Possible topics for the Master/PhD dissertation

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Overview of the Presentation

Introduction

First of all, I strongly encourage students to consider the topics discussed below not only for a potential master, but also as potential topics to be developed further during a future PhD in economics.

 \Rightarrow In this regard, I want to remark that I can be a PhD supervisor at the Moscow School of Economics (MSE-MGU).

Note that at the MSE you can attend either an *academic PhD* (where you get a monthly salary, but you have to be at the faculty every week), or a *paid PhD* for private workers, where you do not need to be a full-time university worker (you only have to pass a certain number of courses and the final defense), but you have to pay the yearly tuition yourself.

Possible topics for master diploma

- What is driving the bitcoin price?
- Is there a Saudi floor and a Chinese ceiling in the oil market?
- Forecasting of Russian inflation using Google Trends and multivariate models.

Some More Details about Each Topic

After my latest paper published in JRFM (https://www.mdpi.com/1911-8074/13/11/263), this is the main question.

I have some clues, like many people dealing with cryptocurrencies. Simply speaking, I have two suspects:

- a) Bitcoin scarcity (bitcoin is deflationary by construction)
- b) Massive liquidity injections by central banks worldwide to offset the Covid-19 crisis (and the past crises as well)
- c) Market Manipulation?

a) Bitcoin scarcity (bitcoin is deflationary by construction)

The post by PlanB $(2019)^1$ represents one of the most impactful articles in cryptoasset valuation research among professionals. PlanB (2019) posits that there is a relationship between the BTC's value and its stock-to-flow ratio, where the stock-to-flow (SF) ratio is defined as the inverse of annualized supply issuance, and represents the BTC's scarcity and suitability as a store of value.



 $^{1} https://medium.com/@100 trillionUSD/modeling-bitcoins-value-with-scarcity-91 fa0 fc0 3e25$

a) Bitcoin scarcity (bitcoin is deflationary by construction)

	Stock (tn)	Flow (tn)	SF	supply growth	Price \$/Oz	Market Value
gold	185,000	3,000	62	1.6%	\$ 1300	\$ 8,417,500,000,000
silver	550,000	25,000	22	4.5%	\$ 16	\$ 308,000,000,000
palladium	244	215	1.1	88.1%	\$ 1400	\$ 11,956,000,000
platinum	86	229	0.4	266.7%	\$ 800	\$ 2,400,000,000



a) *Bitcoin scarcity*: daily updated charts of Bitcoin's stock-to-flow vs price available at https://s2f.hamal.nl/s2fcharts.html



Bitcoin daily stock-to-flow and price

a) *Bitcoin scarcity*: daily updated charts of Bitcoin's stock-to-flow vs price available at https://s2f.hamal.nl/s2fcharts.html



Bitcoin log stock-to-flow vs log price

- \rightarrow Note that there are several ways to measure bitcoin scarcity:
 - Bitcoin balance on exchanges (data from Cryptoquant https://cryptoquant.com/overview/btc-exchange-flows):



- \rightarrow Note that there are several ways to measure bitcoin scarcity:
 - Quantification of the amount of liquid and illiquid BTC supply (data from Glassnode - https://insights.glassnode.com/bitcoin-liquid-supply/):



b) Massive liquidity injections by central banks

"Bitcoin is the new darling among investors in time of negative real rates and as the price of cryptocurrency follows the combined balance sheet of Central Banks" (Die Welt, August 2020)



c) Market Manipulation?

Tether USD: Circulating Supply vs. Bitcoin: Price (USD)



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c) Market Manipulation?

Griffin, J. M., Shams, A. (2020). Is Bitcoin really untethered?. *The Journal of Finance*, 75(4), 1913-1964.



ABSTRACT

This paper investigates whether Tether, a digital currency pegged to the U.S. dollar, influenced Bitcoin and other cryptocurrency prices during the 2017 boom. Using algorithms to analyze blockchain data, we find that purchases with Tether are timed following market downturns and result in sizable increases in Bitcoin prices. The flow is attributable to one entity, clusters below round prices, induces asymmetric autocorrelations in Bitcoin, and suggests insufficient Tether reserves before month-ends. Rather than demand from cash investors, these patterns are most consistent with the supply-based hypothesis of unbacked digital money inflating cryptocurrency prices.

 \Rightarrow Idea 1) Use alternative measures of Bitcoin scarcity (for robustness), the amount of central banks assets, and proxy measures of market manipulation to verify whether these three factors significantly affect the bitcoin price: cointegration tests, Granger-causality tests, etc.

 \Rightarrow Idea 2) Of course, other factors can be used!

 \Rightarrow Note that while some papers found statistically significant cointegration between the bitcoin market value and the stock-to-flow ratio with high goodness of fit², however, there maybe problems with structural breaks and the evidence is not so strong when using ARDL tests for cointegration.

