# RTR-TFM: A Routing Threshold-based Randomized Transaction Fee Mechanism

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#### **ABSTRACT**

In recent years, impossibility proofs have been written claiming the impossibility of achieving efficient and collusion-proof transaction fee mechanisms. In the face of growing consensus that these problems are impossible to solve, this paper offers a dissenting proof, demonstrating the existence of a mechanism that implements the social choice rule of pareto optimality, thereby achieving both incentive compatibility and collusion-resistance.

#### **KEYWORDS**

Transaction Fee Mechanism, Leonid Hurwicz, Incentive Compatibility, Free-Riding, Collective Action Problems, Blockchain, Distributed Systems

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#### 1 INTRODUCTION

Transaction Fee Mechanisms (TFMs) refer to a class of distributed systems in which a consensus mechanism governs the allocation of the same resource that incentivizes its own provision. Unlike traditional mechanisms, where the number of honest and dishonest processes is static, in TFMs voting power is dynamic — it adjusts with the payouts issued by the mechanism. This introduces the ability for Byzantine strategies that increase profits to compromise the security and stability of the mechanism.

Due to their focus on the technical properties of systems, computer scientists often name these attacks after the "mechanism-specific" techniques they exploit, resulting in a wide array of terminology such as sybil attacks, block-orphaning attacks, selfish mining attacks, fee manipulation attacks, eclipse attacks, side-contract payments, and others. While most researchers treat these vulnerabilities as isolated technical challenges, a few scholars have applied concepts from mechanism design to ask whether general solutions are theoretically feasible. Unfortunately, this line of research has led to a series of impossibility results, suggesting that socially optimal TFMs may be infeasible.

This paper challenges these impossibility results by identifying the specific economic equilibrium in which all such attacks

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become irrational. We argue that three distinct types of goal conflict -— self-interest, free-riding, and strategic manipulation —- are the key factors preventing this equilibrium from being realized in most *TFMs*. We then review several commonly cited papers and demonstrate that their conclusions stem from their reliance on auction models rather than market models, a choice which limits their ability to address all three types of goal conflict or handle the informational complexity necessary to compute the required equilibria.

Using the language of mechanism design, this paper demonstrates that the social choice rule needed to achieve fee-optimality and collusion-resilience is *pareto optimality*, but the direct mechanisms used to model TFMs are incapable of implementing this rule, as doing so requires multi-dimensional preference revelation across a high-dimensional preference space – a level of informational complexity that composable algorithms cannot handle. While Maskin's Revelation Principle suggests that a direct mechanism must exist for any indirect mechanism, in this case achieving optimality requires decomposable algorithms that use the "no-trade option" to reduce the complexity of computation and limit the scope of the state transitions proposed to those consistent with an efficiency shift towards *paretop optimality*.

Since familiarity with economics is needed to understand why these problems exist, the next section of this paper begins by identifying the novel characteristics of TFMs, and showing how they create three distinct kinds of goal conflict. We then show why *pareto optimality* is the social choice rule needed to eliminate all three, which leads to a review of the impossibility results mentioned above and a discussion of how the conclusions of these papers reflect the informational limitations of the auction models they use to analyse the problem.

In the second half of this paper, we then introduce a novel class of indirect mechanism that is theoretically capable of achieving *pareto optimality*. We provide the formula for this mechanism and show that it's behavior is inconsistent with the impossibility proofs offered in the general literature and that it successfully manages to eliminate all three types of goal conflict. We then provide a gametheoretic treatment of the mechanism to provide a formal proof of incompatibility with the impossibility results this paper debunks.

#### 2 CHARACTERISTICS OF A TFM

The novel characteristics of *TFMs* that lead to suboptimal provision are *non-excludability*, *self-provision* and *informational decentralization*.

**Non-Excludability** allows anyone to use or provision the networks on equal terms provided they are willing to pay the competitive market price. This economic characteristic underpins the technical properties of *censorship resistance*, *decentralization* and *network* 

*resilience*: censorship requires a mechanism with the power to exclude; centralization creates barriers to entry; resilience comes from the ability to route around byzantine actors by adding new nodes to the network. Non-excludability also contributes to economic efficiency in *TFMs*, as efficiency is maximized when producers build atop blocks proposed by their peers rather than orphaning them.

**Informational Decentralization** refers not to the casual concept of *decentralization* as used in computer science (see: non-excludability) but the economic definition offered by Hurwicz (1972) for mechanisms in which "participants have direct information only about themselves." This characteristic makes *TFMs* vulnerable to Byzantine strategies, as identified by Hurwicz, in which participants manipulate the informational environment that others rely on to make strategic decisions.

**Self-Provision** allow *TFMs* to support themselves without an owner, relying instead on payouts to network participants. While volunteer-run networks are theoretically possible, their designs fall outside the scope of *TFMs* as transaction fees are purely redistributive. For this reason, in volunteer mechanisms the imposition of fees leads to a dead-weight efficiency loss, since any fee-level above zero is strictly suboptimal given the cost structure of the network.

These three characteristics create fundamental tensions that *TFMs* struggle to reconcile. They must permit open access without enabling sybil attacks, offer private benefits without socializing losses, and use decomposable algorithms while resisting byzantine manipulation of the information environment. We can see the importance of all three characteristics from the way they form an *economic trilemma* where the removal of any one property offers immediate relief to the problems created by the other two.

Understanding these characteristics allows us to identify the three types of *goal conflict* that drive byzantine attacks on *TFMs*. The first type, conflict rooted in *self-interest*, occurs when participants prefer to allocate their resources differently than the mechanism designer intends. For example, a user might desire to save a portion of their transaction fee to spend on other goods and services, rather than adhering to the mechanism's optimal allocation. In this case, participants are signalling disagreement with the designer's intended allocation of utility, both *within* the mechanism and *between* the mechanism and other external goods. These attacks consequently involve participants choosing to bid at suboptimal fee levels, as they prioritize their personal preferences over the collective optimal outcome.

Our second form of goal-conflict is *free-riding*, which emerges because the combination of *non-excludability* and *self-provision* creates public goods within the consensus mechanism. While free-rider pressures are common in many mechanisms, in *TFMs* they are more intractable due to the presence of a dual-sided free-rider problem where users and producers can free-ride on the mechanism in different ways: producers by maximizing the revenue they extract from any collective payout like the block reward, and users by minimizing their contribution to the security budget. As our next section explains, these are the class of attacks that manifest in the form of side-contract payments.

Our third form of goal-conflict is *strategic manipulation*, which emerges because – as Leonid Hurwicz observed – in informationally-decentralized mechanisms participants can strategically manipulate

others into suboptimally allocating their own resources by manipulating the informational space in which they form their own strategies. This class of goal-conflict incentivizes producers to create fake transactions, and users to exploit threshold vulnerabilities in auction designs. It is the main problem mechanism designers eliminate when they design mechanisms that achieve bayesian incentive compatibility or incentivize the truthful revelation of preferences.

While conflict over self-interest, free-riding and strategic manipulation are all distinct types of goal-conflict, each type has different causes and manifests in different ways. This is the reason incentive compatibility seems so intractable in *TFMs*, as techniques intended to prevent *strategic misrepresentation* cannot eliminate goal conflict entirely unless conflicts over self-interest and free-riding are also addressed. Any general solution requires the *TFM* to implement an equilibrium in which none of these conflicts exist, which is why the next section pulls back to economic theory to show why *pareto optimality* must be the social choice rule chosen by mechanism that seeks optimal fee-throughput in a collusion-free equilibrium.

