

NO. 1102  
MAY 2024

REVISED  
SEPTEMBER 2024

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*Federal Reserve Bank of New York Staff Reports*, no. 1102

May 2024; revised September 2024

<https://doi.org/10.59576/sr.1102>

### Abstract

This paper considers the “DeFi intermediation chain”—the market structure that underlies the creation and distribution of ETH, the native cryptocurrency of Ethereum—to examine how information asymmetry shapes intermediation rents. We argue that using proof-of-stake blockchain technology in DeFi leads to a novel limit to arbitrage, arising from the tension between arbitrageurs’ privacy needs and blockchain transparency. Using a new dataset which distinguishes private and public transactions in Ethereum, we find that a one percent increase in private information advantage leads to a 1.4 percent increase in intermediaries’ profit share. We develop a dynamic bargaining model that predicts information market power stems exclusively from participants’ private information advantage. Our analysis illustrates how blockchain technology can sustain arbitrage opportunities despite low entry barriers.

JEL classification: G23, D82, L14, L22, G14, D43

Key words: financial intermediation, oligopoly, blockchain, decentralized finance, cybersecurity

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This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author(s) and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the author(s).

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# 1 Introduction

Intermediation is a prevalent feature in many financial markets. Intermediaries perform various crucial functions: they monitor borrowers’ creditworthiness and project quality, make markets, provide liquidity, improve risk sharing, and manage inventory. Moreover, the creation of financial assets often relies on complex intermediation chains. A prime example is the production of mortgage-backed securities (MBS), which involves multiple intermediaries. In the MBS intermediation chain, capital flows from investors through various financial institutions—such as mortgage originators, securitizers, and investment banks—before ultimately reaching homebuyers.

Understanding the factors that shape profit sharing along intermediation chains is crucial for comprehending market efficiency, the allocation of economic rents, and the incentives that drive financial innovation. However, despite extensive theoretical work on intermediation (Leland and Pyle, 1977; Diamond and Dybvig, 1983; Diamond, 1984; Allen and Gale, 1997; Boot and Thakor, 1997; Diamond and Rajan, 2001), empirically identifying the determinants of profit sharing has proven challenging in traditional financial markets. The difficulty in answering this question stems from several factors. First, many financial intermediaries operate as opaque institutions, making it hard to observe their internal operations and profit structures. Second, the complex nature of multi-layered intermediation chains often obscures the flow of capital and fees. Third, the rapid execution of transactions and frequent changes in market conditions make it challenging to isolate the impact of specific factors on profit distributions. As a result, previous studies have largely focused on documenting the existence of intermediation chains and rents (Green et al., 2007; Di Maggio et al., 2017; Hollifield et al., 2017; Li and Schürhoff, 2019), but they do not provide a causal understanding of how profit sharing is determined along the chain.

This paper addresses these challenges by examining a novel setting, the “DeFi intermediation chain”—the market structure that underlies the creation and distribution of ETH, the native cryptocurrency of the Ethereum blockchain. The structure of the Ethereum ecosystem introduces both riskless arbitrage opportunities, as well as a unique limit to arbitrage: the need to execute trades on a public blockchain while maintaining the privacy of arbitrageurs’ information. This tension has led to a multi-layered intermediation structure in DeFi, involving arbitrageurs, block builders, block proposers, and ETH depositors, each playing a specific role in the process of identifying and capitalizing on mispricing opportunities.

The transparent nature of Ethereum allows us to distinguish between intermediaries’ public and private information. All transactions in the Ethereum blockchain ultimately become public, but there’s a crucial temporal distinction in how they reach the network.

Public transactions are immediately broadcast to every block builder in the network, while private transactions are initially sent directly to some block builders, becoming visible to the broader network only when appended to the blockchain. Thus, we are able to observe the value of private information that each intermediary possesses, and how this information affects their profit share.

In order to identify the impact of private information on the intermediaries’ profit share, we utilize two novel instruments: ecosystem-wide crises (such as the FTX or SVB bankruptcies) that increase the value of all transactions, and crypto protocol hacks that differentially increase the value of private transactions. Our empirical analysis reveals that a 1% increase in the value of block builders’ private information leads to a 1.4% increase in their profit share. Furthermore, we find that intermediaries’ market power stems exclusively from their private information, not from the total value of transactions they process.

Finally, we develop a repeated bargaining model that illustrates how the source of information asymmetry affects profit sharing among intermediaries. The model predicts that not every information advantage guarantees larger profit shares for better-informed intermediaries; only private information advantages do. This prediction is consistent with our empirical findings. These results not only shed light on the specific dynamics of DeFi markets but also offer broader insights into how information asymmetry shapes profit sharing in financial intermediation.

As DeFi becomes increasingly interconnected with traditional finance, understanding this market structure becomes crucial for both academics and practitioners. Multiple Ethereum ETFs have been recently approved by the SEC, following the earlier approval of Bitcoin ETFs—which collectively hold tens of billions of dollars of Bitcoin.<sup>1</sup> If Ethereum ETFs gain as much traction as Bitcoin ETFs have, traditional asset managers would become crucial participants in the DeFi intermediation chain that we study in this paper.

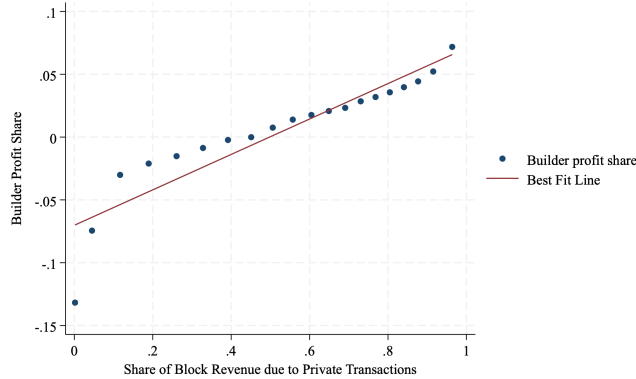
## 1.1 Intermediation and Privacy in a Public Blockchain

Ethereum, the largest platform for DeFi protocols, provides a unique setting to study intermediation chains. Its decentralized structure allows for numerous competing DeFi protocols—including decentralized exchanges, crypto-collateralized stablecoins, and lending platforms. This multiplicity of protocols creates a constant stream of violations of the law of one price, and ensuing arbitrage opportunities.

Importantly, Ethereum allows arbitrageurs who find price discrepancies to obtain a guaranteed non-negative profit by submitting groups of transactions *atomically*—either all trans-

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<sup>1</sup><https://www.theblock.co/post/296304/sec-approves-ethereum-etfs> 8 ETH etfs approved.



**Source:** Dune Analytics and Mempool Guru Project

Figure 1: Block builder’s profit share as a function of the share of the block’s revenue that is due private information. There is a strong positive relationship between the two variables. This figure is generated with binscatter, using 20 bins.

actions are executed, or none of them are. As such, these transactions constitute risk-free arbitrage opportunities.

However, the Ethereum ecosystem also introduces a novel limit to arbitrage in the spirit of Shleifer and Vishny (1997): arbitrageurs with private information need a way to have their trades appended to the public blockchain without alerting potential rivals. This tension between the public nature of blockchain trades and the private needs of arbitrageurs shapes the DeFi intermediation landscape, giving rise to a multi-layered structure: 1) arbitrageurs identify mispricing across different DeFi protocols or between centralized and decentralized exchanges; 2) block builders aggregate transactions into blocks, acting as gatekeepers of private information and potentially extracting rents in the process; 3) block proposers, selected randomly via the proof-of-stake mechanism, choose one winning block among bids from multiple builders; and 4) ETH depositors, including individual holders and centralized exchanges, participate in this process through delegating their stake to proposers, in a process we call *delegated staking*. This introduces an additional layer of intermediation, mirroring traditional financial structures in a decentralized context.

## 1.2 Impact of Private Information on Profit Sharing

We collect a novel dataset where we can observe both private and public transactions, as well as the fees paid to different intermediaries, to quantify how private information affects profit distribution along this intermediation chain. Our analysis reveals new insights into the limits to arbitrage in DeFi, showing how blockchain characteristics create persistent

arbitrage opportunities in spite of the market having low or no barriers to entry.

The level of transparency and granularity in the data allows us to causally identify the impact of private information on profit sharing between block builders and block proposers. Figure 1 depicts our main finding. It illustrates that access to valuable *private* arbitrage transactions by builders—i.e., those arbitrage transactions that are privately submitted to them by an arbitrageur— increase their profit share since they are effectively the gatekeeper for the private arbitrage opportunity. On the other hand, the block revenue that is associated with public arbitrage opportunities is widely accessible to the proposer through other block builders. As such, none of the block builders can gain from the publicly available arbitrage transactions and the proposers capture most of the corresponding revenue.

To address biases from simultaneity and omitted variables, we employ very stringent fixed effects and introduce two novel instrumental variables: a dummy for major crypto market crises and a dummy for hacks of exchanges and decentralized protocols. These instruments are designed to capture variations in both total block revenue and the value of private information. We identify crises as the FTX bankruptcy (November 8-12, 2022) and the SVB run (March 9-12, 2023), which led to a large number of blockchain transactions. The dummy corresponding to crypto hacks is set to 1 on days on which an Ethereum protocol or exchange is hacked, according to data from DefiLlama. As shown in Section 4, both crises and hacks affect overall block value and private information value, but to different degrees. Crises tend to generate more public transactions, while hacks primarily increase private information value. This differential impact allows these two instrumental variables to effectively span our set of two explanatory variables.

Using this instrumental variable approach, we show in Section 4 that a 1% increase in the value of private information leads to a 1.4% increase in the builder profit share. After controlling for the value of private information, the effect of larger block revenue on the builder profit share is negative. This indicates that the builder’s market power is driven exclusively from the value of their private information, and not from the total value of the block they produce.

### 1.3 A Bargaining Model of DeFi Intermediation

We complement our empirical analysis with a dynamic bargaining model to shed light on how information asymmetries in decentralized finance contribute to the distribution of profits along the DeFi intermediation chain. The core economic mechanism is the interaction between the source of information asymmetry between block builders and proposers, the market structure of the block builder segment of the market, and the randomness inherent

in the proof-of-stake technology.

Consider the bargaining process between the block builders and the proposer when adding each block to the blockchain. Observe that the block builders are always better informed than the proposer about the content and the value of the block that they built. However, if the information advantage is common among all block builders, through public arbitrage opportunities, the competition among the block builders prevents them from exploiting it, even if it is very valuable. On the other hand, if the information asymmetry between a block builder and the proposer stems from transactions that are private to that specific builder, through private arbitrage opportunities, it constitutes a “private information advantage.” Unlike a public information advantage, the block builder is able to monetize their private information advantage through the threat of withholding the information in this period and selling it next period to the proposer randomly selected by the proof-of-stake mechanism—who is not necessarily the current proposer.

