Long-term Changes in Ethereum Prices: A Normalized Pandemic Framework

Haiye Huang
Department of Arts and Science, University of Toronto, Toronto, ON M5S, Canada
haiye.huang@mail.utoronto.com

Abstract. As the pandemic, Covid-19, spreading across the world from 2020, it changes the habits of people. It helped the development of the online movement. Cryptocurrency investment was one of them. Ethereum is one of the most significant blockchain-based platforms and the second largest proportion of the cryptocurrency market. The price of Ethereum was examined from the last 3 years. The result shows that the price of Ethereum increases drastically at the beginning of the pandemic due to different influences of Covid-19. However, it is decreasing as Covid-19 has become a normal illness to handle recently. In summary, Ethereum is in a strong correlation with Covid-19 and still can fluctuate by illness or movement that increases the interaction of people on the internet. In this paper, vector autoregression model and ARMA-GARCHX model was constructed where VAR model helped to find the relationship between the new infections of COVID-19 in China and Overseas and the return rate of Ethereum and ARMA-GARCHX model was applied to analyze the volatility of the return and predict the future return rate. The models suggest that the return rate can be affected if the number of new infections increases in a short period. However, the number of new infections is not significant to the volatility of the return rate of Ethereum.

Keywords: Ethereum; Long-term changes; Pandemic.

1. Introduction

Cryptocurrency is a digital P2P system for people to do transactions without central authority [1]. Since the introduction of Bitcoin in 2008 [1], the cryptocurrency universe has been growing rapidly in a short period of time. Through rapid development within less than 10 years, cryptocurrencies have become a major topic in economics and finances. Many different cryptocurrencies and blockchain systems were created after the potential of Bitcoin shined over the world. Despite the success of Bitcoin that everyone knows, Ethereum is one of the most popular cryptocurrencies that follows the steps of Bitcoin and has untouched and intact influences in the cryptocurrency market. Ethereum was launched in 2015 [1]. It was designed to create a complete platform for blockchain [1]. Compared to Bitcoin, Ethereum has a more complete system and solved limitations that Bitcoin has with its built-in Turing-complete programming language, smart contracts that anyone is allowed to write, applications for creating their own rules of ownership, the format of the transaction, and state transition functions [2]. Through the revolution of the internet these years, the commercialization of the internet is a big part of changes in the last decade. Online shopping has become inevitable in life. Almost every purchase can be made through online transactions. Moreover, cryptocurrency benefits from different kinds of online transactions. In recent years, more and more retailers from different industries are accepting cryptocurrency, especially Bitcoin and Ethereum, which illustrates the success of cryptocurrency and the trends of holding properties without banks or physical properties. In 2020, the explosion of Covid-19 caused a change in lifestyle. Most people spent most of their time inside their houses. Whether it is working or socializing, people use phones and computers to connect to each other through the internet, which obviously facilitates internet activities. Because of the strong correlation between the internet and cryptocurrency, the price and popularity of Ethereum were pushed to its peak.

The pandemic was a crisis to the global economic and financial. COVID-19 had a significant negative effect on the stock market with a negative return rate and higher volatility [3]. In China, the COVID-19 reflects a strong negative impact to the stock market in a short period and return normal in a normalized pandemic stage [4]. Based on the research, the pandemic caused contagion effect not only in price and volatility of global financial market but also the market efficiency [5]. The market efficiency of S&P, gold and Bitcoin has all decreased [5]. However, Bitcoin has the least effect of market efficiency decreased [5]. Moreover, in the period of COVID-19, the crypto market seemed to be the safe zone because of its special characteristics [6].

Based on serval research, it is interesting to examine and analysis about the volatility of the return rate of Ethereum throughout the event of Covid-19 and looking at the correlation between Covid-19 and Ethereum based on some data and history to find factors for investing in Ethereum in the future under the light of Covid-19. The remaining parts of this paper are organized as follows: Part 2 is the research design, which includes data source unit root test and model specification; Part 3 is the result and analysis according to graphs and tables from VAR model and ARMA-GARCHX model; Part 4 is the discussion of the results from two models; Part is the conclusion of this paper.

