Price Discovery Auctions*

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General Bonaparte at the Conseil des Cinq-Cents by Bouchot

1 Summary

This paper presents a model for price discovery in the context of initial pricing auctions. The goal of an initial pricing auction is to find the fair-market price without any initial context and under some amount of information asymmetry. The goal of an initial pricing auction is to sell a fixed lot of assets in exchange for the highest price.

First, we walk through an initial model for this auction, show some key extensions to the model to help reflect a more realistic situation, and then discuss implications of the model itself as it relates to designing such auctions.

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2 Introduction

A price discovery auction is an auction designed to aggregate pricing information from many disparate parties. These parties are inherently adversarial and competing for a fixed set of resources. The key problem is that the auction is under extreme information asymmetry, where some participants have more information than others (even potentially the auctioneer). There is a breadth of research examining how under information asymmetry, the auction may have unexpected results [6]. For example, traders under extreme information asymmetry may not trade despite a profitable trade, as it comes at the cost of revealing their information. Implementation details such as these lead to more inefficient pricing in markets due to value loss from resolving underlying contention. The purpose of the auction is to find the accurate price of the assets at the end with as little loss as possible.

We show that the effective price of the asset is a random variable, partially determined by the underlying market structure, meaning that changes in market structure can directly impact the resulting price. This is because there exist multiple auction equilibriums (and thus multiple valid states) in the market. The key is to notice that some of these equilibriums are unstable, and thus collapse when pressured or targeted adversarially, while others are stable. We will extend the model to be two-stages to show how basic models crack under adversarial pressure.

In this extended model, counterintuitively, the best long-term stable price is relatively higher on net **while still remaining below the theoretical value**. In other words, a more stable solution emerges out of pricing an asset slightly higher in offerings markets. Expected underpricing is captured by adversarial parties, which we refer to as resellers, before the long-term believers are able to execute on their beliefs. This means that the underpricing effectively becomes a trap for the believers inadvertently set by the auctioneer. However, a higher price allows more of the value to flow to the auctioneer (and thus the underlying asset creator). This results in a higher price for believers, as they will be holding the asset until expiration. Additionally, the higher price ideally results in a higher composition of believers, which in turn creates a more stable equilibrium than lower priced auctions.

Overall, we argue that users buy because they believe there is underpricing in these auctions. However, by the time they are realistically able to execute, the underpricing is already gone. It was already captured by the resellers. This leads to the initially found price equilibrium collapsing as the resellers exit the position.

This collapse leads to value destruction for both the asset sellers and the believers. The underlying value leaves the system and is captured by the "resellers". By charging a higher price - but still below the theoretical equilibrium, it is more likely that believers end up holding the asset, as their heterogeneity ends up being a benefit. Charging a higher price is also valuable to the project selling the assets, which is in turn beneficial to the believers. Additionally, there is less value growth for capture by the adversarial parties, meaning that they will slowly exit or size down in an iterative game.

This model helps explain some of the price action around initial pricing events, such as initial public offerings and loan syndications. These markets are generally utilized in large-scale capital raises traditionally associated with offerings markets, but could be utilized in many more contexts if the fixed costs for running an auction were cheaper. Additionally, it helps ground some mechanism design questions around initial pricing auctions. By examining how changes in the model affect the price path and equilibrium, auction designers can more effectively design incentive aligned systems.

3 Model Introduction

As previously stated, price discovery auctions are often used when there is information asymmetry - such as during an IPO. In this model, all buyers of the asset (underwriters are the typical buyers in offerings markets) are attempting to purchase it for as little as they can in order to make as much money as possible. At the end of the sale, buyers receive a payoff in the form of a dividend. In reality, this could reflect the price of the asset in the future.

Buyers have varied beliefs over the future value of this asset. These beliefs are also forecasts, so they are not guaranteed to be right (they are both biased and noisy). The distribution of these beliefs is ultimately incredibly impactful, as the process of reconciling these beliefs is what the auction is doing.

The intention behind this auction is to find the ”correct” value for the assets placed into it - generally referred to as the ”market-clearing price”. There is additionally a side goal of achieving as many proceeds as possible. It is very important to notice that static supply curves implies these two goals are one in the same, as the curve are path-independent

For convenience, these assets must be infinitely divisible and fungible. In practice, this means assets like stocks, Arrow-Debreau securities, and tokens, but does not apply to something like a single car.

Asset sellers who wish to have their assets priced provide the auctioneer with a “lot” of tokens. We assume the auctioneer is credible and solely wants to make as much money for asset sellers as possible [2]. The seller wishes to sell this lot of tokens for as much as possible while also finding a stable equilibrium at the end of the auction. As previously stated, buyers have some forecast of the value of the token and will buy the asset if they believe they will make money at the end of the period (including any costs for holding the asset).

Buyers have some amount of *numeraire* asset, which is the asset that the auction will be denominated in. Buyers have a limited amount of this asset and demand all the assets until the marginal cost of the next asset is higher than their price limit. These amounts and price limits are generated from a prior distribution.

