Disentangling the information structure in the bankruptcy liquidation auctions

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Abstract

Understanding the information structure in bankruptcy liquidations is important for designing the optimal bankruptcy and financing market. In this paper, I construct a novel comprehensive bid-level bankruptcy liquidation auction data and structurally estimate the buyers' information structure using a state-of-the-art auction model. I show that there is a heterogeneity in the relevant importance of different information sources across different asset types, with tangible asset depending on the appraisal price, intangible assets depending on private synergies, and financial assets depending on bidder common knowledge not captured by appraisers. I text-analyze the appraisal reports using a natural language processing model and show how heterogeneous information production and bankruptcy liquidation frictions (quality management, relocation cost, and misallocation) contribute to the heterogeneity of information structure. A counterfactual simulation shows that the cost of misallocation is high (16.89%) for intangible assets compared to tangible assets (5.6%). Overall, my results suggest that tangible assets should be liquidated promptly to avoid maintenance failure, while intangible assets require a longer liquidation period to avoid misallocation costs, and financial assets should be financed by investors with expertise.

Keywords— Bankruptcy liquidation, auction, information structure, natural language processing

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1 Introduction

Asset liquidation is the major resolution for a firm in distress. A good understanding of the information structure of the liquidation market helps guide the optimal design of financial markets. Ex-post (post-bankruptcy), understanding what information matters for which type of participants helps with the optimal design of the liquidation market to maximize the sellers' revenue and overall welfare by avoiding misallocation (Shleifer and Vishny, 1992) and promoting competition (Klemperer, 2002; Vasu, 2018). Ex-ante (pre-bankruptcy), understanding the level of uncertainty around asset liquidation results helps banks properly evaluate the value of collateral offered against the debt and determine the optimal haircut (Benmelech and Bergman, 2009). Taking one step further, understanding different financiers' responses to the liquidation results can further guide firms in determining the optimal financing structure for the asset (Murfin and Pratt, 2019; Yuan, 2022).

In this paper, I disentangle the information structure of the bankruptcy liquidation market by constructing a liquidation auction dataset that covers 95% of the judiciary bankruptcy liquidations from 2017 to 2022 in China and structurally estimating an auction model. The bid-level transaction data and auction model allow me to disentangle the buyers' valuations of the asset into three components using two procedures: (1) I decompose the overall value of the asset into a common value component that is constant across bidders and a private value component that is bidder-specific, and (2) I then decompose the common component into two parts, one is correlated with the public benchmark of appraisal price, and another that is not captured by the appraisal prices (common expertise)[1]. The common versus private value decomposition is important in quantifying ex-post the cost of misallocation, limited competition, and ex-ante the investment uncertainty. The appraiser-captured versus not decomposition is important in evaluating the effectiveness of appraisal prices, explaining why they fail, and how to correct the results. I show that there is heterogeneity in the relative importance of each information component across asset types, with tangible assets having a higher weight on the public benchmark, financial assets having a higher weight on the

[1] I name this component common expertise for simplicity. It is "common" because it is a part of the common value component that is constant across bidders, and it is "expertise" because it is not captured by the appraisers.

common expertise among the bidders, and intangible assets relying more on bidder-specific asset value. I then study the determinants and implications for such heterogeneity in the information structure of the bankruptcy liquidation market.

Documenting the information structure for the bankruptcy liquidation market is challenging because there is a lack of data that (1) captures comprehensive liquidation results for different asset types and (2) observes the activity of all market participants, not only the final winning buyer. This is because the liquidation markets for most major economies are fragmented and private. For example, in the United States, airline companies liquidate their fixed assets through privately negotiated transactions (Pulvino, 1998; Franks et al., 2022, 2020), while real estate can be sold through a local broker, dealer, or an open auction platform (Campbell et al., 2011). A large fraction of the documentation of bankruptcy liquidations in the U.S. results comes from tracking the assets instead of observing the market itself.

This paper contributes to this literature by constructing a new dataset that covers all liquidation auctions in a major Economy, China, from 2017 to 2022. This is made available by a law provision that, effective on January 1, 2017, requires all bankruptcy liquidation auctions to go through online auctions in centralized platforms. [2] I collected the description of assets, bidding history, and other auction-related information from the two major auction platforms, Taobao and JD. The rich data allow me to analyze the market participants' information structure through three angles: their valuation, their bidding behavior, and their response to information disclosure. This analysis is complemented by a text description that allows me to quantify what information has been disclosed during this process. The data covers all assets liquidated in the 265,665 auctions from 13,266 firms, covering assorted assets, including tangible assets like real estate, auto vehicles, supplies and inventories, factories, and mineral ownerships; intangible assets like patent and brand; and financial assets like equity and debt (receivables).

Using the data, I first document several facts about the liquidation outcomes. The median sale-price-divided-by-appraisal-price (SAV) is 85%, with a standard deviation of 109%, suggesting that there is a substantial variation in the liquidation price as compared to the appraisal price.

[2] The Provisions of the Supreme People's Court on Several Issues concerning Online Judicial Sale by People's Courts stated that "property disposed of by court auction shall take the way of online judicial auction."

