CAN THE VALUE OF ETHER BE EXPLAINED AND PREDICTED?

by

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ABSTRACT

MORTEN ARRILD JUHL. Can the Value of Ether Be Explained and Predicted?
(Under the direction of DR. CRAIG DEPKEN)

This paper analyzes the Ethereum blockchain and the applicability of models for network valuation in explaining the value of Ether. After examining the fundamentals of the Ethereum blockchain and its associated cryptocurrency, Ether, it is argued that the value of Ether is driven by the demand for computing power, but also that Ethereum shares many similarities with non-blockchain networks. Thus, the analysis applies the network valuation models by Metcalfe (2013), Briscoe, Odlyzko, and Tilly (2006), and Alabi (2017). While these models are based on the number of users, the findings suggest that other measures better represent demand of computing power on Ethereum. Thus, besides daily active IP addresses on Ethereum, the daily number of transactions and daily Gas used are applied as predictors. Contrary to previous findings, the analysis shows that Metcalfe's Law and Alabi's model are not able to explain the value of Ether over time. Metcalfe's Law best explains the early value of Ether, and this paper suggests a combined model of Metcalfe's Law and the model proposed by Briscoe, Odlyzko, and Tilly. The combined model proves to better explain the value of Ether over time compared to the single equation models. No evidence supports that Gas and transactions provide better predictors compared to active IP addresses. As the value of Ether seems to follow the proposed model, the model is used for forecasting to examine the predictability of Ether. The results show that existing models for forecasting activity and the demand for computing power on Ethereum challenge the predictability of the value of Ether. Thus, the final 6-month ahead forecast provides a wide

range, and the value of Ether is forecasted between $96.95 billion and $132.34 billion for July 1, 2018. The forecast implies a gain between 35.36% and 84.78% over six months from December 31, 2017.

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1. INTRODUCTION

Since the initial whitepaper by Satoshi Nakamoto (2008) introduced Bitcoin and the blockchain technology, several blockchains with associated cryptocurrencies and other tokens have emerged. On February 25, 2018, coinmarketcap.com showed 1,491 different cryptocurrencies with a collective market capitalization of just above $430 billion. However, while many cryptocurrencies have emerged, the market is still dominated by a few coins. Bitcoin is still the largest, representing 38% of the market. Second, is Ether at 19%, and third, Ripple, at 9%. Thus, the two largest coins currently represent more than half of the market.

Many of these blockchains and cryptocurrencies build on similar protocols, but their purposes are somewhat different. The purpose of Bitcoin was to create an alternative way of payment and store of value to circumvent the traditional financial institutions and the need to trust any intermediary. Through complex cryptographic "puzzles", consensus on the blockchain is reached in a 100% trustless community of computers (Nakamoto, 2008). Several companies have started to implement Bitcoin as a way of payment, including major companies such as Microsoft. However, as a general method of payment the implementation is still limited (eBay, 2015).

Ether, the cryptocurrency on the Ethereum blockchain, is based on similar technology and consensus algorithm, but unlike Bitcoin, Ether is meant only as a currency for buying computing power on the Ethereum blockchain. Ethereum was created to provide a decentralized world computer and facilitates a much more comprehensive coding language compared to Bitcoin. Thus, Ethereum can host an unlimited variety of small applications that, in theory at least, will run exactly as initially programmed without any downtime, censorship, and risk of fraud (Harm, Obregon, and Stubbendick, 2016).

The increase in market value of Ether indicates that many investors believe in the technology and potential of Ethereum. Figure 1.1 shows that the total market capitalization has reached values above $100 billion since Ethereum's initial coin offering in 2015. Market capitalization was $82.6 billion on February 25, 2018.

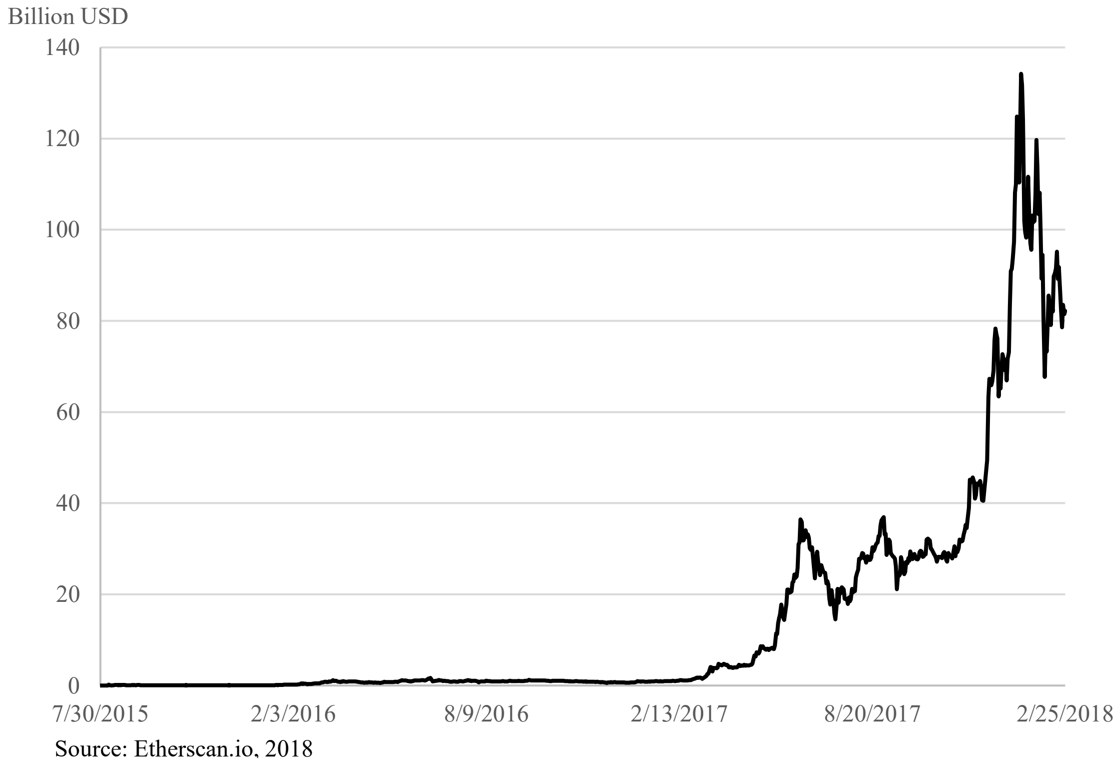

Figure 1.1: Total Market Capitalization of Ether 2015-2018.

With such tremendous growth in recent years, it becomes of high to interest to determine what drives the value of Ether. As Ethereum is a decentralized computer and the medium of exchange needed to utilize Ethereum is Ether, a connection between the use of Ethereum and the value of Ether might exist. Identifying the drivers for the value of Ether can provide valuable information for investors and actors who want to utilize Ethereum.

The link between the use of Ethereum and the value of Ether is what this paper aims to analyze. The research question is formulated as follows:

Can the value of Ether be explained by observable factors on Ethereum, and if so, can value be predicted?

To answer this question, the following questions must be answered:

1. *What is the purpose of Ether and what drives its value?*
2. *Can these drivers be observed?*
3. *How can the relationship between the observable measures and the value of Ether be defined?*
4. *Can the drivers of value be forecasted?*

After a review of previous research, the paper continues with outlining the fundamentals of Ethereum and a theoretical discussion of the drivers of the value of Ether. This is followed by a methodology section outlining how the research question is approached before the results of the analysis will be presented and discussed.

2. PREVIOUS LITERATURE

As blockchains and cryptocurrencies have become more popular among companies, investors, and the general public, the amount of literature on the subject has seen a major rise. Satoshi Nakamoto's (2008) whitepaper not only introduced Bitcoin but also outlined the foundation of the blockchain protocol, which other blockchains have utilized and developed since. The founder of Ethereum, Vitalik Buterin, released his white paper outlining the protocol behind Ethereum and the issuance scheme for Ether in 2013.

Most subsequent research regarding blockchain and cryptocurrencies focus on analyzing the specific protocols underlying these blockchains or the implications of implementation. Research on specific protocols includes Greenspan (2016), who analyzes and compares the technical details of transactions on the Bitcoin and Ethereum blockchains. Bartoletti and Pompiano (2017) investigate the use of smart contracts on the Bitcoin and Ethereum blockchains and the differences between the two.

Regarding implementation, Dai and Vasahelyi (2017) analyze the potential use of blockchains in accounting and assurance. Similarly, O'Leary (2017) analyzes how different architectures of blockchains can be used in accounting and supply chains, and Neyer and Geva (2017) discuss the application of blockchains and cryptocurrencies as general payment systems for domestic and cross-border transactions. While the areas differ, the conclusions are similar. All three papers find potential and beneficial implementations but highlight the current limitations and need for maturity of the technology to gain adoption in these fields.

As for financial markets, Surujnath (2017) discusses the applicability of blockchains to derivatives markets and how regulation should focus on this new technology to prevent potential crises. However, he argues that the current state of this technology requires some hesitation among regulators to let it develop naturally. Sontakke and Ghaisas (2017) analyze cryptocurrencies' potential of becoming an established asset class and find it likely because of recent adoption by major financial institutions. They too raise the issue of regulation and provide a similar conclusion as Surujnath, that regulation in this area will be a determining factor for its success as both no regulation and too extensive regulation might harm the development.

Less literature exists regarding valuation and prediction of the value of cryptocurrencies. Most of the research focuses on Bitcoin and the exchange rate (price) with the US dollar. Li and Wang (2017) utilize and build on this research to find determinants of the exchange rate. They build an autoregressive distributed lag (ARDL) model with a bounds test approach and use multiple time series to test for blockchain specific, economic, and public recognition effects. The blockchain specific variables used are Bitcoin supply, number of transactions, transaction volume, trading volume, mining difficulty, and volatility. Economic variables used are USD money supply, US GDP, US federal funds rate and US inflation rate. Finally, they use Google searches and Tweets on Twitter containing the word "Bitcoin" as proxies for public recognition. They find that the exchange rate between Bitcoin and the US dollar shows systematic differences comparing its early years to later years. In the early years, the main driver was speculation and therefore deviated from economic fundamentals. With the adoption of Bitcoin, interest rate, money supply, GDP, and inflation show a significant effect on the exchange rate.

Blockchain specific variables show mixed results. However, Li and Wang do find significant effects of blockchain activity on the exchange rate both in the long-term and short-term. Their findings provide two valuable insights for this analysis. First, in the early years, speculation makes modeling difficult, which might create challenges for this analysis, as Ethereum is still young compared to Bitcoin. Second, blockchain specific variables show positive relationships with the price of the cryptocurrency, which is highly related to the purpose of this analysis.

Alabi (2017) examines whether Metcalfe's Law can explain the value of the three cryptocurrencies Bitcoin, Ethereum, and Dash. Metcalfe's law was developed as an Ethernet sales tool in the 1980's by Robert (Bob) Metcalfe (2013) and states that the value of a network is the square of its users multiplied by a constant. The intuition is that fundamental value of a network derives from the total number of possible connections. Each node or user can have $N-1$ connections, which result in a total value of the network being proportional to $N(N-1) \approx N^2$ as N increase.

In his analysis Alabi (2017) uses a 30-day moving average of unique daily IP addresses participating on the respective blockchains as a measure for users and fits the price of the underlying cryptocurrencies to Metcalfe's Law and his own proposed model. His own proposed model is:

$$V(N) = Ce^{\lambda \bar{N}_t{}^m},$$

where V is the price of the underlying cryptocurrency in dollars, C, λ, and m are constants, and $\overline{N}_t$ is the 30-day moving average of unique IP addresses. For all three blockchains, he finds that both models explain the growth in value but also that his own proposed model performs better than Metcalfe's Law. For Ethereum he utilizes data from mid-2015 to mid-2017 and estimates the following models:

$$V(N) = (11 \times 10^{-9})N^2$$

$$V(N) = 3e^{0.011 \times N^{0.5}}$$

If moving forward to December 2017, the average daily number of active IP addresses was 594,445. Based on his models, the associated price of Ether would then be \$3,887 and \$14,467, for Metcalfe's Law and his proposed model, respectively. With a price of \$741 on December 31, 2017, and a high throughout the month of \$814, it shows that subsequent growth has not been following the estimated models.

Metcalfe's Law has previously received criticism for a tendency to overestimate value as the number of users grows. Briscoe, Odlyzko, and Tilly (2006) formulated the most notable critique. The main critique is that Metcalfe's Law implies that all compatible networks would benefit equally by interconnecting despite size differences. In their analysis, they consider two networks where network one has n users, with value proportional to n^2, and network two has m users, with value proportional to m^2. If the two networks interconnect, the gain in value for both networks would be proportional to nm. They argue that empirical evidence suggests that large networks seem to resist interconnection with smaller networks. To better explain this behavior, they propose the model $V(N) = kN \times \log_{10}(N)$. If the two networks n and m interconnect, the value gain would be proportional to $n\,(\log_{10}(n+m) - \log_{10}(n))$ and $m\,(\log_{10}(n+m) - \log_{10}(m))$, respectively. For illustrative purposes assume $n = 10{,}000$ and $m = 100{,}000$ and the value gain would therefore be proportional to 10,414 and 4,139 for n and m, respectively. Thus, the value gain for the smaller network significantly exceeds the gain for the larger one. While not applying their model to real data, Briscoe, Odlyzko, and Tilly argue that the difference between the value from Metcalfe's Law and their proposed model can explain the difference between the artificial values of the dot-com years and the actual value generated by the mainstream adoption of the internet.

Metcalfe (2013) answers the critique by modeling user growth over time using a Netoid function, which Alabi (2017) adopts in his analysis:

$$N(t) = \frac{p}{1 + e^{-v(t-h)}},$$

where N is the number of users on the network, p is the asymptote, to which the number of users will converge as time (t) goes to infinity, v is the virality parameter determining how fast the user base is growing, and h is the point in time where the number of users is estimated to experience the highest level of growth. Alabi (2017) finds that the Netoid function explains well the growth in active IP addresses across the three blockchains.

While Metcalfe's Law and the model proposed by Alabi does not seem to explain well the growth in value of Ether in the last half of 2017, defining Ethereum as a network provides models from previous research that can help explain the value of Ether. Thus, this analysis will further examine the fundamentals of Ethereum to determine if it is appropriate to define Ethereum as a network. If so, the models by Metcalfe and Alabi will be re-estimated given more recent data, to examine if the models can still explain the value of Ether.

3. FUNDAMENTALS OF ETHEREUM

Underlying Ether is the Ethereum blockchain. Before deep diving into Ethereum, a general overview of how blockchains work is appropriate. As the name suggests, a blockchain is a chain of blocks. A block consists of some data regarding transactions of cryptocurrency or digital contracts. Each block is a time stamp of the state of the blockchain as blocks enter chronologically and one at a time. Blockchains can be both public and private (Underwood, 2016), but for the sake of this analysis, the focus will be on the public Ethereum blockchain. So, unless explicitly stated, "The Ethereum blockchain" or just "Ethereum" will refer to the public Ethereum blockchain. The main property of a public blockchain is that it is open for everyone with a computer and that every participating computer, called a node, holds a copy of the entire blockchain. Before a block can enter the blockchain, the block must be validated. Validation methods differ, but both Ethereum and Bitcoin currently use the Proof of Work consensus model, where Miners (nodes with specific hardware) compete to first validate the block, by solving a complex computing problem. The winning Miner adds the validated block to the chain and distributes it to all nodes on the blockchain. In that way, as soon as a block enters the blockchain, it cannot be changed. Since every node holds a copy of the blockchain, tampering with an existing block would result in other nodes realizing the unauthorized change. Thus, ownership of more than 50% of the computing power on the blockchain is essentially needed to manipulate it. These attributes allow nodes to execute transactions and contracts without having to pay and trust a specific intermediary (Dannen, 2017; Underwood, 2016).