We are going to start with the most simple possible auction and walk our way out farther by relaxing assumptions. This means that some of the arguments previously presented may not be reflected until later on. For our first model, the buyers approach in a random order, buy what they can, and then move on. In the initial model, we assume that the bag will always be filled by the first round of users and there are no further rounds. This forces buyers to be roughly myopic. There is no long-term strategy possible, because you either get the payoff now or never.

In these auctions, the auctioneer is able to choose the price, and is able to do so dynamically and with public information. We will first walk through a model that assumes the seller has perfect information even on the private beliefs of the buyers, and then slowly add restrictions that help reflect reality. In this model, there is no information asymmetry. This will help give an upper bound limit and try to minimize it slowly with additional restrictions.

To look at the performance and the impact of various trading strategies, we will randomly order the auction and check how the auctioneer fares (how much in proceeds is made). Additionally, we calculate the best and worst possible of these random orderings using a greedy knapsack algorithm. This may not be perfectly optimal, but is quick to calculate and generally close to the upper theoretical bound. This approach was heavily influenced by Milgrom (2017) [5]. Next, we look at how the price is impacted when the seller must choose a fixed price ahead of time. This will help us establish a type of implementation loss in the model. Finally, we will establish a price discovery auction in terms of adversarial actors and how it behaves.

4 The World's Greatest Auctioneer

First, we generate a random number of buyers who have predetermined amounts and prices. These are generated from a normal distribution, $N(\mu, \sigma^2)$, but the impact of changing this distribution is saved for future work.

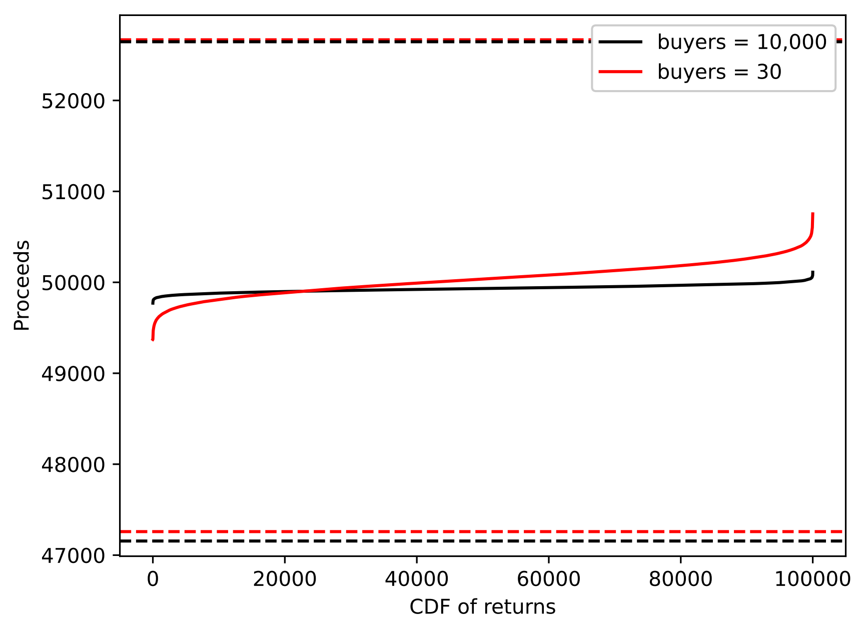
Next, we will generate a large number of random orderings for the buyers in which the buyers will approach in. When a buyer approaches, they will either purchase some assets at the provided price or leave. They do not re-enter the auction. This simplification means that buyers are myopic; they must hold now or never.

The auctioneer wishes to maximize the amount of profits that it is able to capture from the auction at its conclusion, but it also wants to recover a stable equilibrium for the price

Selling a lot of assets to some ordering of buyers can be well modeled via a greedy knapsack algorithm [5], which we will utilize to calculate the bounds on the possible orderings. The knapsack simplifies the problem slightly, but gives us a high-quality estimate.

Next, an ordering is scored by buyers executing their trades at their best possible price. Buyers will purchase as much of the asset as possible with their funds. Once there are no more outstanding assets, the scoring stops and the amount of proceeds are checked. Users cannot sell. They must realize the expected price based on their respective price estimates.

Figure 1: Returns Distribution by Number of Buyers



The dashed bars show the calculated worst and best possible proceeds for generated buyer set

Figure 1 shows the impact on the number of unique buyers on the proceeds generated in the auction. Based on the calculated orderings, the worst and best possible outcomes are also calculated and shown in the dashed bars. The lines inside these bars reflect a rough cumulative distribution function of orderings.