#### 3 THE ECONOMICS OF TFM LIMITATIONS

In the field of economics, the pioneering work on welfare optimality was the publication of Vilfredo Pareto's "Cours d'économie politique" (1896), which introduced the concept of pareto optimality. Pareto defined this state as one where resources are allocated so efficiently that it is impossible to improve overall social welfare by changing the way in which resources are allocated to the production of utility.

From a mathematical perspective, Pareto optimality is achieved when the marginal utility derived from the last unit of each good purchased by each individual is proportional to its production cost. This implies that individuals are spending their resources in a way that maximizes their utility -- essentially, every dollar is spent on whatever good or service provides the greatest marginal benefit to its consumer. This allocation is considered individually rational and provides two important social critera demanded by TFMs. First, mechanisms in a pareto optimality equilibrium are free from conflicts involving self-interest since no party will unilaterally desire to pay a greater or lesser fee. Second, pareto optimality has attractive collusion-proof properties: if no individual can reallocate his own resources without making himself worse off, no group of similar individuals can collude to do so without at least one member of the group suffering as a result. This eliminates all categories of user-user and producer-producer collusion.

But is it possible for *pareto optimal* equillibria to be robust against goal-conflict involving *free riding* pressures or *strategic manipulation*?

The first question was addressed by Samuelson (1954) when he observed that achieving optimal production levels is challenging for goods with non-excludable benefits. If users can lie about the utility they receive from such goods they can pay a lower fee themselves while enjoying the higher level of utility funded by contributions from their honest peers. It was Samuelson's demonstration of this problem – that individual rationality subverted pareto optimality – that led?] to coin the term *incentive compatibility* in reference to the opposite condition, the state in which the utility-maximizing

behavior of individuals is *compatible with* or leads emergently to the desired welfare condition referred to as *social choice rule*.

Samuelson's observation is why free-rider pressures constitute the second type of *goal conflict* within *TFMs*, where they manifest in the form of side-contract payments. From the perspective of users, selling transactions to block producers gives producers the ability to collect their fees without the need to compete so intently for the privilege. Producers will happily accept a lower fee from users as less of their own income need flow into the public security budget. This form of collusion involves producers helping users free-ride on the contributions of other users to the collective security budget, as analogous to the classic free-rider in Samuelson's model.

On the producer side, side-contract payments permit block producers to free-ride on their peers as well. In this second case, producers offer users transaction-inclusion at suboptimal rates because private control of the transaction fee expands the producer's share of blocks committed to the longest-chain, allowing them to extract more income from any non-excludable payout like the block reward than they lose by subsidizing the user's transaction. Once again we have a situation analogous to Samuelson's model, except in this case the incentive to collude comes from producers and the incentive is to collect more in revenue not pay less in fees.

Understanding the two-sided nature of free-riding in *TFMs* is critical for designing mechanisms that eliminate this form of goal conflict. In the absence of this understanding, it is common to consider all forms of user-producer agreement as suboptimal. But this is not the case! If price negotiations between users and producers drive the cost of blockspace towards *pareto optimal* levels without affecting the overall level of public good provision, they technically shift the network into a more efficient equilibrium in which feethroughput level are more optimal and *goal conflict* is avoided. It is also trivial to see that side-contract payments will never drive transaction fees below the cost of blockspace in the absence of public goods, as rational producers cannot sustainably accept transaction fees that are lower than their private cost of providing blockspace.

The inability of proof-of-work and proof-of-stake designs to contain fundamental pressures to free-ride is a major cause of inefficiency and suboptimality in those networks. As we shall see, these pressures are also responsible for a non-trivial number of impossibility results, since the techniques mechanism designers use to prevent other classes of goal conflict – such as inducing truthful preference revelation – can contain adversarial forms of strategic manipulation but fail to prevent the sorts of cooperative attacks we see with free-riding strategies.

Our first two classes of goal conflict are thus "self-interest" and "free-rider pressures". The first exists in mechanisms that lack *pareto optimality* and can be solved only by designing mechanisms that implement that social choice rule. The second subverts the ability of mechanisms to achieve *pareto optimality* and can only be rectified by eliminating the public goods that lurk within their incentive sub-structures.

This leaves our third category of *goal conflict*, which is the practice of *strategic manipulation*. To put this issue in historical context, it is useful to know that by the late 1950s and 1960s, the problems that Samuelson flagged regarding the efficient provision of public goods had become widely accepted in mainstream economics. Nonetheless, most economists still believed the production and

trade of private goods under classical assumptions was more-orless *pareto optimal*. Or so they believed until 1972 when ? ], in his second great contribution to mechanism design, pointed out that similar problems also subvert the *pareto optimal* provision of private goods in informationally decentralized mechanisms.

The cause of the suboptimality Hurwicz identified came from the need for participants to exchange information as part of their price-discovery process. In any situation where agents could manipulate the informational environment they could theoretically induce others to strategically misallocate their own resources. The particular passage in Hurwicz's paper that points this out is worth quoting in full:

Economists have long been alerted to this issue by Samuelson (1954) in the context of the allocation problem for public goods. But, in fact, a similar problem arises in a "nonatomistic" world of pure exchange of exclusively private goods.... If [two parties] were both told to behave as price-takers it would pay one of them to violate this rule if he could get away with it. Now we assume that he cannot violate the rule openly, but he can "pretend" to have preferences different from his true ones. The question is whether he could think up for himself a false (but convex and monotone) preference map which would be more advantageous for him than his true one, assuming that he will follow the rules of price-taking according to the false map while the other trader plays the game honestly. It is easily shown that the answer is in the affirmative. Thus, in such a situation, the rules of perfect competition are not incentive-compatible.

In this case, our form of goal conflict does not involve participants re-allocating their own resources (self-interest) or cooperating with others to exploit public goods (free-riding) but adversarially manipulating the informational environment to frustrate efficient price-discovery. In the context of *TFMs*, we see this exploited whenever producers put their own fees into blocks, or costlessly loop money around the chain.

Awareness of these informational attacks is what led Hurwicz to develop his framework for studying *incentive compatibility*, which asks whether specific market structures (mechanisms) can achieve (implement) specific outcomes (social choice rules) in the presence of participants who make strategic decisions on the basis of private information. This is the reason "truthful revelation of preference" is considered such an attractive property in mechanism design, as it implies the mechanism is not vulnerable to this particularly category of goal conflict.

As an aside, since several papers on *TFMs* declare *incentive compatibility* impossible to achieve, it is useful to remember that Hurwicz never made this claim. As his student Eric Maskin later pointed out, such claims show a misunderstanding of the framework, since all mechanisms are by definition incentive compatible with their outcomes. What a failure of incentive compatibility means is that if private preferences are used to form the strategies adopted by participants in a mechanism, then without an "incentive for truthfulness" mechanisms cannot be assumed capable of implementing any social choice rule.