In order to capture the above intuition, we propose a repeated bargaining model where the outside option of the agents links the different time periods. This simple economic mechanism enables us to simultaneously explain both of our main empirical findings. First, a higher value of private transactions in a block increases the profit share of the block builder. However, controlling for the value of private transactions, higher block revenue increases the profit share of the proposer while decreasing that of the block builder.

## 1.4 Related Literature

There is an extensive literature spanning different aspects of financial intermediation (see Leland and Pyle (1977), Campbell and Kracaw (1980), Diamond and Dybvig (1983), Diamond (1984), Allen (1990), Allen and Gale (1997), Boot and Thakor (1997), Diamond and Rajan (2001), as well as Gorton and Winton (2003) and references therein). The prevalence of intermediation rents in financial markets have been widely documented in the empirical literature (Green et al., 2007; Di Maggio et al., 2017; Hollifield et al., 2017; Li and Schürhoff, 2019; Farboodi et al., 2017). However, identifying the source of these rents empirically has proven challenging as the balance sheet of large financial intermediaries is opaque and it is hard to acquire data about their comparative advantage. We contribute to this literature by first distinguishing the role of financial intermediaries in blockchain systems, crypto currency and DeFi, which represent the most recent developments in financial technology. Second, we identify private information as a source of intermediation rents in this market.

Our paper contributes to a fast-growing literature on blockchain technology. Raskin and Yermack (2018) provide a preliminary overview of financial systems built on blockchains.

Cong and He (2019), Abadi and Brunnermeier (2018) and Biais et al. (2019) expand on consensus mechanisms, focusing on proof-of-work. There is a small but growing body of work that studies the economics of Bitcoin, both theoretically and empirically. Athey et al. (2016), Cong et al. (2021a), Pagnotta and Buraschi (2018) and Sockin and Xiong (2020) develop alternative theoretical frameworks to study the decentralized Bitcoin network. Prat and Walter (2021) provide an estimate of the computing power of Bitcoin network and Cong et al. (2021b) study the effect of mining pools on energy consumption, which is a significant input to proof-of-work consensus.

A number of papers consider the degree of decentralization in blockchain, focusing on proof-of-work consensus protocols (Cong et al., 2023; Huberman et al., 2021; Ferreira et al., 2023; Makarov and Schoar, 2021; Capponi et al., 2023; Cong et al., 2021b; Lehar and Parlour, 2023). In addition, some previous work studies staking systems, including the game-theoretic properties of proof-of-stake consensus mechanisms (Saleh, 2020), the valuation of native tokens such as ETH (Fanti et al., 2019), and the valuation of non-native tokens that can be staked in DeFi protocols (Cong et al., 2022). In contrast to these papers, we focus on the emergence of intermediation in a financial sector built on proof-of-stake technology and study the concentration of this intermediated market. We emphasize the influence of arbitrage opportunities, as documented in Makarov and Schoar (2020), on the degree of market concentration, and show that the combination of proof-of-stake consensus and smart contracts can lead to a high degree of concentration in the Ethereum crypto intermediation market.

The nature and type of arbitrage opportunities in a proof-of-stake blockchain is at the core of our analysis. Daian et al. (2020); Gupta et al. (2023); Heimbach et al. (2024) provide early empirical evidence and classification of MEV and private and public arbitrage opportunities in a blockchain network. Alternatively, Milionis et al. (2023) theoretically models the relationship between public and private transactions and market volatility. Capponi et al. (2024) provide a game-theoretic model of proposer-builder separation. We use a simplified definition of private transactions, where a transaction is private if it is not broadcast to the network before it appears on the blockchain, a simple and intuitive definition that can be measured precisely in the data, in contrast with heuristic based definitions proposed by Gupta et al. (2023) and Heimbach et al. (2024). In Section 6, we use their classification to show the robustness of our empirical findings. Our instrumental variable approach relies on the observation that crypto crises can be an exogenous shock that creates arbitrage opportunities (Liu et al., 2023). To the best of our knowledge, we are the first to use these crises as instrumental variables in empirical analyses of DeFi.



The rest of the paper is organized as follows. Section 2 describes the institutional details of the DeFi intermediation chain. Section 3 provides details of the block level data from Ethereum blockchain that we use for our empirical analysis. Section 4 describes the instrumental variable approach and presents the main empirical results. Section 5 proposes a model to provide the economic mechanism that underlies the empirical findings. Section 6 provides a number of robustness exercises. Section 7 concludes.

## 2 Origins of DeFi Intermediation: The Need for Privacy

The Ethereum blockchain handles two main types of transactions: simple payment transactions and smart contract interactions. Simple transactions transfer ETH or tokens between addresses. Smart contracts are blockchain-stored programs that execute when users send transactions to their addresses, triggering predefined functions. For example, users can interact with decentralized exchange contracts to swap tokens or with lending protocols to deposit collateral. These contracts automatically execute complex financial operations, such as updating inventories or calculating prices and interest rates, without a central operator.

**Risk-free arbitrage.** Ethereum’s diverse ecosystem of competing DeFi protocols creates a large number of violations of the law of one price.<sup>2</sup> Since Ethereum allows for transaction batching, arbitrageurs can submit multiple transactions which are executed atomically—either all together or not at all—ensuring a guaranteed non-negative profit for the arbitrageur. The unique aspect of blockchain-based arbitrage, particularly in Ethereum’s DeFi ecosystem, is the ability to execute truly risk-free arbitrage through atomic transactions that have no execution risk. This feature, combined with the transparency of the blockchain, creates a novel environment for arbitrage that is not directly paralleled in traditional financial systems.

The risk-free nature of these arbitrage opportunities makes them very attractive. Yet, the nature of PoS blockchain technology introduces a novel *limit to arbitrage*: the possibility of front running. The key friction stems from arbitrageurs’ need to keep their transactions private before they are appended to the blockchain if they want to appropriate the corresponding profits. There are constant opportunities for arbitrageurs to identify mispricings across different DeFi protocols or between centralized and decentralized exchanges. However, to capitalize on these opportunities, arbitrageurs require a mechanism to have their

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<sup>2</sup>Most of these violations occur through differences in pricing across exchanges. However, some additional arbitrages are due to automatic liquidations of collateral at fire sale prices, and its resale at market prices.

transactions approved without broadcasting them to the entire network, thus avoiding the risk of being frontrun or having their arbitrage opportunity stolen by competitors.<sup>3</sup>

This privacy requirement is the limit to arbitrage faced by each individual arbitrageur. It introduces unique challenges in exploiting arbitrage opportunities on the Ethereum blockchain and shapes the structure of DeFi intermediation. Moreover, it gives rise to a specific form of information rent captured by some intermediaries in the process of creating the Ethereum blockchain. In this section, we focus on the emergence of the DeFi intermediation chain as a consequence of the need for privacy. Sections 4 and 5 explain the information rents in the DeFi intermediation chain, both empirically and theoretically.

**DeFi intermediation chain.** We define the “DeFi intermediation chain” to be the market structure that underlies the creation and distribution of ETH, the native cryptocurrency of Ethereum. It consists of four groups of agents who interact with each other through an intermediation chain. *Arbitrageurs* form the initial segment of the chain. These are typically high-frequency trading algorithms or bots that continuously scan for profitable transactions, including both arbitrage and non-arbitrage opportunities, to be submitted to the Ethereum blockchain.

The need for privacy by arbitrageurs, as explained above, leads to the rise of *block builders* as intermediaries. Arbitrageurs who find an arbitrage can send their transactions directly to a block builder, who incorporates them into an aggregate block. If these arbitrage transactions are valuable, arbitrageurs usually pay an additional fee or direct payment to the builder in order to make sure the builders incorporate their transactions into blocks. The total value that is generated by adding a block to the blockchain—colloquially known as the block’s Maximum Extractable Value (MEV)—is the sum of arbitrageur profits, transaction fees paid to the block builders, and any direct payments sent by arbitrageurs to builders in order to incentivize them to add their transactions to the block.

The next layer of intermediaries are *block proposers*, who are selected at random via the proof-of-stake (PoS) consensus mechanism—with probability proportional to their stake of ETH—to select a single block to be appended to the blockchain in a given round.<sup>4</sup> Block

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<sup>3</sup>The risk of having a transaction stolen is not only real, but ubiquitous due to the commodification of AI-driven frontrunning bots (Robinson and Konstantopoulos, 2020).

<sup>4</sup>As a brief note on terminology, we note here that the term block proposer is related to the technical architecture of the Ethereum blockchain. Once proposers select a block, they *propose* it to a random small group of *attesters*, who verify that all transactions in the block are valid and there is no double spending in a block. From an economic point of view, the attesters do not receive any revenue related to DeFi intermediation, and therefore we do not study them in this paper. We also highlight that the case where a proposer’s selected block is not accepted by the attesters is extremely rare, and the attester mechanism exists solely to ensure honest behavior by the proposer.

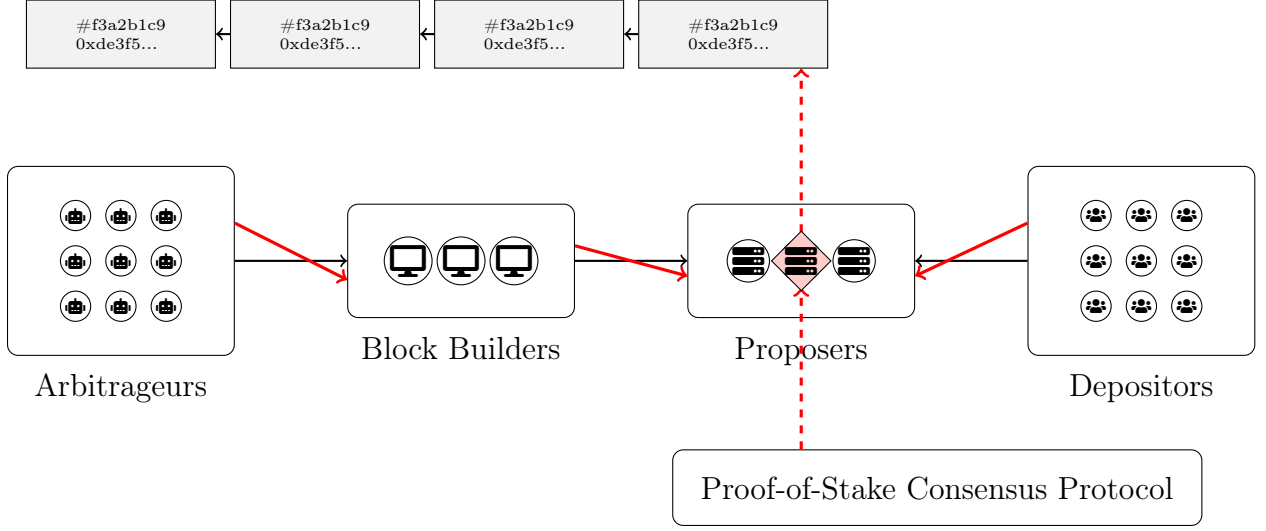


Figure 2: Market structure of the DeFi intermediation chain, Ethereum blockchain’s production network.