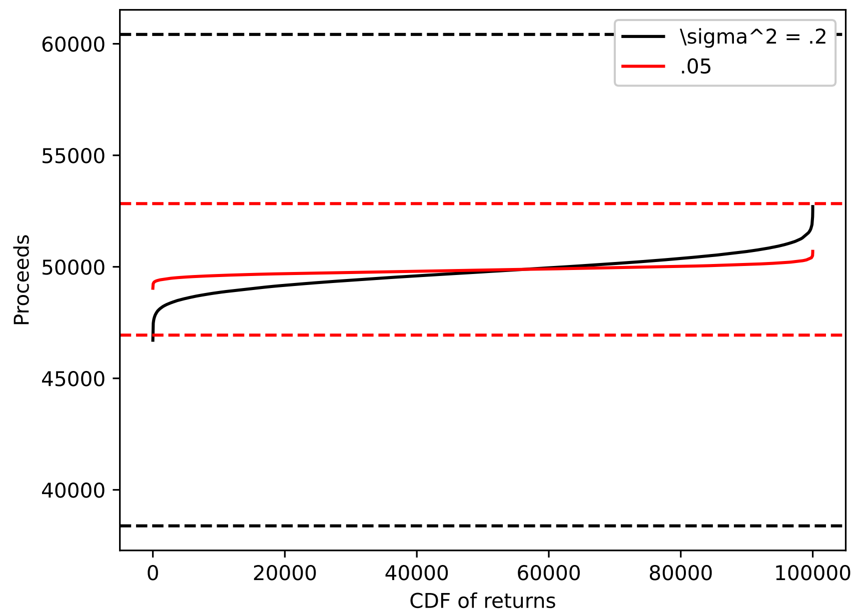
First, notice how the median of the curve is around the current ”theoretical value” for both curves. However, the best and worst case scenarios have only marginally moved, despite the “mass” of the CDF of returns collapsing inward towards the median (and the theoretical best price). We highlight this to show that the worst and best options are more a function of the prior distribution of buyers and less about the number of buyers. This shows that averages can mislead - especially under adversarial conditions. While 30 to 10,000 is enough to collapse the mass of the CDF towards the median, 30 buyers is enough for the extreme orderings to be roughly possible to sample.

Orderings are random, but a real auction only executes once. To simulate this, we need to focus on one ordering for sample statistics. For model selection, we will focus on the median ordering, as it is relatively consistent and is purely a function of the expected value of the asset. From the median ordering, we can calculate a difference in proceeds to calculate the additional revenue from the “skill” of the auctioneer choosing orderings, which is around 4.2% in this basic model with chosen parameters. Comparing the worst model to the best model is around -4.2%, indicating that if the buyers have control over ordering, they could extract 4.2% extra value compared to the median sale.

Notice how there is almost an 8% difference in the skill of the auctioneer in this toy model. We highlight this to show that auction results themselves are random variables and can viably shift in their expected price. We also want to show how results themselves show how dynamics in the sale can impact the price results of the auction itself.

While this may seem like a toy model, we have previously shown that adversarial actors on blockchains are able to extract value (generally referred to as maximal extractable value or MEV) using their monopoly over ordering (which is given to them by the validators) [1]. Thus a model that reflects reality should assume that adversarial actors will always choose the worst possible outcome if given the ability. This is a key assumption of the model as it assumes they want to extract as much value as possible because they are adversarial.

Figure 2: Impact of Heterogeneity on the Distribution of Returns



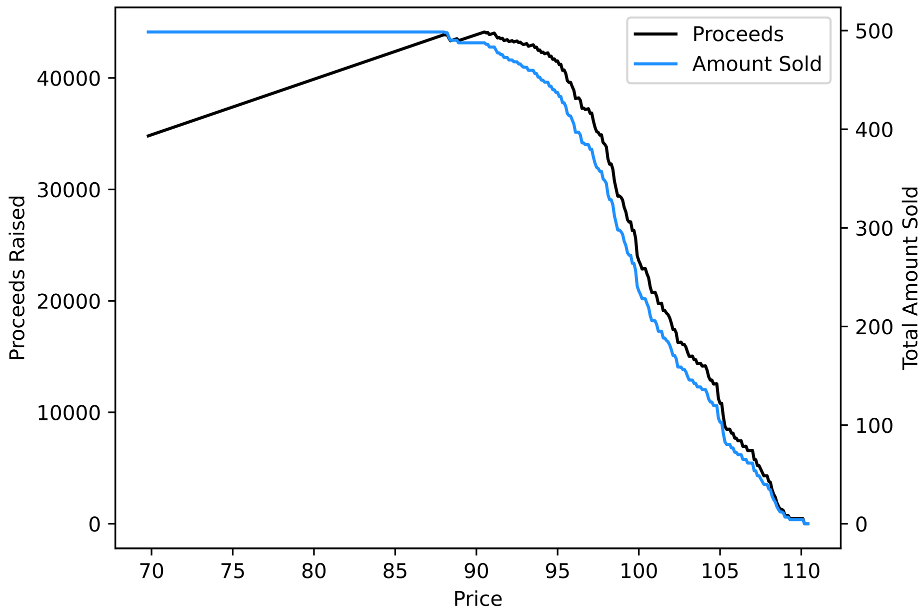
The dashed bars show the calculated worst and best possible proceeds for each set

In the above figure, we show the impact of varying beliefs on the distribution of auction returns. For context, the model generates random prices for buyers to create noise and to simulate heterogeneity in beliefs. This model is rather simplistic $N(\mu, \sigma^2)$. By increasing the σ^2, the resulting distribution of auction results is also increased, resulting in a larger difference between the best and worst possible auction outcomes. In the model where the σ^2 is 4x higher, the resulting best and order possible auctions are now around 40% spread instead of a 8% spread. This is mainly to highlight that the distribution of beliefs (also known as heterogeneity) can itself impact the results of the auction.