3.1 THE ETHEREUM BLOCKCHAIN

3.1.1 Ethereum Virtual Machine

The description of blockchains also applies to Ethereum, but Ethereum has several specific aspects that separate it from other blockchains. At the center of Ethereum is the "Ethereum Virtual Machine" (EVM). EVM is essentially a large virtual computer distributed over every node participating on Ethereum. Unlike desktops and laptops, the EVM is a 100% decentralized computer, where every node runs the same instructions. That every node runs the same instructions might seem highly inefficient and compared to a single hardware-based computer, it is indeed very slow. However, unlike a single computer, it has no off switch and cannot be controlled or tampered with by any single entity. Since the EVM is essentially a computer, it can run applications written in a compatible coding language. Anyone on Ethereum can upload these applications called smart contracts or dApps. As no one owns Ethereum, any program uploaded to Ethereum can only run as initially programmed and cannot be changed unless the initial code includes that option. The blocks of Ethereum only contains the current and all previous states. Thus, the blocks hold the program code, but it is the EVM that executes the code (Dannen, 2017).

3.1.2 Smart Contracts

To support smart contracts, Ethereum includes two types of user accounts. Externally Owned Accounts (EOA) and Contract Accounts. EOA's are the accounts owned and controlled by some entity outside the blockchain. It can be a server but, in the end, owned and controlled by people. These accounts can participate in transactions, mining, and upload of smart contracts. Contract Accounts are the smart contracts. Unlike EOA's smart contracts have no owners as soon as they are in the blockchain and EVM. Smart contracts contain code and can be triggered by transactions from EOA's, make predefined transactions to other smart contracts, and perform transactions to other EOA's. In doing so, smart contracts can also trigger other smart contracts. It is not possible to alter a smart contract as soon as it is part of Ethereum. However, if the smart contract is programmed accordingly, EOA's can trigger predetermined alterations. These alterations are therefore in the contract as it is initially uploaded (Dannen, 2017).

Most research in the application of smart contracts focus on the financial services industry as the general purpose of smart contracts is the transfer of cryptocurrency and other digital tokens. In the case of Ethereum, potential uses are Initial Public Offerings (IPO), derivatives, mortgage lending, invoicing, payments, insurance contracts, and compliance. Within these fields, smart contracts are expected to lower time of execution and costs compared to current practices (Cant et al., 2016). However, because of the programmable nature of smart contracts, the potential is theoretically unlimited. While a detailed analysis of potential and associated risks of smart contracts is outside the scope of this paper, it is worth mentioning that issues with smart contracts still cause problems for mainstream adoption. The Ethereum blockchain is considered un-hackable, but smart contracts are not necessarily un-hackable. Bugs in the code pose a potential risk of unauthorized actions if triggered correctly. An example is the DAO (Decentralized Autonomous Organization), where a hacker managed to steal many of the contract's Ether (Siegel, 2016). Several developers and organizations are working on solutions to these problems. Most notably, Microsoft Azure with the publication of the COCO framework (Russinovich, 2017).

3.1.3 Transactions, Messages, and Gas

A transaction on Ethereum is an instruction from EOA's to the EVM. The instruction can be a simple transfer of Ether between two EOA's, a call for transferring Ether to a Contract Account (smart contract), code and instructions to create new a smart contract, triggering a smart contract, or for the EVM to do some calculations. Thus, creating a new smart contract or triggering an existing smart contract also requires a transaction. Contract Accounts do not make transactions but send messages and only do so, if triggered. A trigger can be both transactions from EOA's or messages from other smart contracts. Also, smart contracts can send messages transferring Ether held by the Contract Account to an EOA. Every transaction or message requires the EVM to perform some computing action, which requires participating nodes to deliver required the computing power. As computing power requires hardware and electricity, the nodes must be compensated. However, while all the nodes essentially run the EVM, it is the Miners who do the work of verifying these transactions and messages. So, only Miners get compensated (Dannen, 2017).

Ethereum has a unit for quoting the price of computing power called Gas. Any computing action has an associated cost quoted in Gas, which remains fixed over time. Thus, Gas cannot be held or traded by EOA's or Contract Accounts, as it would then be a currency affected by supply and demand. Here the purpose of Ether enters. The EOA's and Contract Accounts use Ether to pay for Gas. As Ether is traded, its price varies and likewise, the price of Gas, quoted in Ether, varies (Dannen, 2017).

3.1.4 Mining and Supply of Ether

The nodes that supply computing power to Ethereum and participate in verification of transactions and messages are the Miners. Using the current Proof-of-Work algorithm, Miners compete in verifying a group of transactions and messages to win the right to add these changes to Ethereum. In other words, the winning Miner adds a new block to the blockchain and thereby provides the new state. To win, the Miner must solve a complex computing puzzle, where the degree of difficulty varies with the supply of computing power. When supply decreases, difficulty decreases to attract Miners and vice versa if supply increases. The algorithm defines the equilibrium level of difficulty based on the speed, in which Miners validate new blocks. The current equilibrium blocktime is about 14-15 seconds.

While only one Miner wins the right to add a block, the Miners who "lose", still play a vital role. The "losing" Miners must validate the new block to be allowed to mine for the next block and therefore still participate in securing the blockchain (Dannen, 2017).

The winning miner receives the fees paid by the EOA's and Contract Accounts on top of three Ether created solely to compensate the Miner. Sometimes Miners who solved the puzzle, but did not win, are in total awarded between 0.625 and 2.625 (Ethereum.org, 2017). So, the total of 3-5.625 Ether per block is the only new Ether issued over time.

The developing team behind Ethereum works on a new consensus algorithm called Proof of Stake, which is expected to be implemented sometime in 2018 or 2019. The Proof of Stake model is expected to lower cost of verification, increase scalability, and greatly decrease the issuance of new Ether (Ethereum.org, 2017). Instead of having Miners using lots of computing power to solve a complex puzzle, validators (nodes that participate in verification) deposit some amount of Ether, or in other words, a stake. Only validators can then add new blocks, and other validators must bet on these blocks to gain consensus. If a validator bet on an invalid block or otherwise try to alter the process, the node's deposit will be forfeited, and the node will lose the right to be a validator (Zamfir, 2015). Like Miners, Validators receive the Ether paid for Gas. With Proof of Stake, block rewards are essentially unnecessary, and the issuance of new Ether can potentially stop. The algorithm is still in the making, so it might not stop issuance of Ether at first but is expected to significantly decrease issuance of new Ether (Dale, 2017).

3.1.5 Drivers of The Price of Ether

It is clear by now that Ether is essential to perform any activity on Ethereum. In fact, the sole purpose of Ether is to serve as a medium of payment for computing power on Ethereum. Intuitively, this property implies that the market capitalization of Ether derives from the price (in fiat money) charged for computing power and the total demand for computing power. For simplicity, USD is used instead of referring to fiat money in general.

The US dollar price required by suppliers for computing power is difficult to observe. Unlike most buyer-seller relationships, it is the buyer of computing power who decides how much Ether she wishes to pay for Gas. Miners then include the transactions with highest Gas price in the block. Thus, some pay a high price to get the transactions executed fast, while others pay less and wait until a Miner finds it attractive (Dannen, 2017). However, from economic theory, the price is a function of supply and demand. If demand (D_c) increases, but supply (S_c) is stable (and not abundant), price (P_c) increases and vice versa. Price can therefore be defined as $P_c = f(D_c, S_c)$.

Supply of computing power can be measured by the Hashrate. The total Hashrate is the amount of computing power supplied by all the Miners and thus represents total computing power available on Ethereum. Figure 3.1 graphs daily average Hashrate and daily demand for Gas.

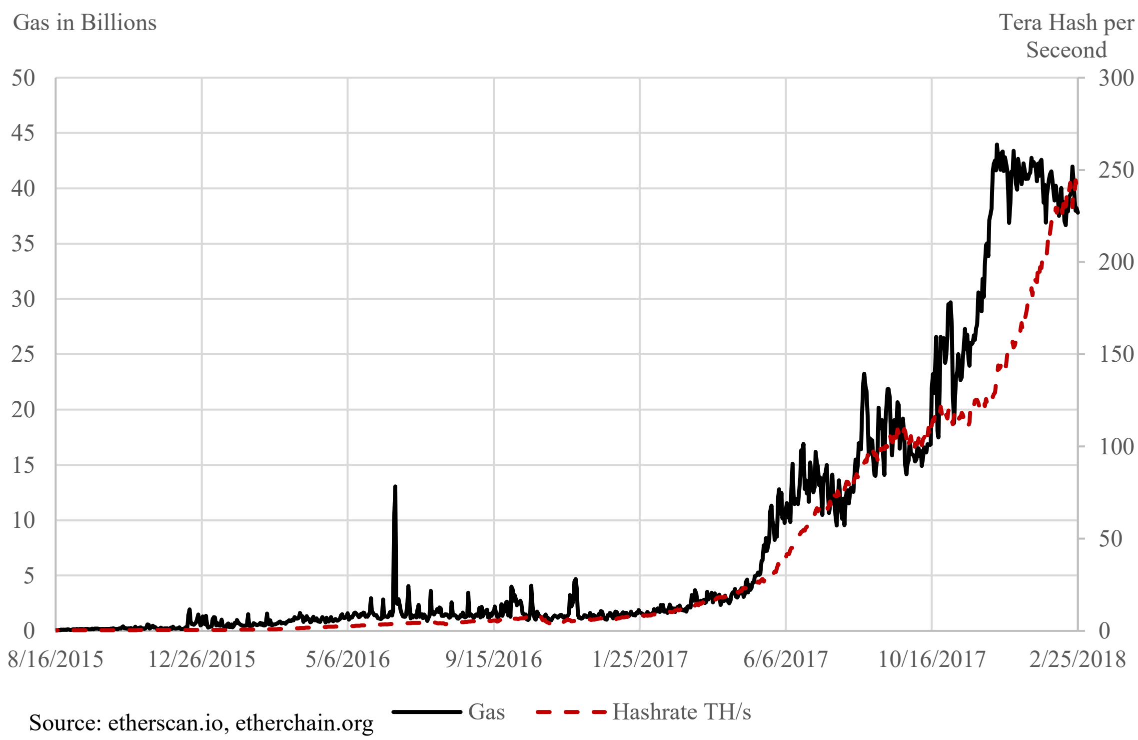

Figure 3.1: Hashrate and Gas 2015-2018.

While demand has experienced significant spikes over time, it seems supply and demand for computing power have experienced similar growth. Applying the Granger Causality test, the relationship can be examined further. To satisfy the assumptions of the test, the series must be transformed to become stationary. Using weekly observations from August 16, 2015, through February 25, 2018, the two series are transformed using natural logarithm, and taking the first difference creates the two series $d\ln(Gas)$ and $d\ln(Hash)$. The transformed series are found stationary using the DF-GLS test in SAS using "proc varmax". Both tests reject the null of a unit root at the 1%-level using single mean test.

Table 3.1: Granger Causality Wald Test for Hashrate and Gas.

Endogenous Variable	Exogenous Variable	Lags	DF	χ^2	p-value
Hashrate	Gas	3	3	12.01	<0.01
Gas	Hashrate	3	3	25.50	<0.01

The results in Table 3.1 show that with 99% confidence the null of no causality is rejected for both tests. Thus, Gas Granger Causes Hashrate and vice versa. Table 3.2 shows the estimated coefficients and standard errors. The three lags of Gas all significantly and positively affect Hashrate and the results are similar, considering the effect of lags of Hashrate on Gas, where only the second lag is insignificant. The F-stats represent the tests for the null that the coefficients of the three lags of the exogenous variable are jointly zero.

Table 3.2: VAR(3) Models using Hashrate and Gas.

Indep. / Dep. Variable	Hashrate	Gas
Constant	0.043 (0.010)***	0.076 (0.037)*
Gas Lag 1	0.050 (0.02)*	-0.409 (0.09)***
Gas Lag 2	0.055 (0.02)*	-0.121 (0.09)
Gas Lag 3	0.064 (0.02)**	-0.146 (0.08)
Hashrate Lag 1	0.117 (0.09)	1.175 (0.32)***
Hashrate Lag 2	-0.155 (0.09)	-0.185 (0.33)
Hashrate Lag 3	0.026 (0.09)	-0.968 (0.32)**
F-stat	4.10*	8.71***

*Signifance levels: *p<0.05, **p<0.01, ***p<0.001*

The analysis supports the pattern in Figure 3.1. It seems that as demand grows, so does supply. So, demand has predictive power over supply. With that in mind, it should be possible to determine supply as a function of demand, so $S_c = f(D_c)$. However, demand alone might not be able to determine supply. The cost of supplying computing power and potential entry barriers affects the entry of new suppliers.

Ethereum is fully decentralized, and everyone has access to the technology. So, the entry barriers for suppliers of computing power are limited to hardware and access to electricity. Currently, the cost of hardware necessary for mining starts at a few thousand dollars. The minimum stake required in the coming Proof-of-Stake algorithm is still unknown, but in September 2016 Vitalik Buterin presented a paper, claiming a minimum stake of 32 Ether (Rivlin, 2016). At the time, 32 Ether totaled $300-$400. So, entry barriers are low both regarding cost and technology. Thus, it seems fair to assume that the main driver of supply is in fact demand for computing power, as new suppliers will quickly enter in case of increasing demand. The price of computing power can now be redefined as a function of demand for computing power:

$$P_c = f(D_c, S_c) = f\big(D_c, f(D_c)\big) = \ g(D_c).$$

It was argued above, that the market capitalization of Ether (V) derives from the price and demand of computing power. Define the relationship as $V = f(P_C, D_c)$, then $P_c = g(D_c)$ leads to $V = f\big(D_c, g(D_c)\big) = h(D_c)$. Thus, the market capitalization of Ether should derive from the demand of computing power.

3.2 ETHEREUM AS A NETWORK

Ethereum is essentially a platform that allows entities to conduct transactions and execute contracts in a digital and trustless environment. As such, Ethereum shares some fundamental properties with other networks. Like other networks, the value for the individual user can be divided into two components. First, the functionality of the network provides value for users. For Ethereum, this value comes from the potential of smart contracts and how these can enable a variety of contractual agreements to be executed with higher efficiency. Second, value comes from the number of users on the network. For example, Facebook will not have the same value for a person whose personal network does not use Facebook, compared to someone who has her entire personal network on

Facebook. The same logic applies to Ethereum. As more people and corporations use the blockchain, the more relevant applications exist for the individual.

The current use of smart contracts is still limited. Thus, the associated value comes from a perceived future potential. As the network grows, the associated value for the individual increases as adoption increases the likelihood of future utilization. Thus, value grows non-linear in users, as the value increases in users but the average value per user also increases in users. This intuition is exactly the argument behind Metcalfe's Law, as value is proportional to the total number of possible connections. As users increase, the number of possible connections for each user also increases, leading to value growing proportional to N^2.

3.3 VALUE OF ETHEREUM

Unlike most other networks, it is not possible to own Ethereum. Entities can participate, but it is not possible to own a share of Ethereum. As such, every participating node owns Ethereum and yet no one owns Ethereum. Thus, the total value of the network must be determined differently than based on expected future earnings for the owners. The value of Ethereum is represented by the value it can create for all its users, so the intrinsic value comes from the functionalities that Ethereum provides. Ether is needed for any interaction on Ethereum, and so, the value represents the expected future consumption of computing power on Ethereum. Thus, the value of Ether represents how much value investors associate with the future utilization of Ethereum. As such, the value of Ether is the best available measure of the value of Ethereum. That said, the total value of a public blockchain is somewhat misleading as no one can ever own it and thus never trade it. As the technology matures and proves its real potential, other measures and definitions might be more appropriate, but for now, the total market capitalization of Ether is considered to represent the value of the Ethereum blockchain.

3.4 MODELING NETWORK VALUE

Metcalfe's Law is one of the most utilized models for network valuation, and most subsequent research builds on it.