**Notes:** The figure depicts the proof-of-stake consensus protocol (bottom row), the key participants of the DeFi intermediation chain: arbitrageurs, block builders, proposers and depositors (middle row), and the produced Ethereum blockchain (top row). The interactions at each time period  $t$  (time slot of 12 second) are depicted in red. The red arrows among the market participants indicate the selected paths in the DeFi intermediation chain required to produce each block, while the black signify alternative paths that were not selected. The dashed red arrow from the consensus protocol to the proposers indicates that at each time  $t$ , the random outcome of the proof-of-stake consensus protocol is a proposer, with the red diamond displaying the randomly selected proposer. Finally, the dashed red arrow from proposer to the blockchain at the top represents the block proposal process. The blockchain is the outcome of these interactions repeatedly.

builders compete with each other to create the most valuable block they can. They then submit a cryptographic commitment to the block along with a bid to the block proposer, who chooses one winning (block, bid) pair without being able to view the block’s contents. To prevent the proposer from front-running arbitrageurs’ transactions, the encrypted block is only decrypted and revealed once the proposer has accepted the bid.<sup>5</sup>

Because block proposers are selected at random with probability proportional to their stake, proposers who have larger amounts of ETH obtain a much more consistent stream of revenue than proposers with a very small amount of ETH. This leads to the final layer of the intermediation chain, where *ETH depositors* pool their assets together into large staking pools, and get a share of the profits that these pools obtain from proposing blocks.

Figure 2 illustrates the market structure of the Ethereum blockchain’s production network, highlighting the DeFi intermediation chain. The diagram shows four key participant groups: arbitrageurs, block builders, proposers, and depositors. Arbitrageurs and depositors

<sup>5</sup>We provide more details of this procedure in the Appendix.

are represented by multiple icons, indicating their larger numbers and diverse nature. Block builders and proposers have fewer icons, reflecting their more concentrated roles. The arrows between groups represent the flow of transactions within the DeFi intermediation chain. Importantly, the arrow from Depositors to Proposers reflects that depositors choose proposers to stake their ETH with, influencing the distribution of staking power.

The solid red arrows indicate the selected paths during the matching process in each time slot, to build a single block. Furthermore, in each time slot the Proof-of-Stake consensus mechanism selects the proposer for each single block (dashed red arrow pointing to the red proposer), who in turn adds a block to the Ethereum blockchain (dashed red arrow pointing from the proposer to the blockchain).

**Delegated Staking** Many ETH holders do not participate in the above protocols directly, but rather through intermediaries such as centralized exchanges or liquid staking smart contracts. A centralized exchange is a company such as Coinbase, Binance, or Kraken, which takes depositors' ETH and uses it to participate in the proof-of-stake Ethereum consensus protocol. By staking their depositors' ETH, these centralized exchanges earn returns, which they then pass on to their customers after taking a spread.<sup>6</sup> These intermediaries arise because they have the technological sophistication to participate in the proof-of-stake protocol.<sup>7</sup> ETH holders who do not have this level of sophistication may still earn returns by buying ETH from a centralized exchange, and asking the exchange to stake their ETH for them. As such, proposers are *delegated stakers* in the DeFi intermediation chain.

Throughout the chain, each node receives a payoff for their service. Arbitrageurs keep a large amount of their arbitrage profits, but pay transaction fees to the builders. The builders pay the block proposers to ensure their blocks are added to the blockchain. As such, the block proposer's net revenue is equal to the bid of the winning bidder, while the winning block builder's net revenue consists of all transaction fees and direct payments to them, minus the bid that they pay to the block proposer. Finally, block proposers who represent staking pools pay a large share of their revenues to the individual investors who pooled their ETH with them.

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<sup>6</sup>Recently, the SEC has reached a settlement with Kraken to prevent it from acting as such an intermediary for American customers.

<sup>7</sup>In particular, participants need to continuously run a server which listens for transactions, engages with block builders, proposes valid blocks when called upon to do so, and verifies other proposers' blocks. Any deviation from the protocol, due for example to a software bug, a hardware failure or a network outage, is penalized by debiting ETH from the participants' account—a process known as slashing. In equilibrium, sophisticated agents can easily satisfy these requirements, so slashing is extremely rare, with only 0.04% of participants having been slashed according to CoinTelegraph <https://cointelegraph.com/news/only-0-04-of-ethereum-proposers-have-been-slashed-since-2020-says-core-dev>.

Number of Builders		Number of Proposers	
167		221,534	
Builder			
Address	Share of Total Builder Revenue		Share of Blocks
beaverbuild.org	42.32%		25.05%
Titan Builder	14.63%		15.41%
builder0x69	13.69%		14.94%
Proposer			
Entity	Share of Total Proposer Revenue		Share of Blocks
Lido	31.38%		31.75%
Coinbase	10.31%		10.20%
Kraken	5.53%		5.56%
Binance	5.20%		5.71%
Stakefish	4.61%		4.90%

**Source:** Dune Analytics

Table 1: The first panel reports the total number of block builders and proposers. The second panel shows that the largest 3 block builders account for more than 50% of aggregate builder revenue, and more than 50% of the number of blocks added to the Ethereum blockchain. The third panel shows that the largest 5 block proposers account for more than 50% of aggregate proposer revenue, and more than 50% of the blocks added to the Ethereum blockchain.

Even though the Ethereum blockchain is permissionless and there is near free-entry into intermediation, informational frictions and risk-sharing in DeFi lead to concentration among intermediaries as demonstrated in Table 1. Of the 167 known builders, 3 capture more than 50% of all the builder revenue and blocks proposed. Similarly, even though there are 156,150 block proposers, five large staking pools capture more than 50% of all the proposer revenue and blocks proposed.

### 3 Data

We use Dune Analytics<sup>8</sup> to obtain block-level data, the identity of the builder and proposer, the MEV revenue for the block, and the revenue split between the builder and the proposer. We use data from the Secure Decentralized Systems Lab’s Mempool Guru project (Yang et al., 2023) to keep track of which transactions were broadcast to the network before being appended to the blockchain, and which were not broadcast to the network. We classify

<sup>8</sup><https://www.dune.com>

transactions broadcast to the network as public, and transactions not broadcast as private.

Let  $B_t$  denote the block added to the blockchain at time slot  $t$ . We consider the block to be an MEV block if two conditions hold. First, the block builder is different than the block proposer. Second, the last transaction of the block is issued from the block builder to the block proposer. In our sample—which spans from the switch to proof-of-stake in September 15, 2022, to January 31, 2024—75.9% of the blocks satisfy both of these conditions, and are considered MEV blocks.<sup>9</sup>

The key independent variable in our analysis is the value of private transactions in the block generated at time  $t$ . We define private and public transactions as follows.

**Definition 1.**

**Public Transaction** *A transaction in the block added at time  $t$  is public if it is broadcast to the network before time  $t$ , and is not a direct payment to the builder who built the block generated at time  $t$ .*

**Private Transaction** *A transaction in the block added at time  $t$  is private if either it is not broadcast to the network before time  $t$  or it is a direct payment addressed to the builder who built the block generated at time  $t$ .*

The key concept behind this definition is that public transactions are *non-exclusive*: any builder can collect their value if they are chosen as the block builder at time  $t$ . Private transactions, however, are *exclusive*: only the builders that know about them, or the builder whom the payment is addressed to, can collect the value of these transactions.

Let  $Rev_t$  denote the total revenue from block  $t$ . Moreover, let  $\Pi_{B,t}$  and  $\Pi_{P,t}$  denote the net profit of the block builder and proposer, respectively. The net profit for the builder,  $\Pi_{B,t}$ , consists of the sum of direct payments they receive and priority gas fees,<sup>10</sup> minus the payment to the proposer at the end of the block. The net profit for the proposer,  $\Pi_{P,t}$ , is the value of the block’s final transaction. The key dependent variables in our analysis are the profit shares of the builder and proposer are denoted as  $\theta_{B,t} = \frac{\Pi_{B,t}}{Rev_t}$  and  $\theta_{P,t} = \frac{\Pi_{P,t}}{Rev_t}$ , respectively.

Table 2 presents the summary statistics of the key variables. It shows that all profits are highly skewed to the right, with the majority of blocks generating minimal revenue. On

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<sup>9</sup>The total number of blocks in our sample is 3,588,414, and the number of blocks satisfying the MEV conditions is 2,723,653. Of these, we remove 138 blocks that have zero revenue, to end up with 2,723,585 positive-revenue MEV blocks.

<sup>10</sup>Any Ethereum transaction must pay a base gas fee  $Fee_{Base}$  to be included in the block. This fee is always “burnt” and removed from the system, and is not part of the builder’s revenue. However, if the transaction is valuable or important, the user who submits the transaction may choose to pay the builder an excess gas fee  $Fee_{Excess}$ , which is part of the builder’s revenue.

	Mean	Std. Dev.	Min	5th	Median	95th	Max	Skewness	Kurtosis
$Rev_t$	0.14	1.52	0.00	0.02	0.06	0.37	691.96	225.07	76506.49
$\Pi_{B,t}$	0.01	0.40	-0.30	-0.00	0.00	0.02	386.27	474.65	366718.03
$\Pi_{P,t}$	0.14	1.39	0.00	0.02	0.05	0.35	691.96	254.00	95968.37
$\theta_{B,t}$	0.03	0.08	-0.10	-0.02	0.01	0.16	1.00	4.66	32.36
$\theta_{P,t}$	0.97	0.08	0.00	0.84	0.99	1.02	1.10	-4.66	32.36
$\log Private_t$	0.07	0.17	0.00	0.00	0.03	0.27	6.54	8.44	119.52
$\log Public_t$	0.03	0.05	0.00	0.01	0.02	0.07	5.20	24.48	1115.99
Hack Dummy	0.07	0.26	0.00	0.00	0.00	1.00	1.00	3.23	11.46
Crisis Dummy	0.02	0.14	0.00	0.00	0.00	0.00	1.00	6.95	49.32
Observations	2627618								

**Source:** Dune Analytics and Mempool Guru Project

Table 2: Summary Statistics

average, a block generates 0.14 ETH in revenue, more than 90% of which is captured by the proposer.