In this base model, the auctioneer has perfect information about the willing price of the buyer and charges that price. These users are effectively being forced to price the asset at their highest possible price, which is very unrealistic. Sellers rarely have perfect information about their buyers and being charged your theoretical realized value would lead to an extreme amount of winner's curse for the buyers.

Instead, what if the seller must place their bid first? Instead of executing the sale on the internal bid of the buyers, the seller is forced to quote a price and the buyers respond by purchasing the asset if they want. Buyers still buy up to their amount and price limit (as they will not be coming through the auction again). This functionally gives information asymmetry to the buyer, as the seller must pre-commit to their bids.

Figure 3: Fixed Price Sale vs. Proceeds Raised for Median Ordering



$$buyers = 500$$

Because the price of the auction is now fixed, the question becomes more one about the demand of the sale. This is because proceeds raised equals the amount of tokens sold times the fixed price, thus only proceeds raised is a direct mapping to the amount out. In other words $proceeds = price \cdot amtSold$. In effect, this creates a simulated aggregate demand curve.

In the above model, the fair market value of this asset is pegged to \$100, but the sale price with the highest proceeds is far less, around \$91. There hits a point where less proceeds are raised, as the simulated demand curve for the buyers falls off. This is due to the amount that the auction is "oversold". In the model, there are more buyers than available space in the knapsack. However, depending on the price of the auction, these buyers may not want to participate. Additionally, because the auction price is fixed, the more optimistic buyers still clear at a lower rate, which should lead to a better outcome from them. While the auction is oversold by 3x in the above model, the auction still must clear lower than the "expected" value. With a higher percent oversold, there is less of a requirement for this underpricing. Additionally, added potential assumptions like carrying costs and risk premium could force the optimal sale to clear below the current fundamental price.

This is one of the many reasons underlying the desirable IPO pop, where desirable IPOs have a price increase their first day of trading. A very rational explanation for the underpricing is that there needs to be some non-negative carrying cost for asset buyers to park their capital into the sale. We are not arguing against the pop - the fundamental problem of the pop is who captures the proceeds from the pop and the other incentive failures that it can cause. Starting the price too high has other downsides. It may result in a higher winner's curse in these markets and it could increase the number of market failures.

However, we argue that socializing the winner's curse could result in better outcomes, as it is possible that informational asymmetries could be better priced and lead to a more accurate market pricing (similar to a prediction market). Additionally, the excess value accrues directly to the company as their resulting pricing event is higher. This could additionally be seen as a benefit for those who have belief in the asset, but does create potentially perverse incentives.

These two arguments are meant to highlight how a simple model for price discovery will result in auctions that underprice the expected value of the token, and this actually might be preferable. This slight underpricing is beneficial because carrying costs, oversubscription, and adversarial behavior to "optimal price discovery" are likely to cause the auction to clear lower than a theoretical best. An auction that is priced too high also brings its own issues, because not enough tokens (or none with perfect information) will be sold, which could result in a market failure.

However, underpricing repeatedly has a key issue - it incentivizes rushing into the market on every asset. The obvious next question to ask is "what is the negative cost of pricing an auction too low?" and additionally how can you minimize the cost?