This point is important for ultimately implementing pareto optimality within a distributed system. For while Hurwicz is often misinterpreted as implying that the direct revelation of preferences is a pre-condition for achieving pareto optimality, the truth is more nuanced - market structures still exist which lack the problems Hurwicz identified with strategic manipulation, the key exceptions being atomistic markets characterized by perfect competition, markets in which the utility purchased varies with price paid, and markets lacking a pre-exchange messaging step. Eric Maskin, who later win the Nobel Prize for his work on the revelation principle, confirmed Hurwicz's intuition when he found that pareto optimality is possible in some market structures without the need for truthful preference revelation as an intermediary step.? ]. His revelation principle also illustrates this in a more subtle way, by showing that a symmetry of outcomes must exist between mechanisms where information is computed in decomposable fashion using agent-level functions, and mechanisms where the exact same information is revealed truthfully and the computation is performed by a centralized mechanism in a non-decomposable fashion. As Maskin showed, if the centrally-computed outcome does not result in a Nash Equilibrium then the decomposable function cannot have one and at least one agent must be lying about their true preferences.

Maskin's work revealed a deeper truth: all incentive compatible mechanisms will induce the revelation of private information one way or the other, meaning that the difference between mechanisms is not whether they reveal user preferences so much as whether they reveal those preferences directly or indirectly. In direct mechanisms participants share their preferences truthfully in the pre-exchange negotiation step, while in indirect mechanisms they reveal them either obliquely in the price-discovery process (such as by negotiating for bundles of goods) or by skipping the price-discovery stage and simply submitting purchase orders directly onto the market.

Back on topic, since TFMs are informationally decentralized mechanisms that involve users and producers making strategic decisions on the basis different preferences for the allocation of resources within the mechanism, if our social choice rule is pareto optimality, we cannot achieve it in any mechanism where participants can costlessly mislead others by manipulating any information relevant to fee-levels in the state of consensus. If a mechanism permits block producers to costlessly include their own transactions in blocks we thus have de facto grounds for concluding that incentive compatibility with pareto optimal fee-throughput will be impossible to achieve in that mechanism. Strategic manipulation can only be eliminated in mechanisms that make the inclusion of self-generated transactions costly, such that the decision by a block producer or user to include their own fees in a block reveals private information that the mechanism can exploit to shift its own provision into a more efficient equilibrium.

Hurwicz (1973) provides several other conditions any *TFM* will need to meet in order to successfully implement *pareto optimality*. The first is that one-shot mechanisms are insufficient, since algorithms with *inertia* are required to iterate price levels into their optimal positions over time [CITE]. This suggests that the information required to calculate the price of blockspace must be somehow calculable from the state of consensus rather than collected exclusively from peers. And as Jordan (1986) observes, some form of smoothing of costs or payouts is beneficial to prevent mechanisms

from unpredictably oscillating around the desired equilibrium point. As we shall see in the next section, these requirements are also incompatible with the vast majority of papers attempting to model the feasibility of building a dream TFM.

In summary, our three types of goal conflict – self-interest, freeriding, and strategic manipulation – are distinct issues that affect most *TFMs*. All three undermine the ability of any mechanism to achieve *pareto optimality* which in turn prevents them from targeting a highly efficient and collusion-proof equilibrium. Each type of goal conflict manifests as unique technical attacks involving different actors, different types of messaging, and targeting different steps in the operation of the consensus mechanism. A block producer who floods the network with spam transactions to drive up fees is engaging in strategic manipulation. A threshold user who underbids in a Vickrey-Clarke-Groves auction is exhibiting self-interest. Users who conspire with producers to defund the security budget are free-riding on their non-colluding counterparts. All three classes must be eliminated to achieve an optimal *TFM*, which is why is why achieving it is so difficult in practice.

With this framework in place for understanding the categories of problems *TFMs* face, in the following section we turn our attention to the existing literature on *TFMs* in computer science, with the goal of showing why the impossibility results in these papers reflect the limitations of their models rather than the limits of what is possible in distributed systems.

# 4 THE TFM LITERATURE IN COMPUTER SCIENCE

To our knowledge, this is the first paper to show how goal conflict prevents *TFMs* from achieving *pareto optimality* and makes auction models informationally incapable of resolving conflict within *TFM*. In order to understand the exact problem, this section reviews how computer scientists have studied this issue to show the general issues with approaches used.

Early attempts to model *TFMs* as auctions were Bitcoin-specific, starting with "Redesigning Bitcoin's Fee Market", which proposed using a "monopolistic auction" to stabilize miner revenue, followed by Andrew Yao's "An Incentive Analysis" which showed this maximized miner revenue at scale. Basu, Easley, O'Hara, Sirer then proposed a modified Vickrey-Clarke-Groves mechanism as a better choice for maximizing the collective welfare of both users and miners.

While all three papers focused explicitly on Bitcoin, the concerns over efficiency showed awareness *TFMs* are not just resource allocation mechanisms, but are themselves subject to conflict over resource allocation within the broader economy! Computer science was on the cusp of seeing the underlying economic nature of their problem, identified by Hurwicz in 1973 as "goal conflict", and realizing that *pareto optimality* would be the social choice rule required to solve it.

Computer science pulled back slightly in 2021 when Tim Roughgarden??] offered a paper that modelled Transaction Fee Mechanisms (TFMs) as two-sided auctions in which block producers are given a temporary monopoly over the production of a block and must strategically allocate a subset of transactions into it. Looking beyond Bitcoin towards a landscape of competing consensus

mechanisms, Roughgarden returned to characterizing the incentive-alignment issue as resulting from internal rather than economy-wide conflict over resource allocation. He was the first to highlight the difficulty of achieving incentive compatibility for both users (UIC) and block producers or miners (MIC), leading to seminal works [??] on the limitations of Bitcoin's "first-price auction" and Ethereum's EIP-1559 [?] among others. Roughgarden [??].

Since 2021, the vast majority of academics working on *TFM design* have followed Roughgarden in modelling *TFMs* as two-party auctions in which producers clash with users over how to allocate blockspace. The attractiveness of the approach is obvious: it focuses on internal rather than external motivations for conflict, it targets an essential step in the formation of consensus, and it uses a two-sided game that is tractable to model. Significantly, Myerson's lemma and virtual valuations can also be used to generalize the rational strategies of participants in these games so they can be asserted to hold in larger games with many players. Unfortunately, the work is simply producing a series of impossibility results.

Since one of the purposes of this paper is to present a mechanism that evades these problems, it is useful show how this choice of modeling *fee mechanisms* has created structural incompatible with a productive solution. In this light, the first problem is methodological treatment of UIC and MIC as properties which can exist outside the context of a social choice rule. Instead of identifying an equilibrium like pareto optimality that guarantee both fee-optimality and collusion-resistance for users and producers alike, and asking what private information both participants would need to disclose for any *direct mechanism* like an auction to achieve it, the literature assumes that truthful preference revelation is a sufficient goal in-and-of-itself. This is typically done by citing the Revelation Principle and observing that any mechanism capable of achieving a nash equilibrium must have an equivalent in which (see Roughgarden p. 13) truthful bidding is a dominant strategy.

The problem with this assumption is that the preference information any algorithm needs to be revealed depends on the social choice rule at stake, and specifically on whether we are in the presence of a problem that requires high-dimensional preferences to calculate.

Viewed sympathetically, we can intuit that the field's implicit social choice rule is an "efficient allocation" of blockspace. This seems fair to assume given Roughgarden's citation of the Vickrey-Clarke-Groves (VCG) mechanism as being UIC and the lack of any seeming challenge to this assumption. If this auction is considered to reveal truthful information sufficient for optimizing participant utility in one mechanism, it seems intuitive that it would collect the same information needed to optimize utility in a different mechanism, but the information required actually depends on the social choice rule and the difference between the types of conflict mechanisms are intended to address requires a very different type of "utility" information to be collected in our case.