2. Design

2.1 Source of Data

The use and price of Ethereum outbursts like Covid-19 and spread across the world. A large number of people pour into the Ethereum market for investment. The Ethereum daily price data was used from Investing.com from 2020/01/20 to 2022/08/10 because the main focus is on how the pandemic influences the price of Ethereum and the data is based on USD for the price of Ethereum. Moreover, the cumulative infected Covid-19 data was applied from Choice. The cumulative infected numbers were analyzed separately by China and outside China because Covid-19 was first started in China and expanded around the world and it is interesting to see that the rate of infection from this comparison has moved differently through time flies. Also, it is ideal to have a comparison while analyzing the model and situation.

2.2 Augmented Dickey-Fuller (ADF) Test

Now the dates were set by numbers in order to make a time series set. Then, a log transformation was applied to the return rate. Testing whether the data is stationary was the primary. Assuming the null hypothesis is that the model is not stationary. From Table 1, the Mackinnon approximate p-value of Z(t) for the log of return rate and the daily infections of COVID-19 overseas are both equal to 0.000. Also, the p-value of the daily infections in China is equal to 0.0237. The p-values are all less than 0.05, which the data is statistically significant. Therefore, the null hypothesis is rejected that the data is stationary and feasible. This is a crucial step because the stationary property is significant to generating models. The model cannot be constructed with non-stationary data.

Table 1. ADF test

Variables	t-statistic	p-value
	Ethereum	
Index	-0.602	0.9789
Yield	-21.185	0.0000***
Proxy variable of normalized Covid-19: newly confirmed cases		
China	-3.680	0.0237**
Overseas	-16.685	0.0000***

2.3 Vector Autoregression（VAR）Model Design

The vector autoregression model was advocated by Sims in 1980 while multivariate simultaneous equations model was used in the majority for macro econometric analysis [7]. VAR model is useful for describing the dynamic behavior of economic and financial time series and for forecasting [8]. The VAR mixes variables together as a system to make prediction mutually consistent and it can easily find the relationship between variables without using economics theory as a base. Therefore, it is flexible. Since the price blooming of Ethereum happens nearly the same time as the spread of

COVID-19, the correlation between two is inevitable. The VAR model was chosen in this case with three different time series variables, y_{1t}, y_{2t}, y_{3t}, to create a trivariate system VAR(p) model.

$$y_{1t} = \beta_{10} + \beta_{11}y_{1,t-1} + \cdots + \beta_{1p}y_{1,t-p} + \gamma_{11}y_{2,t-1} + \cdots + \gamma_{1p}y_{2,t-p} + \varepsilon_{1t} \quad (1)$$
$$y_{2t} = \beta_{20} + \beta_{21}y_{1,t-1} + \cdots + \beta_{2p}y_{1,t-p} + \gamma_{21}y_{2,t-1} + \cdots + \gamma_{2p}y_{2,t-p} + \varepsilon_{2t} \quad (2)$$
$$y_{3t} = \beta_{30} + \beta_{31}y_{1,t-1} + \cdots + \beta_{3p}y_{1,t-p} + \gamma_{31}y_{2,t-1} + \cdots + \gamma_{3p}y_{2,t-p} + \varepsilon_{3t} \quad (3)$$

In equations (1), (2), (3) above, they represent the return rate of Ethereum, the daily infections in China and the daily infections overseas. Note that, these three equations are identical in structure. Therefore, they can be put together as a matrix. In more detail, (1), (2) and (3) are representing the past lag of the return rate of Ethereum, the past lag of the daily new infections in China and the past lag of the daily new infections overseas with the error terms, ε_{1t}, ε_{2t} and ε_{3t}.