Metcalfe's Law states:

$$V(N) = kN^2,$$

where N is the total number of users (or nodes), $V(N)$ is the value of the network, and k is a constant. The value of the network experiences slow growth in the beginning, but growth increases as more users participate on the network. In more formal terms, $\frac{\partial V(N)}{\partial N} = 2kN$ and $\frac{\partial^2 V(N)}{\partial^2 N^2} = 2k$, so the marginal value of additional users is increasing in number of users, while the second-order effect is constant. In other words, the model proposes that network value will grow exponentially in users, regardless of the number of users.

Briscoe, Odlyzko, and Tilly (2006) criticize Metcalfe's Law and propose the following model:

$$V(N) = kN \times \log_{10}(N).$$

For the sake of simplicity, this analysis will apply the model using the natural logarithm as the relationship between $\ln(N)$ and $\log(N)$ is linear and will thus only affect the estimated constant. Compared to Metcalfe's Law, the model predicts a more modest growth pattern as users increase:

$$V(N) = k \ln(N)\, N$$

$$\frac{\partial V(N)}{\partial N} = k(\ln(N) + 1)$$

$$\frac{\partial^2 V(N)}{\partial N^2} = \frac{k}{N}$$

The marginal value is still increasing in N, but the second-order condition is decreasing in N. As the second-order derivative converges to zero as N goes to infinity, the value of the network will start to grow in a linear fashion.

Metcalfe (2013) responded to the critique by Briscoe, Odlyzko, and Tilly (2006) by proposing a Netoid function to model the growth of users used in his model:

$$N(t) = \frac{p}{1 + e^{-v(t-h)}},$$

where N is the number of users, p is the upper bound for users, to which N will converge as time (t) goes to infinity, v is virality, where a higher value means faster adoption, and h is the center of the Netoid function, where growth peaks. Thus, when $t > h$ growth is decreasing.

More formally, p, t, v, and h are assumed to be non-negative, therefore:

$$\frac{\partial N(t)}{\partial t} = \frac{vpe^{v(t-h)}}{(1 + e^{v(t-h)})^2} > 0 \quad for\ 0 \leq t < \infty\,,$$

$$\frac{\partial^2 N(t)}{\partial^2 t^2} = -\frac{pv^2\left(e^{v(t-h)} - 1\right)e^{v(t-h)}}{(e^{v(t-h)} + 1)^3} \begin{cases} \geq 0 & for\ \ 0 \leq t \leq h \\ < 0 & for\ \ t > h \end{cases}.$$

Thus, the Netoid function is graphically represented by an S-curve. While it does not directly address the proposed critique, the Netoid function does prevent the value from reaching extreme levels and does have some interesting properties for networks. It seems reasonable to apply the Netoid function in determining the growth pattern of participation on a network as adoption is unlikely to occur linearly. In the beginning, a few early adopters will begin to use the network. If the network provides value for these users, they are likely to share that value-proposition in their personal network leading to new users. These new users then share the value-proposition and attract additional users. Thus, growth will be slow in the beginning but will increase as more people join and share the network with others. The increasing growth will continue until a certain amount has entered the network. At some point, there are not enough potential new users to maintain exponential growth. Thus, the growth will start to decrease and finally converge to the maximum potential of the network. In the case of an Internet-based network, a natural upper bound would be the total number of people with internet access. Similar logic applies to Ethereum. As mentioned, the increase in the value of Ether seems to come from perceived future potential. If current participants on Ethereum present the value proposition to their personal network, it can be expected that a ratio of these will also participate directly or indirectly by acquiring Ether through an exchange. Like other networks, this will result in slow but increasing growth initially. As more users share the value proposition, growth will increase, but only as long as new potential users are available. Thus, at some point, growth peaks and the Blockchain will move towards saturation (Alabi, 2017).

In his application to cryptocurrencies, Alabi (2017) also utilizes the Netoid function and finds that the growth in IP addresses on the respective blockchains, seems to follow the model.

Besides Metcalfe's Law, Alabi proposes a new model for value as a function of IP addresses on blockchains:

$$V(N) = Ce^{\lambda N^m},$$

where C, λ, and m are constants. C is a linear growth factor and λ is an exponential multiplier for user-growth. His model provides more flexibility compared to Metcalfe's Law as it does not include a pre-defined exponent like N^2. Thus, it should apply to networks where value does not grow proportional to the quadrate of users. Alabi finds his model provides better results for all three cryptocurrencies he investigates.

The first and second order derivatives, with respect to N, show significantly different growth patterns compared to the two previously examined models. As it is assumed that C, λ, and m are positive, the first derivative is positive for any value of N, but the second derivative can take negative values.

$$\frac{\partial V(N)}{\partial N} = C\lambda m N^{m-1} e^{\lambda N^m},$$

$$\frac{\partial^2 V(N)}{\partial N^2} = C\lambda m N^{m-2}(\lambda m N^m + m - 1)e^{\lambda N^m}.$$

In his analysis, Alabi estimates the following for Ethereum, $C = 3$, $\lambda = 0.011$, and $m = 0.5$, which results in:

$$\frac{\partial^2 V(N)}{\partial N^2} \begin{cases} < 0 & for\ N \leq 8{,}246 \\ > 0 & for\ N \geq 8{,}247 \end{cases}$$

In his model, marginal value decreases until the blockchain reaches about 8,200 users, where the second derivative becomes positive and marginal value increases in N. Based on the assumptions of positive constants, the general model shows that $\frac{\partial^2 V(N)}{\partial N^2} < 0$ if $\lambda m N^m + m < 1$. Thus, Alabi's model implies that marginal value of additional users is decreasing, until it reaches a certain threshold, and marginal value starts to increase.

To further build and improve on the work by Alabi, the three models for network valuation will be applied to examine if any of the models can explain the value of Ether from activity on Ethereum. The Netoid model will be applied to see if participation still follows the proposed pattern and if so, it will be applied in forecasting the value of Ether.

3.5 USERS ON ETHEREUM

When applying the three models to Ethereum the first step is to determine how to measure participation. One way is the number of IP addresses on the blockchain, following Alabi (2017). Among available variables, IP addresses are the closest to the traditional measure of users. However, IP addresses have some shortcomings considering the nature of Ethereum. First, it is possible to interact with the blockchain without being on the blockchain. Due to the programmable nature of smart contracts, off-chain interactions are possible. Thus, some IP addresses potentially represent thousands or millions of users, while others only represent one. Second, one user might be represented by multiple IP addresses by participating with multiple computers/servers. Third, the number of IP addresses does not represent the utilization of the users. In other words, users can be represented by an IP address with only a few transactions.

On a platform like a cellular network, the functionality is more limited, and thus the number of users is likely to be a very good predictor of value. While social networks provide more options, the functionality is still limited. Thus, users provide a good predictor. On Ethereum, functionality is potentially unlimited, and users alone might not explain all variation in value. To clarify, it helps to consider Metcalfe's Law. Metcalfe defines total value by $V(N) = \hat{k}N^2$, where the hat simply states that k is uncertain and must be estimated. The average value per user is therefore $\bar{v} = \hat{k}N$. If we measure users as one-for-one in N, the average utilization is incorporated in $\hat{k}$ and therefore estimated. If measuring the activity of users, N can be substituted with $A = \bar{a}N$, where $\bar{a}$ is a measure for average utilization per user and A is the total activity on the blockchain. Instead of using the traditional formula, define $\hat{k} = \hat{c}\bar{a}^2$ and therefore $V(N) = \hat{k}N^2 = \hat{c}\bar{a}^2N^2 = \hat{c}A^2 \rightarrow V(A) = \hat{c}A^2$. As pointed out, the true number of users on Ethereum is difficult to measure, but total activity can be measured more precisely.

One way to measure activity is by the number of transactions. Every activity by an EOA is in the form of a transaction. One issue with transactions is that they do not measure the magnitude of activities, as transactions can also hold smart contracts. It is difficult to assign a value to each contract, and so, the true value of each transaction is difficult to estimate.

Another measure of activity is the amount of Gas used. As any activity requires Gas, it accounts for transactions, the complexity of smart contracts, and messages from smart contracts. Thus, Gas accounts for most activities and the complexity of smart contracts making it a potentially good measure of activity. Gas does not account for the Ether volume of transactions and messages since a transaction of 1 Ether uses the same amount of Gas as a transaction of 1,000 Ether. Thus, Gas has similar problems as transactions, yet is still considered to be the best available measure for utilization of Ethereum. Like IP addresses, transactions and Gas are both imperfect measures, so all three will be used in this analysis to determine, which is the best predictor of the value of Ether.

3.6 USERS AND DEMAND FOR COMPUTING POWER

As it turns out, the appropriate measures for users are also measures for the demand of computing power on Ethereum. The amount of Gas used in a day measures the demand for computing power, and as any interaction requires Gas, active IP addresses and transactions also serve as measures of demand. Thus, combining the analysis, demand for computing power as the driver of value coincides with the notion of Ethereum as a Network with Ether representing the value of Ethereum. The models for network valuation are therefore found appropriate to explain the relationship between activity (demand) on Ethereum and the value of Ether. It is also argued that the current value of Ether comes from expected future utilization of Ethereum. As an increase in activity or current demand increases the probability of future utilization of Ethereum, the observed demand of computing power should represent the expectation of future demand. However, this relationship is unlikely without frictions. New information might not directly affect current demand but positively or negatively affect value. Thus, deviations from the values predicted by the models are expected, but as expectations change, the observed demand should adjust. If the expectations of future demand increase, then Ether becomes more attractive for investors who will then acquire Ether. Thus, number of transactions increases and therefore demand for computing power increases. Assuming the demand for computing power explains the value of Ether, deviations from predicted values are therefore expected to be temporary.

4. DATA AND METHODOLOGY

4.1 DATA

The independent variables for the analysis will be IP addresses, transactions, and the amount of Gas used. Active daily IP addresses are available from bitinfocharts.com. Daily number of transactions and total daily Gas used are available from etherscan.io. For the dependent variable, daily price in USD and total daily supply of Ether are available from etherscan.io and are used to calculate total market capitalization of Ether. Ethereum was first released on July 30th, 2015 and data are available from then until the present day.

Ether is a very volatile asset. In fact, the standard deviation of daily returns on Ether was 7.1% for 2017 compared to 0.4% for S&P500. To minimize the effects of volatility, a weekly frequency will be used. For prices, and thus market capitalization, the quoted price from etherscan.io on every Sunday will be applied. For the independent variables, a daily average from Monday through Sunday will be applied. Thus, market capitalization on every Sunday will be a function of the average daily measure of activity over the week ending that Sunday. Averaging, number of IP addresses, transactions, and Gas used is found appropriate as daily fluctuations might be caused by many factors and not correctly represent the general activity on Ethereum, during that period. As the price of Ether was zero during the first week, the first week is excluded from the analysis. The sample period is therefore from August 10, 2015, through December 31, 2017, providing a total of 125 observations. Table 4.1 summarizes applied variables.

Table 4.1: Summary of Applied Variables.

Variable	Notation	Description
Market Capitalization	V	Price of Ether multiplied by the supply of Ether for every Sunday.
Active IP Addresses	N_1	Average daily active IP addresses on Ethereum from Monday through Sunday.
Transactions	N_2	Average number of daily transactions from Monday through Sunday.
Gas	N_3	Average Gas used per day from Monday through Sunday.

4.2 MODELS AND ESTIMATION

To model market capitalization as functions of active IP addresses, transactions, and Gas, the three models examined in the previous section will be applied.

4.2.1 Estimation

The models proposed by Metcalfe (2013) and Briscoe, Odlyzko, and Tilly (2006) are both linear in the parameter k. So, Ordinary Least Squares (OLS) method is applied. While the series are expected to suffer from both autocorrelation and heteroscedasticity, OLS is still found applicable as parameter estimates are still unbiased and statistical inference is of minor importance in this analysis. However, Newey-West standard errors will be applied in estimation for more robust standard errors.

The model proposed by Alabi requires a non-linear estimation method. In this analysis, the SAS 'proc nlin' function is applied using the default Gauss-Newton algorithm. While the technical details of the Gauss-Newton algorithm are outside the scope of this paper, a few should be mentioned. Gauss-Newton is a non-linear least squares iterative optimization method. As the sample size is relatively small, parameters are likely to be biased, following non-normal distribution, and not minimum variance. Thus, t-test, F-test, and R^2 are not meaningful statistics (Gujarati and Porter, 2009). So, in the analysis, a fit will be found for the equation and compared to the two other models as described in Section 4.2.3.

4.2.2 Robustness of Models

The proposed models are deterministic in nature. As econometric methods are applied, it raises the issue of non-stationarity, which can cause spurious results. The discussion in Section 3 argues why the activity on Ethereum should determine the value of Ether. However, there is no exogenous justification for the applicability of the proposed models. To see if these deterministic models explain the value of Ether, a simple test will be conducted following the estimation of the models.

First, take the natural logarithm and first difference of Metcalfe's Law:

$$\ln\big(V_t(N_t)\big) = \ln(kN_t^2) = \ln(k) + 2\ln(N_t)$$

$$\ln\big(V_t(N_t)\big) - \ln\big(V_{t-1}(N_{t-1})\big) = \ln(k) + 2\ln(N_t) - \ln(k) - 2\ln(N_{t-1}) = 2(\ln(N_t) - \ln(N_{t-1}))$$

Define:

$$d\ln(V_t) = \ln(V_t) - \ln(V_{t-1}) \quad and$$

$$d\ln(N_t) = \ln(N_t) - \ln(N_{t-1}).$$

The result is the log-difference version of the model.

$$d\ln(V_t) = 2d\ln(N_t).$$

Subtracting the right-hand side from the left-hand side provides:

$$d\ln(V_t) - 2d\ln(N_t) = 0.$$

The result implies, that if above relationship holds, the value of Ether follows Metcalfe's Law using the applied measures of activity. As deviations between predicted and observed values are expected, a new time series z_t, is created.

$$d\ln(V_t) - 2d\ln(N_t) = z_t$$

For the model by Briscoe Odlyzko, and Tilly, the result is:

$$d\ln(V_t) = d\ln(N_t) + \ln\left(\frac{ln(N_t)}{ln(N_{t-1})}\right).$$

Define:

$$\left(d\ln(N_t) + \ln\left(\frac{ln(N_t)}{ln(N_{t-1})}\right)\right) = X_N$$

$$d\ln(\mathrm{V_t}) - X_N = 0 \rightarrow d\ln(\mathrm{V_t}) - X_N = z_t.$$

For the model by Alabi, the result is:

$$d\ln(V_t) = \lambda(N_t^m - N_{t-1}^m).$$

Define:

$$Y_N = \lambda(N_t^m - N_{t-1}^m)$$

$$d\ln(\mathrm{V_t}) - Y_N = 0 \rightarrow d\ln(\mathrm{V_t}) - Y_N = z_t.$$

If z_t has zero mean and the mean is constant over time, it implies, that the models explain the value of Ether, but other factors cause the price of Ether to fluctuate around the predicted values. In other words, when comparing the results to actual price data, temporary deviations can have two interpretations. First, deviations can be interpreted as mispricing and provide valuable information for investors. Second, the deviations can also be a result of temporary misalignment between current and expected future demand of computing power on Ethereum.

Determining if the true mean is exactly zero, is not possible. However, it is possible to test if the null of $\mu(z_t) = 0$ can be rejected using a t-test:

$$t = \frac{\mu(z_t) - 0}{SE(\mu(z_t))},$$

where $\mu(z_t)$ and $SE(z_t)$ are the mean and standard error of z_t. From the t-value, the p-value is determined. The null hypothesis is that $\mu(z_t) = 0$ and the p-value represents the probability of rejecting the null, when it is in fact true. The decision rule usually applied to econometric analysis is rejection of the null if $p < 0.05$ or $p < 0.01$. However, as the relationship between the value of Ether and activity on Ethereum only shows to hold if the null is not rejected, the decision rule is chosen at $p < 0.2$. A higher p-value indicates less evidence against the null hypothesis and to increase the power of the test, models are rejected even with relatively weak evidence against the null.

To see if the mean is constant over time, the series will be tested for a unit root using the Augmented Dickey-Fuller (ADF) test with zero mean. If the presence of a unit root is rejected at the 5%-level, the series is accepted as stationary, and the mean of zero assumed to be constant over time.