On the asset type front, the median liquidation discount for the real estate and property, plant, and equipment (PPE) are around 81%, 100% for consumption goods and intangibles, 74% for equities, and 8% for debts and receivables. The within-asset type variation is high, especially for intangibles whose standard deviation is as high as 224%. The liquidation discount for receivables is exceptionally high, due to the difficulty in recognizing and collecting the receivables and because the firm's customers might be distressed and more prone to default on the debt.

The descriptive statistics show that the liquidation outcomes resulting from the bidders' and sellers' decisions are based on their information. To recover the information structure, I follow the model by Freyberger and Larsen (2022). The advantage of the model is that it allows for identification with unobserved heterogeneity. This maps to the real-world practice that when bidders make their investment decisions, they observe both quantifiable benchmarks (appraisal price) and other common value signals that are public information like asset quality, firm fundamentals, and macro industry conditions. This model allows me to estimate how much of the common value of the asset is captured by the appraisal price and how much weight investors put on public signals that are not reflected in appraisal prices.

The model disentangles the bidder's valuation (seller's reserve price) into three components: a non-bidder-specific common component correlated with the appraisal price, a common component not correlated with the appraisal price, and a bidder-specific private value component. I identify the common appraisal-correlated component using a truncated regression regressing bids on the appraisal price. I identify the non-appraisal correlated common factors using the correlation of reserve price and bids. The remaining valuation is the bidder-specific private valuation.

The estimated result shows heterogeneity in the information structure across asset types. Tangible assets rely heavily on appraisal prices: the correlation between bidder valuation and the appraisal price is around 0.9 for tangible assets, compared to only 0.5 for intangible and financial assets. Instead, financial assets put a higher weight on common expertise: the size and the standard deviation of common expertise is triple that of tangible assets. Intangible assets, in addition, have a higher variation in bidder-specific valuation, which is nearly double in size to that of the remaining asset types.

The model provides the general quantification of the information structure. But what contributes to the heterogeneity in the information structure? A natural starting point is to examine the information provision by appraisers: does the information quality of appraisal reports differ across asset classes? To answer this question, I conduct a textual analysis of the appraisal reports. I adopt the Bidirectional Encoder Representations from Transformers (BERT) topic modeling method to analyze the content of the text descriptions. I show that appraisal reports for intangible and financial assets have worse quality than appraisal reports for tangibles: the appraisal reports are shorter, contain less quantifiable topics, and include more disclaimers about how the appraisal price estimation might not be reliable.

Given the heterogeneity in information production by appraisers, it is interesting to ask what factors they miss. I run a battery of analyses on different frictions that affect bankruptcy liquidation results and see if they affect the appraisal price. I construct some friction measures from the topic words from my previous textual analysis, and some separately from other datasets like industry-geographic conditions. The frictions not incorporated include relocation costs and industry conditions. Relocation cost refers to the cost incurred in transferring an asset, which includes storage, (un)installation, transportation for tangibles, and registration and professional service fees for intangibles. Industry condition refers to the macroeconomic industry condition, which could impair the asset value by reducing its fundamental economic value, as well as impair the asset value by impacting the financial soundness of its potential industry insider buyers, which is the fundamental idea of bankruptcy firesales by Shleifer and Vishny (1992). Following the idea of Shleifer and Vishny (1992), I construct an industry-province level macro condition measure as the ratio between the number of firms in distress over the number of firms entering the industry in the past quarter. Both relocation costs and industry conditions affect the bidders' asset valuation negatively, but not the appraisal price. I propose three explanations based on anecdotal evidence as to why appraisers fail to capture these frictions: the appraisers do not specialize in appraising bankruptcy liquidation sales, the time constraints in bankruptcy liquidations[3] give the appraiser little time to conduct a proper evaluation, and some costs, especially the industry condition, are difficult to predict because appraisers conduct the appraisal 3 to 6 months before the auction.

[3] Iverson (2018) explored this idea in chapter 11 reorganization on courts: time constraint judges make suboptimal bankruptcy decisions.

Third, I supplement the analysis with bidder behavior analysis. In the auction literature (Fishman, 1988; Hirshleifer and Png, 1989), jump bidding behavior is observed when there is private information on private value. I find that bidders for intangible assets tend to signal their high private value by jump bidding at the beginning of the auctions to crowd out competitors.

The information structure analysis provides rich policy suggestions for ex-post bankruptcy procedures, ex-ante bank lending, and firm financing decisions. A major difference across asset types is how important is their private value, which has important implications for the cost of misallocation, limited competition, and uncertainty. I simulated the model to calculate the difference in valuation between the highest-valued buyer and the second-highest-valued buyer. This practice (1) estimates the lower bound for the welfare cost of misallocation if the asset is not sold to the optimal buyer, (2) estimates the surplus lost due to limited competition in an English auction by the seller because the highest bidder pays the valuation of the second highest bidder, and (3) estimates the lower bound of potential uncertainty ex-ante bankruptcy and lending decision makers face regarding the potential recovery results. The results show that the median cost is as high as 16.9% for intangible assets, while only 5.6% to 7% for tangible assets and 5% to 9% for financial assets. The results suggest that the cost for misallocation, limited competition, and uncertainty is high for intangibles. Thus ex-post when designing the optimal liquidation market for intangibles, the asset should be liquidated through market mechanisms that minimize the search friction and allow matching with the optimal buyer. Such a process might request a longer liquidation period, which is usually less possible when the firm is under liquidation pressure. This suggests room for distress investment specializing in intangibles, which can be both profitable and welfare-improving. Ex-ante, when making lending decisions using intangibles as collateral, the higher uncertainty for intangible assets means that they should have a higher haircut because the nature of debt instruments makes creditors more vulnerable to high uncertainties. Taking one step further, when innovative firms are financing for intangible assets, they should finance them with equity-like instruments to avoid such higher financing costs.