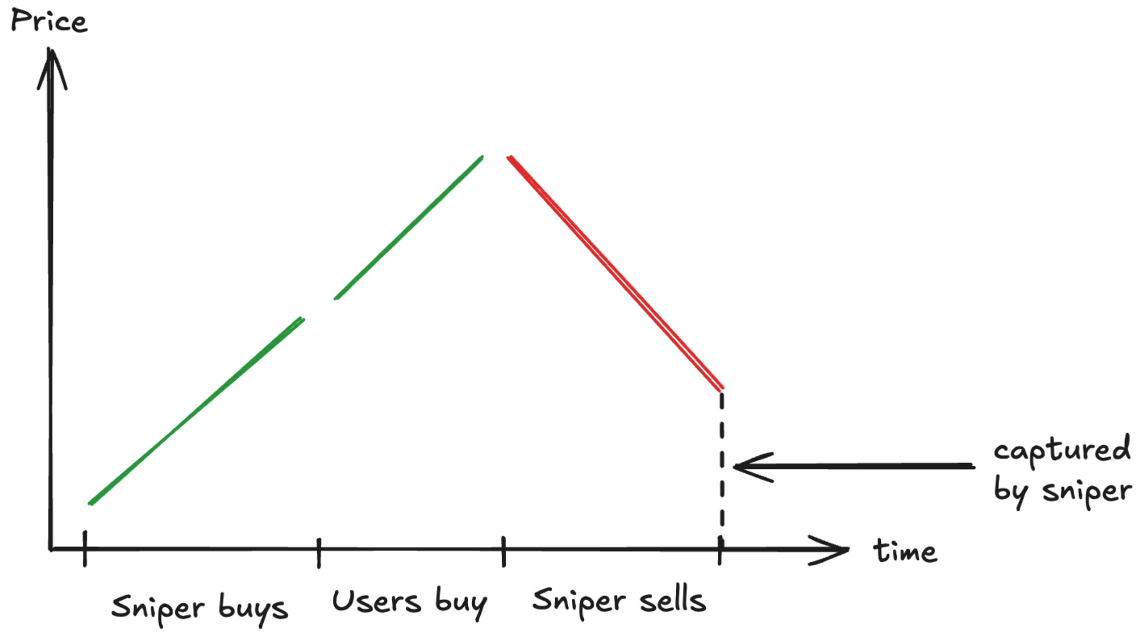
5 The Price is Wrong

In a non-iterative game, starting the price lower seemingly has few drawbacks. However, when iterated, substantial drawbacks emerge. We have previously shown that a proceeds-maximizing auction likely needs to start lower than the fair market price in order to generate enough demand to absorb the entirety of the sale. However, in an iterative game, users become accustomed to the underpricing and respond by buying as soon as possible at any given price - making them inelastic buyers.

Inelastic buyers bring one main problem in which a malicious party is able to front-run their purchase and extract value. A malicious user is able to buy and wait to resell to users purchasing after them. The mental model should be similar to sandwiching in blockchain-based markets [4]. In the case of a normal sandwich on a swap, the sandwiched user broadcasts their transaction and publicly declares their price elasticity in the form of the minimum amount out. The malicious user is able to push the market price right up to the victim's elasticity, wait for the trade to come in, and then reset the price to its "true value". This captures excess premium from the swap by making it execute at a worse price than without the malicious user.

In recent years, we have seen probabilistic sandwiching even merge. In price discovery auctions, this results in probabilistic flow-based sandwiching where the entry of the sandwich and exit may differ by multiple periods and at different prices. Empirically, this has been seen on Solana, but likely occurs on all chains.

Figure 4: Sniping is sandwiching



Note, the exact value captured by the sniper may vary based on the curvature and fees of the supply curve

To model the effect of these two parties, we will utilize an asset pricing model from Scheinkman and Xiong (2003) [7]. In their model, there are two types of market participants. One participant who wants to capture the potential resale value to a future customer (we refer to them as "reseller") and another participant who wants to hold the asset as part of their portfolio ("believer"). In their paper, Scheinkman and Xiong find that this model can help explain bubble-like behavior as a result of the heterogeneity in beliefs.

Using this model, we can evolve our game into another step. Both users will enter in the auction as previously done, but the "resellers" will collectively sell at the end of the first period. Afterwards, believers will re-enter the market until all the tokens are sold. Since the believers will hold the assets until market resolution, this results in a stable equilibrium. In reality, resellers would re-enter the market with believers and redo the process continuously until a stable equilibrium is reached or the market fails.

This means resellers cause the market to come to an unstable solution, which decays back into a stable solution. This decay comes at the expense of the believer group and minimal benefits (volume-based fees) back to the auctioneer. In the long-run, we argue that these fees do not make up for the future value lost from the inefficiency - a mental model similar to Akerlof's Market for Lemons (1970) [3].

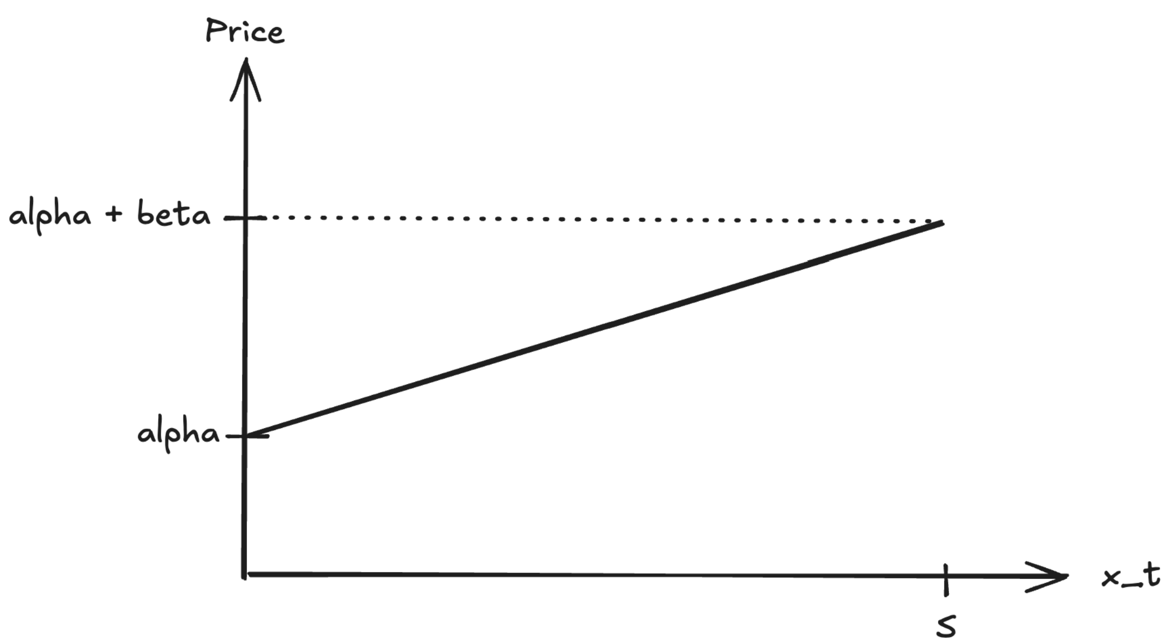
In this new model, the auctioneer still wants to maximize the proceeds raised at the end of the sale. However, we will track the amount of value lost from the group of believers. We will argue that value lost from believers is a metric that the auctioneer should track, but designing a theoretical model for this argument is out of the scope of this piece.