The power of the test is weak, as it does not test for $\mu(z_t) = 0$ directly. However, if the null is not rejected and the series is found to be stationary with zero mean, the model is assumed to have $\mu(z_t) = 0$ and will be utilized further in the analysis.

As the test for Alabi's model requires the estimates of λ and m, the tests will be done after estimating the models.

4.2.3 Comparison of Models

To compare models, R^2, the Root Mean Square Error (RMSE), and an adjusted version of RMSE will be applied. As Alabi's model and the Netoid function are non-linear in parameters, the residuals do not necessarily sum to zero, and the sum of the estimated sum of squares and residual sum of squares does not necessarily equal total sum of squares. Thus, R^2 for all models will be computed as proposed by Gujarati and Porter (2009):

$$R^2 = 1 - \frac{\sum_{t=1}^{T}\left(Y_t - \hat{Y}_t\right)^2}{\sum_{t=1}^{T}\left(Y_t - \bar{Y}_{t,T}\right)^2},$$

where Y_t is the actual value of the dependent variable at time t, $\hat{Y}_t$ is the predicted value of the dependent variable at time t, and $\bar{Y}_{t,T}$ is the mean of observed values of the dependent variable from time t to T.

RMSE is defined as:

$$RMSE = \sqrt{\sum_{t=1}^{T}\left(\frac{\left(Y_t - \hat{Y}_t\right)^2}{N}\right)},$$

where N is the total number of observations. From Figure 1.1, market capitalization experienced relatively slow growth and low variation in absolute terms from mid-2015 to the beginning of 2017 compared to the more recent observations. Thus, RMSE will be likely to favor models that better explain recent value compared to early value. To better compare models, the following measure will also be applied:

$$RMSE_{\Delta Y} = \sqrt{\sum_{t=1}^{T}\left(\frac{\left(\frac{Y_t - \hat{Y}_t}{Y_t}\right)^2}{N}\right)},$$

where $RMSE_{\Delta Y}$ weights each residual by the inverse of the observed value of Y_t. Thus, predictions associated with lower values of Y_t receive the highest weights. So, in this case, $RMSE_{\Delta Y}$ favors models that better explain early market capitalization. Combined with $RMSE$, this measure provides a more holistic picture of the models' ability to explain the observed values of Ether over time.

4.2.4 In-Sample versus Out-of-Sample Performance

The last observation in the sample period is the week ending December 31, 2017. To see how the different models perform out of sample, data have been collected for the 8-week period from

January 1, 2018, through February 25, 2018. Observed values for the independent variables will be utilized to see how well the estimated models perform out of sample.

4.3 FORECASTING

The purpose of this analysis is first to examine if the applied network valuation models and activity measures can explain the value of Ether over time. Second, the models will be used for forecasting. An appropriate forecasting horizon was chosen at 6-months from the first Sunday in January 2018 (7^{th}) through Sunday, July 1, 2018. Weekly forecasts in the 6-month period will also be presented and discussed to see how the models perform in the very short-term.

To forecast the value of Ether, the independent variables must also be forecasted. The chosen approach is to use the Netoid function proposed by Metcalfe (2013) and later used for cryptocurrencies by Alabi (2017). To estimate the model, a time variable is created with the value of 1 at Sunday, August 16, 2015, the value of 2 at August 23, 2016, and so on through December 31, 2017. The model is estimated using the Gauss-Newton algorithm with the time variable as the independent variable. All models applied in the analysis are summarized in Table 4.2. For further reference, all models have been named according to author besides the Netoid function. The model by Briscoe, Odlyzko, and Tilly is referred to as Odlyzko's Law following Metcalfe (2013).

Table 4.2: Summary of Applied Models.

Model	**Equation**	**Dependent Variable**	**Independent Variable**
Metcalfe	$V(N) = kN^2$	Market capitalization	Active IP addresses, Transactions or Gas
Odlyzko	$V(N) = k \ln(N)N$	Market capitalization	Active IP addresses, Transactions or Gas
Alabi	$V(N) = Ce^{\lambda N^m}$	Market capitalization	Active IP addresses, Transactions or Gas
Netoid	$N(t) = \frac{p}{1 + e^{-v(t-h)}}$	Active IP addresses, Transactions or Gas	Time

4.3.1 Assumptions for Forecasting

As the Netoid function requires an iterative estimation method, many solutions can provide good fits for the equation. From preliminary analysis, estimation without upper bounds tends to produce unrealistically high values of p. The current Proof-of-Work algorithm implies some restrictions on the use of Ethereum. At the time, Ethereum supports around 15-16 transactions per second, or around 1.3-1.4 million transactions per day. The coming Proof-of-Stake algorithm is anticipated to drastically increase the limit to thousands per second but is not expected to be implemented in the first half of 2018 (Karnjanaprakorn, 2017). As of December 31, 2017, the number of daily transactions was just shy of 1 million and has previously reached levels just above 1.1 million. Thus, it is fair to assume, that with current technology, Ethereum is entering the latter part of the Netoid function, with diminishing growth. For estimation, the value of p will be fixed at 1.4 million representing the absolute maximum for the current state. While extensive growth might come because of a new consensus algorithm, the growth pattern will likely change and is therefore not accounted for in this analysis due to the forecasting horizon.

For active IP addresses, the average daily transactions per IP was 1.48 in December 2017. Given a maximum of 1.4 transactions that gives a maximum around 950 thousand active IP Addresses. However, larger values have been observed, and the average transactions per active IP address have generally been decreasing over time, so a maximum of 1.4 million daily IP addresses will be used. As EOAs interact with Ethereum through transactions, the average transactions per active IP cannot fall below 1, and thus 1.4 million seems to be a reasonable upper bound.

The average Gas per transaction was just above 46 thousand in December 2017. Appropriate assumptions are more difficult to determine, as Gas per transactions can be very high, and values above 200 thousand were observed in 2016. However, due to data limits on blocks, values at such levels are unlikely to occur as the number of transactions has increased. As levels just above 50 thousand were experienced during December 2017, an upper bound of 55 thousand is assumed. This assumption leads to an upper bound for daily Gas of 77 billion.

5. RESULTS

5.1 RESULTS OF MODEL ESTIMATION

Tables 5.1 to 5.3 show the estimated coefficients and error measures for the applied models and Figures 5.1 to 5.3 show visual representations of results.

Table 5.1: Estimated Models using Active IP Addresses as Predictor.

	Metcalfe	Odlyzko	Alabi
k	0.19 (0.011)***	8,661.10 (713.840)***	
C			9.91E-09 (0.000)
λ			32.62 (0.252)
m			0.02 (0.001)
R^2	0.592	0.934	0.950
RMSE	9,774,976,003	3,933,450,863	3,416,675,679
$RMSE_{\Delta Y}$	0.85	1.20	3.96

**** p<0.001. Significance level not included for non-linear least squares*

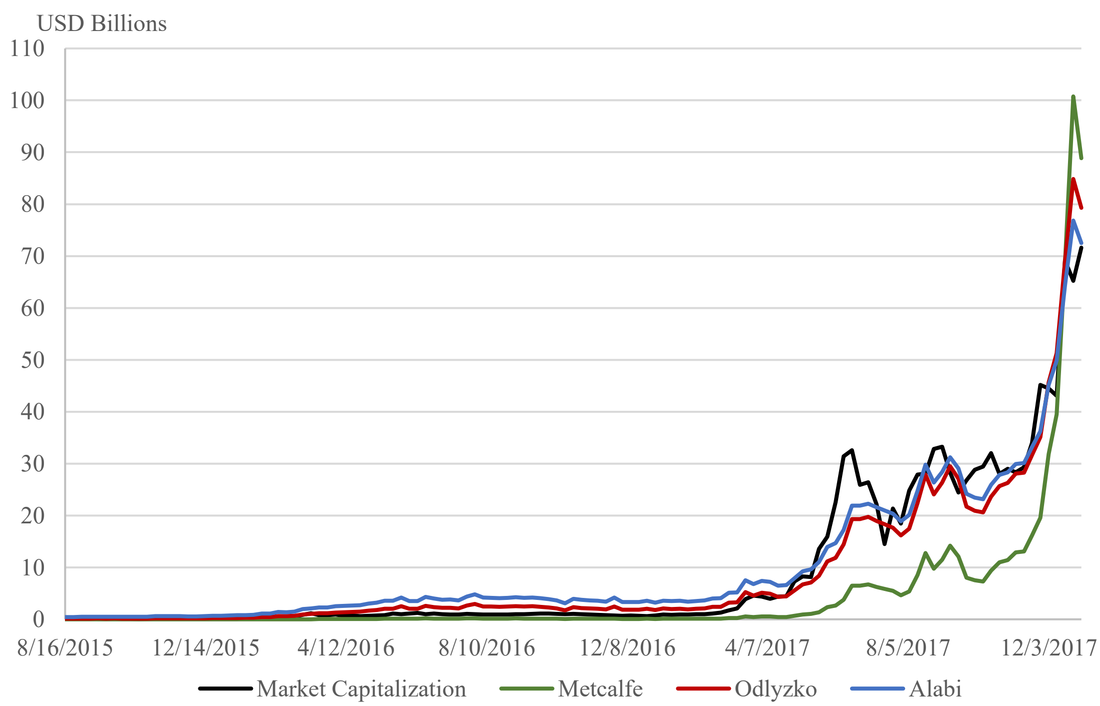

Figure 5.1: Ether Market Capitalization and Predictions using Active IP Addresses 2015-2017

Table 5.2: Estimated Models using Transactions as Predictor.

	Metcalfe	Odlyzko	Alabi
k	0.10 (0.022)***	5,529.33 (250.250)***	
C			9.93E-09 (0.000)
λ			31.61 (0.310)
m			0.02 (0.001)
R^2	0.690	0.938	0.941
RMSE	8,504,016,087	3,817,503,842	3,719,750,360
$RMSE_{\Delta Y}$	0.78	2.67	5.09

**** p<0.001. Significance level not included for non-linear least squares*

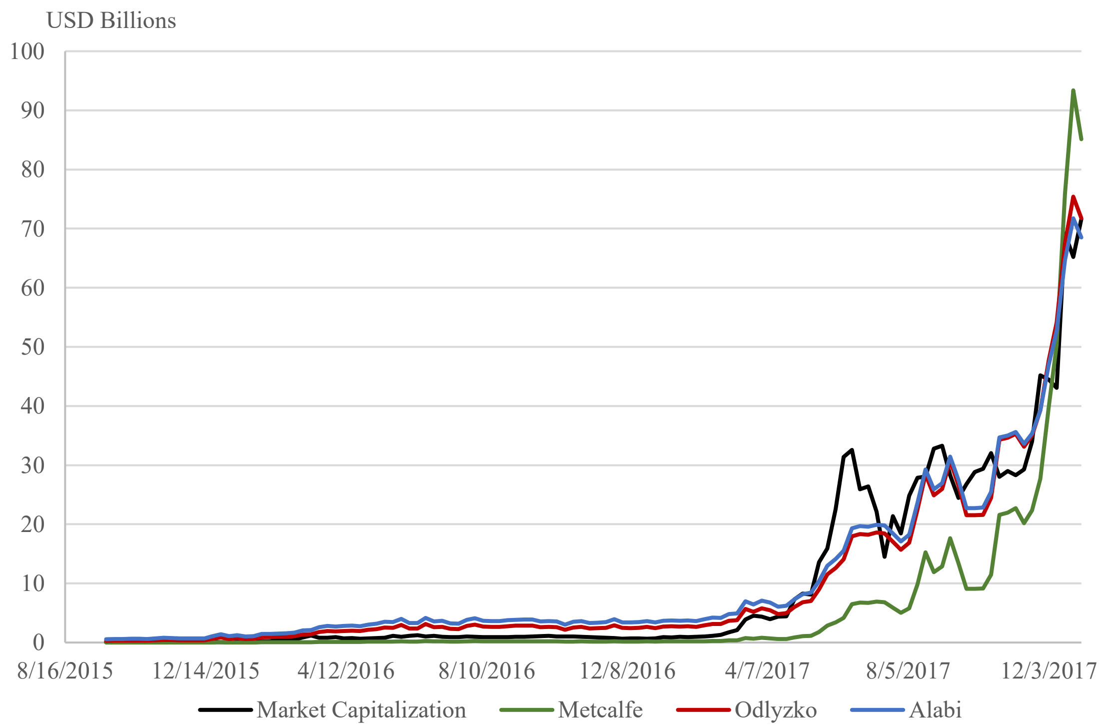

Figure 5.2: Market Capitalization of Ether and Predictions using Transactions 2015-2017.

Table 5.3: Estimated Models using Gas as Predictor.

	Metcalfe	Odlyzko	Alabi
k	4.61E-11 (7.98E-12)***	0.06 (0.003)***	
C			9.95E-09 (0.000)
λ			24.62 (0.485)
m			0.02 (0.001)
R^2	0.751	0.943	0.944
RMSE	7,636,100,031	3,655,907,306	3,633,675,513
$RMSE_{\Delta Y}$	0.81	3.07	4.60

**** p<0.001. Significance level not included for non-linear least squares*

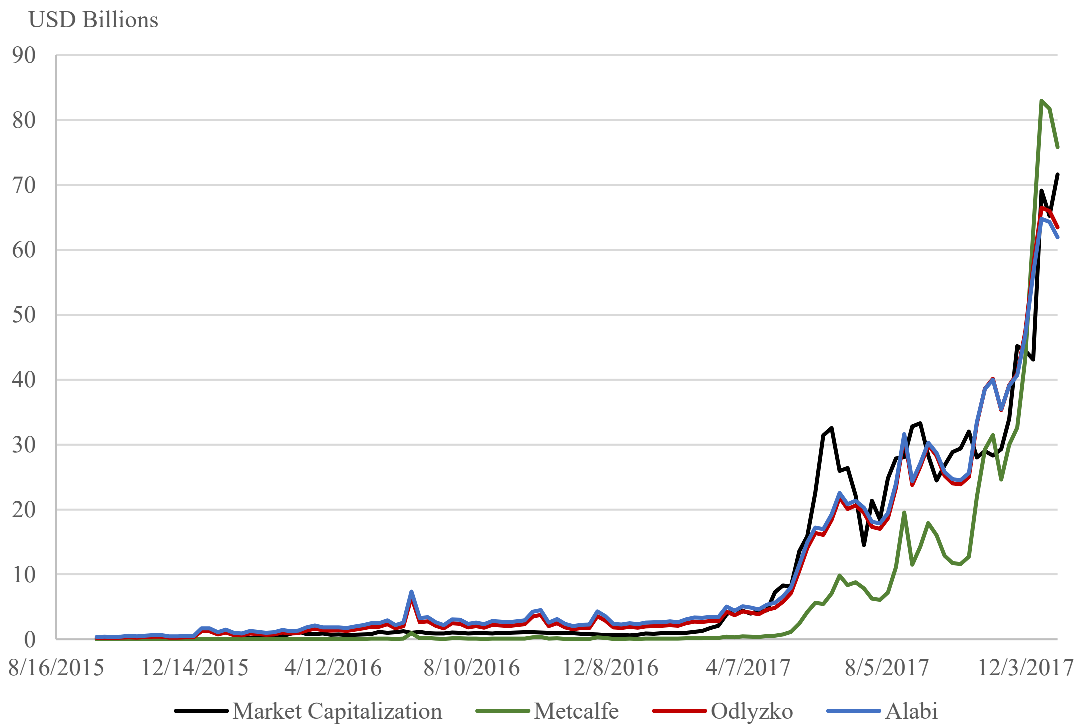

Figure 5.3: Market Capitalization of Ether and Predictions using Gas 2015-2017.