There are many blocks where the builder makes negative profits. This behavior is likely to ensure that the builder’s block is chosen and is adopted as strategy to build market share: by subsidizing proposers during regular periods, builders aim to dominate the market share of proposed blocks, attracting arbitrageurs with lucrative arbitrage opportunities when they arise, thereby securing blocks that yield positive profits.<sup>11</sup> Our main analysis considers only blocks where the builder profit share is greater than  $-10\%$ , which represent 96.5% of the blocks in our sample.<sup>12</sup>

## 4 Market Power in the Ethereum Intermediation Chain

In this section, we estimate how a block’s share of private revenue affects the builder’s profit share. The simplest specification would be a regression of the form

$$\theta_{B,t} = \alpha + \beta \log Private_t + \epsilon_t.$$

However, estimating this regression with OLS would introduce biases in three ways. First, there is simultaneity bias because the block builder simultaneously decides their payment to the proposer (determining  $\theta_{B,t}$ ) and the transactions that they want to insert into the

<sup>11</sup>Primarily empirical evidence support the outcome of this strategy. Results are available upon request.

<sup>12</sup>In Section 6, we show that our results also hold for the full sample, as well as a further restricted sample that contains only blocks where the builder makes non-negative profits.

block. That is, the builder has to decide how much of their private information they want to capitalize in during this block, and how much of that value they want to share with the proposer. Second, there is an omitted variable bias because there are many characteristics of the block which can affect  $\theta_{B,t}$  which are not captured in the specification. The most important variable that is missing from the specification is the revenue  $Rev_t$  of the block. Finally, the specification above does not capture any relationships between builders and proposers which may lead the builders to treat some proposers more or less favorably.

To address the potential for omitted variable bias and pre-existing relationships between builders and proposers, we estimate the slightly more complicated regression (1):

$$\theta_{B,t} = \beta \log Private_t + \gamma \log Rev_t + \psi_{i(t)} + \eta_{j(t)} + \phi_{i(t),j(t)} + \epsilon_t. \quad (1)$$

Including the revenue term allows us to capture the effect of both private information, as well as the total revenue of the block. The fixed effects terms  $\psi_{i(t)}, \eta_{j(t)}, \phi_{i(t),j(t)}$  capture relations between the builders and proposers.

Finally, to address simultaneity, we use an instrumental variables approach with two instruments, both of which are dummy variables. The first dummy,  $Hacked_t$ , is equal to 1 if block  $t$  is appended to the blockchain on a day where there is a crypto protocol hack, and 0 otherwise.<sup>13</sup> The second dummy,  $Crisis_t$  is equal to 1 if block  $t$  is appended to the blockchain during either the FTX or SVB crises.<sup>14</sup> The first-stage specification is given by

$$\begin{aligned} \log Private_t &= \hat{\beta}_1 Hacked_t + \hat{\gamma}_1 Crisis_t + \widehat{\psi_{1,i(t)}} + \widehat{\eta_{1,j(t)}} + \widehat{\phi_{1,i(t),j(t)}} + \widehat{\epsilon_{1,t}}; \\ \log Revenue_t &= \hat{\beta}_2 Hacked_t + \hat{\gamma}_2 Crisis_t + \widehat{\psi_{2,i(t)}} + \widehat{\eta_{2,j(t)}} + \widehat{\phi_{2,i(t),j(t)}} + \widehat{\epsilon_{2,t}}. \end{aligned}$$

The exclusion restriction for our two instruments — crypto hacks and major market crises — assumes that these events influence the builder share exclusively through their impact on the composition of blocks, particularly the balance between private and public transactions, rather than through any direct effect on the builder-proposer negotiation process. Furthermore, the instruments are exogenous, since both hacks and crypto crises are unexpected and not caused by the bargaining process between builders and proposers.

These two instruments span our two explanatory variables, due to the distinct ways in which hacks and crises affect the DeFi ecosystem. Crypto crises, such as the FTX collapse

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<sup>13</sup>The list of hacks is obtained from DefiLlama (<https://defillama.com>), and we keep only hacks which affected only the Ethereum chain.

<sup>14</sup>The FTX crises occurred between November 8 2022, and November 12 2022. The SVB crisis unfolded between March 9 2023, and March 12 2023. Other crypto crises, such as the Terra crash, occurred before the transition to proof of stake and are therefore not in our sample.



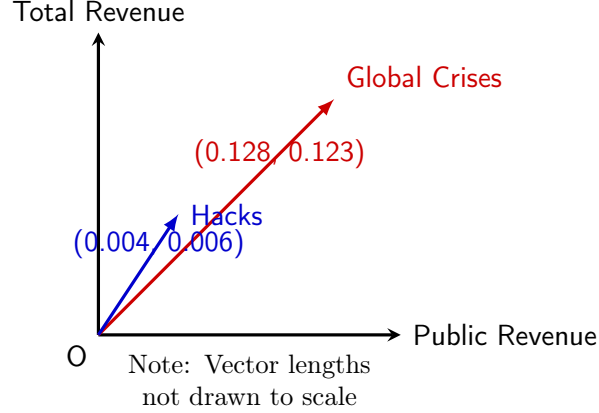


Figure 3: Effect of the instrumental variables on an average block’s private and total revenue. Crypto crises increase private and total revenue by similar amounts, while Hacks tend to increase private revenue disproportionately—spanning our space of explanatory variables.

or the SVB crisis, impact the entire crypto market in a broad, systemic manner. This is reflected in our first-stage results shown in Table 3. During crises, both overall revenue and private revenue increase proportionally, with coefficients of approximately 0.12 for both log revenue and log private revenue. In contrast, hacks typically affect individual protocols or platforms within the Ethereum ecosystem. These events are more likely to generate private revenue opportunities for insiders or those with early knowledge of the hack, rather than increasing overall transaction volume uniformly. This is evidenced by the differential impact of hacks in our first-stage results: the coefficient on log private revenue (0.006) is notably higher than the coefficient on log revenue (0.004). Figure 3 illustrates the differential impact of the two instruments, and shows how they span the space of explanatory variables.

**Results** Table 4 shows the results of OLS and 2SLS regressions where  $\theta_{B,t}$  is the dependent variable, and  $\log Private_t$ ,  $\log Rev_t$  are the independent variables. Columns (1) and (2) show the OLS results without and with builder  $\times$  proposer fixed effects. Columns (3) and (4) show the results from the instrumental variable regressions using the Hacks and Crises dummies as instruments—again without and with builder  $\times$  proposer fixed effects.<sup>15</sup> The results using instrumental variables and fixed effects are very strong, showing that a 1% increase in the value of private arbitrages increases the builder’s revenue share by 1.4%. We highlight that the coefficient on the revenue control is negative. This follows from a simple economic

<sup>15</sup>We use the commands *reg*, *reghdfe*, *ivreg2* and *ivreghdfe* to compute each of these four columns. Note that when using *reghdfe* or using *ivreghdfe* the constant is not reported because it is a normalization factor chosen algorithmically to ensure all fixed effects have zero mean.

	(1) $\log Private_t$	(2) $\log Rev_t$	(3) $\log Private_t$	(4) $\log Rev_t$
Hack Dummy	0.0072*** (0.0007)	0.0039*** (0.0007)	0.0059*** (0.0006)	0.0043*** (0.0007)
Crisis Dummy	0.1208*** (0.0092)	0.1300*** (0.0093)	0.1236*** (0.0099)	0.1289*** (0.0100)
Constant	0.0715*** (0.0022)	0.0985*** (0.0020)		
Observations	2607730	2607730	2277574	2277574

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** This table shows the first stage estimation results for our different 2SLS specifications. Columns (1) and (2) show how  $\log Private$  is affected by these instruments, with Column (1) having no fixed effects, and Column (2) having builder, proposer and builder  $\times$  proposer fixed effects. Columns (3) and (4) show analogous results for  $\log Public$ , the log of the value of Public arbitrages in a given block. Columns (5) and (6) show analogous results using  $\log Rev$ , the log revenue of the block. All standard errors are clustered at the builder  $\times$  proposer level.

Table 3: First Stage Regression Results

intuition: since a block can contain multiple sources of revenue, many of which are public, a larger revenue after accounting for private arbitrages will shift market power to the proposer, and away from the builder.

## 5 Model: Information-Driven Market Power

In this section we provide a stylized model to illustrate the determination of profit shares of the proposers and block builders in the DeFi intermediation chain. In order to clarify the mechanism, we will abstract away from the rest of the DeFi intermediation chain and restrict attention to the bargaining game between the proposers and block builders in the process of building the blockchain.

We model the construction of the blockchain as an infinitely repeated game between two types of agents—proposers and block builders. Time is indexed by  $t = 0, 1, \dots$ . There are  $N$  proposers, indexed by  $n \in \{1, \dots, N\}$ , each with stake  $w_n$ . Motivated by the empirical observation that proposers’ market shares of staked coins are very stable over time, we assume that proposers’ stake is constant. There are  $M$  block builders, indexed by  $m \in \{1, \dots, M\}$ . Agents are profit maximizers and they do not discount the future.

In each period  $t$ , a proposer  $n$  is chosen among the  $N$  proposers via the proof-of-stake

	Builder Profit Share $\theta_{B,t}$			
	(1)	(2)	(3)	(4)
	OLS No FE	IV No FE	OLS FE	IV FE
$\log Private_t$	0.143*** (0.0138)	1.367*** (0.177)	0.111*** (0.0149)	1.484*** (0.235)
$\log Rev_t$	-0.0713*** (0.00906)	-1.240*** (0.175)	-0.0511*** (0.00950)	-1.360*** (0.223)
Constant	0.0237*** (0.00244)	0.0511*** (0.00535)		
N	2607730	2607730	2277574	2277574
F Statistic		583.25		127.22
Robust F Statistic		220.937		26.100

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** This table shows our multivariate estimation results when the builder profit share is the dependent variable. Columns (1) and (2) show OLS results, without and with builder  $\times$  proposer fixed effects, respectively. Columns (3) and (4) show 2SLS results, without and with builder  $\times$  proposer fixed effects, respectively. All standard errors are clustered at the builder  $\times$  proposer level. The instrumental variables are  $Hacked_t$  and  $Crisis_t$ .

Table 4: OLS and Two-Stage Least Squares Results

consensus mechanism with probability  $\psi_n = \frac{w_n}{\sum_{i=1}^N w_i}$  to add the next block to the blockchain. Let  $B_{m,t}$  denote the block built by builder  $m$  at time  $t$  with total value  $R_{m,t}$ .<sup>16</sup> We denote the set of all the blocks created at time  $t$  by  $\mathcal{B}_t = \{B_{m,t}\}_{m \in \{1, \dots, M\}}$ .