The second implication comes from the fact that there are high negative common expertise for both intangible assets and financial assets that are not captured by general appraisers. The implication is that such assets should be financed by investors with relative expertise in these assets. This is observed in real-world practices: receivables are often financed through special bank branches and fintech companies specializing in accounts receivable financings. Yu (2022) shows that account receivable finance providers specialize in screening the quality of account receivables; Innovative firms investing in intangibles are mostly financed by VCs specializing in the relative industry.

As for tangible assets, it is shown that their value is generally well summarized by appraisal prices and are less susceptible to misallocation costs. The bankruptcy literature (Franks et al., 2022) has shown that tangible assets are more vulnerable to quality impairment due to poor management and lack of labor. This is also illustrated by my text-analysis results: tangible assets mention more about quality concerns in their appraisal reports (which are appropriately reflected by the appraisal prices), and quality-related topic words are more common when the industry is distressed. It is thus suggested that tangible assets will benefit from a prompt liquidation process. Ex-ante, this importance of asset quality for tangible assets rationalizes the fact that durable goods are commonly financed by their manufacturers (also called captive financing), who provide quality management services.

My study contributes to multiple strands of literature. First, I contribute to the literature on bankruptcy liquidation by constructing a new dataset covering all industries, asset types, and firm sizes in the bankruptcy liquidation market. Previous papers (1) only focuses on certain submarkets and (2) does not document the market details due to fragmented market and the lack of documentation, including aircraft (Pulvino, 1998; Ramey and Shapiro, 2001; Franks et al., 2022), real estate (Campbell et al., 2011; Bernstein et al., 2019), and shipping (Franks et al., 2020). Ma et al. (2022) examine the reallocation of patents in Chapter 11 reorganizations. Most previous studies only document liquidation results by observing the final price or asset utilization but cannot answer anything related to the market's microstructure.[4] This paper contributes to this literature in two ways. First, my paper covers the whole bid and transaction history of the market, allowing me to recover the information structure of different participants, especially for participants who did not win an auction. Second, this paper covers a complete set of assets liquidated in bankruptcy

[4]The only literature that examined how assets are sold in bankruptcy is Ramey and Shapiro (2001). They compared the liquidation results of one plant closure with private negotiation and two plant closures with the public auction. Given the sample size, their result is closer to a case study practice.

auctions from all different industries. These two features jointly allow me to compare the liquidation results and information structure for different asset types across different industries. Thus, I can provide separate policy suggestions based on the heterogeneity in the nature of the assets.

Secondly, this paper contributes to the literature on nontraditional asset types. A strand of literature has explored the rise in non-traditional assets and its implications in asset pricing, investment, productivity, market concentration, and inequality (see Crouzet et al. (2022) for a summary of intangible assets). While the literature has focused on the nature of non-traditional assets from the perspectives of their production and utilization, this paper, to my knowledge, provides the first comparison of different types of assets in the liquidation market. Because the setting allows me to control for the market composition, my cross-asset comparison reflects the heterogeneity in the assets' nature, especially their specificity (private value vs. common value) and information quantifiability. I am also the first to quantify these concepts based on revealed preference based on transaction-level data. This practice, in turn, allows me to rationalize the current market structure for different asset types, which is a promising yet understudied topic in alternative asset literature.

Thirdly, this paper contributes to the literature on information finance and rating agencies. This literature studies third-party information providers' incentives, quality (informativeness), and the implications for decision-makers who rely on the third parties' information. For example, Becker and Milbourn (2011); Bernstein et al. (2023); Griffin and Tang (2012) studies the credit rating agencies, and Malenko and Malenko (2019) studies the proxy voting agencies. Most closely related to this paper, Ayotte and Morrison (2018) studies the valuation in the bankruptcy reorganization market. This paper contributes to this literature by providing the first documentation about the informativeness of the information production by third parties in the liquidation market and providing a detailed examination of the information set faced by them. Specifically, I text-analyze the report provided by the third party and explain what factors contribute to their price formation and what factors affect the quality of their benchmarks. I show what factors affecting liquidation results are not predicted by the appraisers, the reasons, and the economic implications. As far as the author knows, this is the first paper applying text analysis on appraisal reports to extract the information component.