Figures 5.1 to 5.3 indicates that value and activity have grown together, but it is also evident that the models cannot explain all the variation in the value of Ether. R^2 and RMSE show that Odlyzko's Law and Alabi's model seem to explain most variance in market capitalization with R^2 ranging from 93.4% to 95.0%. Metcalfe's Law shows less ability to explain the value of Ether with R^2 ranging from 59.2% to 75.1%. When considering $RMSE_{\Delta Y}$, Metcalfe's Law provides the lowest values, but highest RMSE. These results suggest that Metcalfe's Law best explains early market capitalization, but that value as a function of activity has recently experienced more modest growth. To further examine these results Metcalfe's Law and Odlyzko's Law are presented visually. Figures 5.4 and 5.5 show the market capitalization of Ether on active IP addresses squared, and the market capitalization of Ether on the natural logarithm of active IP addresses times active IP addresses, respectively. For Metcalfe's Law to hold, a linear relationship should be evident in Figure 5.4. However, what seems to be closer to a logarithmic relationship confirms the critique of Metcalfe's Law as the value seems increasing less than proportional to N^2 at higher levels of N. From Figure 5.5 the pattern does seem to be somewhat linear and explains why Odlyzko's Law performs better in explaining the value of Ether over time.

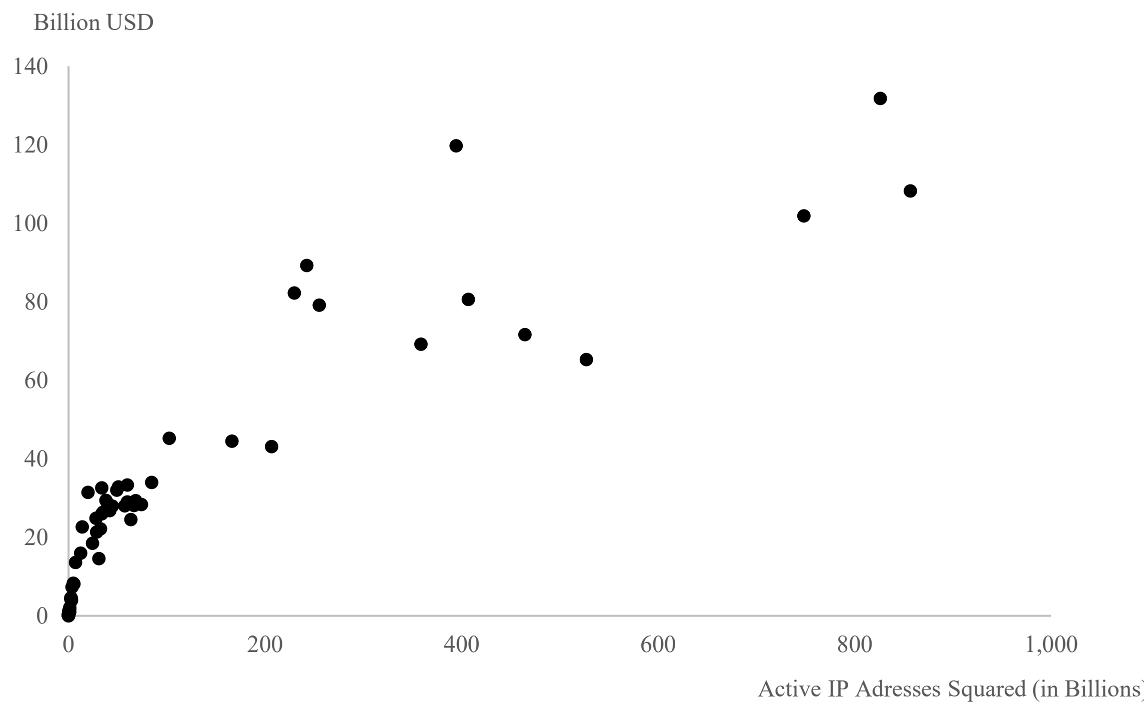

Figure 5.4: Market Capitalization of Ether on (Active IP Addresses)^2.

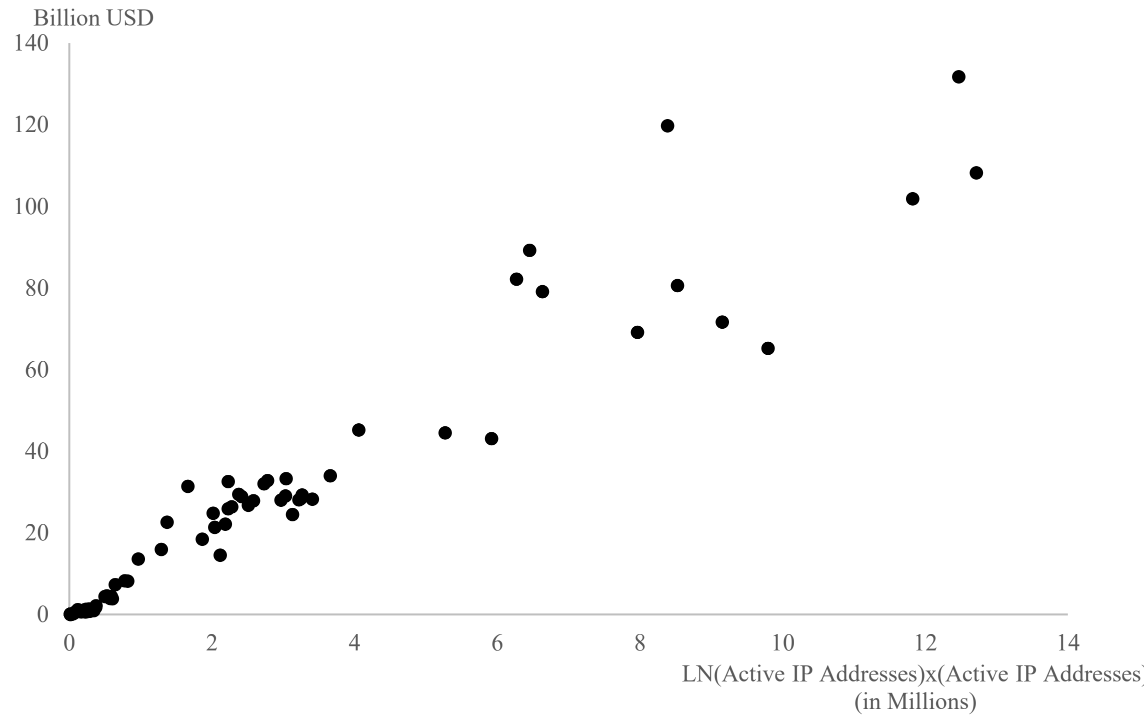

Figure 5.5: Market Capitalization of Ether on LN(Active IP Addresses)x(Active IP Addresses).

The model proposed by Alabi shows slightly higher R^2 and slightly lower RMSE compared to Odlyzko's Law. However, Alabi's model provides the highest $RMSE_{\Delta Y}$ for all activity measures. So, Alabi's model best explains later value but, evident from graphical representations, his model quite significantly overestimates the early value of Ether. Also, for both Alabi's model and Odlyzko's Law, a tradeoff is apparent between explanatory power of the early value versus the later value of Ether as $RMSE_{\Delta Y}$ decrease as RMSE increase.

Theory suggests that transactions and especially Gas should better explain the value of Ether as they incorporate average utilization by each node. RMSE and R^2 provide mixed results as Alabi's model provides the lowest RMSE (highest R^2) using active IP Addresses, whereas Odlyzko's Law provides the lowest RMSE (highest R^2) utilizing Gas as the predictor. Thus, there is no compelling evidence that Gas and transactions are better predictors of the value of Ether.

5.2 RESULTS OF ROBUSTNESS TEST

Tables 5.4 to 5.6 present results of the t-tests. The null is rejected for Metcalfe's Law using active IP addresses as $p < 0.2$, but not rejected for the other models. The confidence, at which the null can be rejected, does support the previous findings, that Metcalfe's Law is not able to explain the value of Ether over time, and Metcalfe's Law using active IP addresses is excluded from further analysis.

Table 5.4: t-test: Mean of z_t using Metcalfe's Law.

	IP	Transactions	Gas
Mean	-0.0441	-0.0427	-0.0514
Standard Error of Mean	0.0239	0.0355	0.0652
t-value	-1.8441	-1.2006	-0.7890
DF	123	123	123
p-value	0.068	0.232	0.432

Table 5.5: t-test: Mean of z_t using Odlyzko's Law.

	IP	Transactions	Gas
Mean	-0.0002	-0.0036	-0.0015
Standard Error of Mean	0.0168	0.0362	0.0365
t-value	-0.0099	-0.0983	-0.0404
DF	123	123	123
p-value	0.992	0.922	0.968

Table 5.6: t-test: Mean of z_t using Alabi's Model.

	IP	Transactions	Gas
Mean	0.0111	0.0086	0.0048
Standard Error of Mean	0.0159	0.0208	0.0328
t-value	0.6997	0.4151	0.1463
DF	123	123	123
p-value	0.4855	0.6788	0.8839

Appendix 1 shows the results of the ADF tests. Across all models, the null of a unit root is rejected at the 0.1%-level. Thus, except for Metcalfe's Law using active IP addresses, it is not possible to reject that change in value predicted by the applied models and activity measures, in fact, explain the change in the value of Ether over time.

5.3 OUT-OF-SAMPLE RESULTS

To examine the out-of-sample performance, the market value of Ether was predicted using observed values of the three activity measures. Table 5.7 shows that all three models provide very high RMSE independent of utilized activity measure. From Appendix 2, it is evident, that results suffer from a large value bubble in this period and so the results are found inapplicable in the analysis.

Table 5.7: Out-of-Sample RMSE: January 2018 to February 2018.

	Metcalfe	Odlyzko	Alabi
Active IP Addresses	N/A	25,460,038,461	30,180,672,303
Transactions	25,085,506,865	29,367,365,136	32,439,548,548
Gas	29,245,236,743	40,076,735,439	41,451,820,041

To further examine the robustness of the models over time, all models were re-estimated utilizing data through May 2017 to mimic the sample period used by Alabi (2017). Table 5.8 shows the results for out-of-sample RMSE and Figure 5.6 depicts the models using transactions as predictor. In Figure 5.6 the y-axis is limited to $200 billion but, as can be seen in Appendix 3, Metcalfe's Law and Alabi's model predict market values as high as $700 billion. Appendix 3 shows similar results using active IP addresses and Gas.

Table 5.8: Out-of-Sample RMSE: June 2017 to December 2017. Estimates through May 2017.

	Metcalfe	Odlyzko	Alabi
Active IP Addresses	N/A	7,758,615,744	180,021,995,294
Transactions	166,877,518,136	9,405,821,287	215,160,699,293
Gas	123,658,737,527	7,991,294,433	43,120,537,913

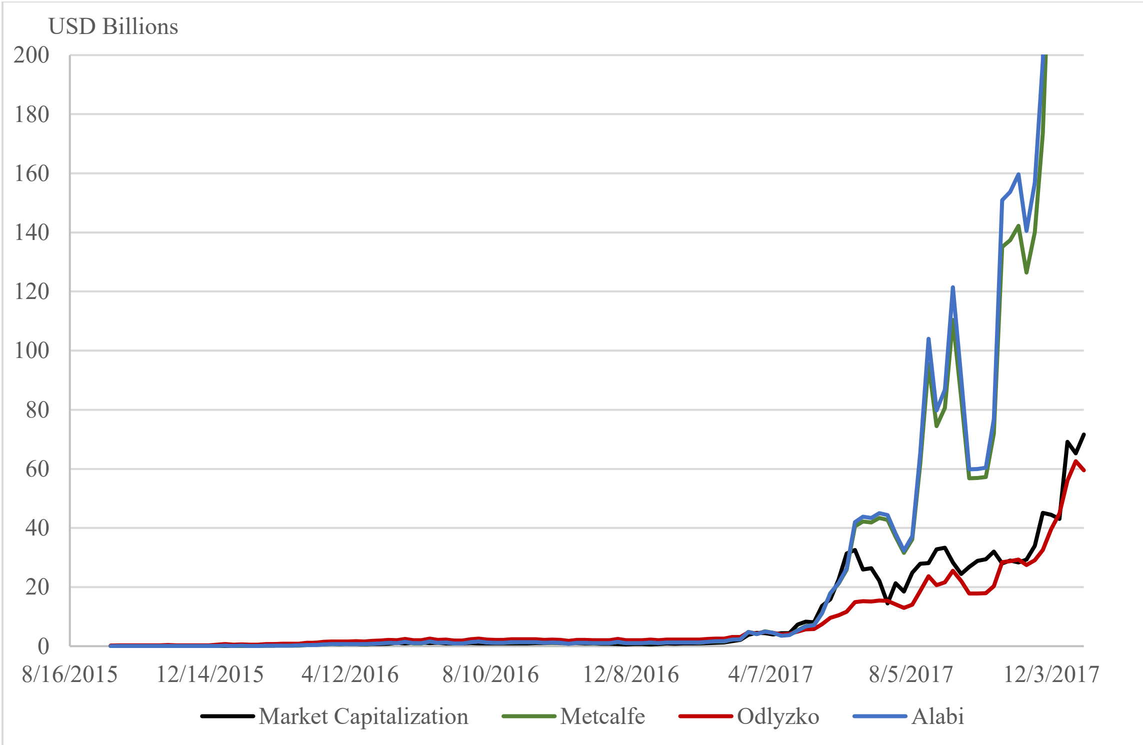

Figure 5.6: Market Capitalization of Ether and Models Estimated through May 2017, using Transactions.

Again, it seems that Metcalfe's Law overestimates growth but so does the model by Alabi. Unlike Metcalfe- and Odlyzko's Law, the model proposed by Alabi provides multiple parameters for estimation. More parameters seem to allow the model to explain more variation in-sample, but also results in different growth patterns depending on the sample composition. So, while Alabi's model provides the lowest RMSE in-sample, it is less robust out-of-sample compared to Odlyzko's Law.

The analysis shows that Metcalfe's Law best explains early market capitalization whereas recent data suggests that market capitalization follows Odlyko's Law. To further examine this, hybrid models of the two laws are estimated. Several models were estimated and evaluated based on combined RMSE to find the appropriate break date. The break date indicates the last observation for Metcalfe's Law. Table 5.9 shows estimated coefficients, standard errors, R^2, and error measures for the final models. Figure 5.7 shows the graphical representations of the models compared to observed market capitalization. Figure 5.8 shows the hybrid model compared to Metcalfe's Law and Alabi's model using transactions as a predictor.

Table 5.9: Estimated Hybrid Models of Metcalfe's Law and Odlyzko's Law.

	Active IP Addresses	Transactions	Gas
Metcalfe k	1.57	0.57	2.19E-10
	(0.010)***	(0.020)***	(2.77E-12)***
Odlyzko k	8580.87	5456.47	0.06
	(590.980)***	(182.760)***	(0.003)***
R^2	0.950	0.962	0.958
RMSE	3,371,975,098	2,985,576,877	3,131,837,120
$RMSE_{\Delta Y}$	0.46	0.38	0.65
Break Date	6/11/2017	6/18/2017	6/18/2017

*Signifance levels: *p<0.05, **p<0.01, ***p<0.001*

The hybrid models outperform the previous models considering R^2, RMSE, and $RMSE_{\Delta Y}$. From the statistical results and graphical representations, it is clear that the hybrid models are better able to explain the value of Ether compared to the three previously examined models. The results confirm that early market capitalization of Ether seems to follow Metcalfe's Law, but later value seems to follow Odlyzko's Law. Applying the test from Section 4.2.1 shows that for all three models the null of a unit root is rejected at the 0.1% level. However, the model using active IP addresses provides a p-value from the t-test of 0.17. Thus, the model should be excluded, but if the break date is changed to January 29, 2017, the p-value is 0.39. So, the break date might be incorrectly estimated when chosen using RMSE. Also, forecasting only applies the part of the model using Odlyzko's Law. If only considering that part of the model the p-value is 0.51 and so, the model is still applicable for forecasting.