2.4 ARMA-GARCHX Model Design

ARMA-GARCHX model is to apply ARMA model into the GARCHX model. ARMA is a combination of AR model and MA model. ARMA-GARCHX is outstanding to predict the return rate of Ethereum and the volatility by the infections of COVID-19. The research suggest that ARMA-GARCH model has better yield prediction than AR model and AR-GARCH model [9]. Now, this paper is going to explain the model design of ARMA and then GARCHX.

$$x_t = \phi_0 + \sum_{i=1}^{p} \phi_i x_{t-i} + \alpha_t - \sum_{i=1}^{q} \theta_i \alpha_{t-i} \quad (4)$$

The equation (4) above is an expression of ARMA model. This equation is easier to understand by spliting it to half. First, $\phi_0 + \sum_{i=1}^{p} \phi_i x_{t-i}$ is the AR(p) part model of the ARMA model. It represents predicting the return rate of Ethereum in the future. Then, $\alpha_t - \sum_{i=1}^{q} \theta_i \alpha_{t-i}$ is the MA(p) part model of the ARMA model, which represents the volatility of Ethereum by the COVID-19 infections. Note that, the equation cannot have common demoninators for AR(p) model and MA(p) model otherwise the lag of model can be decreased.

The ARCH model was proposed by Engle in 1982, which the conditional variance of the errors changes through time [10]. Then, in 1986, Bollerslev introduced GARCH model which is derived from the ARCH model [10]. The GARCH model reduces the amount of parameters of ARCH to make better and more acurrate prediction.

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2 \quad (5)$$

The equation (5) above is the GARCH model, where the $\alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2$ part is the ARCH and the $\gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2$ is the GARCH. The σ_t^2 is the conditional variance of ε_t^2 over time t.

3. Result and Analysis

3.1 VAR Model Identification

First, a VAR model identification is needed in order to find the ideal lag order of a VAR model. By calculating the LR, p-value, FPE, AIC, HQIC and SBIC, the best lag order has the smallest value on these variables.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2363.21				.089355	6.09849	6.10541	6.11648
1	-1383.56	1959.3	9	0.000	.007322	3.5968	3.62449	3.66877
2	-1270.09	226.93	9	0.000	.005594	3.32756	3.37602	3.45351
3	-1221.44	97.303	9	0.000	.005051	3.22537	3.29459	3.4053
4	-1212.21	18.47	9	0.030	.005048	3.22476	3.31475	3.45867
5	-1198.62	27.182	9	0.001	.004988	3.21293	3.32368	3.50081
6	-1017.16	362.92	9	0.000	.003198	2.76845	2.89997	3.11031
7	-578.268	877.78*	9	0.000	.001056*	1.66048*	1.81277*	2.05633*
8	-573.634	9.2677	9	0.413	.001068	1.67174	1.84479	2.12156
9	-566.938	13.392	9	0.146	.001075	1.67767	1.87149	2.18147
10	-560.329	13.217	9	0.153	.001081	1.68384	1.89842	2.24162
11	-557.921	4.8162	9	0.850	.0011	1.70083	1.93618	2.31259
12	-553.443	8.9561	9	0.441	.001113	1.71248	1.9686	2.37822

In Table 2, it generates the first 12 lags for VAR model identification and the smallest value has the * sign. As we can observe, lag 7 has the smallest LR, FPE, AIC, HQIC and SBIC out of 12 lags. Therefore, without question, lag 7 is the optimal lag order for our VAR model.

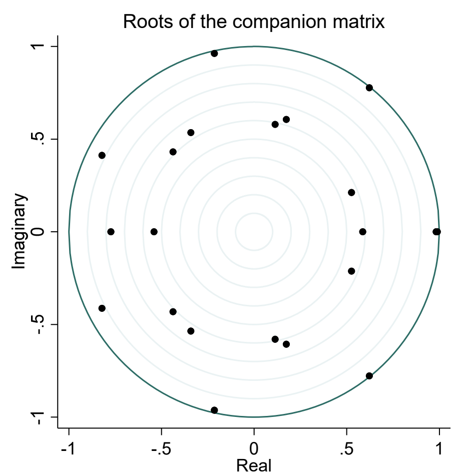

Figure 1. VAR stability
Photo credit: Original

Then, Figure helps to check whether the VAR model in lag 7 is stationary. If all the dots are within the circle of radius 1, the conclusion that VAR(7) is stationary can be drawn. From Figure 1, it seems like 2 dots that do not belong inside the circle of eyes. However, by checking the result of running code, both dots are less than 1, which means VAR(7) is a stationary VAR model. This identification of stationary lag is important because it will be difficult and complicated to overview the prediction because the model is hard to capture patterns from the data.