One consequence of this model is that fixed price auctions no longer are viable. Resellers enter the market if they believe there is positive resale value. $q(x) >= q(-x) + c$ where c is the cost of executing the trade and q(-x) is price risk. The resale option is path-dependent, but notice how the path of the asset directly emerges as a result of the design of the auction.

In a fixed price auction, the reseller takes on no price risk ‘q(-x) = 0‘ and thus is only charged with the trading costs (which are generally negligible and fixed). Because of this, they will always buy the auction and wait to resell it to believers later (if there is price evolution). If not, they lost a fixed amount of value from the cost of trading. We expand on this effect in a previous piece. One assumption of the model is that the price must eventually converge to its true value. If the true value is above the initialization price of the fixed price auction, then the initial sale will mainly be of resellers, because there is no price risk.

Instead of fixing the price, we can float the peg programmatically based on demand. We can construct a curve with a linear price increase with the formula $p(t) = \alpha + \beta \cdot \frac{x_t}{S}$ where α is initialized price at the start of the auction, $\alpha + \beta$ is the final price once all assets are sold, and x_t is the net amount of tokens sold.

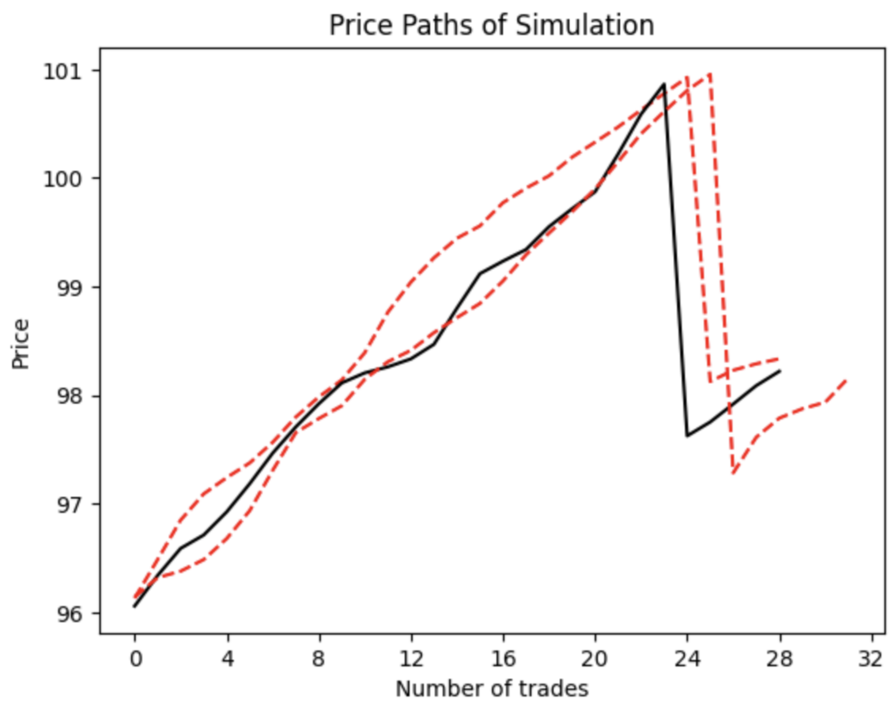
Figure 5: Sample Supply Curve



Just like in the previous section, we will now simulate orderings with the above methodology and check how key statistics change over time. The same buyers are now given one of two roles to play - either the reseller or the believers. At the end of the auction, the reseller will sell the assets into the pool to realize their profit. However, if the reseller had some type of statistical price forecasting relationship, then they could execute at that value instead. Notice that this is functionally a form of alpha. We argue that this impact to the price path likely would only add noise (or further accelerate the decline due to autocorrelation). This also could be seen as similar to migration conditions (especially when impacting liquidity curvature) in some modern issuance protocols.