Interpretation of the estimated parameters is somewhat difficult due to the nonlinearity of the models. If considering Metcalfe's Law, define the change in N from N_t to N_{t+1} as $N_{t+1} = N_t + \lambda$, where λ is the absolute change in activity. Then $V(N_{t+1}) - V(N_t) = k\lambda(\lambda + 2N_t)$ and for

Odlyzko's Law, $V(N_{t+1}) - V(N_t) = k \times \ln\left(\frac{(N_t+\lambda)^{N_t+\lambda}}{N_t^{N_t}}\right)$. Thus, the paramters do not provide any intuitive interpretation, besides the positive relationship between value and activity. For easier interpretation, the first-order conditions can be used if the change in N is sufficiently small.

The hybrid models show some variation in RMSE and R^2 given the activity measure applied, with transactions proving to be the best predictor. However, differences are too small to make any definitive conclusions. The R^2 of the hybrid models indicate that these explain 95.0% to 96.2% of the variation in market capitalization. As the hybrid models provide better results than both Metcalfe's Law and Alabi's model, only the hybrid models will be used in forecasting. Forecasting using the hybrid models implies using Odlyzko's Law, and so, the initial estimates of Odlyzko's Law will also not be used for forecasting.

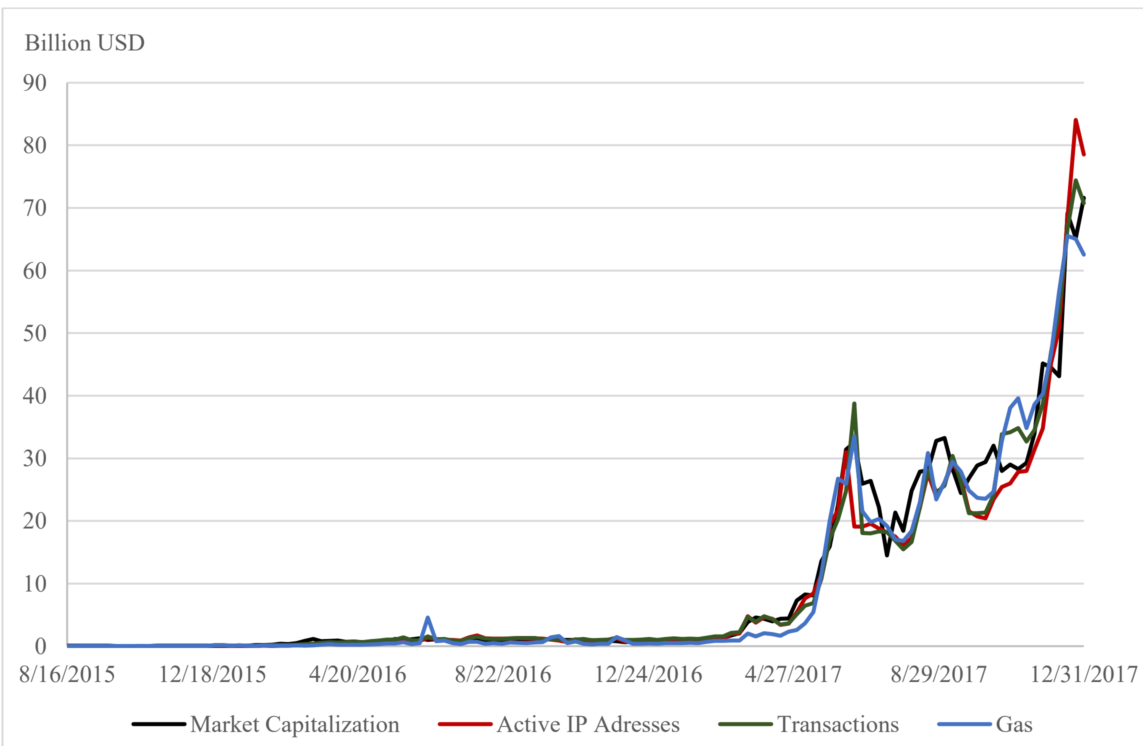

Figure 5.7: Market Capitalization of Ether and Predictions using Hybrid Models 2015-2017.

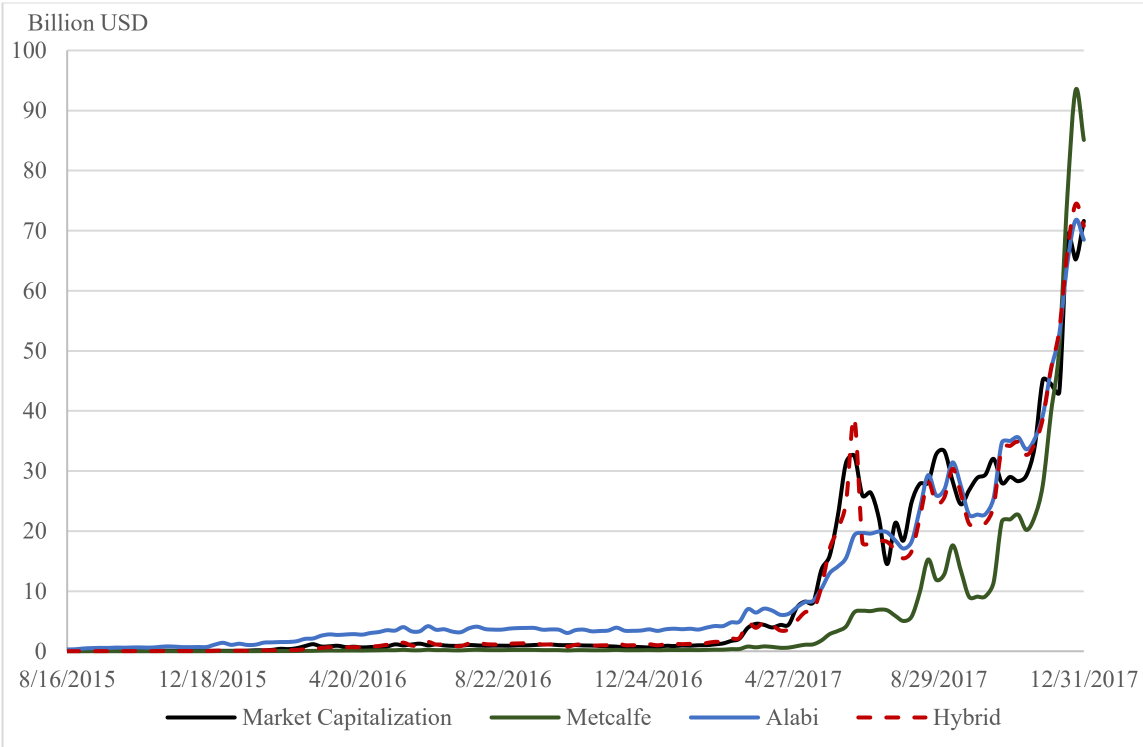

Figure 5.8: Ether Market Capitalization and Predictions using Transactions 2015-2017.

5.4 FORECASTING

5.4.1 Forecasting Activity Measures

Table 5.10 shows the estimated coefficients for the Netoid functions used to model active IP addresses, transactions, and Gas as functions of time. Figures 5.9 to 5.11 show the predictions compared with observed values of the activity measures. The values of p were achieved by the assumptions in Section 4.3.1, so only parameters v and h were estimated using non-linear least squares estimation.

Table 5.10: Estimated Netoid Models.

	Active IP Addresses	Transactions	Gas
p	1,400,000	1,400,000	77,000,000,000
v	0.071 (0.004)	0.075 (0.003)	0.072 (0.003)
h	132.1 (1.027)	122.6 (0.617)	125.8 (0.574)
R^2	0.900	0.931	0.953
RMSE	41,573	51,728	2,067,841,695
$RMSE_{\Delta Y}$	0.64	0.67	0.64

From R^2 and visual representations, it seems that the Netoid function can largely explain the growth of active IP addresses, transactions, and Gas over time. However, when using time as an independent variable, the Netoid function is not expected to explain weekly fluctuations. Estimates for v are very similar but as the models utilize different independent variables, the estimates are difficult to compare. The estimates for h show some differences across the activity measures. The models estimate the point of maximum growth at mid-February 2018, mid-December 2017, and the beginning of January 2018 for active IP addresses, transactions and Gas respectively.

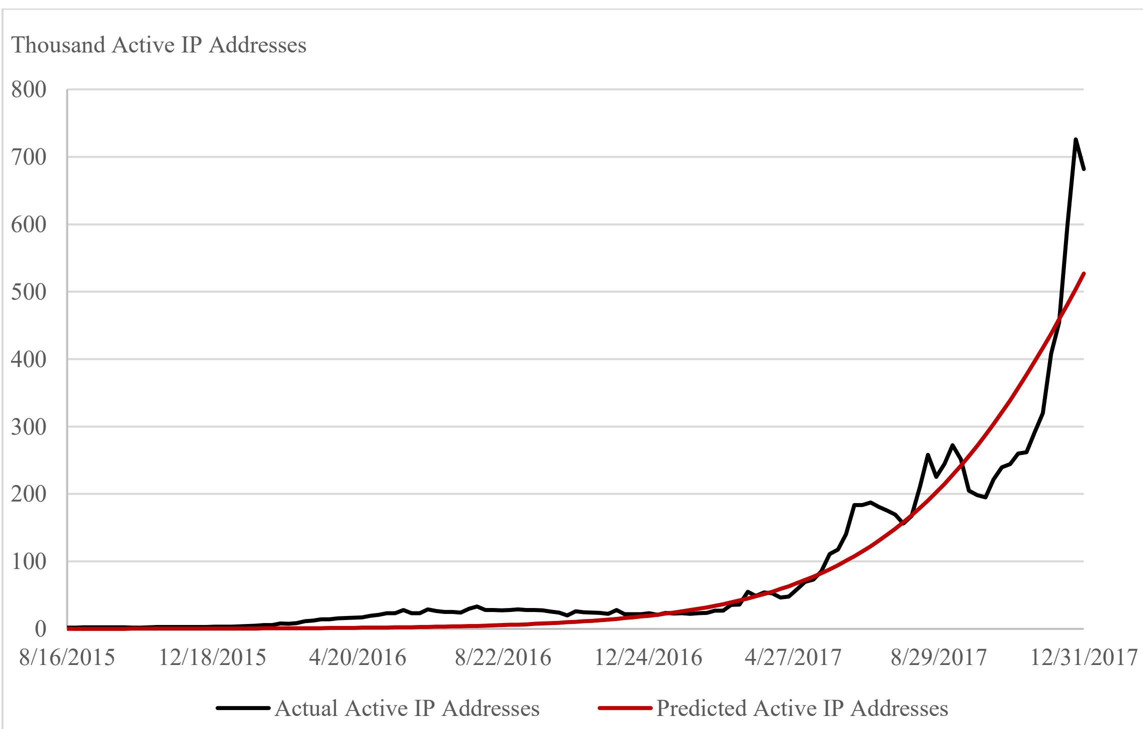

Figure 5.9: Active IP Addresses and Predictions using Netoid Function 2015-2017.

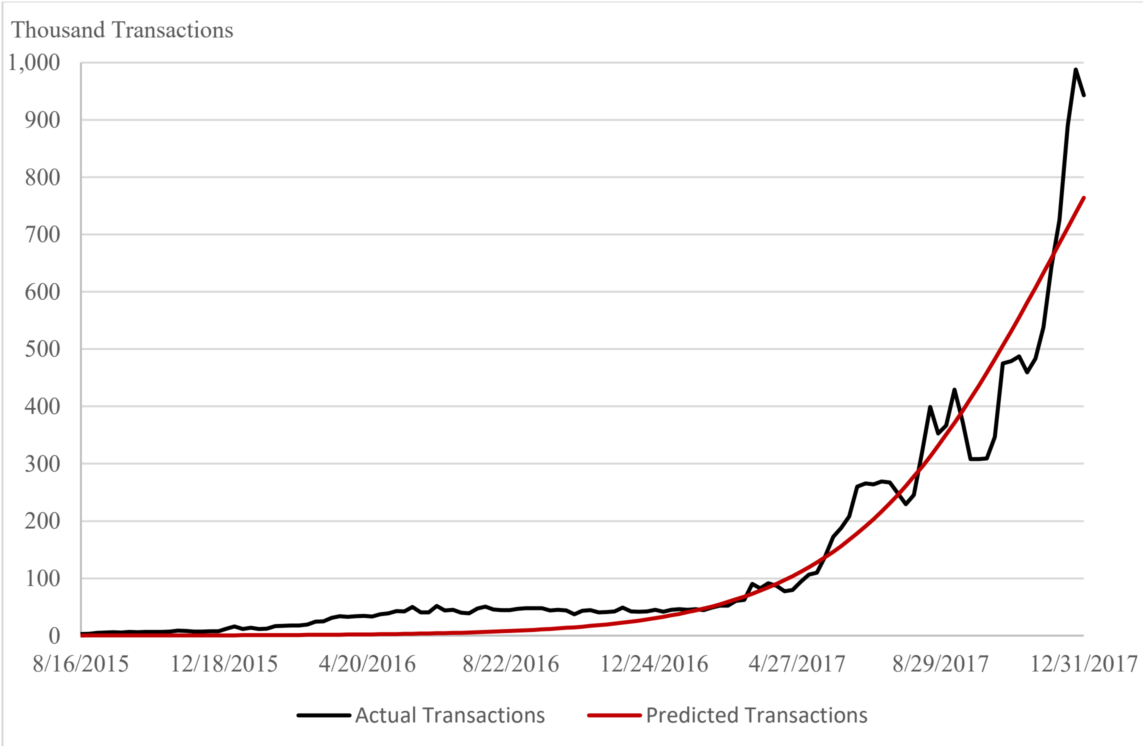

Figure 5.10: Transactions and Predictions using Netoid Function 2015-2017

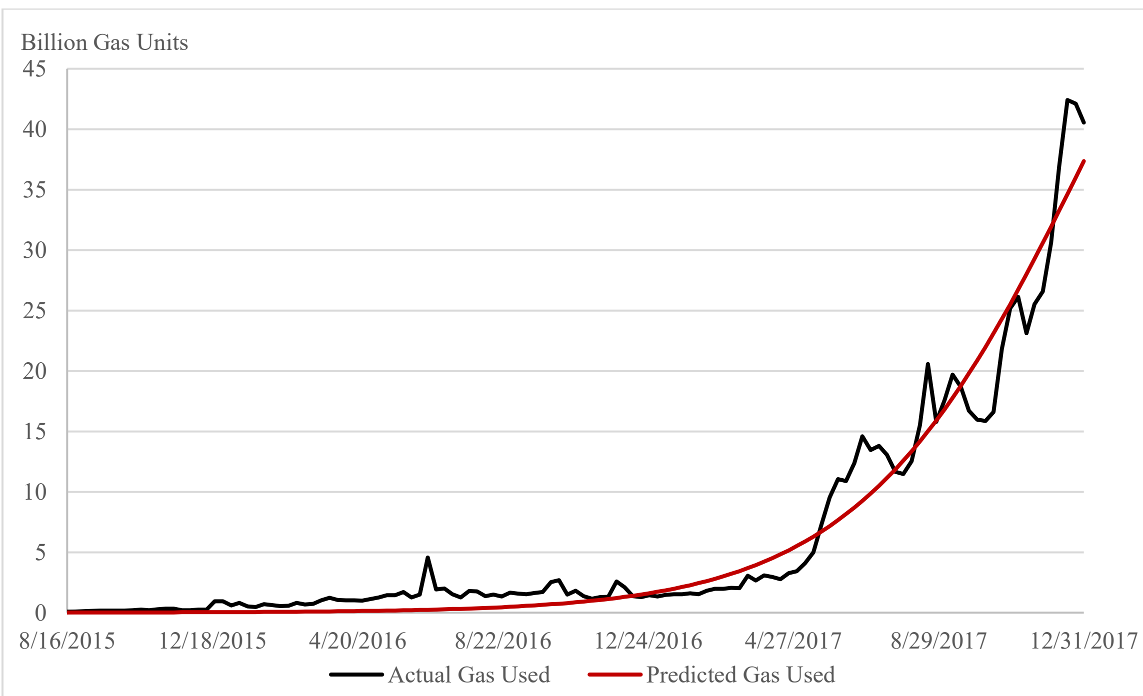

Figure 5.11: Gas and Predictions using Netoid Function 2015-2017

5.3.2 Forecasting Market Capitalization

Tables 5.11 and 5.12 show the results of the 6-month forecasts for market capitalization and price per Ether respectively. The price estimates for Ether depend on estimated values of supply. Since the last hard fork of Ethereum in October 2017, the daily increase has been stable around 20,500 Ether per day. No public announcements exist regarding a change in the mining reward, and so, it seems reasonable to assume similar growth and use the average of 20,500 as the daily growth rate. Thus, price forecasts contain additional uncertainty but are considered low due to the stability of supply growth.