 $^{^2 {\}sf See https://medium.com/burgercrypto-com/reviewing-modelling-bitcoins-value-with-scarcity-part-ii-the-hunt-for-cointegration-66a8dcedd7ef}$

Other useful references (with some good survey):

- Marthinsen, J. E., Gordon, S. R. (2022). The price and cost of bitcoin. The Quarterly Review of Economics and Finance, 85, 280-288.
- Ahmed, W. M. (2022). Robust drivers of Bitcoin price movements: An extreme bounds analysis. The North American Journal of Economics and Finance, 62, 101728.
- Bakas, D., Magkonis, G., Oh, E. Y. (2022). What drives volatility in Bitcoin market?. *Finance Research Letters*, 50, 103237.
- Koutmos, D. (2023). Investor sentiment and bitcoin prices. Review of Quantitative Finance and Accounting, 60(1), 1-29.
- Clark, E., Lahiani, A., Mefteh-Wali, S. (2023). Cryptocurrency return predictability: What is the role of the environment?. *Technological Forecasting and Social Change*, 189, 122350.

The concept of a "Saudi floor" and a "Chinese ceiling" in the oil market refers to the perceived roles that Saudi Arabia and China play in influencing oil prices by adjusting their production and consumption levels.

Saudi Floor: Saudi Arabia is one of the largest oil producers and exporters in the world. Historically, the country has acted as a swing producer, meaning it adjusts its oil production levels to help stabilize prices. The Saudis have sometimes increased or decreased production to counteract extreme price fluctuations. They have an interest in preventing oil prices from falling too low, as this can hurt their economy, which heavily relies on oil revenue. This behavior can be seen as providing a "floor" to prevent prices from crashing too low.

Chinese Ceiling: China is one of the world's largest oil consumers and importers. As its economy has grown, its demand for oil has also increased significantly. When oil prices rise too high, it can have negative effects on China's economy, as it becomes more expensive to fuel its industries and transportation systems. Therefore, China might take measures to limit its oil consumption or find alternatives when prices become too high, potentially creating a "ceiling" on how much they are willing to pay for oil.

While the idea of a Saudi floor and a Chinese ceiling might have some basis in reality, it's important to note that the global oil market is incredibly complex, influenced by a multitude of factors beyond just the actions of these two countries.

Idea 1: verify this hypothesis using dynamic threshold cointegrated models, where the thresholds can depend on Saudi and Chinese oil data.

- Yang, L. (2021). Time-varying threshold cointegration with an application to the Fisher hypothesis. *Studies in Nonlinear Dynamics and Econometrics*, 26(2), 257-274. ⇒ Free Gauss code available.
- Park, H., Mjelde, J. W., Bessler, D. A. (2007). Time-varying threshold cointegration and the law of one price. *Applied Economics*, 39(9), 1091-1105. ⇒ You can estimate the model in a 2-step process and the tsDyn R package in the second step.

Idea 2: Verify that the influence of Saudi an Chinese oil market interventions changed over time using time-varying VAR models:

- Bayesian time-varying VAR by Primiceri (2005, Time Varying Structural Vector Autoregressions and Monetary Policy, *Review of Economic Studies*) implemented in the bvarsv R package;
- Bayesian time-varying VAR by Chan, J. C., Jeliazkov, I. (2009, Efficient simulation and integrated likelihood estimation in state space models, *International Journal of Mathematical Modelling and Numerical Optimisation*) implemented in Eviews 13.
- Non-parametric time-varying VAR by Casas, Isabel and Fernandez-Casal, Ruben (2022, tvReg: Time-varying Coefficient Linear Regression for Single and Multi-Equations in R, *R Journal*)

The starting point is the benchmark forecasting model by Kilian and Murphy (2014) and Baumeister, Kilian and Lee (2014),

$$B(L)\mathbf{Y}_t = \boldsymbol{\nu} + \mathbf{u}_t$$

where $\mathbf{Y}_t = [\Delta prod, rea_t, r_t^{oil}, \Delta inv_t]'$ refers to a vector including

- the percent change in global crude oil production,
- a measure of global real economic activity,
- the log of the U.S. refiners' acquisition cost for crude oil imports deflated by the log of the U.S. CPI,
- and the change in global crude oil inventories,

where ν denotes the intercept, B(L) is the autoregressive lag order polynomial of order 24 and \mathbf{u}_t a white noise innovation. Centered seasonal dummies are also added.