Last but not least, this paper combines the recent developments in the auction literature [see Hortaçsu and Perrigne (2021) for a summary] to estimate the asset's value to all liquidation participants. Auction is a common selling mechanism in the finance market, including corporate takeovers (Gorbenko and Malenko, 2014), exchange trading (Jagannathan, 2022), Treasury bonds (Hortaçsu et al., 2018), and IPOs (Jagannathan and Sherman, 2006). This paper studies the application of the auction mechanism in the bankruptcy liquidation market.

Most closely related to my paper, there is a strand of studies examining bankruptcy auctions in Sweden. The Swedish setting is similar to the Chinese setting in that bankrupt firms are automatically turned over to a court-appointed trustee for an open, cash-only auction. The setting is different in that (1) the auction is effectively a combination of piecemeal liquidation and going-concern sale, where firms who fail to be sold as a going concern in an auction would be put on a piecemeal auction, and (2) the auction is not conducted through the online auction format, making it harder to track details in the auction. Thus, these studies focus more on discussing the efficiency of the going-concern sales against piecemeal liquidations and less on the details of the piecemeal liquidation. For example, Thorburn (2000) shows that such liquidations are more efficient than the Chapter 11 system in the US, Eckbo and Thorburn (2008) shows that the piecemeal liquidation is more susceptible to firesale discounts than going-concern sales, and Eckbo and Thorburn (2003) show that this going-concern sale system induces managerial conservatism that reduces their inefficient risk-shifting behavior. This paper, instead, aims to better explain the piecemeal liquidation market with a much more detailed description at the asset level and at the bid level, which is made available by the online auction setting. These bid-level observations uniquely allow me to examine the information structure, which is not possible in the Swedish setting literature.

The rest of the paper is organized as follows. Section 2 explains the institutional setting of judiciary liquidation auctions and the data construction. Section 3 presents several facts about bankruptcy liquidation using descriptive statistics. Section 4 introduces the auction model to estimate the information structure. Section 5 combines text-analysis, bidder behavior analysis and other empirical results to explain the information structure estimated from the model. Section 5.5 applies the information structure to provide suggestions for optimal bankruptcy, lending, and financing policies. Section 7 concludes the paper.

2 Institutional details and data

In this section, I describe the institutional details related to the liquidation auctions including the legal foundation for the liquidation auctions, the market setup, the important players and their incentives. Then I introduce the data used for this study.

2.1 The 2017 supreme court provision and online auctions

On 05/30/2016, the Chinese Supreme Court Committee passed the *Provisions of the Supreme People's Court on Several Issues concerning Online Judicial Sale by People Courts*: effective in 1/1/2017, *A people's court that disposes of property by auction shall take the way of the online judicial sale, except under the circumstance for which other disposal methods shall be taken as prescribed by any law, administrative regulation, or judicial interpretation or whereby online auction is inappropriate (Article 2).* The new law provision, with the purpose of "open, fair, impartial, safe, and efficient judicial sale", has provided an ideal information source for bankruptcy liquidation cases and asset sales.

The Supreme Court has assigned three platforms for the auctions: *Taobao, JD, and ICBC.* Over 98% of the auction activities take place in Taobao and JD due to their advantage in their infrastructure and market power in an Amazon-like online marketplace. See Figure 1 for a screenshot of the auction website. The website discloses detailed information regarding the asset, including text description and photos of the asset, name of the bankrupt firm (selling firm), the geographic location of the asset, appraisal report, etc. The website also discloses detailed information about the auction process, including the bidding rule (reserve price, minimum bid increment, auction time) and the bidding history. This rich information allows me to dissect the information structure by examining the variation in information provided and the reviewed information through the bidders' bidding behavior.

I use an example of bankruptcy liquidation cases of industrial equipment to illustrate the timeline of relevant processes in the online auction of bankruptcy liquidation:

- 2019/11/13 creditor filed for bankruptcy, the court approved, and the trustee assigned
- 2019/11/13 to 2020/06/25 Trustee count the asset
- 2020/07/16 Appraisal report
- 2020/09/19 Auction announced. Bidders begin to register for the auction and pay the security deposit
- 2020/10/07 Trustee organizes offline auction item display
- 2020/10/14 Auction starts
- 2020/10/15 Auction ends
- 2020/10/25 Property right transferred to the buyer
- 2021/01/21 Bankruptcy case closed

Overall, the whole bankruptcy process takes 6 months to 3 years. It takes several months for the trustee to document the asset to be liquidated and hire an appraiser to come up with the appraisal price that serves as the benchmark price for the asset on sale. The appraisal is conducted after the firm has filed for bankruptcy but before the auction is announced, typically 3 to 6 months before the auction. Thus, the appraisal price reflects the benchmark value of the asset after the firm is bankrupt. After the auction is announced, bidders interested in the asset register for the auction and pay the deposit. [5] The trustee will hold an offline asset inspection after the auction announcement. This inspection is typically scheduled one to two weeks before the auction.

The auction format is an open outcry ascending auction (English auction). The auction begins with a starting bid (reserve price) that the trustee strategically sets to maximize the expected sell price of the asset, given the minimum payment the creditors are willing to sell the asset for.

[5] The deposit will be refunded after the auction. It would only be non-refundable if the winning bidder fails to close the payment.