3.2 Impulse and Response

In general, the global economic recession was caused by the outburst of COVID-19. In the short term after the widely spread of COVID-19, majority investors were panic and the risk-averse tendency of funds leads to a huge amount of capital escaping from the financial market, which has a strong relationship to the dramatic fall of index in the financial market. The limitation from COVID-19 strongly influences many industries and the investors were urgent to find a safe-zone.

However, there were some rare industries that avoid the damage from COVID-19. The precious metal, medical and cryptocurrencies are the examples of industries that has an excellent market in the short run during the COVID-19 period. The excellent growth of the markets was reflected by the compound annual growth rate.

Moreover, the value of cryptocurrencies was growing like a rocket within a year after the spread of COVID-19. For example, Bitcoin is most iconic cryptocurrency. In the end of 2020, the price of bitcoin grew almost 5 times comparing to the price in the beginning of 2020. However, after 2021, the price of bitcoin appears to plummet. The situation can interpreted as an overreacting by the COVID-19. Since the COVID-19 limiting the real life, the investors were urgently finding a safe zone for funds and the concept of digital was perfectly fitting the situation of COVID-19. The panic of human to an unknown situation pushes the cryptocurrency to the level which it does not belong. In a long run, when everything returns to standard with a good understanding of COVID-19, the correlation between cryptocurrency and COVID-19 needs to have further verification and experience.

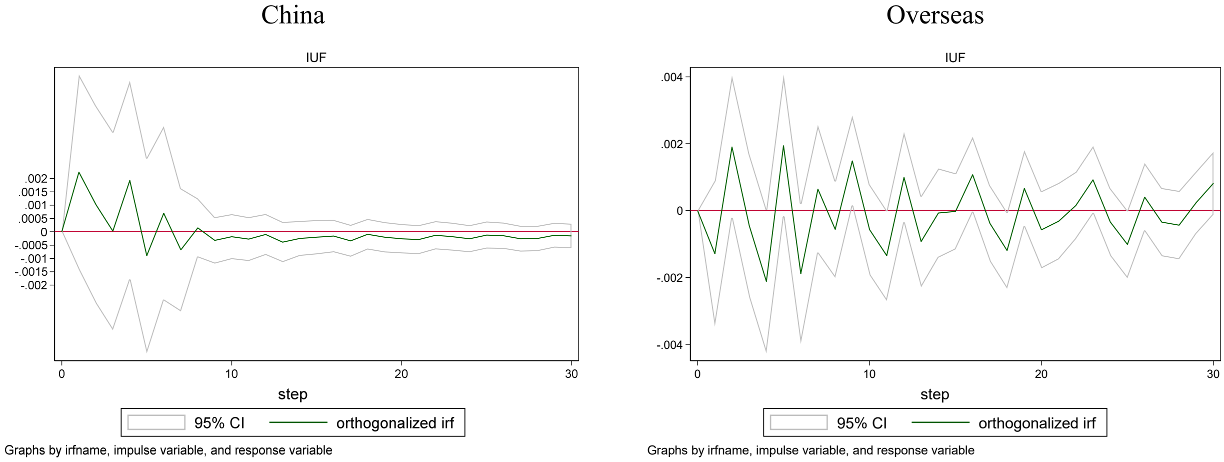

Figure 2. Impulse and response
Photo credit: Original

By our observation from impulse and response in China of Figure 2, when t is equal to zero, the new infection in China increases by 1 percent. In addition, the return rate of Ethereum has a positive impact from t = 0 to t = 4. The highest positive impact appears when t = 1 which is 0.02 percent higher when t = 4. The first negative impact was presented after 5 steps with size between 0.05 percent and 0.1 percent. From time perspective, the impulse starts weakening after 10 steps. From previous analysis, Chinese investors seems to be not reflecting from the past. The return rate of Ethereum was a repeat of the past but in a shorter period. However, if the number of new infections has increases in a short term, the price of Ethereum will potentially increase. But the difference is that the unsettlement of Chinese investors will not be as serious as the beginning. Therefore, the change of return rate of Ethereum will not dramatically fluctuated like the beginning of COVID-19.