Other useful references:

- Kilian, L., and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3), 454-478.
- Baumeister, C., Kilian, L., Lee, T. K. (2014). Are there gains from pooling real-time oil price forecasts?. *Energy Economics*, 46, 33-43.
- Miao, H., Ramchander, S., Wang, T., & Yang, D. (2017). Influential factors in crude oil price forecasting. *Energy Economics*, 68, 77-88.
- Lycheva, Maria, Alexey Mironenkov, Alexey Kurbatskii, and Dean Fantazzini (2022). Forecasting oil prices with penalized regressions, variance risk premia and Google data. *Applied Econometrics*, 68: 28-49.
- Kilian L., Zhou X. (2023). The econometrics of oil market VAR models. Advances in Econometrics, 45,65-95.

Mandatory Requirements:

- Very good knowledge of multivariate time series analysis.
- Very good knowledge of programming (R, Python, etc.);

Note that to do this work you need to have access to a good long time series of Chinese oil market data, including production, exports and, most importantly, Chinese oil stocks (that is, oil inventories):

https://twitter.com/anasalhajji/status/1687929464439623680



The topic of inflation forecasting with Google Trends is one of the few topics relatively unexplored in this field of work, but recently some major international financial organizations have started having a look at it, see Narita and Yin (2018, IMF), Samanta (2021, RBI), and Woloszko (2021, OECD).

Moreover, a couple of papers in the Russian literature recently used simple univariate models and Google data to forecast the Russian inflation, see Petrova (2019) and Yurevich M. (2021). In this regard, we remark that inflation expectations represent an important ingredient to monetary policy formulation, particularly under the Inflation Targeting approach.

However, the forward-looking assessment for forecasting inflation has been an extremely challenging task. The time lag in the release of official statistics on inflation often aggravates the problem further. To address the issue, the conventional literature suggests two broad approaches: either developing forecasting models, or conducting surveys for measuring inflation expectations.

However, conducting surveys may be costly in terms of monetary expenditure, time requirement and human resources. Further, for the time requirement, survey-based results may fail to capture information on a real-time basis.

To address these issues, many researchers have explored the vast metadata and documents freely available on the web to track and predict economic variables, see Jun et al. (2018) and references therein.

The models proposed in the Russian literature so far are limited to rather simple univariate models, which are not able to deal with the large information set typically used for forecasting the inflation rate, particularly at medium and long-term horizons, see for example Faust and Wright (2013) and Oguns et al. (2013) for two reviews.

Idea: use modern multivariate models such VAR with LASSO (Nicholson et al. (2021), Wilms et al. (2021)), Bayesian VARs (see the survey by Demeshev and Malakhovskaya (2016)), time-varying VARs models (Casas and Fernandez-Casal (2022)) and shrinkage methods for VAR models (Hoerl and Kennard (1970), Ni and Su (2005), Opgen-Rhein and Strimmer (2007), Lee, Choi, and Kim (2016)) to forecast the Russian inflation rate with Google data and a large set of economic and financial variables.

References:

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- Jun, S.P., Yoo, H. S. and Choi, S. (2018). Ten years of research change using google trends: From the perspective of big data utilizations and applications, *Technological Forecasting and Social Change*, 130: 69-87.
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- Lee, N., H. Choi, and S.-H. Kim. (2016). Bayes Shrinkage Estimation for High-Dimensional Var Models with Scale Mixture of Normal Distributions for Noise. *Computationl Statistics and Data Analysis* 101: 250–76.
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- Nicholson William B., Wilms Ines, Bien Jacob and Matteson David S. (2020), High-dimensional forecasting via interpretable vector autoregression, *Journal of Machine Learning Research*, 21(166), 1-52.
- Oguns, F., Akdogan, K., Baser, S., Chadwick, M. G., Ertug, D., u, T., Tekatli, N. (2013). Short-term inflation forecasting models for Turkey and a forecast combination analysis. *Economic Modelling*, 33, 312-325.
- Opgen-Rhein, R., and K. Strimmer. (2007) Learning Causal Networks from Systems Biology Time Course Data: An Effective Model Selection Procedure for the Vector Autoregressive Process. *BMC Bioinformatics* 8 (2): S3.
- Samanta, G. (2019). Does google search index help track and predict inflation rate? An exploratory analysis for India. *Reserve Bank of India*.
- Wilms Ines, Basu Sumanta, Bien Jacob and Matteson David S. (2021), Sparse Identification and Estimation of Large-Scale Vector AutoRegressive Moving Averages, Journal of the American Statistical Association, 1-12
- Woloszko, N. (2021) Tracking activity in real time with Google Trends", OECD Economics Department Working Papers, No. 1634, OECD Publishing, Paris.
- Yurevich M. (2021). INFLATION EXPECTATIONS AND INFLATION: NOWCASTING AND FORECASTING. *Journal of Economic Regulation*, 12(2), 22-35 (in Russian).
- Petrova D. (2019). Inflation Forecasting Based on Internet Search Queries. ECONOMIC DEVELOPMENT OF RUSSIA, 26(11), 55-62 (in Russian).