Note, for instance, that the VCG auction is a *direct mechanism* that does not require high-dimensional preference information as part of its process of truthful preference revelation. Users share information on the maximum price-point at which they are willing to purchase the single privte good being allocated given a fixed price and production schedule for everything else, not their comparative preference for how to divide their resources between all goods and

services competing for consumption of the same transaction fee at all viable price equilibria as required for implementing *pareto optimality*. The VCG auction is thus informationally inadequate for eliminating byzantine strategies motivated by "self-interest" – our first class of incentive to suboptimality. Similarly, the VCG auction has no informational basis for combatting *free-riding*, since those are cooperative strategies to defund the production of a form of utility not covered by models that treat blockspace like a private good.

Roughgarden's papers were quickly followed by papers from Elaine Shi and Hao Chung, who offered technical definitions like "side-contract proof" ("no utility increase from off-chain payments") rather than using Roughgarden's technical definition of OCA-Proof. The difference between the two is essentially the difference between whether collusion maximizes revenue in the context of a single block or across potential forks in a chain. The concept of OCA-Proof thus encompasses types of collusion that lead to block orphaning while SCP-based approaches do not. Pareto optimality eliminates both possibilities on the fundamental grounds that there is no rational strategy for colluding in either case. The mechanism proposed later in this paper also elegantly sidesteps Roughgarden's concerns that any "fee burn" must invite collusion because "because OCAs allow the miner and users to coordinate and evade the intended burn." This is of course not possible in routing work mechanisms where the burn is the cost of producing a block, as it cannot be evaded by moving the payment off-chain.

A more subtle problem applies to the treatment of block producers, who are simply asked to implement the fee mechanism. The lack of any need for producers to reveal private information raises questions about why we are modelling this game as a twosided strategic interaction, and points to a deeper methodological problem. For as noted in our first section, the class of TFMs we are studying contain dual-sided free-rider problems. This specific class of vulnerability makes it impossible to achieve pareto optimality for both parties if we require truthful preference revelation from only one party. For both parties have private incentives to adopt byzantine strategies that are driven by a desire to free-ride on their peers. Eliminating collusion thus requires either eliminating collective action problems generally (and the auction mechanism cannot handle this as it focuses exclusively on a single private good) or by identifying a kind of "private information" which can by leveraged by a mechanism to motivate producers to shift their strategies away from defunding fection and towards cooperation. By denying producers the ability to act strategically on the basis of private preferences, modelling blockchains as auction mechanisms leads inescapably to impossibility results as they prevent the most critical party from behaving strategically!

The third and most fundamental problem with the auction model generally is that it is impossible to generalize its impossibility results, since the existence of an impossibility proof for this specific type of *direct mechanism* can never eliminate the possibility that an *indirect mechanisms* might exist that can achieve the desired results through the solicitation of a different kind of preference. Since this is a somewhat subtle point, note that while Maskin's relevation principle teaches us that all nash equilibria which are reachable by *indirect mechanisms* can be implemented as *direct mechanisms*,

the opposite is not true. So even if the auction model was informationally appropriate for implementing *pareto optimality*, we cannot conclude from an impossibility proof generated assuming the limitations of a direct mechanism that no indirect mechanism exists which is capable of skirting that problem.

Understanding this point is important for seeing how the mechanism described later in this paper solves the problem. For Maskin's revelation principle is based on logical reasoning about the consistency of outcomes between decomposable algorithms (where participants compute their preferences privately) and composable algorithms (where users reveal their preferences to a centralized mechanism that does the work for them). In situations where the amount of information required to calculate an optimal solution is so large as to make disclosure impractical or impossible to calculate in a centralized mechanism, such as exists with the highdimensional preference data needed to compute pareto optimal equilibria in informationally decentralized environments, indirect mechanisms that use decomposable algorithms to filter and transform participant preferences prior to their revelation can be informationally necessary to achieve incentive compatibility. It should be noted that Maskin's revelation principle still holds - truthful preference revelation happens in both types of mechanism – but it can happen in a different stage, either in the "action stage" identified by Hurwicz where bids are submitted directly to the market, or obliquely in the "pre-exchange negotiation stage" in a more indirect and filtered form.

The presence of public goods in consensus mechanisms is what forces the need for high-dimensional preference measurement, as they pull focus away from maximizing the kind of "single welldefined objective function" Hurwicz associated with computational models and towards the more complicated multi-variate forms of goal conflict suitable for economic analysis. Perhaps because of this, it is not surprisingly to see mechanism designers with stronger economic backgrounds explicitly recognize the presence of public goods, as is the case in a recent paper by Elijah Fox, Mallesh Pai, and Max Resnick on "Censorship Resistance in On-Chain Auctions". While the assumptions these authors make are not strictly true - transactions fees induce both private and public goods and only incentivize the provision of public goods to the extent they circulate openly for competitive inclusion - these authors are absolutely correct that off-chain payments involve a form of free-riding and addressing this problem is the key challenge for mechanism designers.

While the proposal by Fox fails on technical grounds (the degree of competition for fee collection can be manipulated by collusion in any non-excludable mechanism), their insight helps explain why *indirect mechanisms* are traditionally used in economics when optimizing resource allocation to non-excludable goods and eliminating free-rider pressures. *Indirect mechanisms* are the preferred approach for solving these class of problems, such as in the curious case of the Clarke-Groves mechanism (not to be confused with the VCG mechanism), a indirect mechanism in which users are asked to submit bids across bundles of goods, some of which may include public goods. Given the parallels between the information requirements to solve both problems, it is likely no accident that the solution this paper identifies is an *indirect mechanism* that leverages decomposabitility to avoid the need for truthful preference revelation during

the "pre-exchange negotiation step" as a necessary precondition for achieving incentive compatibility.

Returning to our review of the related literature, a second influential string of papers has come from Hao Chung and Elaine Shi in their work on *side-contract payments* and the *zero-revenue bound*. Specifically, Hao and Chung advance claims that side-contract payments (SCP) are impossible to disincentivize in any mechanism where the income for block producers is above zero.

The same methodological problems apparent elsewhere replicate here, as Hao and Chung treat truthful preference revelation as if it is a valid social choice rule rather than an intermediary step to achieve one in the presence of private information. The most significant difference with this approach is that unlike academics who view an "efficient and fee-stable blockspace allocation" as the implicit social choice rule, for Hao and Chung it is the possibility for a collusion-free environment that takes center stage, with results suggesting that collusion is impossible to eradicate in *TFMs* with revenue above the *zero-revenue bound*.

The framework provided above provides an intuitive explanation of why Hao and Chung stumble into their zero-revenue bound. As explained in Section 2, the underlying source of suboptimal forms of user-producer collusion is the existence of dual-sided free-rider problems embedded in the mechanisms. Their results follow deductively from this problem. At any positive fee-level users have an incentive to collude with producers to free-ride on the contributions of their peers to the security budget. This problem can be avoided by compensating producers through an inflationary block reward, but that invites producers to free-ride on the supply-side payout. Avoiding one trap pushes us into the other, so the only situation in which we avoid collusion completely in their model is if neither fees nor block rewards exist.