For overseas impulse and response, because the difference interpretation on COVID-19 which more people in overseas treat COVID-19 as a normal illness, the overseas does not have a similar effect comparing to China in a long run. It only affects the return rate to change around 0 in a long run.

3.3 ARMA Model Identification

In Figures 3, PACF and ACF were created for the rate of return of Ethereum to select the lag of AR(p) and MA(p) for the ARMA-GARCH model. Observing from the two figures, by selecting lag 1 for the purpose of getting a simple model, both AR(1) and MA(1) has the value exceeding the critical value. Then, an ARMA-GARCH model can be constructed with AR(1) and MA(1).

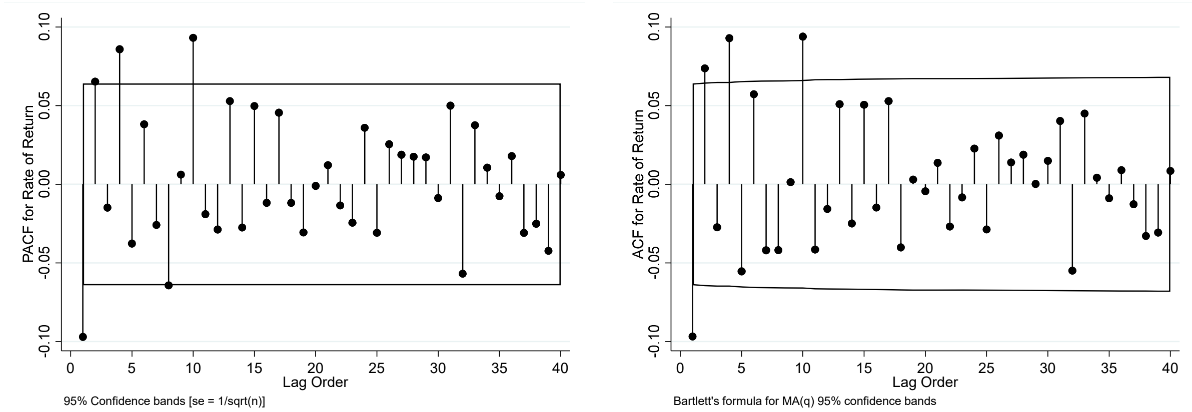

Figure 3. PACF and ACF
Photo credit: Original

3.4 ARMA-GARCHX Estimation Results

From Table 3, based on the statistical summary, the p-values of ARCH, L1 and GARCH, L1 of two models are 0.000, which indicates that the models are significant. It serves as strong evidence of conditional heteroskedasticity in order to build a GARCH model. For new infections of COVID-19 in China and overseas, the p-value are 0.748 and 0.308, which are both larger than 0.05. Hence, the number of new infections is not significant to the return rate of Ethereum. Hence, the conclusion is that the number of new infections does not have influence to the volatility of the return rate of Ethereum.

Table 3. ARMA-GARCHX estimation results

	(1)			(2)		
	Coefficient	Std. err	p>|Z|	Coefficient	Std. err	p>|Z|
			Mean equation			
AR, L1	-.8394063	.1771003	0.000	-.7808703	.2313101	0.001
MA, L1	.7996372	.1991766	0.000	.733695X1	.2528242	0.004
Constant	.0038638	.0016484	0.019	.0040645	.0016795	0.016
			Variance equation			
New confirmed cases						
China	.0231253	.0719817	0.748			
Overseas				-.0351628	.0344997	0.308
ARCH, L1	.1291716	.0125281	0.000	.1193017	.0136865	0.000
GARCH, L1	.8475891	.0157591	0.000	.8536893	.0161298	0.000
Constant	-9.131148	.3967624	0.000	-8.624654	.4969397	0.000

4. Discussion

Through the process of analyzing the data on the price of Ethereum and the global COVID-19 infections, the VAR model suggests that the impulse and response of return can be affected by the understanding of COVID-19 based on the difference between Chinese investors and overseas investors. The price of Ethereum will increase by prediction if the number of new infections dramatically grows in a short period in China. The ARMA-GARCH model illustrates that volatility of the price of Ethereum has almost no correlation with the number of infections. Based on literature review where others consider cryptocurrency market as a safe haven [5] and claim that Bitcoin has the least decreasing on market efficiency [4], the ARMA-GARCHX model serves as a good standpoint to agree with these concepts because the model suggests that the number of new infections of the pandemic has non-significant and direct influence on the volatility of Ethereum. In addition, from the model, the return rate of Ethereum is going positive by prediction. On the other hand, even though the model shows that the new infections of COVID-19 do not have a direct and significant correlation with the return rate of Ethereum, there might be other COVID-19-related factors that can influence the return rate of Ethereum. The risk of investing in Ethereum cannot be dismissed when COVID-19 mutates and has a huge influence globally or another global pandemic happens.