Bidders whose valuation is greater than the current bid raise their bid, and the current bid raises accordingly. This process proceeds until the second last bidder stops raising the price, and the last remaining bidder pays the price at which the second last bidder drops out. See 10 for a reference for the bidding process.

2.2 Appraisers

All auction items should have an appraisal report for the online auction process, except for the cases where either (1) the asset's value is small, or (2) all parties involved in the liquidation process (namely shareholders and creditors) agree on not hiring the appraiser. The appraiser is randomly drawn from the eligible pool of appraisers that the local court determines, and this pool is a subset of appraisers hired by local banks when they are making the lending decision. When conducting the estimation, the appraiser should provide a truthful, unbiased estimation of the value of the items. There are two major reasons why this is the case. First, from the auctioneer's perspective, truthfully disclosing the information maximizes the revenue from the auction (Milgrom and Weber, 1982). Second, from the court's perspective, it is important to maintain justice in the judiciary auction system. They examine the performance of appraisers annually, and appraisers providing noticeably biased, unjustifiable appraisals will be removed from the service list by the bank or the court.

The appraisers evaluate the value of the auction item mainly through 3 methodologies: the market method, the cost method, and the discounted cash flow method (DCF). The market method estimates the asset's value by comparing the selling price of similar assets on the market. The market-based method is often used for items with higher liquidity and more established secondary market like residential real estate and vehicles. The cost method depreciates the book value of the asset. The discounted cash flow method discounts future cash flow generated by the asset. The future cash flow is based on the past performance of the asset by explicitly assuming that the asset can generate the same cash flow under an alternative user as the original user.

2.3 Data

The auction data is collected from the two major judiciary auction platforms that jointly cover around 95% of the total listings, Taobao and JD. I collected 265,665 auctions from January 2017 to March 2022. 13,266 firms are covered in the sample. This covers all firms liquidating assets through judiciary auctions in the corresponding period on these two platforms. I collected asset-level information (liquidating company, asset type, location, asset appraisal price, asset description and appraisal report) and auction-level information (mainly reserve price, minimum increment, and bid history) from the auction platform. I additionally collect the bankrupt case information from *National Corporate Bankruptcy Information Disclosure Platform*. I collected the firm's fundamental information from the National Enterprise Credit Information Publicity System. Finally, I collected the industry-geographic economic and financial data from the National Bureau of Statistics.

2.4 External validity

This paper uses data from China. I provide three arguments for why this research is relevant for non-Chinese readers. First, the results draw similar conclusions to the literature that uses US data. Quantitatively, I find a similar liquidation discount rate with the US-based literature that uses a similar market-price-based definition of liquidation discounts: the liquidation discount in my data for real estate is 19%, which is similar to the 27% found in Campbell et al. (2011). The liquidation discount in my data for equipment is 19%, and that ratio by Pulvino (1998) is 14%. Qualitatively, my paper finds a higher recovery rate from intangible assets, and this is consistent with the recent paper by Kermani and Ma (2020a). Secondly, the process is not China-specific because the auction is based on public marketplace platforms where information is previously disclosed and participants are anonymous. All these features make it difficult to manipulate or collude during this auction process. In addition, the bankruptcy firms are mostly non-state-owned, which are less subject to political considerations than state-owned firms. Last but not least, the topic of bankruptcy in China itself is important and understudied. China has the second largest bond market in the world, around 3.5% of which is owned by global investors. The recent default of large Chinese real estate companies like Evergrand has posed a great default risk to many Chinese companies.

Global investors largely exposed to the Chinese bond market have been worried about it becoming China's Lehman moment and posing a threat to global financial stability. Chinese bond default has not been interesting to global investors because it was assumed that the government would intervene to backstop any company in difficulty pre-2015 (see Figure 4). However, bond default has become more common as the government takes a less interventionist stance. It is thus important to understand the potential recovery given the bankruptcy case.

3 A descriptive analysis of liquidation auctions

This section provides a granular description of bankruptcy liquidation auctions. I will first introduce how the auctions are organized, the timeline, the participants, and the auction mechanisms. I then provide summary statistics of auction results, discuss the liquidation recovery rate by asset type, and show that information affects the recovery result.

3.1 Bankruptcy liquidation in China

Figure 13 provides a big-picture summary of the online judiciary bankruptcy auction from 2014 to 2021. The online auction platform was first introduced by Taobao in 2014. The online liquidation auctions for bankruptcy cases stayed rare until the 2017 provision. Now, there are, on average, 2500 monthly listed auctions, among which 1300 are sold and 1200 are unsold. While we haven't seen a significant increase in the supply of auctions listed, there has been a noticeable increase in the number of auction bids (auctions that successfully sold the item) 6 months into the pandemic. This result can be cross-referenced with figure 4.

3.2 What firm is liquidating assets and what are they liquidating?

My sample consists of 13266 firms. Among these, only 11 are public companies. [6] 406 are fully or partially state-owned. The majority of my firms are private, non-state-owned companies. This sample composition gives me several unique strengths: first, because most of the firms are non-state-owned, my results are free from political or institutional concerns. Secondly, my paper covers more than public companies, providing a more comprehensive picture of the bankruptcy liquidation results.