What percentage of the remaining papers are writing about blockchains and what percentage are simply writing about auctions? Making similar assumptions as their predecessors (auction model, no clear social choice rule, costless manipulation of informational environment), Aadityan Ganesh, Clayton Thomas and Matthew Wienberg not surprisingly end up in the same place, with the value of their work consisting mostly of several new terms like "off-chain influence proofness" that capture specific forms of collusion. While the authors identify "external opportunities" for profit not captured within the fee mechanism (implying goal conflict), they fail to follow their observations to their obvious conclusions: that the auction model itself is an inappropriate tool for analysing this problem. But the proof-of-stake models they study cannot address any of these problems. So how could they - or any of their peers - be expected to find a solution, when their focus is examining mechanisms designed by developers who also fail to understand the underlying problems they face?

There are some positive results, interesting primarily for showing that market mechanisms – not auctions – hold the key to solving these problems. Rejecting the tendency to treat auctions as one-shot games, CITATION find that repeated-games. This works for the same reason that?] finds – it creates the form of "inertia" required in free markets for price levels to move closer to pareto optimal levels in equilibrium. Ferreria's finding also shows the benefit of moving pricing information into the state of consensus itself, minimizing opportunities for *strategic manipulation* by shifting the market price

into the environment rather than making it only accessible through unreliable peer messages.

The tendency in computer science papers to treat the conclusions of earlier papers as axioms in new lemmas intended to develop new theorems has exacerbated the tendency for impossibility results to be exaggerated and amplified.

? ] introduce a "Burning Second-price" TFM that compromises allocative efficiency to guarantee user and block producer IC. In their model, the authors tweak the utility model with "y-Strict" utility for users/producers. The new model captures the future cost of introducing fake transactions discounted by a public parameter  $\gamma \in [0, 1]$ . We believe compared to " $\gamma$ -Strict" utility RTR-TFM's incentive rule introduces a natural cost for introducing fake transactions to the users/producers. Moreover y-Strict utility does not prevent free-riding.

### 5 A SOLUTION

TFM. Figure ??.

RTR-TFMis a Dutch clock auction where producers compete to purchase blocks by collecting transactions and burning their fees. A costly lottery which follows the production of each block has the potential to resurrect and redistribute these burned fees, with this same lottery providing wrap-around sybil-resistance for the chain. The economic innovation of the approach is that it makes the production of blocks costly for attackers who spend their own fees to extend the chain.

In the section that follows, we provide game-theoretic characterization of this approach. This is handled by examining what Hurwicz referred to as the *formula* or mathematical properties of the approach. The challenge in developing a mechanism that implements this formula is ensuring that half of the fees-in-block are always pulled away from the block producer. This can be handled in practice through the use of a payout to non-mining and non-routing nodes known as an "ATR payout", through the use of algorithms that smooth payouts, as well as through consensuslayer logic that punishes sharp spikes in inbound fee flows with asymmetrical deflationary burns.

# **Game Theoretic Characterization**

In RTR-TFM, when users send transactions to nodes in the network, they include cryptographic routing signatures indicating the first hop node. Each node adds its signature as it propagates the transaction deeper into the network, creating within each transaction an unforgeable record of the path the transaction has taken from the user to the block producer offering inclusion.

The "routing work" needed to purchase blocks is derived from this chain of signatures. Specifically, the amount of routing work that is available to a producer from any transaction is given by  $c \cdot \frac{1}{2h-1}$ , where c is a network-determined constant and h is the node's hop for that transaction. E.g., a node hearing about a transaction at its third hop receives  $\frac{c}{4}$  routing work for that transaction. Each node gathers transactions until they have enough total routing work to meet a network-determined difficulty threshold,  $\tau$ . At this time, the node may become a block producer and broadcast its block with its set of transactions whose total routing work crosses  $\tau$ .

The existence of multiple nodes processing transactions allows us to model RTR-TFM as a game with a set of  $m \in \mathbb{N}$  block producers,  $\mathcal{P} := [m]$ . We consider each producer  $i \in \mathcal{P}$  to be myopic and strategic. To simplify analysis, we assume that each transaction is of the same size, with each block's capacity denoted by  $k \in \mathbb{N}$ . Furthermore, we let  $n \in \mathbb{N}$  denote the total number of users, denoted by  $\mathcal{U} := [n]$ . We assume that each user  $j \in \mathcal{U}$  is also myopic and strategic [?????]. A user  $j \in \mathcal{U}$  is interested in getting a slot in the block for its transaction. Let  $\theta_j \in \mathbb{R}_{\geq 0}$  denote user j's private valuation for its transaction's confirmation and  $b_i \in \mathbb{R}_{>0}$  as its transaction's public bid.

As common in distributed consensus mechanisms, each block producer  $i \in \mathcal{P}$  has its private copy of the set of outstanding transactions, known as mempool. The presence of routing signatures within transactions means that in RTR-TFM producers store both the transaction bids and the specific hop at which they received the transaction. That is, producer i's mempool is the tuple  $\mathcal{M}_i = (F_i, H_i)$ . This section introduces RTR-TFM: a Routing Threshold-based Randomized  $\mathcal{M}_i$  comprises the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and their corresponds to the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and the set of user bids  $F_i = (b_1, \ldots, b_n)$  and  $F_i$ sponding hops  $H_i = (h_{i,1}, \dots, h_{i,n})$ .

> This lets us define the routing work for any transaction  $(b, h) \in$  $\mathcal{M}_i$ . Consider a function  $\omega: \mathbb{R}_{>0} \times \mathbb{N} \to \mathbb{R}_{>0}$  that represents the amount of routing work gained by a block producer at the  $h^{th}$  hop. In RTR-TFM, the routing function  $\omega$  is:

$$\omega(h) := c \cdot 2^{1-h} \tag{1}$$

That is, RTR-TFM offers 1st-hop nodes  $c \in \mathbb{R}_{\geq 0}$  units of routing work,  $2^{\text{nd}}$ -hop nodes  $\frac{c}{2}$  units of routing work,  $3^{\text{rd}}$ -hop nodes  $\frac{c}{4}$  units of routing work, and so on.

The algorithm for calculating the routing work available to block producers allows us to provide the optimization function, denoted by OPT<sub>RTR</sub>, which involves each production  $i \in \mathcal{P}$  selecting transactions from  $M_i$  for inclusion in their proposed blocks:

$$\begin{cases} \arg\max & \min_{(b_t,h_t) \in S} b_t \\ S \subseteq \mathcal{M}_i \end{cases}$$
 s.t. 
$$\sum_{(b_t,h_t) \in S} \omega(h_t) \geq \tau$$
 
$$|S| \leq k$$
 (OPT<sub>RTR</sub>

The first constraint ensures that  $S \subseteq \mathcal{M}_i$  clears the *network*determined threshold for routing work,  $\tau^1$ . For the second constraint, recall that each transaction is of the same size. This implies that the total transactions in a block cannot exceed its capacity,  $|S| \le k$ . Throughout this paper, we refer to  $S \subseteq \mathcal{M}_i$  as the subset that satisfies these two constraints and  $S^*$  as the solution to OPT<sub>RTR</sub>.