Table 5.11: Forecasted Market Capitalization of Ether from January to July 2018.

(USD Billion)

Date	Observed	Active IP Addresses	Transactions	Gas
January 7, 2018	108.17	62.43	58.55	59.63
January 14, 2018	131.76	65.33	60.60	61.84
January 21, 2018	101.83	68.29	62.63	64.04
January 28, 2018	119.72	71.28	64.63	66.24
February 4, 2018	80.57	74.30	66.60	68.42
February 11, 2018	79.09	77.35	68.54	70.57
February 18, 2018	89.23	80.41	70.43	72.71
February 25, 2018	82.17	83.49	72.29	74.81
March 4, 2018	N/A	86.56	74.09	76.88
March 11, 2018	N/A	89.63	75.84	78.90
March 18, 2018	N/A	92.68	77.53	80.89
March 25, 2018	N/A	95.71	79.17	82.82
April 1, 2018	N/A	98.70	80.76	84.71
April 8, 2018	N/A	101.67	82.28	86.54
April 15, 2018	N/A	104.58	83.74	88.32
April 22, 2018	N/A	107.45	85.14	90.04
April 29, 2018	N/A	110.26	86.48	91.71
May 6, 2018	N/A	113.01	87.77	93.31
May 13, 2018	N/A	115.69	88.99	94.85
May 20, 2018	N/A	118.30	90.15	96.33
May 27, 2018	N/A	120.84	91.26	97.75
June 3, 2018	N/A	123.30	92.30	99.11
June 10, 2018	N/A	125.68	93.30	100.41
June 17, 2018	N/A	127.98	94.24	101.65
June 24, 2018	N/A	130.20	95.13	102.83
July 1, 2018	N/A	132.34	95.96	103.96

The results for the first eight weeks of 2018 show contradicting movements as the observed price has been decreasing whereas forecasts are increasing. However, the price of Ether experienced a value bubble in January 2018 and prices returned to levels slightly above those observed in December 2017 during February 2018.

Table 5.12: Forecasted Price per Ether from January to July 2018.

(USD)

Date	Observed	Active IP Addresses	Transactions	Gas
January 7, 2018	1,117.75	645.07	604.96	616.20
January 14, 2018	1,359.48	674.09	625.21	638.04
January 21, 2018	1,049.09	703.51	645.20	659.78
January 28, 2018	1,231.58	733.24	664.86	681.38
February 4, 2018	827.59	763.22	684.14	702.75
February 11, 2018	811.24	793.36	703.00	723.86
February 18, 2018	913.90	823.59	721.38	744.64
February 25, 2018	840.31	853.80	739.24	765.05
March 4, 2018	N/A	883.94	756.56	785.03
March 11, 2018	N/A	913.91	773.30	804.56
March 18, 2018	N/A	943.64	789.44	823.58
March 25, 2018	N/A	973.05	804.96	842.07
April 1, 2018	N/A	1,002.07	819.85	860.00
April 8, 2018	N/A	1,030.63	834.09	877.34
April 15, 2018	N/A	1,058.66	847.69	894.06
April 22, 2018	N/A	1,086.10	860.63	910.16
April 29, 2018	N/A	1,112.89	872.93	925.63
May 6, 2018	N/A	1,138.98	884.58	940.44
May 13, 2018	N/A	1,164.34	895.60	954.61
May 20, 2018	N/A	1,188.91	905.99	968.12
May 27, 2018	N/A	1,212.67	915.77	980.98
June 3, 2018	N/A	1,235.59	924.96	993.20
June 10, 2018	N/A	1,257.65	933.58	1,004.78
June 17, 2018	N/A	1,278.83	941.63	1,015.73
June 24, 2018	N/A	1,299.13	949.15	1,026.07
July 1, 2018	N/A	1,318.53	956.15	1,035.81

Forecasts in Tables 5.11 and 5.12 show significant differences across the applied activity measures. When considering the last forecast on July 1, 2018, the forecast from active IP addresses is an increase of 37.91% compared to using transactions and a 27.30% increase over the forecast using

Gas. The final 6-month ahead forecast for market capitalization of Ether thus ranges from $96.95 billion to $132.34 billion representing a gain between 35.36% and 84.78% over six months from December 31, 2017.

6. DISCUSSION OF RESULTS

Alabi (2017) finds that both Metcalfe's Law and his own proposed model well explain the price of Ether given active IP addresses as predictor. Utilizing more recent data, this analysis finds that this is not the case. The market capitalization of Ether has recently experienced a more modest growth pattern than proposed by Metcalfe's Law and while Alabi's model provides low RMSE and high R^2, it is less robust over time compared to Odlyzko's Law.

Comparing Alabi's estimation of his model, it becomes evident that estimation on new data provides a significantly different growth pattern. In Alabi's analysis, marginal value is decreasing in active IP addresses until around 8,200 active IP addresses. From this analysis, that number is just above 9 million. So, based on the arguments by Alabi (2017), Ethereum has not yet reached a critical mass and started to experience exponential growth. However, using transactions and Gas as predictors, this point is estimated at 370,809 thousand transactions and about 15 billion Gas. These numbers for transactions and Gas were both reached in late 2017, so are in sharp contrast to Alabi's estimate of around 8,200 active IP addresses, which were reached at the beginning of 2016.

Alabi's model assumes positive parameters. In the process of estimation, the algorithm applied found C to converge to zero and was limited by the defined bound. The implications are standard errors of zero and might suggest an issue in applying the model to current data. Further analysis of this issue is left for future research but might explain the significantly different results compared to Alabi's own analysis.

The pseudo-out-of-sample predictions further confirmed that the value of Ether, as explained by activity on Ethereum, seems to have experienced a structural change over time. Early value of Ether is found to follow Metcalfe's Law, while Odlyzko's Law best explains later value. These results provide valuable information as it is evident that growth patterns can change. As a new consensus algorithm is expected sometime in 2018-2019, the issue of structural changes further challenges the ability to forecast the value of Ether.

The robustness tests applied to the models show that the models and applied predictors seem to explain the value of Ether and that results are not spurious even with apparent non-stationarity. The results are interesting in the context that deviations from predicted values can then be interpreted as mispricing and provide valuable insights for investors. However, the results are subject to some uncertainty, and further research is encouraged. First, the tests applied do not directly test for $\mu(z_t) = 0$ and do not provide the probability of the true mean of z_t being zero. Thus, more powerful tests might shed further light on this relationship. Second, deviations from predicted values can also be interpreted as misalignment between observed demand and expected future demand of computing power on Ethereum. Thus, while some mispricing seems apparent because of value bubbles over the life of Ether, more research is needed to explain the deviations observed in this analysis.

To forecast the activity on Ethereum, the Netoid function is applied. The results show that in general the growth of active IP addresses, transactions, and Gas has followed the pattern proposed by the model, but due to the Netoid function being a strictly increasing function in time, weekly fluctuations are not well explained. The results for the first eight weeks of 2018 also show contradicting movements between forecasts and observed values. While it is evident that Ether experienced a value bubble in January 2018, the question arises whether the results are based on incorrect forecasts of activity measures or if the applied hybrid models fail to predict value given activity.

Table 6.1 shows the predicted values using observed activity from January 1, 2018, through February 25, 2018, compared to observed values of market capitalization. The predicted values using active IP addresses and transactions show similar patterns as the observed values. However, while active IP addresses largely followed the increase in value in January, transactions did less so and result in predictions that are much lower than observed. Gas was more stable, and the predicted values of Ether show only slightly higher values in January compared to February. That the model using active IP addresses provides better results in this period implies that the number of active nodes better captures expected future demand for computing power, as Gas does not increase with value. However, the predictions for February show more aligned results across the activity measures and thus the conclusion of this analysis must be, that no significant difference in predictive power is found between the applied measures for activity. That the predictions for February are much lower than the observed values also suggest that potential mispricing and misalignment between expected future demand and observed demand for computing power provide challenges for forecasts.

Table 6.1: Predicted Market Capitalization of Ether using Out-of Sample Values for Activity.

(USD Billion)

Date	Observed	Active IP Addresses	Transactions	Gas
January 7, 2018	108.17	109.12	90.50	63.83
January 14, 2018	131.76	107.02	89.35	63.94
January 21, 2018	101.83	101.48	87.00	64.53
January 28, 2018	119.72	71.97	67.08	61.97
February 4, 2018	80.57	73.18	67.63	62.43
February 11, 2018	79.09	56.92	60.19	60.10
February 18, 2018	89.23	55.37	56.28	58.74
February 25, 2018	82.17	53.81	57.82	60.58

The final 6-month ahead forecast for market capitalization of Ether for July 1, 2018, is in the range of \$96.95 billion to \$132.34 billion. That results show such a wide range raise the questions of the predictability of both Odlyzko's Law, the applied activity measures, and the Netoid function.

The predicted activity measures depend on assumptions about p, and so, the large variations might be a result of these. For transactions, the assumption is based on known limitations and thus no better assumption is readily available. However, if transactions per active IP address remains around 1.5 as observed in December 2017, the upper bound for active IP addresses changes to approximately 950,000. Similarly, if assumed, that Gas per transaction remains around its December 2017 level of 46,500 the upper bound for Gas is approximately 66 billion. Using these assumptions and re-estimating the Netoid models provide the forecasts for July 1, 2018, shown in Table 6.2.

Table 6.2: Forecasted Market Capitalization of Ether for July 1, 2018, with New Assumptions. (USD Billion)

Date	Active IP Addresses	Transactions	Gas
July 1, 2018	99.21	95.96	91.79

With the new assumptions, the largest difference between forecasts is 8% of the lowest forecasts. Thus, the forecasts' sensibility to applied assumptions further discourages any reason to conclude any differences in the models' ability to explain and predict the market capitalization of Ether. However, the results imply further issues in applying the Netoid function for predicting the activity and thus, demand for computing power on Ethereum. Being subject to assumptions and strictly positive in time the Netoid function results in large errors and variance of forecasts. Thus, more data-based models might provide more robust results but are left for future research.

6.1 FUTURE PERSPECTIVES

That market capitalization of Ether seems to be explained by the demand of computing power raises some additional questions for future research. If a holder of Ether can manipulate the market's expectations of future demand of computing power on Ethereum, the results of the analysis imply that the price of Ether can be manipulated. Manipulating current demand is costly, but if someone can send a credible signal of increased future demand and sustain it over a sufficient time span, the potential gains can be significant. With the current lack of regulation and the global nature of Ethereum, such strategies pose a challenge for regulators.

If Ethereum gains widespread adoption for real application, the need for more stable prices of Ether is apparent. With more applications, the expectation of future demand is likely to converge to observed demand, and thus, the results of this analysis imply more stable prices. As Ether then serves as an input for companies utilizing Ethereum, Ether is likely to become a commodity. Unlike many other commodities the supply of Ether over time is very predictable, and so the value of Ether might become highly predictable.

7. CONCLUDING REMARKS

The analysis finds that most of the variation in market capitalization of Ether can be explained by the activity on Ethereum also representing the demand for computing power. The empirical analysis shows that the early value of Ether follows Metcalfe's Law, whereas later value follows Odlyzko's Law. Thus, the results by Alabi (2017) can only be partially confirmed, as his proposed model proves inconsistent over time. As a result, hybrid models of Metcalfe's Law and Odlyzko's Law are estimated and prove to better explain the value of Ether compared to any of the single equation models. Both the theoretical and empirical analyses imply that the value of Ether can be explained by the demand for computing power on Ethereum. Thus, observed deviations from predicted values are argued to be a result of potential mispricing and misalignment of observed demand and expectations of future demand for computing power.

The theoretical analysis of the Ethereum blockchain suggests that Gas should provide a better predictor of the value of Ether compared to transactions and active IP addresses. However, this cannot be confirmed with current data.

Besides determining the drivers of the value of Ether, the purpose of this paper is to examine its predictability. Forecasting the value of Ether proves difficult because of volatility of activity on Ethereum. The applied Netoid function seems to explain overall growth over time but does not account for weekly fluctuations. Furthermore, forecasted values of Ether are sensitive to assumptions needed in applying the Netoid function to Ethereum. Thus, the final 6-month ahead forecast is a wide range, and the total market capitalization of Ether is forecasted at between $96.95 billion and $132.34 billion for July 1, 2018, representing a gain between 35.36% and 84.78% over six months from December 31, 2017. The paper concludes that more research is needed in predicting the demand of computing power on Ethereum to provide forecasts of higher quality.

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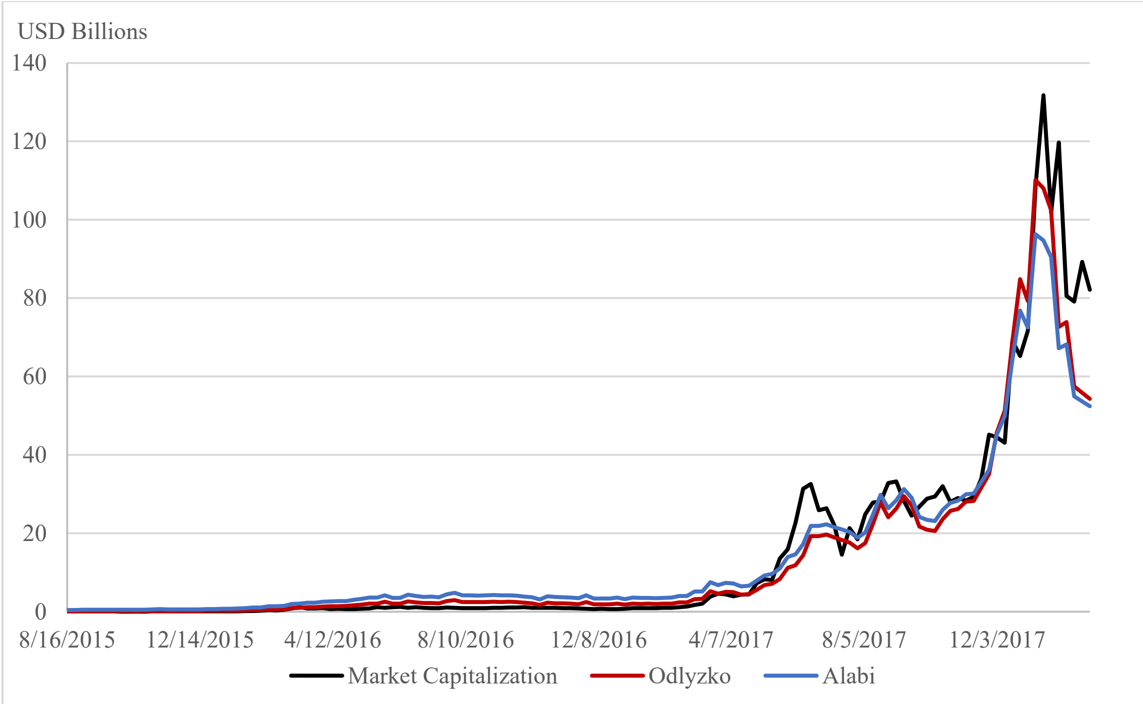
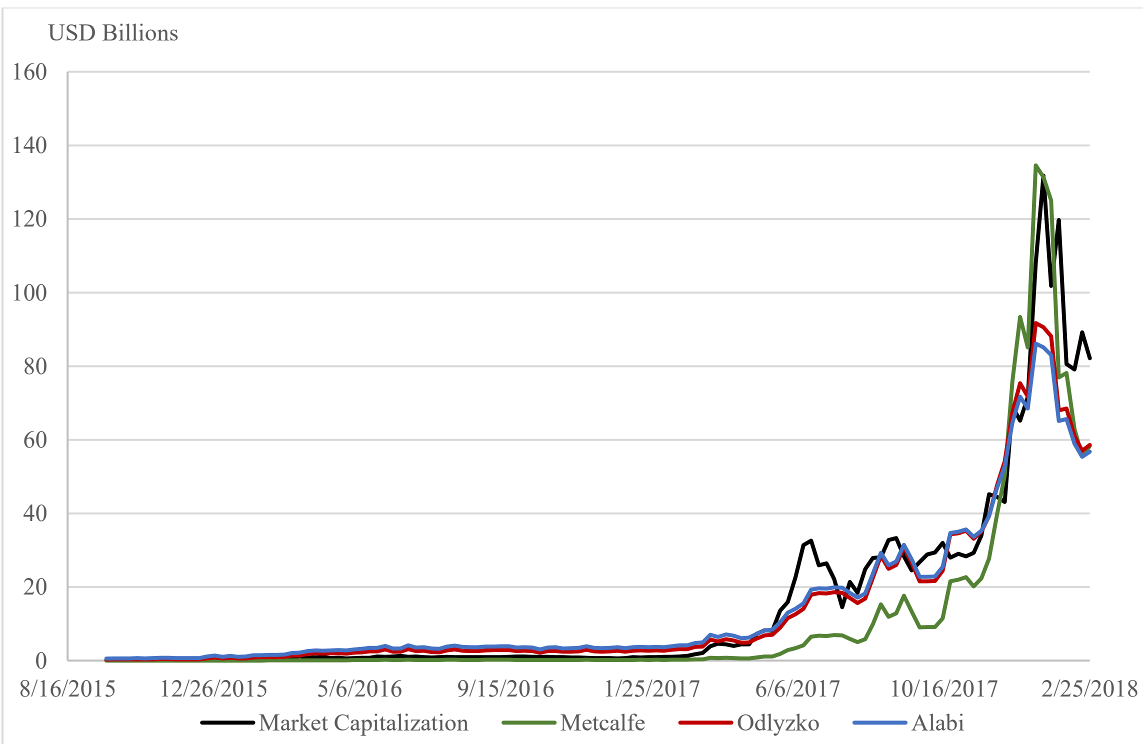
APPENDIX 1: AUGMENTED DICKEY FULLER TEST RESULTS