Table 1 summarizes the industry composition of my sample firms, and table 2 summarizes what assets they are liquidating. Manufacture (34.6%) and retail (35.2%) are the most commonly liquidated industries. Category real estate is the most commonly liquidated asset type across most industry types and is especially important for industries like accommodation and food services (80%), real estate (88.3%), construction (43.2%), utilities (54.83%), retail (42.97%) and rental and renting (50.35%). Category consumptions include consumer goods like office supplies, motor vehicles (excluding industrial vehicles), digital items, and collectibles. It's most important for industries like finance (54.79%) and transportation (56.06%). Category PPE includes equipment, transportation, unfinished projects, and the ownership of mining, forest, and fishing. Category intangibles mainly include patent, brand names, copyrights, and trade secrets. Intangible assets are the most liquidated assets for service-based industries like professional, scientific, and tech services (30%) and information services (50%). Equity is the equity ownership of other related companies. Debt is the debt contract with other companies. Most of the debts are receivables from the firm's customers. Construction is the industry that liquidates a lot of account receivables (10%). Pooled assets are assets sold as a bundle. It is also worth mentioning that the manufacturing industry liquidates a balanced set of assets with around 20% of consumption goods, real estate, and PPE, and a joint 20% of intangible and financial assets.

[6] This is mostly due to the special rules in the Chinese stock market. On the one hand, firms are delisted if they firm has three consecutive years of negative profit. On the other hand, because the IPO in the Chinese equity market is difficult and time-consuming, many distressed public firms are acquired before they go bankrupt simply for the value of their public company status.

3.3 Auction results: recovery rates

The liquidation discount rate is defined as sale-price-over-appraisal-price (SAV). While the literature (Kermani and Ma, 2020b) has commonly used the sale-price-over-book-price measure (SBV), I choose to use SAV as the major measurement of firesale discount for three reasons. Firstly, the SAV measurement is more relevant for measuring fire sale discounts. It reflects the asset's value at the time of the auction, not the historical price at which the asset was purchased. Thus, it is immune to historical event shock or unaccounted depreciation and amortization. Secondly, the SAV measurement is more relevant for finance practitioners: when making a collateralized loan, lenders benchmark their lending on the asset's appraisal value, not the book value. In practice, banks hire the same sets of appraisers as the appraisers who provide appraisal services for the auction. SAV is informative for the bank when deciding its haircut for the collateral. Lastly, while I observe the appraisal price for 80% of my data, I only observe the book value for about 2% of the assets and the total book value for the whole firm (not asset-specific) for 20% of the firms because most of the bankrupt firms are private firms[7] and I have limited access to their book value of assets. The drawback of the SAV measure is that it relies heavily on the accuracy of the appraisal value to work as an appropriate measure of the bankruptcy discount. The appraisers have the incentive to provide reasonable and accurate estimations because their appraisal report is examined by the court annually. There is no bunching of valuation around the kink of the appraiser's compensation function, and 2) supplementing my analysis with additional information of SBV.

3.4 A discussion of SAV as a measurement for recovery rate

One relevant question is what SAV measures. The numerator seems obvious: it measures the price at which it is sold. It does not exactly reflect the value of the final buyer, but for simplicity of understanding, we assume it is a noisy measurement of the buyer's value for this section. I will discuss the difference between the buyer's value and the price in section 4. The denominator is

[7]Two factors jointly make public firm bankruptcy a rare event in China. Firstly, public firms are frequently delisted: firms get delisted if they have a negative net profit for 2 to 3 consecutive years. Secondly, failing public firms are more likely to be acquired as shell companies instead of going directly into bankruptcy. Due to the stringent listing requirement and the slow approval process by *China Securities Regulatory Commission*, most failing public companies are acquired as a shell company rather than go directly bankrupt. In 2021, the average value of a public shell company is around 2.4 billion RMB (337 million USD).

less obvious. What it measures depends on the appraising method. I obtained all public appraisal reports and OCRed the text to understand what appraisal methods they have been using. There are three major types of appraisal methods: cost-based (Cost), discounted-cash-flow (DCF), and match-to-market (Mkt). The cost-based method uses the book value of the asset and adjusts for depreciation and amortization. This measurement is more closely related to the literature on SBV measures. Because it is based on past prices when the asset is purchased, SBV might reflect the change in the price of the asset. Such price changes can come from the change in asset quality (Franks et al., 2022) or change in demand over the years (technology obsolete). Some appraisers further adjust the depreciation that comes from economic factors like obsolete technology, but they do not provide detail on how such depreciation is calculated. The cost-based method is most commonly used by consumption goods, PPEs, and intangibles. The Matched-to-market method is estimated by referring to the market price of similar assets. Because the appraising process is conducted before the auction (typically a month before the auction date), this measurement should be free from the aforementioned quality and change in the market condition concerns if the benchmark asset is appropriately chosen. The matched-to-market method is most commonly used in real estate, equity, and consumer goods. The discounted cash flow method uses the past cash flow generated by the asset and discounts it by a proper discount rate that adjusts for the risk factor to create the appraisal value. For example, the cash flow for patents and brands is mostly royalties from authorization, and the cash flow for real estate is rents collected in the past. Cash flow for PPEs is cash flow from the specific production line. PPEs that use such appraisal methods are typically sold together within a production line.