As follows, a producer  $i \in \mathcal{P}$  computes  $S \subseteq \mathcal{M}_i$ , such that the transactions in S clear  $\tau$ , or,

$$\sum_{(b_t, h_t) \in S} \frac{c}{2^{j-1}} \ge \tau.$$

In order to keep block production stable over time, the consensus mechanism adjusts  $\tau$  over time to target a constant pace of block production. If fee-throughput increases,  $\tau$  is increased to force blocktime back into its desired pace by making block production

 $<sup>^1{\</sup>rm The~threshold}~\tau$  is a network-determined dynamic parameter and increases upon block production, and slowly decreases until the next block is produced as similar to other Dutch clock auctions, similar in principle to the role of the base fee in EIP-1559 [? ]. As we consider myopic block producers and users, we omit additional details on the

more expensive. If fee-throughput decreases,  $\tau$  is reduced slightly to make block production cheaper.

We now progress how to fees are collected and payouts are issued. The first thing that happens after a block is produced is that half of its fees are removed from circulation. This can be done in a pure implementation by having the consensus mechanism simply destroy half of the tokens collected in network fees. A more practical implementation can use a costly method of random-number generation such as hashing to power the payout lottery and give miners half the block reward. Penalizing fee-throughput spikes is also helpful. Given that this paper focuses on the forumula for routing work, and set the fraction of network fees that are burned in RTR-TFMas 1/2, i.e.

$$\delta(S) := \frac{1}{2} \sum_{(h_t, h_t) \in S} p_t \tag{2}$$

As an aside, while it is not necessary for RTR-TFMto have a second-price payment rule, we adopt it here for the convenience of demonstrating UIC. Under this second-price payment rule, the payment collected from *each* user whose transactions are confirmed in *S* is the lowest winning bid (say) *p*. The total payment collected is  $\frac{1}{2} \cdot |S| \cdot p$  (recall that the other half is burned).

Whether a second-price payment rule is used or not, the lottery that determines the winner of the payout begins after the production of the block. This lottery first selects a random transaction from within the block, and then a random node from within the routing paths of the selected transaction.

The revenue,  $\frac{1}{2} \cdot |S| \cdot p$ , collected when a block is produced is given to the winner sampled from the following distribution. All sampling is done on-chain, i.e., in a trusted manner [??].

- (1) Sample a transaction  $t^* \in S$  uniformly, i.e.,  $t^* \sim \text{Uniform}(S)$ .
- (2) From the routing path of  $t^*$ , sample a node through a probability distribution that weighs each node by their share of the routing work available at their hop over the total sum of routing work available to all nodes in the routing path of the transaction as included in the block.
  - Let the producers part of t<sup>\*</sup>'s routing path be (w.l.o.g.)
    P<sub>t\*</sub> = {1,..., l}.
  - Any producer's  $i \in \mathcal{P}_{t^*}$  routing work for the transaction  $t^*$  is  $\omega(t^*; h_i)$ . Likewise, the total routing work for  $t^*$  is  $\sum_{i \in \mathcal{P}_{t^*}} \omega(t_*; h_i)$ .
  - We sample a producer  $i^* \in \mathcal{P}_{t^*}$  from the following weighted probability distribution:

$$\Pr(i^{\star}) \sim \frac{\omega(t^{\star}; h_{i^{\star}})}{\sum_{i \in \mathcal{P}_{i^{\star}}} \omega(t_{\star}; h_{i})}$$

• The producer  $i^*$  receives the payment  $\frac{1}{2} \cdot |S| \cdot p$ .

Figure 1: RTR-TFM: Revenue Lottery given S (refer OPT<sub>RTR</sub>)

For an intuitive example, if a transaction is sampled that has two nodes in its routing path, the total routing work for all nodes in the routing path is  $c+\frac{c}{2}=\frac{3c}{2}$ . The sampling probability of the first-hop node is  $\frac{c}{3c/2}=\frac{2}{3}$  while the sampling probability of the second-hop node is  $\frac{c/2}{3c/2}=\frac{1}{3}$ .

This allows us to define the probability of an arbitrary producer i winning the lottery, which depends on the efficiency with which it sends fees into the burning mechanism, denoted by  $\alpha_i$ , as:

$$\alpha_i = \sum_{i=1}^m \Pr(\mathbb{I}_i = 1|S_j) \cdot \Pr(S_j)$$
 (3)

Here, the indicator variable  $\mathbb{I}_i = 1$  denotes the event that producer i is selected as the winner (recipient) of the block's payment;  $\mathbb{I}_i = 0$  otherwise.  $\Pr(S_j)$  denotes the confirmation of the set  $S_j$  owned by the j<sup>th</sup> producer.

The dynamics of the routing work mechanism. Producers minimize their losses in the payout lottery if they spend their own fees, but doing so also burns half of their own money. Adding transactions which have been routed by other nodes adds fees that can subsidize the unlock cost, but also introduce competing claims-on-payout that grow faster than the work provided. As our next sections will show, in a competitive dynamic this lose-lose situation dissuades rational producers from using their own money to extend the chain, ceteris paribus.

# 5.2 Incentive Compatibility

The standard way TFM papers examining for UIC and MIC is to establish incentive compatibility for users following Myerson's Lemma, and then examine whether producers have an incentive to faithfully implement the mechanism assuming that the probability of block production – and thus the utility offered to users for transaction inclusion – is held constant. In this section we take the same approach to prove the impossibility results of earlier papers do not apply to RTR-TFM.

**User Incentive Compatibility.** As mentioned above, Myerson's Lemma [?] provides a condition under which any mechanism (like an auction) ensures users bid the maximum amount they are willing to pay irrespective of what every other user does. According to the lemma, the allocation rule must be monotone in the user bids, given other bids are constant. Further, it must follow the proposed payment characterization. E.g., it is well known that the generalized second-price auction (or VCG) is a special case of Myseron's Lemma and thus incentive compatible for users. The TFM literature considers the single-demand, homogeneous setting, i.e., each user has a requirement of at most one item, and all the available items are copies of a single item. The VCG auction allocates to the highest k users and charges them the  $(k+1)^{th}$  bid.

In RTR-TFM, the block producers must consider both the bids and the routing work corresponding to each transaction. Due to the additional requirement of the routing work threshold, producers may not follow the standard VCG allocation. That is, the highest k bids may not clear the routing work threshold if they have propagated deeply into the network and their transactions provide less "routing work" for the production of a block. Therefore, in order to demonstrate that Myerson's Lemma holds we must first show that the proposed allocation rule is monotonic.

LEMMA 5.1. For any user  $i \in \mathcal{U}$ , RTR-TFM allocation rule x is monotone with respect to their bid (transaction fees), given the remaining bids  $\mathcal{U} \setminus \{i\}$  do not change.

PROOF. A strategic producer selects transactions that clear the routing work threshold and satisfy the block capacity constraint, captured by  $\mathsf{OPT}_{\mathsf{RTR}}$ 's feasibility constraints. Note that, the routing work of any transaction is independent of the user's bids. Let  $\mathcal S$  be the set of the subset of feasible transactions. The producer selects the subset that maximizes the minimum bid (objective of  $\mathsf{OPT}_{\mathsf{RTR}}$ ). If a user's transaction belongs to any feasible subset, increasing the bid will have the following effect.

If the said bid is the minimum in S, increasing it will increase the chance of confirmation. It will not affect the chance of confirmation if it is not the minimum in S. Changing the bid does not have any effect if the transaction does not belong to any feasible subset (due to the constraints in  $\mathsf{OPT}_{\mathsf{RTR}}$ ). Hence, the allocation is non-decreasing with increasing bid.