	ADF Zero-Mean Test		
Model and Variable	Lags	T	Pr < T
Metcalfe's Law			
Active IP Addresses	0	-16.2664	< 0.0001
Transactions	0	-16.0347	< 0.0001
Gas	0	-16.7337	< 0.0001
Odlyzko's Law			
Active IP Addresses	0	-14.7521	< 0.0001
Transactions	0	-16.2224	< 0.0001
Gas	0	-16.2106	< 0.0001
Alabi's Model			
Active IP Addresses	0	-13.2937	< 0.0001
Transactions	0	-13.9677	< 0.0001
Gas	0	-15.9238	< 0.0001

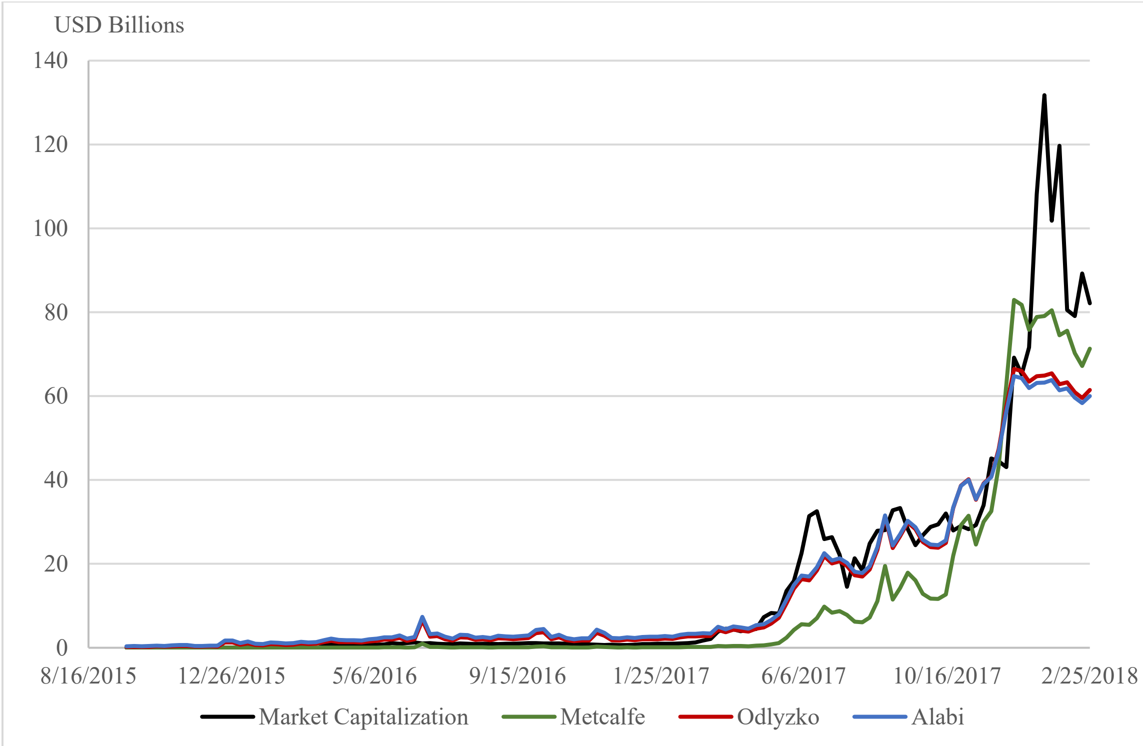
APPENDIX 2: OUT-OF-SAMPLE RESULTS JANUARY 2018 TO FEBRUARY 2018.



Out-of-Sample Results for Models using Active IP Addresses.



Out-of-Sample Results for Models using Transactions.



Out-of-Sample Results for Models using Gas.

APPENDIX 3: MODELS ESTIMATED THROUGH MAY 2017 AND OUT-OF-SAMPLE RESULTS JUNE 2017 TO DECEMBER 2017.

Estimates through May 28, 2017 using Active IP Addresses:

	Odlyzko	Alabi
k	8,294.07	
	(1587.900)***	
C		9.93E-09
		(0.000)
λ		24.99
□		(0.296)
m		0.04
		(0.001)
R^2	0.772	0.958
RMSE	1,203,207,146	517,186,630
RMSEy	1.28	0.44

*Signifance levels: *<0.05, **<0.01, ***<0.001*

Significance level not included for non-linear least squares

Estimates through May 28, 2017 using Transactions:

	Metcalfe	Odlyzko	Alabi
k	0.60	4,590.01	
	(0.027)***	(642.380)***	
C			9.93E-09
			(0.000)
λ			23.32
□			(0.315)
m			0.05
			(0.001)
R^2	0.958	0.702	0.955
RMSE	519,353,249	1,375,112,185	534,107,054
RMSEy	0.43	2.43	0.43

*Signifance levels: *<0.05, **<0.01, ***<0.001*

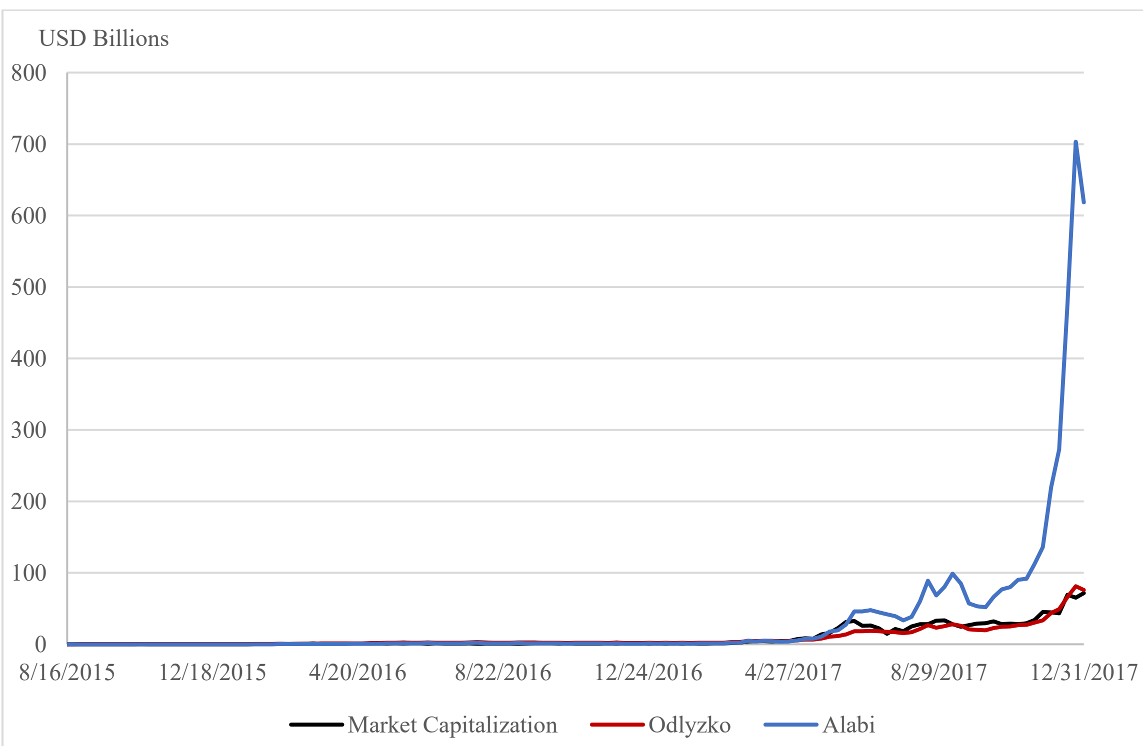
Significance level not included for non-linear least squares

Estimates through May 28, 2017 using Gas:

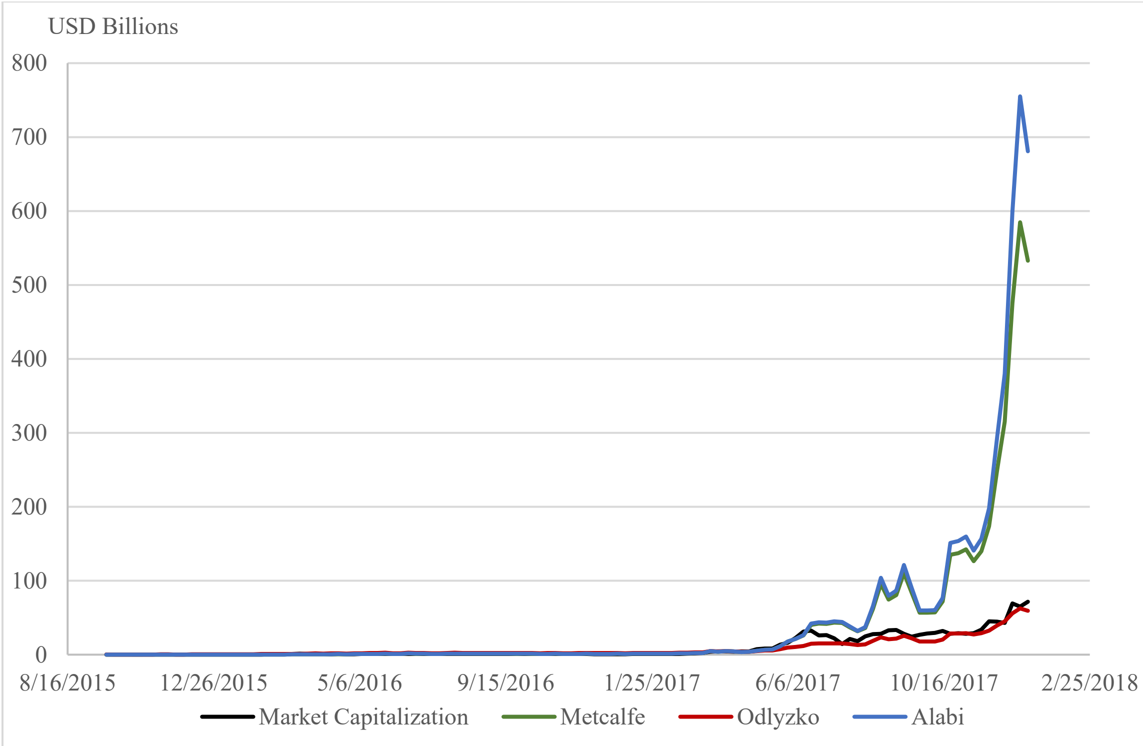
	Metcalfe	Odlyzko	Alabi
k	2.21E-10	0.06	
	(0.000)***	(0.035)	
C			1.00E-08
			(0.000)
λ			18.45
□			(0.592)
m			0.04
			(0.001)
R^2	0.778	0.772	0.867
RMSE	1,187,427,559	1,204,019,364	920,599,174
RMSEy	0.75	3.09	1.48

*Signifance levels: *<0.05, **<0.01, ***<0.001*

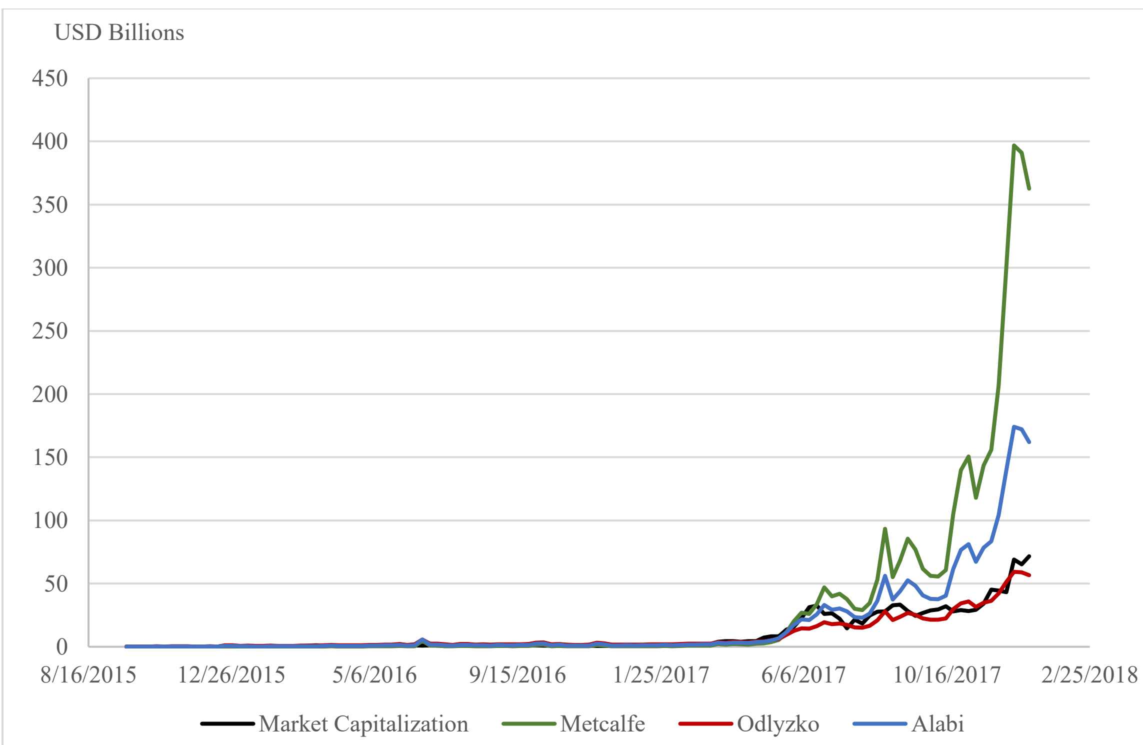
Significance level not included for non-linear least squares



Out-of-Sample Results for Models using Active IP Addresses.



Out-of-Sample Results for Models using Transactions.



Out-of-Sample Results for Models using Gas.