finance

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Outline

Event studies and causal inference

Contribution: synthetic portfolio/matching

Simulation

Applications

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, CRISP 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 description or association. 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, 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).

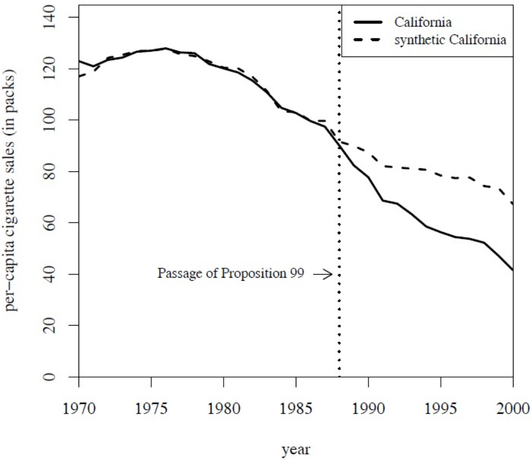
Potential outcomes for observational studies

In observational studies is 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.



Traditional event studies

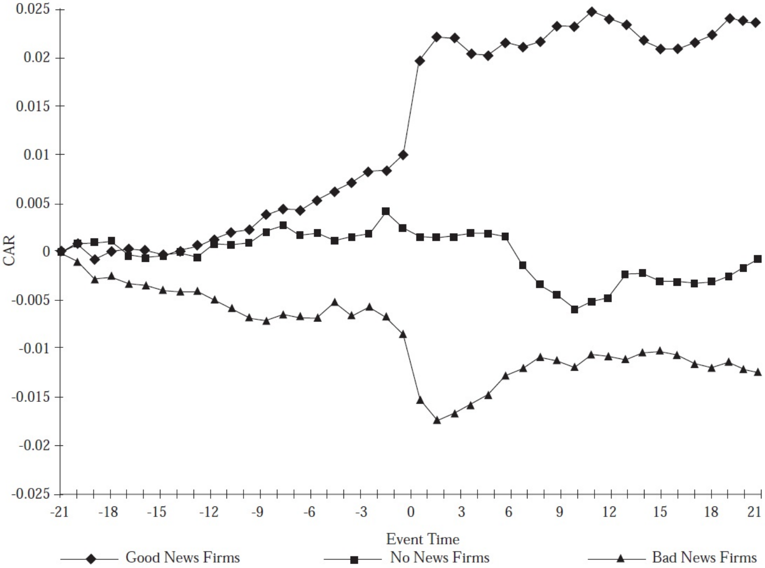
In traditional event studies (model based imputation) the potential outcome are the "normal" returns, $R^N_{1,t} := E[R_{1,t} \mid R_{m,t}]$,

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

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.
- Provide a set of estimators that can handle high-dimensional problems.
- 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 an portfolio optimization problem it is possible to include additional restrictions: non-negative weights $(w_j \geq 0)$, $\sum_{j=2}^{J} w_j = 1$.

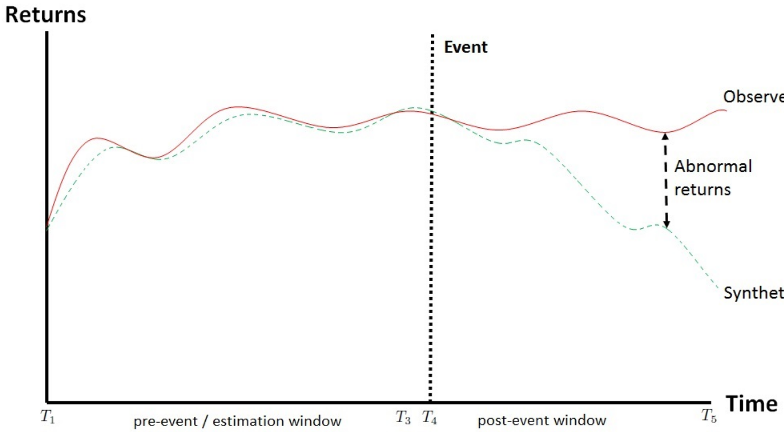
Synthetic Portfolio Method

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).