Believers will still re-enter the market afterwards, as they still desire the payoff at the end of the auction. Their price assumptions are not impacted and they continue to buy at their predetermined price and rate. This will impact the shape of the price path on the upswing when believers begin to buy again.

Figure 6: Medianized Price Path in Simulations



The red error bars represent the 5th and 95th percentile of orderings by amount sold at the end of the auction

Notice that fundamentally, this model creates a price path that has a jump diffusion as the resellers exit their position on the bonding curve. The ordering of the paths is based on the amount of value captured by resellers. More value captured by resellers leads to lower prices - less value captured by resellers leads directly to higher prices.

This is why counterintuitively a higher price is actually better for believers. Resellers move first, meaning they will always capture the perceived underpricing that induces believers to enter the market. In reality, believers have higher price expectations for the asset, thus a slightly higher price for them is a small price to pay for a stable equilibrium.

Extending this model further requires a model for price forecasting by the resellers. We imagine that the model likely looks autocorrelated and flow-based. Resellers ideally want to wait as long as possible to capture as much possible value as believers pour in. In this model, the resellers sell as a block and divvy up the profits. In reality, the resellers as a whole are playing an iterative coordination game within their own group. Once the first one sells, it may induce other resellers to sell. This effectively pops the bubble, but leads to no further profit. Resellers want to wait as long as possible, but are consistently playing a form of prisoner's dilemma, where it is better to be the first out the door when selling.

Additionally, price forecasting for resellers and believers will enable the initial bubble to grow larger or smaller based on the prior distribution of believers. Currently the resellers all sell at the end of the first auction based on the fixed amount of assets being sold. In reality, this market continues trading past this step and there is no requirement for resellers to sell. With more heterogeneity, believers can continually inflate the bubble far past the current equilibrium. As the price continues to go up, believers may actually increase their optimism on their position. This makes them both less likely to sell and "sidelined" believers may respond by buying at higher prices than their initial prior, further inflating the bubble.

As the price goes up, the most optimistic believers continue to pour in, until resellers are induced to sell. The most fervent believers (the best holders of assets) who are buying at the end are the largest losers, as they both are impacted by the winners curse, deflation of the bubble, and some amount of negative price forecast as the auction composition is revealed. It is more likely that past the fair market value of the asset that it is a believer buying, thus making them a higher portion of the harmed users from this phenomenon.

We argue that it is important to trigger the collapse of the initial price auction as soon as humanely possible. This is because it enables the market to collapse to a stable equilibrium, which is then "safe" for believers to buy at this new price. However, we argue that the inflation/deflation dynamic is likely iterative as well, so may require the auction design to continually induce collapses to keep the resellers away.

6 Discussion

This model helps establish a mental model for both auction participants and designers of such auctions. We will discuss several assumptions and implications as a direct result of this model to help elucidate potential inaccuracies. Additionally, we will highlight the takeaways from the model and what it says about initial pricing auction design.

6.1 Assumptions

There are several assumptions in the model itself that could be seen as problematic.

First, a common argument might be that the bonding curve assumption fundamentally induces the price collapse. We disagree - the bonding curve represents a simplified supply curve, but more complex supply curves still have this reseller issue. In this model, the supply curve's function is linear, but any monotonic supply curve will induce their behavior. In fact, we have seen a similar effect on non-bonding curve based trading platforms, as the designated market maker functionally mimics a supply curve.

In reality, the auctioneer itself only has a rough guess of what the accurate price of the market is and must update their beliefs to remain market making (especially if contractually or programmatically required). A dynamic supply curve (like one maintained by a traditional market maker) may help mitigate some of this loss by potentially increasing losses to resellers when exiting their position. However the bursty nature of the reseller phenomenon makes it hard to capture, as most of the value is lost atomically before the auctioneer can respond. Fundamentally, the auctioneer must update their prices in response to buying - this creates a price increase and thus the profit for the reseller.

Because there is heterogeneity in beliefs, it is difficult for the auctioneer to find a price function that does not have this impact. Fundamentally, this collapse is a function of heterogeneity in beliefs being extracted from users. Due to the design of the auction, the impact of the auctioneer's supply side curve is mainly reactive to updates by the demand side.

However, intelligent curve design can help mitigate some of the impact in the price path of the market. Indeed, Doppler Multicurve is one such curve designed to mitigate exogenous losses to believers. It does this by selling fewer shares earlier on and concentrating the amount of value around the end of the curve. This creates a smaller dip in price when resellers exit and also lowers the gains from resellers, as they are more likely to enter the market at a higher price (getting in later). As the game is probabilistic and likely long-tailed (few winners make up for a lot of losers), lowering the benefit to resellers combined with creating more games directly can impact the amount of resellers that are willing to enter the market.

Second, another assumption of the model is that users trade myopically - that is they trade if they think there is a profit to be made. We argue that this assumption is fair, because believers are unable to disentangle whether their beliefs were correct or if there is a trap being set for them by the resellers. This myopic trading induces the resellers to enter the market, which harms the believers.