At each time  $t$ , blocks are made up of three type of transactions: Normal transactions, which have a low payoff and arise every period, and two types of arbitrage transactions that are high payoff but arise rarely. Thus, the majority of time periods are normal periods with no arbitrage opportunities. An arbitrage opportunity arises at small Poisson rate  $\rho \ll 1$  per period, and disappears at Poisson rate  $\rho_d < 1$  per period, where  $\rho_d \gg \rho$ . The arbitrage opportunity is public with i.i.d. probability  $\pi_u$  and private with complementary probability  $\pi_r = 1 - \pi_u$ . Public arbitrage transactions are identified by many different arbitrageurs and thus are known to all block builders who all include it in their respective block. As such, a **public** arbitrage transaction in period  $t$  is included in every  $B_{m,t} \in \mathcal{B}_t$ .

Let “public blocks” denote all the blocks in a normal period or a in a period with public arbitrages. For simplicity, assume all public blocks in period  $t$  have the same value  $\widehat{R}_t$ . The

<sup>16</sup>One can assume that there is fixed cost  $c > 0$  associated with building a block. It does not change any of the results and does not add any intuition, thus we set  $c = 0$ .

value  $\widehat{R}_t$  varies across periods— low in normal periods,  $\underline{R}_t$ , and high in periods with public arbitrages,  $\bar{R}_t$ . Thus,  $\widehat{R}_t \in \{\underline{R}_t, \bar{R}_t\}$ .<sup>17</sup> Table 2 documents that the distribution of block revenue is strongly skewed to the right. Motivated by this empirical evidence, we assume  $\bar{R}_t \gg \underline{R}_t$ .

Alternatively, a private arbitrage that arrives in period  $t$  is identified by a single arbitrageur and picked up by a single builder,  $\tilde{m}$ , who incorporates it in his block  $B_{\tilde{m},t}$ .<sup>18</sup> In that sense, the private arbitrage opportunity is the “private information” of builder  $\tilde{m}$ . We call  $B_{\tilde{m},t}$  the “private block” at time  $t$ . Every other block at time  $t$  is a public block with low total revenue, i.e.,  $\forall B_{m,t} \in \mathcal{B}_t, m \neq \tilde{m}$ , we have  $R_{m,t} = \underline{R}_t$ . For simplicity, assume the value of a private arbitrage block is governed by the same random variable as a public arbitrage block, and  $R_{\tilde{m},t} = \bar{R}_t$ .

With a slight abuse of notation, let  $p_t$  denote the proposer selected,  $b_t$  the block builder,  $B_t$  the block added to the blockchain, and  $R_t$  denote the block’s revenue, in period  $t$ . Proposer  $p_t$  and block builder  $b_t$  *trade* and divide the *net* block value with exogenous bargaining powers  $(\xi_P, \xi_B) = (1 - \delta, \delta)$ , and *endogenous* outside options  $\Upsilon_{P,t}$  and  $\Upsilon_{B,t}$  for the proposer and the block builder, respectively. The asymmetric bargaining powers can be simply derived from a variation of an alternating-offer bargaining game a la Rubinstein (1982) played by the proposer and block builder in virtual time within each period.<sup>19</sup>

The net value from adding block  $B_t$  to the blockchain is given by  $R_t$ , the total value generated by block  $B_t$ , minus the sum of outside options of the block proposer and the block builder,  $S_t = R_t - \Upsilon_{P,t} - \Upsilon_{B,t}$ . Consistent with the notation in Section 3, let  $\Pi_{P,t}(\theta_{P,t})$  and  $\Pi_{B,t}(\theta_{B,t})$  denote the profit (profit share) of the proposer and builder in period  $t$ , respectively. They are given by:

$$\begin{aligned}\Pi_{B,t} &= \delta S_t + \Upsilon_{B,t}, \\ \Pi_{P,t} &= (1 - \delta)S_t + \Upsilon_{P,t}.\end{aligned}$$

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<sup>17</sup> $\underline{R}_t$  and  $\bar{R}_t$  can be random variables themselves, with different supports.

<sup>18</sup>The assumption that an arbitrageur with a private arbitrage offers his block to a single block builder is consistent with the empirical pattern that block builders try to build market share in order to capture arbitrageurs. It is also the optimal strategy for the arbitrageur, as it ensures a high profit for him while almost certainly being added to the chain by safeguarding his information advantage.

As long as few arbitrageurs identify each arbitrage opportunity and few block builders incorporate each arbitrage opportunity in their block, the same argument goes through.

<sup>19</sup>To be precise, assume the proposer and the block builder play an alternating-offer bargaining game a la Rubinstein (1982) in virtual time in each period  $t$ , and the block builder always makes the first offer. The proposer and the block builder face probabilities of within-period trade-breakdown  $1 - \delta_1$  and  $1 - \delta_2$ , respectively. This implies  $\delta = \frac{\delta_2(1-\delta_1)}{1-\delta_1\delta_2}$ . Thus, in equilibrium, the initial block builder’s offer, i.e. the observed bid of the block builder for each block, is set to achieve the profits implied by the bargaining game with bargaining powers  $(\xi_P, \xi_B) = (1 - \delta, \delta)$  and endogenous outside options  $(\Upsilon_{P,t}, \Upsilon_{B,t})$ .

Table 2 shows that the mean block builder's profit is very low, close to zero. As such, we are particularly interested in the case where  $\delta \rightarrow 0$ , in which case  $\Pi_{B,t}$  and  $\Pi_{P,t}$  simplify to

$$\Pi_{B,t} = \Upsilon_{B,t}, \quad (2)$$

$$\Pi_{P,t} = R_t - \Upsilon_{B,t} \quad (3)$$

which in turn imply

$$\theta_{B,t} = \frac{\Upsilon_{B,t}}{R_t}, \quad (4)$$

$$\theta_{P,t} = \frac{R_t - \Upsilon_{B,t}}{R_t} = 1 - \frac{\Upsilon_{B,t}}{R_t} \quad (5)$$

Recall that block builder and proposer outside options,  $\Upsilon_{B,t}$  and  $\Upsilon_{P,t}$ , are equilibrium outcomes that are determined endogenously. In turn, they determine the profit levels and profit shares of the block builder and the proposer. Equations (2), (3), (4) and (5) highlight the main intuition of the model— that the source of block builders' revenue is their outside option.

Proposition 1 summarizes the main theoretical results of the model that rely on this intuition and tightly connect to the empirical patterns documented in Section 4.

**Proposition 1 (Information-Driven Market Power).** *Existence of private arbitrage transactions in a given block increase the profit share of the block builder and decreases that of the proposer. Alternatively, higher total block revenue has the opposite impact on the profit share of the block builder and the proposer, controlling for the value of private arbitrages.*

The proof of proposition 1 shows that block builders' outside option is governed by their private information. We call this the information-driven market power of block builders. In order to get some intuition for this result, it is most insightful to consider the determination of the outside options.

First, assume period  $t$  is a period with only public blocks, i.e., with no private arbitrage transactions. In this case, the selected proposer  $p_t$  can choose any  $B_{m,t} \in \mathcal{B}_t$  and none of them has an advantage over the others. On the other hand, block builders cannot do anything other than offering their block to proposer  $p_t$  only in period  $t$ . In particular, any block that is chosen as  $B_t$  and is added to the blockchain at time  $t$  includes the same set of transactions. As such, all the other blocks in  $\mathcal{B}_t$  lose their value as soon as  $B_t$  is added to the blockchain. This implies that the block builder  $b_t$ 's outside option is zero. Thus, for the

public blocks added to the blockchain Equations (2) and (3) reduce to

$$\Pi_{B,t}^{\text{public}} = 0 \quad (6)$$

$$\Pi_{P,t}^{\text{public}} = \widehat{R}_t \quad (7)$$

Next, consider a period  $t$  when there is a builder with a private block,  $B_{\tilde{m},t}$  and let  $n$  denote the proposer who is chosen in period  $t$ ,  $p_t = n$ . Furthermore, let  $X$  denote the maximum profit that proposer  $n$  can obtain from existence of the private block  $B_{\tilde{m},t}$  in the future if he does not choose  $B_t = B_{\tilde{m},t}$ .  $X$  is also the maximum that proposer  $n$  can extract from the total revenue of the private arbitrage block  $B_{\tilde{m},t}$  at time  $t$  if he decides to choose  $B_t = B_{\tilde{m},t}$ .

If proposer  $n$  does not choose the private block  $B_{\tilde{m},t}$  in period  $t$  to add to the blockchain, it remains in the pool of available blocks for future proposers, until the private arbitrage opportunity disappears (at rate  $\rho_d$ ). Meanwhile, as this private arbitrage transaction is not included in any other block, its corresponding value remains unexploited. Proposer  $n$  has an i.i.d. probability  $\psi_n = \frac{w_n}{\sum_{i=1}^N w_i}$  to be chosen each period after  $t$ . In each future period  $\tau > t$  that  $n = p_\tau$ , if block  $B_{\tilde{m},t}$  is still available,  $n$  can obtain at most  $\bar{R}_t$  from choosing  $B_\tau = B_{\tilde{m},t}$ . Finally, when  $n$  does not choose  $B_t = B_{\tilde{m},t}$ , he chooses a public block with normal transactions only in period  $t$ , with total value  $\underline{R}_t$ . Thus, Equation (7) implies that he receives  $\underline{R}_t$  today. As such, an upper bound for  $X$  is given by

$$\left(1 - \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)}\right) \bar{R}_t + \underline{R}_t$$

Since  $\underline{R}_t \ll \bar{R}_t$ ,  $X < \bar{R}_t$ . In other words, proposer  $n$  is willing to leave profit  $\frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)} \bar{R}_t - \underline{R}_t$  for block builder  $\tilde{m}$  in order to be able to add the block  $B_{\tilde{m},t}$  in period  $t$  to the blockchain. Thus, for a private block, using Equations (2) and (3) we have

$$\Pi_{B,t}^{\text{private}} \geq \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)} \bar{R}_t - \underline{R}_t \Rightarrow \theta_{B,t}^{\text{private}} > 0 \quad (8)$$

$$\Pi_{P,t}^{\text{private}} \leq \left(1 - \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)}\right) \bar{R}_t + \underline{R}_t \Rightarrow \theta_{P,t}^{\text{private}} < 1 \quad (9)$$

Comparing Equation (6) with (8) and (7) with (9) clearly illustrate the opposite impact of the private arbitrage opportunities on profit shares of block builders and proposers. It also shows that higher block revenue leads to a higher share for the block builder only if the block revenue comes from private arbitrages. All the rest of the block revenue is captured by the proposer and thus increases his profit share, while decreasing the profit share of the block

builder. As such, Proposition 1 provides a consistent mechanism for the empirical findings of Table 4.