We note that RTR-TFM has a monotonic allocation rule, it does not entirely satisfy Myerson Lemma's [?] payment characterization in the absence of a price-setting transaction. As we have yet to establish that it is costly for producers to include their own price-setting transactions in the block. Therefore, similar to ?], we suggest using the minimum bid in  $S^*$  as the price-setting bid. Theorem 5.2 shows that this payment rule ensures almost URC. That is, when there are sufficient transactions and the difference between transaction pairs is small, the incentive from deviating is negligible.

THEOREM 5.2. RTR-TFM is incentive compatible for users

PROOF. We prove UIC through a case-by-case analysis.

Let  $S^*$  be the block producer's optimal subset of transactions based on the bids, computed via OPT<sub>RTR</sub>. The utility to the user is the value of inclusion in the blockchain at the level of security generated by the user if they bid their true value.

Let  $B = \min_{(f,h) \in S^*} f$  be the minimum accepted transaction.

- Case 1.  $\theta_i < B$  for any user i, if  $b_i = \theta_i$  the user does not get selected in  $S^{\star}$  and gets zero utility. If the user under-bids, i.e.,  $b_i < \theta_i$  the utility remains zero. Upon overbidding, i.e.,  $b_i > \theta_i$ , the user might get selected, but the user's utility will be  $\theta_i B < 0$ . For Case 1, bidding true value maximizes the utility.
- Case 2.  $\theta_i > B$ , if  $b_i = \theta_i$  and  $b_i \in S^*$ , i.e., the user is truthful and other constraints (independent of bid) ensures the selection of i and utility of  $\theta_i B$ . As long as the bid value  $b_i > B$ , the user might get a utility  $\theta_i B$ . If the bid  $b_i < B$ , the utility will be zero. Hence, the maximum utility is obtained at truthful bidding. In the other scenario where  $b_i = \theta_i$  and  $b_i \notin S^*$ , i.e., the user does not get included due to other constraints, the user's utility is zero. Changing the bid does not impact its inclusion; thus, the utility remains zero.
- Case 3.  $\theta_i = B$ , in this case, the user can deviate by bidding the lowest value needed to qualify for  $S^*$ . Since this deviation explicitly lowers fee-throughput relative to the optimal level at which user utility is assumed,  $\tau$  is lowered by consensus and the amount of utility received by the user is also lowered. As per our starting assumptions, this is a suboptimal outcome as

the reduction of the fee is not costless in terms of the utility purchased.

This proves the theorem.

**Producer Incentive Compatibility**. The standard way in which MIC is examined is to demonstrate that block producers with a temporary monopoly over block production have incentives to manipulate fee-levels. In this section we show the same assumptions lead to different results in RTR-TFM. To do this, we first show that RTR-TFM incentivizes producers to propagate transactions without engaging in malicious routing strategies: either the hoarding of transactions or the addition of fake identities on the routing network. We then show that the inclusion of fake transactions is irrational.

LEMMA 5.3. In RTR-TFM, routing is a Dominant Strategy over hoarding transactions for any block producer  $i \in \mathcal{P}$ .

PROOF. Consider four block producers, say  $A_1$ ,  $A_2$ ,  $B_1$ ,  $B_2$ , such that  $A_1$  and  $A_2$  are connected (i.e., messages from  $A_1$  reach  $A_2$  in single hop). Also, consider  $B_1$  and  $B_2$  as connected. We assume  $A_1$  and  $B_1$  receive the same transaction as first hop nodes. Now, we examine 2 cases: (1) when  $B_1$  hoards transactions, and (2) when  $B_1$  routes transactions. We show that, in either case,  $A_1$  receives a higher utility on routing than hoarding.

For the proof, we quantify  $u(A_1 \text{ routes}|B_1 \text{ hoards})$  as the utility  $A_1$  receives from routing the transaction in the event  $B_1$  decides to hoard it. Further,  $u(A_1 \text{ hoards}|B_1 \text{ hoards})$  denotes the utility for  $A_1$  when both choose to hoard. Likewise,  $u(A_1 \text{ hoards}|B_1 \text{ routes})$  and  $u(A_1 \text{ routes}|B_1 \text{ routes})$  correspond to utilities for  $A_1$  when  $B_1$  decides to route to  $B_2$ .

**Case 1:**  $B_1$  **hoards the transaction.** If  $A_1$  hoards then the probability of  $A_1$  and  $A_2$  producing the block is  $\Pr(A_1) = \Pr(A_2) = \frac{1}{2}$ , that is, both are equally likely. Let p be the payment received, implying  $A_1$ 's utility is  $u(A_1 \text{ hoards}) = \frac{1}{2} \cdot p$ . When  $A_1$  propagates instead of hoarding and given  $\Pr(A_1) = \Pr(A_2) = \Pr(B_1) = \frac{1}{3}$ , i.e., all the three nodes involved are equally likely to produce a block,  $u(A_1 \text{ routes}) = \Pr(A_1) \cdot p + \Pr(A_2) \cdot \frac{2}{3} \cdot p = \frac{5}{9} \cdot p$ . Thus  $u(A_1 \text{ routes}|B_1 \text{ hoards}) > u(A_1 \text{ hoards}|B_1 \text{ hoards})$ .

**Case 2:**  $B_1$  **routes the transaction to**  $B_2$ . If  $A_1$  hoards then  $u(A_1 \text{ hoards}) = \frac{1}{3} \cdot p$  where  $\Pr(A_1) = \frac{1}{3}$ . If  $A_1$  decides to route to  $A_2$ , and given that all the four nodes involved are equally likely to produce the block, we get  $u(A_1 \text{ routes}) = \Pr(A_1) \cdot p + \Pr(A_2) \cdot \frac{2}{3} \cdot p = \frac{1}{4} \cdot p + \frac{1}{4} \cdot \frac{2}{3} \cdot p = \frac{5}{4} \cdot \frac{1}{3} \cdot p$ . Thus,  $u(A_1 \text{ routes}|B_1 \text{ routes}) > u(A_1 \text{ hoards}|B_1 \text{ routes})$ .

While we can observe that forwarding transactions does modify the probability of producers proposing a block, probability analysis shows that forward-propagation is still statistically dominant. As with our section on UIC, what is really happening is that the impossibility results created by the assumption of "temporary monopoly" are overcome by the use of a work function that explicitly links fee-levels to the pace of block production and the collective security levels provided by the chain.

Similar logic shows that fake transactions (producer-initiated fees) are also disincentivized under temporary-monopoly assumptions.

# **Fake Transactions**

We consider the case of a block producer who is able to produce a block that solves OPTRTRusing at least a subset of the transactions in their mempool. The question is whether this block producer is advantaged by the manipulation of the set transactions in their block. We prove on a case-by-case basis that they are not by showing that there is only one situation in which fee-manipulation can be profitable and then showing that this situation is incentive compatible with pareto optimality:

THEOREM 5.4. Accellerating the burn fee is the only non-losing strategy for producers

PROOF. Let  $S^*$  be the block producer's optimal subset of transactions based on the bids, computed via OPTRTR. The utility to the producer is at most the value of half of the fees in the block minus at minimum the value of the half the fees in the block that originate from the block producer.