- 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.

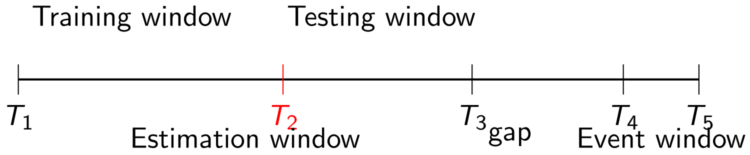
Regularized Synthetic Portfolio Method

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)

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



Regularized Synthetic Portfolio Method

Naive synthetic portfolio (equal weights, no estimation)

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

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

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

where $\bar{w}_j$ is the weight of stock j in a benchmark portfolio, such as the value weighted market portfolio or the naive (equal) weighted portfolio, X_j are standardized cross-sectionally characteristics of the stock j and θ is a set of parameters to estimate that modify the benchmark portfolio in (or away) the direction from an specific anomaly (size, value and momentum).

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, -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, RR: *International Review of Finance*.
- Regularization ($J >> T_3 - T_1$), $J > 5000$ and daily data, 250 data points.
  joint work with Cristian Pinto (UCONN).
  - Merger announcements: re-examine under (over) performance for the public bidder (target).
  - Seasoned equity offerings (new equity issue by an already publicly traded company): re-examine long run under performance that is documented in the literature.

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.

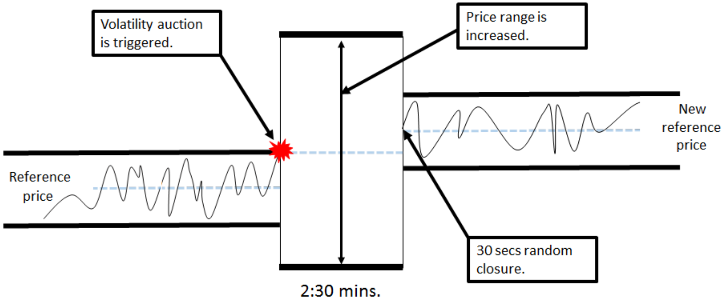
Trading Halts

- 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.

Volatility auctions, volatility interruptions, reservation period

- 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



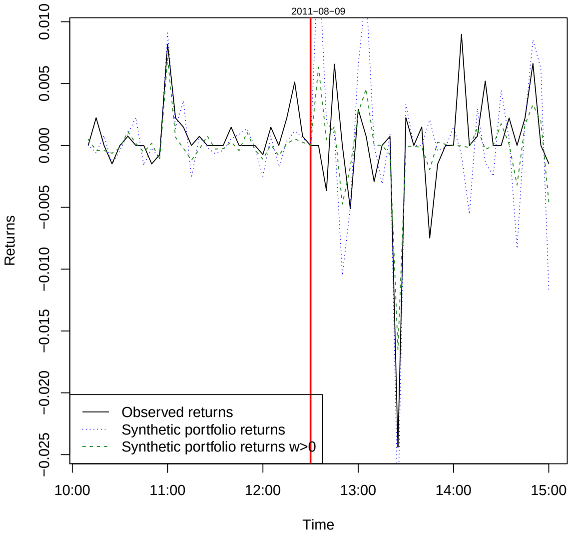
Volatility call auctions and data

- 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.