Equation (8) also implies that shorter lived private arbitrage opportunities lead to a higher profit share for the block builder. This is intuitive as it corresponds to a more limited availability of the private arbitrage opportunity, which in turn makes the private information of the block builder more valuable and improves his bargaining position.<sup>20</sup>

## 6 Robustness

In this section we show the robustness of our empirical results in two dimensions.

In Section 6.1 we change the sample of blocks in two different ways. First, we extend the sample to include the blocks in which the block builder subsidizes the proposer at very high rates. Second, we limit the sample only to blocks in which block builders make weakly positive profits.

In Section 6.2 we use a more involved algorithm to measure builder’s private information. In particular, we employ the heuristic introduced by Heimbach et al. (2024). This heuristic classifies a transaction as a private arbitrage only if it is based on information that is not in the blockchain.

Appendix C presents the results of these robustness estimation exercises. Importantly, in every exercise all the instrumental variable regression coefficients have the same sign as the baseline estimation and remain statistically significant.

### 6.1 Blocks With And Without Subsidies

In our main analysis, we removed blocks where the builder profit share was less than  $-10\%$ , consisting of about  $3.5\%$  of the sample, to prevent outliers from skewing the results. In this section, we show our results hold when we don’t remove these blocks. We also show that the results hold when we condition on the builder profit share being non-negative, and when we use alternative definitions of private transactions. In each of these robustness checks, we obtain a significant positive effect for the value of the builder’s private information

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<sup>20</sup>It is worth mentioning that we have abstracted away from any relationship building between proposers and block builders, which is what gives rise to the negative builder profit shares. Furthermore, this simplified model does not address the determination of stakes of the proposers and the detailed interaction between block builders and arbitrageurs. These simplifications are crucial to highlight the main mechanism that gives rise to information-driven market power for block builders. We plan to incorporate the stylized model in a full model of the DeFi Intermediation chain that includes arbitrageurs, block builders, proposers and depositors and features inter-period dependencies. The full model includes optimal strategy of arbitrageurs as well as depositors and determines  $M, N$  and  $\{w_1, \dots, w_n\}$  endogenously.

on their profit share. Furthermore, our instrumental variables based on crypto crises and cyber-attacks remain strong throughout all our alternative specifications.

Table 5 in Appendix C shows that there exist blocks where the builder gives a very large subsidy to the proposer, with the largest subsidy being 56.13 ETH. This heavily skews the builder profit share  $\theta_{P,t}$ , with the share being highly negative for blocks with large subsidies. We show in this subsection that our results apply even when we restrict ourselves to blocks with a builder profit share  $\theta_{B,t} \geq -0.1$ , and when we restrict ourselves only to blocks with non-negative builder profit share  $\theta_{B,t} \geq 0$ .

The results for these specifications are shown in Tables 6 through 9 in Appendix C. Tables 6 and 7 show the first and second stage estimation results for the full sample. Alternatively, Tables 8 and 9 show the results conditioned on  $\theta_{B,t} \geq 0$ . While the effect of private information is slightly attenuated from 5.5 to around 1.5, all coefficients are still significant and the instruments are still strong.

## 6.2 Alternative Definition of Private Information

In our main analysis, we use the simplest possible definition of private information, where a transaction is private if and only if it is not broadcast to the network before being appended to the blockchain. However, there may be many arbitrage opportunities trades—while sent privately to a builder—are observed by many entrepreneurs. For example, any price discrepancies between decentralized exchanges (DEXs) on the blockchain may be observed by multiple entrepreneurs who have algorithms scanning the blockchain for such trades. Even if we observe an arbitrageur sending such transactions privately to a builder, it is possible that other arbitrageurs have sent them to other builders, making the arbitrage essentially public.

As an alternative measure of private information, we use the heuristic introduced by Heimbach et al. (2024), who consider only arbitrage transactions which are based on information that is not in the blockchain. Under this heuristic, a group of transactions is private if and only if one of the transactions involves a direct transfer to the builder, the transactions do not appear in the public mempool, one of the transactions is a DEX swap as classified by the ZeroMEV API,<sup>21</sup> and the swap involves a token that is traded in a centralized exchange.

The intuition for this heuristic is that an arbitrage is private if it can only be discovered using some private, off-chain signal. The vast majority of private arbitrages are arbitrages between centralized exchanges (CEXs) and decentralized exchanges. A CEX-DEX arbitrage

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<sup>21</sup>A DEX swap is an exchange of one token for another in a decentralized exchange. We use the ZeroMEV API for a classification of swap transactions<sup>22</sup>



takes advantage of mispricings quoted between two or more exchanges, but one is a centralized exchange whose prices and orders are off-chain. In contrast to DEX-DEX arbitrages, its legs are not executed simultaneously, so there is inventory risk as the arbitrageur holds the off-chain position. For this reason, an arbitrageur wants their public position to execute as soon as possible and exclusively, so they will certainly include a direct payment to a block builder and do so privately. Moreover, as only the on-chain leg is observable on the blockchain, the strategy looks like a swap between two tokens, one of which is traded on a centralized exchange.

Tables 10 and 11 show the first-stage and 2SLS regression results using the alternative definition of private information. We can see that the instruments are still strong, the results are significant, and there’s a positive effect for the value of private information. The only qualitative difference is that all of our other regression results have a negative coefficient for  $\log Rev_t$  in all columns, while in Table 11 the OLS coefficient for  $\log Rev_t$  is positive, and it becomes negative only when using instrumental variables. The intuitive explanation for this is that our definition of private arbitrage is much more restrictive, and many transactions which would have been classified as private in our main analysis are no longer classified as such. Therefore, a block with a large number of transactions has many other sources of revenue for the builder that are not covered in the alternate definition of  $\log Private_t$ .

## 7 Conclusion

We examine the impact of private information on the profit shares of financial intermediaries in Decentralized Finance (DeFi). Using novel DeFi transaction data, we find that the need for privacy—driven by the commodification of AI frontrunners—leads to the emergence of block builders as intermediaries, who capture a share of the block revenue by incorporating private transactions into aggregate blocks.

Employing an instrumental variable approach using crypto crises and thefts of funds from crypto institutions and protocols as instruments, we find that a 1% increase in the value of private information leads to a 1.4% increase in the block builder profit share. We propose a repeated bargaining model to provide an economics mechanism for our empirical findings. This evidence highlights the crucial role of private information in determining the revenue shares of intermediaries in decentralized financial markets. As traditional and decentralized finance become increasingly interconnected, understanding the dynamics of intermediation in decentralized markets becomes increasingly relevant for both academics and practitioners.

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# Appendix

## A Institutional Details

**The Bitcoin Blockchain and Proof-of-Work** The bitcoin blockchain (Nakamoto (2008)) is both the first blockchain ever created, and the largest by market capitalization. The goal of the blockchain is to achieve consensus about who owns how many units of a digital asset, the bitcoin cryptocurrency (BTC). This consensus is established by a proof-of-work protocol, where (approximately) every 10 minutes a new block of transactions is “mined” and appended to the blockchain. As a payment for their service, the miner receives both a mining reward—reflected by the minting of new bitcoin which are credited to the miner’s balance—and transaction fees paid by users who want their transactions included in the block. In every one of these 10 minute intervals, there is competition among users to be the miner and collect the rewards. In the most simple terms, the miner is the first user who can solve a cryptographic puzzle—the solution of which can be verified by all other participants.<sup>23</sup>

Because there is a competition to mine the next block, the bitcoin blockchain essentially has an all-pay auction every 10 minutes, where prospective miners perform trillions of computations attempting to be the first to solve the cryptographic puzzle. This competition is very wasteful and does not allow for high throughput of transactions. In addition, the bitcoin blockchain has a drawback in that it only keeps track of bitcoin balances, but does not have provisions for generating consensus on the balances of other assets.

**The Ethereum Blockchain and Smart Contracts** The Ethereum blockchain is the second largest blockchain by market capitalization, and the largest blockchain that allows the execution of general smart contracts (Buterin (2014)).<sup>24</sup> The native cryptocurrency of the Ethereum blockchain is Ether, or ETH for short.

Up until September 2022, Ethereum achieved consensus through a proof-of-work algorithm, which immediately led to challenges for operating smart contracts at scale. Since proof-of-work algorithms have very low throughput, the demand for smart contract operations was much larger than the available computing power of the Ethereum Virtual Machine,<sup>25</sup> leading to high transaction fees and very volatile congestion charges.

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<sup>23</sup>The consensus algorithm of bitcoin is more complex than described in this short paragraph, with incentives designed to prevent participants from re-mining a block. Interested readers are directed to the original bitcoin whitepaper in Nakamoto (2008).

<sup>24</sup>The Bitcoin blockchain allows the execution of a restricted set of smart contracts through bitcoin script, but the feasible operations are very limited compared to the Turing-Complete Ethereum Virtual Machine.

<sup>25</sup>The bottleneck here is not the raw computing power of an individual node, but rather the amount of

**Proof-Of-Stake Consensus** One way to address these challenges is a proof-of-stake algorithm, where block proposers get chosen randomly with probability proportional to their stake.<sup>26</sup> To prevent a rogue block proposer from appending an invalid block to the blockchain (e.g. one that has double spending), a small group of verifiers is also chosen at random. The verifiers attest to the block’s validity. As long as the stake is sufficiently distributed, the block proposer and verifiers will be independent with very high probability, and a valid block will be added to the chain. Since only a very small fraction of participants needs to be sampled to ensure the correctness of each new block, the amount of computation needed to obtain consensus is vastly reduced.

**Consensus Layer Yield** In Ethereum, all participants who stake their ETH receive some yield for accurately executing the consensus protocol. For every block, both the block proposer and verifiers receive some reward (in ETH) for accurately participating in the protocol. This reward varies depending on how much aggregate ETH has been staked, the time it takes for the verifiers to produce their attestation of correctness, and of course, the correctness of the proposed block. We define the Consensus Layer Reward as the expected payment (in ETH) to the block proposer and verifiers for correctly participating in the consensus protocol.

$$R_{consensus} = \mathbb{E}[\text{Reward from Participating in Consensus}]$$

Since the probability of being chosen as a proposer or verifier is proportional to the amount of ETH staked, the expected reward that one obtains from participating in the protocol is also proportional to the amount of ETH one has staked. Therefore, this reward can be interpreted as a yield on the staked Ether.

$$y_{consensus} = \frac{\mathbb{E}[R_{consensus}]}{\text{Amount of ETH staked}}.$$

**Execution Layer Yield** The most popular smart contracts on Ethereum are decentralized finance applications, including Crypto-Collateralized stablecoins such as MakerDAO, and decentralized exchanges such as Uniswap and Curve. Any user of the Ethereum blockchain can attempt to find arbitrage opportunities arising from these protocols. For example, an underwater MakerDAO loan can be liquidated at fire sale prices, and the collateral can be

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computing power needed to agree on the state of the blockchain at any given time, including the state of all the smart contracts being executed.