Additionally, the ability to express your belief immediately without execution risk additionally makes it more likely that users execute myopically. We highlight that depending on the amount of believers entering the market, there could simply be enough buyers that the impact from the resellers is marginal. Thus, the user must execute myopically **even knowing that reselling will happen**, as their expected payoff is still higher than the price they are able to execute at currently. They may not be able to execute again later. Ideally, the market mechanism must respond and improve this game, as the reseller behavior creates a socialized loss.

6.2 Takeaways

The underlying model depicts price discovery auctions as miniature bubbles that are effectively popping when the resellers sell. However, we note that this game is perfectly rational and additionally, this model is well suited to explain price discovery in auctions like IPOs. The problem fundamentally is that the mechanisms are poorly designed to capture heterogeneity in beliefs.

Heterogeneity of beliefs is generally not something that is well-captured by the traditional underwriting auction in IPO markets - therefore skeuomorphic representations of IPOs pick up have the same problems. Early IPOs were incredible financial undertakings and required an immense amount of risk, capital, and belief. To reasonably execute these auctions, banks pooled money in a syndicate to spread out the risk. This syndicate enforces a strict homogeneity in beliefs (fixed price). We argue that increased IPOs are easier to bootstrap now because of the improvement in financial technology, levels of capital, and thus the need for the protective power of a syndicate is less important. Note that this reseller effect still happens due to the underpricing itself even in IPO markets. You can see a familiar pattern in some recent IPOs with a bit of eyeball econometrics.

One key takeaway is that current mechanisms need to add price risk to the market. Without price risk, the resellers have a free option. Removing this free option should allow more value to flow to both believers and the auctioneer. Notice how fewer resellers (or more specifically fewer value at risk from resellers) directly results in a higher price and more value flowing to the auctioneer. This is because for a fixed amount of funds, by lowering the share to the resellers, you increase the shares to the others.

Adding price risk is far from trivial as there exists few models for price discovery. Doppler-core attempts to do this by streaming assets into the pool and dynamically adjusting the price and curvature. When there are not enough new marginal buyers, the auction itself lowers the price at which it's willing to buy back. By being willing to trade against the traders as a group if the auction is behind schedule, it slowly adds price risk by locking users out of selling back at those higher prices. By lowering the effective price the auction is willing to pay, the auction path adds price risk as the payoff to resellers slowly goes down over time.

This model also shows how bubbles can actually destroy underlying value when utilized in context with the IPO process. It is possible for larger price collapses to leak so much value that the assets being sold are not enough to make up for it to the group of believers. If the "correct" amount of value is sold on the market, and the market achieves a lower price because of implementation details, then that could be seen as a market failure.

Assume all value flows back to the holders after payment to the auctioneer. Notice how the price at the end of some of the auctions is less than the maximum price at the end of the auction. With a lower price, the holders receive less of the value at the end (because they undersold the amount). Some of the value flowed out of the system to the resellers.

7 Conclusion

Price discovery auctions allow for assets to transition from private to public assets. By finding the correct price for as cheaply as possible (both fixed and variable costs), net-new markets emerge due to the ability to create viable markets for lower priced assets (as the fixed price of running a price discovery auction is lower). However, the coordination required to execute this auction and find the market price is far from trivial and results in some amount of value loss. By lowering the value lost, we directly enable more value to flow to the hands of those who both wish to buy and sell their assets.

Designing such auctions is complex, because the process leaks value, the implementation is complex, and is not fully solved. Creating an auction where the dominant strategy is to cooperate is an entire field of study. It has also been difficult for market designs to get enough control to impact the real implementation of some of the largest auctions (though it does happen). We hope that shedding more light on potential asset pricing models can lead to better design of these auctions.

References

Adams, Austin, Benjamin Y Chan, Sarit Markovich, and Xin Wan (2024). "Don't let MEV slip: the costs of swapping on the Uniswap protocol". In: *International Conference on Financial Cryptography and Data Security*. Springer, pp. 172–191.

Akbarpour, Mohammad and Shengwu Li (2020). "Credible auctions: A trilemma". In: *Econometrica* 88.2, pp. 425–467.

Akerlof, George A (1978). "The market for "lemons": Quality uncertainty and the market mechanism". In: *Uncertainty in economics*. Elsevier, pp. 235–251.

Daian, Philip, Steven Goldfeder, Tyler Kell, Yunqi Li, Xueyuan Zhao, Iddo Bentov, Lorenz Breidenbach, and Ari Juels (2019). "Flash boys 2.0: Frontrunning, transaction reordering, and consensus instability in decentralized exchanges". In: *arXiv preprint arXiv:1904.05234*.

Milgrom, Paul (2017). *Discovering prices: auction design in markets with complex constraints*. Columbia University Press.

Milgrom, Paul and Nancy Stokey (1982). “Information, trade and common knowledge”. In: *Journal of economic theory* 26.1, pp. 17–27.

Scheinkman, Jose A and Wei Xiong (2003). “Overconfidence and speculative bubbles”. In: *Journal of political Economy* 111.6, pp. 1183–1220.