Table 7 provides the summary statistics for the 3 different appraisal methods. On average, matched-to-market appraisal method has the best prediction of the actual sale price with a mean SAV of 1.03. Cost based method under-predicts the price with a mean SAV of 1.31, and the discounted cash flow method over-predicts the price with a mean SAV of 0.82. This means that on average, the actual trading price of similar assets from similar markets have the best predicting power of the liquidation value of the asset. Book value underestimates such value, and past cash flow overestimates the liquidation value. However, this conclusion should not be taken as causality statement because the appraisal methodology is endogenously chosen by the appraiser.

For example, appraisers estimating real estate with the DCF method state that they are not using the match-to-market method because they cannot find transaction prices for similar real estate located in the same location. In addition, similar to the comparison across industries and asset classes, the difference in SAV across appraisal methods is insignificant, given the high standard deviation.

4 Auction model

The descriptive liquidation results are equilibrium outcomes from the agents' optimal decisions based on their information structure. While the description statistics provide some initial intuition about what information is important, an auction model will help map the descriptive results to the underlying structure. I formulate an ascending English auction model and estimate it based on the bid history and reserve price. The identification strategy is based on the method developed by Freyberger and Larsen (2022), which overcomes the unobserved number of bidders problem and the unobserved heterogeneity problem. This feature allows me to cleanly dissect the information structure and quantify the relative importance of each information portion.

The auction format is an open outcry ascending auction (English auction). The auction begins with a starting bid (reserve price) that the trustee strategically sets to maximize the expected sell price given the minimum payment the creditors are willing to sell the asset for. Bidders whose valuations are greater than the current price bid a higher price and raise the current price. This process proceeds until the second last bidder stops raising the price, and the last remaining bidder pays the price at which the second last bidder drops out. In a private value auction setting where the bidders do not update their beliefs of the valuation from other bidders' behaviors, each bidder has a weakly dominant strategy to bid up to their own valuation. Thus, in equilibrium, the bidder with the highest valuation wins and pays the valuation of the second-highest bidder (or the reserve price in the case only one bidder bids in the auction).

4.1 Model setup

The model is a static, single-unit ascending auction model where bidders have symmetric private values and a common value that is common knowledge to all auction participants. For each bidder j, his log valuation for the asset i takes the form of

$$v_{ij} = \alpha A_i + X_i + U_{ij} \tag{1}$$

The bidder j's valuation consists of three mutually independent parts. The observable common part (αA_i), the unobservable common part (X_i), and the unobservable idiosyncratic private part (U_{ij}). The "unobservable" here refers to the fact that this value is unobservable to the econometrician. The observable common value refers to the common value that the econometrician could observe. Here I use the appraisal price as the observable common value because, as shown in section **??**, the log appraisal price has a high prediction power of the bidder's log valuation with an overall adjusted R-squared over 0.8. The unobservable common value refers to the common value that is not observable to the econometrician or the appraiser but is observable to the bidder and the seller. Such unobservable common value factors can come from the bidders' common knowledge of the economic and industry's outlook or the asset's potential productivity. I model the valuation in this form for three reasons. First, in an IPV framework, it is important to control for heterogeneity across auctions so that the bidder participating in different auctions indeed draws their private values **independetly** from the same distribution. The observable and the unobservable common values help me to control for auction-level heterogeneities. Secondly, I want to understand separately the part of the value common across bidders versus the part that is individual bidder specific. I will show in section 6.1 that a greater variance of the private value is correlated with higher firesale distress in the economic downturn. Third, while I have common-observable, common-unobservable, and idiosyncratic-unobservable, I do not have the idiosyncratic-observable component due to data constraints. I do not observe any information about the bidder except their auction-specific digital bidder ID which is not constant across auctions. [8]

[8] The above model setup follows the model structure in the empirical auction literature. The setup can be translated to the information economic literature in the following way: consider appraisal price A_i as a noisy signal of the bidder's true valuation B_{ij}, where A_i follows normal distribution $N(\rho B_{ij}, \Delta_{ij})$. This model can

To sum up, for the auction participants, the common value αA_i and X_i are common knowledge. Bidder-specific private value U_{ij} is private knowledge only known to the bidder himself. For the econometrician, α is an unobserved constant parameter. X_i and U_{ij} are unobserved random variables. I assume U_{ij} and X_i to follow the unknown distribution with a cumulative distribution function of F_U and F_X, and a probability density of f_U and f_X. U_{ij} and X_i are mutually independent.