<sup>26</sup>In practice, the participants in proof-of-stake algorithms use a decentralized pseudorandom number generator, which is implemented with cryptographic tools to prevent any coalition below a given size from biasing the random number generation process.

immediately sold in a decentralized exchange at a higher price, yielding an instant arbitrage in two transactions.<sup>27</sup> Similarly, price discrepancies among the hundreds of different decentralized exchanges can lead to arbitrage opportunities.

Since the data on these applications is public, there can be many arbitrageurs competing to exploit all of these arbitrage opportunities. This gives Ethereum block proposers some power to decide who obtains these arbitrage profits. When determining the order of transactions in a block, the block proposer can prioritize some arbitrageurs over others. The extreme case of this is when the block proposer observes the incoming transactions and frontruns arbitrage opportunities that are suggested to them by potential arbitrageurs. In the long run, this would dissuade the arbitrageurs from operating, or would lead to vertical integration between arbitrageurs and block proposers. In the data we don't observe this vertical integration. Instead, we see that there are specialized arbitrageurs—called *block builders*, who share some of their surplus with the block proposers. This sharing of the surplus of the execution layer reward gives the block proposers some expected income per block from arbitrage opportunities. We define the Execution Layer Reward as the expected payment to the block proposer (in ETH) from arbitrageurs for incorporating their transactions into a block.

$$R_{execution} = \mathbb{E}[\text{Block Proposer Reward from Arbitrage Opportunities}]$$

Since the probability of being a block proposer is proportion the amount of ETH staked, we can interpret this as a yield

$$y_{execution} = \frac{\mathbb{E}[R_{execution}]}{\text{Amount of ETH staked}}.$$

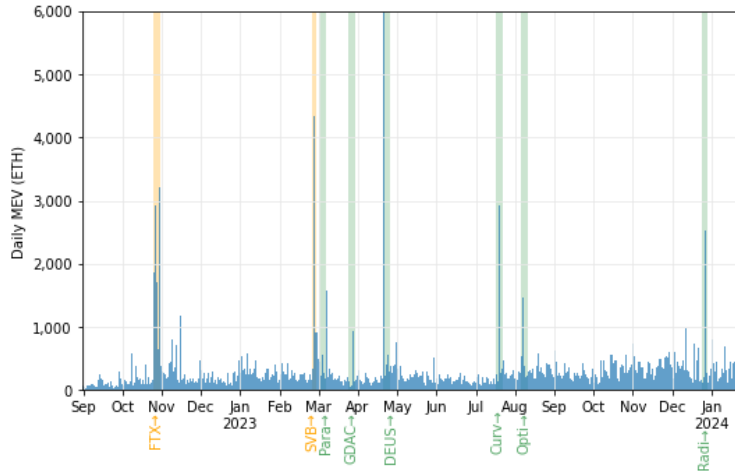
**Maximal Extractable Value (MEV)** The Maximal Extractable Value of a block represents the revenue that can be extracted from the ordering of transactions in a block, which is in excess of revenue from the value of transactions alone. Figure 4 shows the time series of MEV since the merge. We observe that the execution layer component is more volatile than the consensus layer component.

**MEV Searchers** MEV searchers are automated arbitrageurs who identify mispricings and the potential for near-riskless profit and bundle together transactions that, upon being incorporated into the blockchain, execute their arbitrage strategy. The success of these

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<sup>27</sup>The arbitrage is instant because the transaction that buys the collateral at fire sale prices and the one that sells the purchased collateral in decentralized exchanges occur in the same block.





Source: Dune Analytics

Figure 4: Daily Gas and MEV Revenue

strategies is contingent on immediately capitalizing on public and private information, so their transactions carry high priority fees and even direct payments to builders in order to guarantee their incorporation towards the front of the next block. Because the immediacy and position of these transactions matter, their value is considered MEV.

**The Market Inefficiencies of MEV** The arbitrage opportunities in decentralized finance, combined with the decentralized consensus protocol of the Ethereum blockchain, create economic inefficiencies. First, there may be competition among arbitrageurs to get their transactions incorporated into blocks—and to prevent competitors from placing their transactions. For example, an arbitrageur may pay transaction fees high enough to buy the entire space in a block, preventing anybody else from interfering in their trades. Additionally, there is a problem with frontrunning. If an arbitrageur finds a profitable trade and submits it directly to a block proposer, there is no inherent reason besides reputation for why the proposer can't just clone the transaction and submit it themselves to collect the profit. In the long run, this discourages arbitrageurs from participating in the market.

**Proposer-Builder Separation** To prevent frontrunning, members of the Ethereum community advocated for the principle of *Proposer-Builder Separation* (PBS). Under this principle, the *builder* who collects all the transactions in a block, including the profitable arbitrage opportunities, is not the same as the *block proposer* who is chosen by the consensus protocol to propose the next block. Instead, there are multiple builders—in essence arbitrageurs—who compete to build the most profitable block of transactions. The builders will collect all

the MEV of the block, and split this revenue with the proposer through a *proposer fee*—essentially a bid that incentivizes the proposer to choose the builder’s block over all others. In order to prevent frontrunning, the process through which these blocks are proposed is as follows

- **Block Builder’s Action** Block builder  $i$  creates a block  $B_i$ . She submits a pair  $(B_i, p_i)$  to a relay, where  $p_i$  is the proposed payment to the proposer.
- **Relayer’s Action** The relay  $j$  receives multiple pairs  $(B_{i_1}, p_{i_1}), \dots, (B_{i_n}, p_{i_n})$ . The relay verifies that the blocks are valid (and potentially, that they don’t have transactions from sanctioned Ethereum accounts), and chooses the highest bid  $(B_j^*, p_j^*)$  among the valid block proposals.

Each relay  $j$  communicates  $(H_j^*, p_j^*)$  to the block proposer, where  $H_j^* = H(B_j^*)$  is a hash function of the block  $B_j^*$ . Since the block proposer only observes a hash of the block—and hash functions are essentially random<sup>28</sup> the block proposer at this time learns nothing which would allow her to frontrun the arbitrage opportunities collected in the block.

- **Block Proposer’s Action** The block proposer may either
  1. choose a relay  $j^*$  who “wins” the round—in which case the relay  $j^*$  reveals the block  $B_j^*$  to the block proposer; or
  2. the block proposer rejects all bids and proposes some “outside-option” block  $B_{out}$  that they construct themselves.
- **Payoffs** The payoffs of the game are as follows

1. If the block proposer accepts the bid  $(H_j^*, p_j^*)$ , she will receive a payoff of  $p_j^*$ . The block builder will receive both the consensus layer and execution layer reward. We assume the relay is competitive, and receives zero payoff.<sup>29</sup>

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<sup>28</sup>The technical term here is that a hash function is computationally hiding. Under widely accepted computational assumptions such as the existence of one-way functions, the receiver of a message  $H_j^*$  would have to do an astronomical amount of computation to recover an input  $B_j^*$  such that  $H(B_j^*) = H_j^*$ . This is also true if the receiver wanted to partially recover some bits from the input  $B_j^*$ .

<sup>29</sup>The assumption that relays are competitive seems to line up with the observed data. There are multiple relays, and both block builders and block proposers can connect to more than one relay. Furthermore, the code for relays is open-source, and therefore non-exclusive and non-rival. In practice, there is some vertical integration between relayers and block builders, with flashbots and Bloxroute operating both block builder bots as well as relays. Since the builders have to trust the relays not to frontrun them, there is an informational advantage for blockbuilders to operate their own relaying software.

2. If the block proposer rejects all bids, she receives both the consensus layer and execution layer rewards associated with  $B_{out}$ . In this case, the payoff to the block builder is 0. In addition—as in the previous case—the relay is assumed to be competitive and has 0 payoff.

**MEV-Boost** In practice, there is open source software, called *MEV-Boost*, which implements this proposer-builder separation. After the transition to proof-of-stake, MEV-Boost gained widespread adoption, with around 90% of blocks in Ethereum being selected through MEV-Boost, and around 75% of all blocks having different builders and proposers.<sup>30</sup> The most popular relay is the flashbots relay. However, it has recently faced increased competition from other relays. The main difference between flashbots and their competitors is that flashbots will not accept any block that contains transactions with accounts sanctioned by the Treasury’s Office of Foreign Asset Control (OFAC). Many other relays, including Bloxroute-Max-Profit, do not take OFAC regulations into account when deciding which blocks to accept.

## B Proofs

*Proof Proposition 1.* Consider a period  $t$  with a private block  $B_{\tilde{m},t}$  and proposer  $n$  chosen (i.e.,  $p_t = n$ ). Assuming  $\delta \rightarrow 0$ , the builder and proposer profit shares are given by Equations (4) and (5), respectively. Let  $X$  be the maximum profit proposer  $n$  can obtain from the existence of the private block  $B_{\tilde{m},t}$  in the future if he doesn’t choose  $B_t = B_{\tilde{m},t}$  now.

It is sufficient to characterize  $\Upsilon_{B,t}$  across different periods. Classify periods into two groups: First, periods where all transactions are public, (whether a public arbitrage opportunity is present or not), and second, periods where a private arbitrage transaction happens. Note that as arbitrage opportunities arise with a small Poisson rate independently, the probability that two arbitrage opportunities of any kind happen in the same period is vanishingly small. Furthermore, we can assume that proposers can infer the actual value of the block from the offer that the builder submits. This is because, after each period, all asymmetric information about the block added to the blockchain is publicly revealed to all market participants. This information was previously known only to the builder who constructed the block, or to all builders in the case of a public period.

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<sup>30</sup>The data on MEV-Boost, including relay and block builder market shares, is obtained from Toni Wahrstätter’s website <https://mevboost.pics/>, and is augmented with data from the individual relays’ websites.

In a public period, every block has the exact same value. As such, all block builders act as perfect competitors and undercut each other. Therefore, all the profits from adding a block to the blockchain in this period are appropriated by the proposer chosen by the PoS consensus mechanism. As such,  $\Upsilon_{B,t} = \theta_{B,t} = 0$ ,  $\theta_{P,t} = 1$ .