Let  $B = \min_{(f,h) \in S^*} f$  be the minimum accepted transaction.

- Case 1. If the block producer eliminates Bitnolongerhasadequaterouting to produce about the sold producer eliminates Bitnolongerhasadequaterouting to produce about the block producer eliminates Bitnolongerhasadequaterouting to be about the block producer eliminates Bitnolongerhasadequaterouting the Bitnolongerhasadequaterouting the Bitnolongerhasadequaterouting t Case 2. If the block producer replaces Bwithanidenticaltransaction, its production is production in the block production is produced by the block producer replaces and its production is produced by the block producer replaces and its production is produced by the block producer replaces and its production is produced by the block producer replaces are the block producer replaces and the block producer replaces are the block producer replaces
- replacementstrategy.

The situation that must be analyzed is the third case. But note a fundamental difference between RTR-TFMand other TFMs. In this case, by attempting to increase the fees they are able to collect, the block producer is forcing up the burn-fee and pushing the network into a higher-throughput equilibrium that is more secure and more costly to re-organize. The decision to speed-up the blockchain is also tantamount to an increase in the overall supply of blockspace. Supply is expanding to fill an increase in demand.

Any strategy that accellerates the burn fee involves the block producer subsidizing security for the subset of users who have paid a levelsthatusershavealreadyindicatedisoptimal.

# Genuine Incentive Compatibility

We can move beyond "faithful implementation" and towards full incentive compatibility. To see this, observe that the decision to self-generate a transaction is rational if the block producer earns enough in profit to outweigh the costs they bear from the inclusion of their own fee-bearing transaction. Even in the hypothetical case where generating such a transaction is profitable, there is a cost to be paid in accepting a lower marginal profitability.

As such, the decision to self-generate is a strategic decision the rationality of which depends on private information available only to the block producer about their own cost structure. Producers who are efficient at gathering high-fee transactions may choose to self-generate if they fear competition from peers. This shift pushes the network towards a higher-throughput equilibrium in which larger losses must be borne to provide such attacks are no longer rational or possible.

We thus have a functioning market. Users desire transaction inclusion at the lowest rates possible, while competing in ways that drive fees up. Producers desire transaction inclusion at the highest rates possible, while competing in ways that drive down marginal profits. The network reaches equilibrium at the point where these two forces come into balance.

# **COMPATIBILITY WITH PARETO OPTIMALITY**

In the body of this paper, we demonstrated previous impossibility results simply universalize the limitations of direct mechanisms (auctions) and their implicit choice of social choice rule. We then introduced an indirect mechanism which is not subject to these limitations.

While the previous section shows the preceding impossibility results do not apply to RTR-TFM, it does not establish that the mechanism is incentive compatible with the social choice rule of pareto optimality. To do that, we must return to economics and discuss how the RTR-TFMovercomes the foundational informational impediments to implementing pareto optimality: Samuelson's objection based on the existence of public goods, and Hurwicz's

Samuelson and Free-Riding • Case 3. If the block producer replaces Bwithaself—generated transaction that pays a higher for all transactions in the block will pay a higher for This is the only produced by the block producer replaces Bwithaself—generated transaction that pays a higher for a little pays a higher for This is the only produced by the block producer replaces Bwithaself—generated transaction that pays a higher for This is the only produced by the block producer replaces Bwithaself—generated transaction that pays a higher for This is the only produced by the block producer replaces Bwithaself—generated transaction that pays a higher for This is the only produced by the block producer replaces Bwithaself—generated transaction that pays a higher for This is the only produced by the block produced by the block produced by the block produced by the block pays a higher for This is the only produced by the block produced by the block produced by the block produced by the block pays a higher for This is the block produced by the block produce generatedtransactionthathasthepotentialtobeprofitable. It will require alar genumber of users keen for fastering lusion and will ling to of fersignificantly high all which describes all points at which

> economic production is pareto optimali. His observation was that achieving this equation and thus pareto optimality is problematic in the presence of

#### **CONCLUSION & FUTURE WORK**

In the body of this paper, we demonstrated that the impossibility results of previous papers do not apply. We showed that results are a product of the decision to model blockchains as direct mechanisms (auctions) in which both parties are faced with strategic choices but only one party is required to truthfully reveal their preferences to the mechanism. We also showed that the informational require-

higher fee than Bandwhohavesignalledapre ference for fasterinclusionat along the fee than Bandwhohavesignalledapre ference for fasterinclusionation for fasterinclusionation for the fee than Bandwhohavesignalledapre ference for fasterinclusionation for fasterinclusion for fasterinclusionation for fasterinclusion fasterinclusionation faster levelsthatrequiresbothtomoveinunion. I fwetakethenarrowde finition of McMcanfloith fulimplementation of themechanism the nour producers are by definiti

While the previous section establishes the preceding impossibility results do not apply to RTR-TFM, it does not establish that the mechanism is incentive compatible with the social choice rule of pareto optimality. To do that, we must return to economics and discuss how the RTR-TFMovercomes the two informational impediments to implementing pareto optimality: Samuelson's objection based on the existence of public goods, and Hurwicz's objection about the need for a pre-exchange negotiation step that can be strategically manipulated by participants.

# Samuelson and Free-Riding

Samuelson's objection is based on the .

We observe that transaction inclusion is neither a private good as conceptualized by Roughgarden or a public good as conceptualized by Fox. The fee paid for blockspace is privately-collected and can be privately-negotiated, but induces a public good to the extent that its existence induces competition between producers for the right to use the blockchain to collect the fee. Open competition reduces the marginal profitability of any transaction by inducing producers to provide

In atomistic markets there are no public goods. Atomistic markets

This is why off-chain payments, transaction hoarding,

This is why off-chain payments that restrict competition . But it is also why transaction hoarding accomplishes the same result.

In lieu of a direct we can offer a much simplier proof that RTR-TFMis in fact pareto optimal, which is to note its compatibility with the "greed process" . Both users and producers are

As outlined in our discussion of economics,

The

As can be seen, RTR-TFMis an "indirect mechanism" in which Users can be

The history of the

In order to do this, we can simply observe compatibility between the routing work mechanism and

Competition between users pushes them in

In this paper, we introduced RTR-TFM: a novel TFM that addresses the incentive misalignment in classic transaction fee mechanisms (TFMs) by introducing a novel routing-based block production rule and a revenue scheme. RTR-TFM rewards block producers in proportion to their contribution to the propagation of transactions. Such a reward ensures that block producers actively participate in the blockchain network upkeep instead of free-riding on other participating nodes. We also provide a game-theoretic characterization of the underlying game in RTR-TFM. We prove that RTR-TFM effectively discourages transaction hoarding, ensures Sybil resistance, and achieves incentive compatibility for both users and block producers under reasonable assumptions.

**Future Work.** With RTR-TFM, we introduce a TFM revenue rule that links a direct cost to the block producers to create fake transactions. However, our BPIC analysis assumes a bootstrapped blockchain (Assumption 1). While Assumption 1 is practical, we can look towards BPIC guarantees without constraints on the blockchain state. Furthermore, the TFM literature also looks at off-chain collusion between users and producers. [?] show the impossibility of a deterministic TFM simultaneously satisfying the UIC, the BPIC, and the resistance to off-chain collusion between a user and a producer. Future work can also study off-chain collusion guarantees for RTR-TFM.