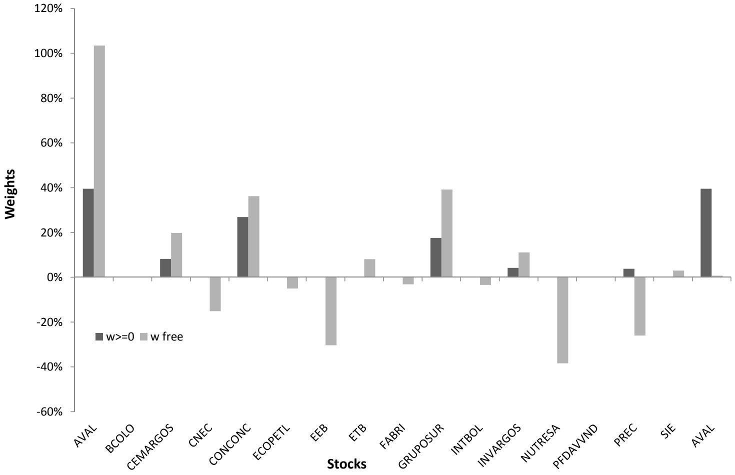
Trade and Quote data (TAQ)

- 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).

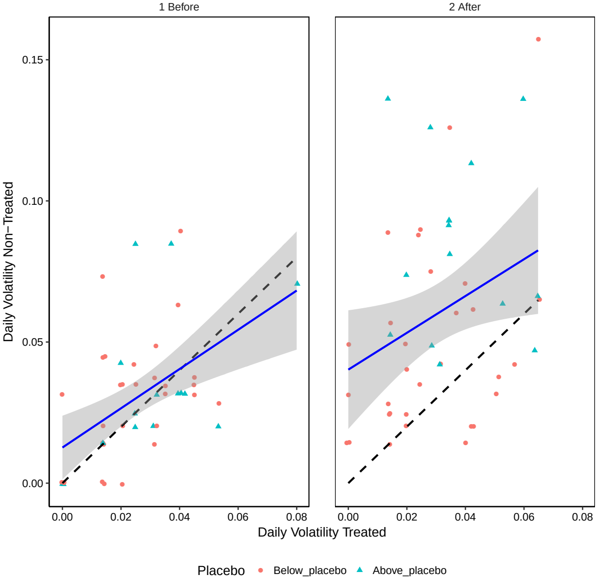
Synthetic portfolio performance



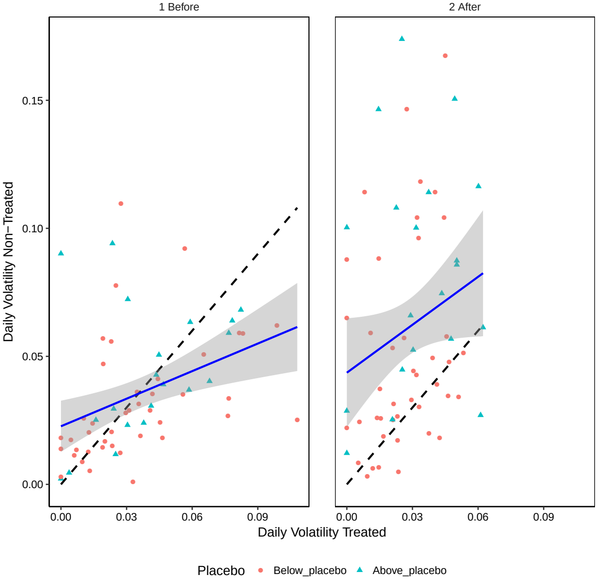
Synthetic portfolio performance



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

Conclusions

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 estimated 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.

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.

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.

Propensity score matching: applications in finance

Li and Zhao (2006), Propensity score matching and abnormal performance after seasoned equity offerings, Journal of Empirical Finance

- Result with traditional is under performance (anomaly) why buy SEO.
- Propensity score matching (size, book-to-market ratio, momentum) issuer and non-issuers, under performance is economically and statistically not significant.

Svetina (2012), Managerial motives in mergers: propensity score matching approach, Managerial and decision economics.

- Traditional methods show that managers of public firms overpay for acquisitions relative to private equity acquires.
- After accounting for biased in the sample (using propensity score). Public and private acquires select firms that have significantly different characteristics and the deals are also different and this accounts for the difference.