It remains to put a strictly positive lower bound on  $\Upsilon_{B,t}$  in private periods. To do so, it is easier to put an upper bound on  $X$ , smaller than  $\bar{R}$ . To derive this bound, consider the following observations: 1) the private arbitrage opportunity disappears at rate  $\rho_d$ , 2) the proposer  $n$  chosen at time  $t$  has probability  $\psi_n = \frac{w_n}{\sum_{i=1}^N w_i}$  to be chosen each following period, 3) if chosen in a future period  $\tau > t$  and  $B_{\tilde{m},t}$  is still available,  $n$  can obtain at most  $\bar{R}_t$ , and 4) if  $n$  doesn't choose  $B_{\tilde{m},t}$  now, he chooses a public block with value  $\underline{R}_t$  in period  $t$ .

Thus, for the proposer, the expected value of not choosing this block today and leaving it for the future is given by:

$$\begin{aligned} & \sum_{\tau=t+1}^{\infty} \psi_n(1 - \rho_d) ((1 - \psi_n)(1 - \rho_d))^{\tau-t-1} \bar{R}_t \\ &= \psi_n(1 - \rho_d) \frac{1}{1 - (1 - \psi_n)(1 - \rho_d)} \bar{R}_t \\ &= \left(1 - \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)}\right) \bar{R}_t \end{aligned}$$

Thus, an upper bound for  $X$  is:

$$X \leq \left(1 - \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)}\right) \bar{R}_t + \underline{R}_t$$

Since  $\underline{R}_t \ll \bar{R}_t$ , we have  $X < \bar{R}_t$ . As such, proposer  $n$  is willing to leave profit  $\frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)} \bar{R}_t - \underline{R}_t$  for block builder  $\tilde{m}$  to add  $B_{\tilde{m},t}$  to the blockchain in period  $t$ .

Using equations (2) and (3), we derive:

$$\Pi_{B,t}^{\text{private}} \geq \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)} \bar{R}_t - \underline{R}_t \quad (8)$$

$$\Pi_{P,t}^{\text{private}} \leq \left(1 - \frac{\rho_d}{\psi_n + \rho_d(1 - \psi_n)}\right) \bar{R}_t + \underline{R}_t \quad (9)$$

These inequalities directly imply  $\theta_{B,t}^{\text{private}} > 0$  and  $\theta_{P,t}^{\text{private}} < 1$ . □

## C Robustness Regression Tables

In this Appendix, we show the robustness regression Tables described in Section 6. Table 5 shows summary statistics for the full sample. Tables 6 through 9 show our regressions using different subsamples of our dataset. Tables 10 and 11 show the regressions using an alternative definition of private information.

	Mean	Std. Dev.	Min	5th	Median	95th	Max	Skewness	Kurtosis
$Rev_t$	0.14	1.49	0.00	0.02	0.05	0.36	691.96	229.03	79243.77
$\Pi_{B,t}$	0.01	0.40	-56.13	-0.00	0.00	0.02	386.27	472.18	369899.17
$\Pi_{P,t}$	0.13	1.36	0.00	0.02	0.05	0.35	691.96	257.98	99142.42
$\theta_{B,t}$	0.01	0.90	-947.07	-0.06	0.01	0.15	1.00	-555.01	495297.49
$\theta_{P,t}$	0.99	0.90	0.00	0.85	0.99	1.06	948.07	555.01	495297.57
$\log Private_t$	0.07	0.17	0.00	0.00	0.03	0.27	6.54	8.55	122.62
$\log Public_t$	0.03	0.05	0.00	0.01	0.02	0.07	5.20	24.77	1146.61
Hack Dummy	0.07	0.26	0.00	0.00	0.00	1.00	1.00	3.24	11.50
Crisis Dummy	0.02	0.14	0.00	0.00	0.00	0.00	1.00	6.88	48.39
Observations	2723585								

**Source:** Dune Analytics and Mempool Guru Project

Table 5: Summary Statistics for the Full Sample

	(1) log <i>Private</i> <sub><i>t</i></sub>	(2) log <i>Private</i> <sub><i>t</i></sub>	(3) log <i>Rev</i> <sub><i>t</i></sub>	(4) log <i>Rev</i> <sub><i>t</i></sub>
Hack Dummy	0.0076*** (0.0007)	0.0063*** (0.0006)	0.0045*** (0.0007)	0.0048*** (0.0007)
Crisis Dummy	0.1141*** (0.0094)	0.1162*** (0.0101)	0.1228*** (0.0094)	0.1212*** (0.0101)
Constant	0.0699*** (0.0022)		0.0968*** (0.0019)	
Observations	2679416	2341828	2679416	2341828
Standard errors in parentheses				
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$				

**Note:** This table shows the first stage estimation results with our full sample. Columns (1) and (2) show how log *Private* is affected by these instruments, with Column (1) having no fixed effects, and Column (2) having builder, proposer and builder  $\times$  proposer fixed effects. Columns (3) and (4) show analogous results for log *Public*, the log of the value of Public arbitrages in a given block. Columns (5) and (6) show analogous results using log *Rev*, the log revenue of the block. All standard errors are clustered at the builder  $\times$  proposer level.

Table 6: Full Sample First Stage Regression Results

	(1) OLS No FE	(2) OLS FE	(3) IV No FE	(4) IV FE
log <i>Private</i> <sub><i>t</i></sub>	0.154*** (0.0245)	0.138*** (0.0358)	3.004*** (0.771)	5.512*** (1.759)
log <i>Rev</i> <sub><i>t</i></sub>	-0.0449*** (0.0137)	-0.0401** (0.0193)	-3.396*** (0.928)	-5.886*** (1.908)
Constant	0.00176 (0.00333)		0.128*** (0.0359)	
N	2679416	2341828	2679416	2341828
F Statistic			592.33	128.77
Robust F Statistic			230.179	24.570
Standard errors in parentheses				
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$				

**Note:** This table shows our multivariate estimation results with our full sample. Columns (1) and (2) show OLS results, without and with builder  $\times$  proposer fixed effects, respectively. Columns (3) and (4) show 2SLS results, without and with builder  $\times$  proposer fixed effects, respectively. All standard errors are clustered at the builder  $\times$  proposer level. The instrumental variables are *Hacked*<sub>*t*</sub> and *Crisis*<sub>*t*</sub>.

Table 7: Full Sample OLS and Two-Stage Least Squares Results

	Builder Profit Share $\theta_{B,t}$			
	(1)	(2)	(3)	(4)
	$\log Private_t$	$\log Private_t$	$\log Rev_t$	$\log Rev_t$
Hack Dummy	0.0086*** (0.0008)	0.0069*** (0.0007)	0.0052*** (0.0009)	0.0052*** (0.0008)
Crisis Dummy	0.1406*** (0.0161)	0.1440*** (0.0182)	0.1493*** (0.0163)	0.1494*** (0.0184)
Constant	0.0801*** (0.0030)		0.1081*** (0.0028)	
Observations	2134770	1862430	2134770	1862430

Standard errors in parentheses  
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** This table shows the first stage estimation results when  $\theta_{B,t} \geq 0$ . Columns (1) and (2) show how  $\log Private$  is affected by these instruments, with Column (1) having no fixed effects, and Column (2) having builder, proposer and builder  $\times$  proposer fixed effects. Columns (3) and (4) show analogous results for  $\log Public$ , the log of the value of Public arbitrages in a given block. Columns (5) and (6) show analogous results using  $\log Rev$ , the log revenue of the block. All standard errors are clustered at the builder  $\times$  proposer level.

Table 8: First Stage Regression Results when  $\theta_{B,t} \geq 0$

	Builder Profit Share $\theta_{B,t}$			
	(1)	(2)	(3)	(4)
	OLS No FE	OLS FE	IV No FE	IV FE
$\log Private_t$	0.160*** (0.0142)	0.128*** (0.0163)	1.586*** (0.164)	1.596*** (0.215)
$\log Rev_t$	-0.101*** (0.00900)	-0.0786*** (0.00966)	-1.455*** (0.162)	-1.468*** (0.198)
Constant	0.0351*** (0.00277)		0.0670*** (0.00461)	
N	2134770	1862430	2134770	1862430
F Statistic			441.75	113.99
Robust F Statistic			164.056	34.042

Standard errors in parentheses  
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** This table shows our multivariate estimation results when  $\theta_{B,t} \geq 0$ . Columns (1) and (2) show OLS results, without and with builder  $\times$  proposer fixed effects, respectively. Columns (3) and (4) show 2SLS results, without and with builder  $\times$  proposer fixed effects, respectively. All standard errors are clustered at the builder  $\times$  proposer level. The instrumental variables are  $Hacked_t$  and  $Crisis_t$ .

Table 9: OLS and Two-Stage Least Squares Results where  $\theta_{B,t} \geq 0$

	(1) log $Private_t$	(2) log $Private_t$	(3) log $Rev_t$	(4) log $Rev_t$
Hack Dummy	0.0055*** (0.0004)	0.0051*** (0.0005)	0.0035*** (0.0007)	0.0046*** (0.0008)
Crisis Dummy	0.0582*** (0.0059)	0.0580*** (0.0069)	0.1486*** (0.0108)	0.1451*** (0.0119)
Constant	0.0174*** (0.0013)		0.1003*** (0.0020)	
Observations	2242059	1933070	2242059	1933070
Standard errors in parentheses				
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$				

**Note:** This table shows the first stage estimation results for our different 2SLS specifications. Columns (1) and (2) show how log  $Private$  is affected by these instruments, with Column (1) having no fixed effects, and Column (2) having builder, proposer and builder  $\times$  proposer fixed effects. Columns (3) and (4) show analogous results for log  $Public$ , the log of the value of Public arbitrages in a given block. Columns (5) and (6) show analogous results using log  $Rev$ , the log revenue of the block. All standard errors are clustered at the builder  $\times$  proposer level.

Table 10: First Stage Regression Robustness Results Using Private Arbitrages

	Builder Profit Share $\theta_{B,t}$			
	(1) OLS No FE	(2) OLS FE	(3) IV No FE	(4) IV FE
log $Private_t$	0.106*** (0.00937)	0.0847*** (0.0110)	1.283*** (0.186)	0.964*** (0.226)
log $Rev_t$	0.0210*** (0.00317)	0.0222*** (0.00430)	-0.464*** (0.0862)	-0.317*** (0.102)
Constant	0.0234*** (0.00251)		0.0513*** (0.00660)	
N	2242059	1933070	2242059	1933070
F Statistic			177.95	93.52
Robust F Statistic			63.502	25.051
Standard errors in parentheses				
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$				

**Note:** This table shows our multivariate estimation results when the builder profit share is the dependent variable. Columns (1) and (2) show OLS results, without and with builder  $\times$  proposer fixed effects, respectively. Columns (3) and (4) show 2SLS results, without and with builder  $\times$  proposer fixed effects, respectively. All standard errors are clustered at the builder  $\times$  proposer level. The instrumental variables are  $Hacked_t$  and  $Crisis_t$ .

Table 11: OLS and Two-Stage Least Squares Using Private Arbitrages