5. Conclusion

This paper observes the influence of global COVID-19 infections on the return rate of Ethereum to determine whether COVID-19 is a factor in the volatility of the rate of return of Ethereum by using data from Jan 10th, 2020, to Aug 10th, 2022, which is the period from COVID-19 started, and predict the rate of return of Ethereum. By creating and examining the ARMA-GARCH model, this paper draw the conclusion that the number of COVID-19 infections is not significant to the volatility of the return rate of Ethereum. It is surprising because the time of the rise of Ethereum overlaps with the time of COVID-19. The model suggests not taking the influence of global infection of COVID-19 as a major factor while dealing with Ethereum investment. Furthermore, this model predicts that the return rate of Ethereum will be slightly positive in the future, so it is necessary to assess the balance of risk and return for the investment of Ethereum. It can be clear in this study that using the number of infections of COVID-19 cannot be the comprehensive factor that can embrace the whole idea and situation of COVID-19, which caused the factor that it cannot have a crystal-cleared vision of the relationship between COVID-19 and the volatility of the rate of return of Ethereum. Future needs to consider more factors related to the event or to find a comprehensive factor in order to get a precise result.

References

[1] Mukhopadhyay U, Skjellum A, Hambolu O, et al.,. A brief survey of cryptocurrency systems. IEEE Xplore, (2016) [2022-11-01]. https://ieeexplore.ieee.org/abstract/document/7906988.

[2] Buterin V,. Ethereum: A next-generation smart contract and decentralized. Ethereum, 2014. (2014) [2022-11-01]. https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf.

[3] Haldar A, Sethi N,. The news effect of COVID-19 on Global Financial Market Volatility. (2021-01-31) [2022-11-01]. https://bulletin.bmeb-bi.org/cgi/viewcontent.cgi?article=1032&context=bmeb.

[4] Yan L, Qian Y,. The Impact of COVID-19 on the Chinese Stock Mark: An Event Study Based on the Consumer Industry. semantic scholar, (2020) [2022-11-02]. https://pdfs.semanticscholar.org/aae9/4123b0f35b6a828075029ae3132652d8366f.pdf.

[5] Wang J, Wang X,. Covid-19 and financial market efficiency: Evidence from an entropy-based analysis. Finance research letters, Elsevier Inc. (2021-10) [2022-11-01]. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8450754/.

[6] Vukovic D, MAITI M, GRUBISIC Z, et al.,. Covid-19 pandemic: Is the crypto market a safe haven? the impact of the first wave MDPI, Multidisciplinary Digital Publishing Institute, (2021-07-31) [2022-11-01]. https://www.mdpi.com/2071-1050/13/15/8578.

[7] L¨utkepohl H,. EUI Working Papers - European University Institute. (2011) [2022-11-01]. https://cadmus.eui.eu/bitstream/handle/1814/19354/ECO_2011_30.pdf.

[8] Tang H, Chiu K-C, XU L,. Finite mixture of Arma-GARCH model for stock price prediction. (2003) [2022-11-03]. http://www.cs.cuhk.hk/~lxu/papers/conf-chapters/TangCIEF2003.pdf.

[9] Vector autoregressive models for multivariate time series. [2022-11-01]. https://faculty.washington.edu/ezivot/econ584/notes/varModels.pdf.

[10] Ling S, McAleer M,. ASYMPTOTIC THEORY FOR A VECTOR ARMA-GARCH MODEL. THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY. (2003) [2022-11-01]. https://repository.hkust.edu.hk/ir/bitstream/1783.1-1401/1/cup_lings19.pdf.