The parameters to be estimated are α, f_U and f_X. f_X and f_U are not separately identifiable with only the bid price. Correlation between two bids cannot fully identify the common value X_i when the reserve price is binding: only bids greater than the reserve price are observed, which introduces a correlation between bids. To identify f_X, I additionally use the correlation between the bid price and reserve price (also known as bid starting price or opening bid). The identification logic is as follows: when the common value among bidders is known to the seller, the seller's optimal strategy is to set the reserve price equal to that common value plus some other terms that are uncorrelated with that common value (Krasnokutskaya, 2011; Decarolis, 2018)[9]. Thus the correlation between the reserve price and the bids will only depend on the common value. Following the literature, I specify the seller's reserve price as

$$R_i = \alpha A_i + X_i + W_i \tag{2}$$

map back to the result in this paper by having the following relationship: $\alpha = \frac{\rho E(B_{ij}^2) - \rho E^2(B_{ij})}{\rho^2 E(b^2) + E(\Delta_{ij}^2) - \rho^2 E^2(B_{ij})}$, and $\Delta_{ij} = x_i + u_{ij}$

[9]Consider the following setup: the bidder's common value is $\alpha A_i + X_i$ and the seller's value of the asset is $\alpha A_i + X_i + S_i$, where the bidder-specific value S_i is independent of X_i and U_{ij}. Myerson (1981) shows that the optimal reserve price should satisfy the following structure:

$$\begin{aligned} R_i &= \alpha A_i + X_i + S_i + \frac{1 - F_B(R_i)}{f_B(R_i)} \\ &= \alpha A_i + X_i + S_i + \frac{1 - F_U(R_i - \alpha A_i - X_i)}{f_U(R_i - \alpha A_i - X_i)} \\ &= \alpha A_i + X_i + W_i \\ Where\ W_i &= S_i + \frac{1 - F_U(W_i)}{f_U(W_i)} \end{aligned}$$

Define $W_i = S_i + \frac{1-F_U(W_i)}{f_U(W_i)}$. The optimal reserve price can thus be written to the form $R_i = \alpha A_i + X_i + W$, i.e. the sum of the common value and a value W that is independent of the realization of U_{ij} and X_i. Notice that here F_U is a constant parameter, so even if W depends on F_U, the distribution of U_{ij}, it is still independent from the realization of U_{ij}

R_i consists of the common observable part (αA_i), the common unobserved part (X_i), and the seller-specific unobservable part (W_i). W_i F_W and W, U, X, N are mutually independent.

4.2 Model Identification

In this subsection, I explain how to use the data to identify α, F_W, F_X, F_U. For simplicity of illustration, this section assumes X_i, W_i, U_{ij} to follow the normal distribution. Thus to identify the distribution of X_i, W_i, U_{ij}, I only need to identify their mean and standard deviation. The nonparametric estimation can be achieved through the kernel method. The kernel method equation will be discussed in subsection 4.3.

In the data, I observe the bidder's bid B_{ij}, reserve price R_i, and appraisal price A_i. I denote the exit bid for the z-th highest bidder as B^z. In the English auction, the dominant strategy for the bidder is to stay in the auction until the current price exceeds his valuation. Thus, in equilibrium the bidder with the highest valuation wins and pays the valuation of the second-highest bidder or the reserve price, whichever is higher (Haile et al., 2003). Denote the $z-th$ highest bidder's valuation in the auction as V^z. Thus for $j \neq 1$, we have

$$V_i^z = B_i^z \tag{3}$$

Following equation 1, because X_i, U_{ij} are independent of A_i, α is identified through the truncated regression: $B_{ij} = \alpha A_i + X_i + U_{ij}$, where $X_i + U_{ij}$ is the error term. The regression is truncated instead of OLS because only bids above the reserve price are observed. The mean of U_{ij} is set to be 0. Mean of X

Denote $\hat{B} = B - \hat{\alpha_B} A$, and $\hat{R} = R - \hat{\alpha_R} A$. Because X, U, W are mutually independent, $E[\hat{B} * \hat{R}] = E[X^2] + E[X * W] + E[X * U] + E[U * W] = E[X^2]$. $E[X] = 0, E[X^2] = E[\hat{B} * \hat{R}]$, normally distributed variable X is identified. Following equation 3, $E[W] = E[\hat{R}] - E[X] = E[\hat{R}]$, and $var(W) = var(\hat{R}) + var(X)$, normally distributed variable W is identified. Similarly, following equation 1, $E[U] = E[\hat{B}]$, and $var(U) = var(\hat{B}) + var(X)$. [10]

[10] The discussion in this section assumes X, W, U to be normally distributed. For a more general scenario, f_X is identifiable if $\hat{B}, \hat{R}$ are observable, $\hat{B} = X+U$, $\hat{R} = X+W$, and X, W, and U are mutually independent. See Lemma 1 of Evdokimov and White (2012) for the proof. W, U are identified once f_X is identified.

4.3 Model estimation

In this section, I derive the likelihood function for the Maximum Likelihood Estimation (MLE) method. In classic IPV identification methods, the likelihood function of $Prob(B^j = b)$ requires observing the number of bidders N. This is not observable in my setting because the reserve price is binding, and I do not observe bidders whose values are below the reserve price. (Song, 2004) shows that, instead, $Prob(B^j \mid B^k)$ can be expressed as a function of f_U that does not depend on N. Specifically,

$$f_{U^2|U^3}\left(b_2 - x, \mid b_3 - x\right) = \frac{2\left(1 - F_U\left(b_2 - x\right)\right) f_U\left(b_2 - x\right)}{\left(1 - F_U\left(b_3 - x\right)\right)^2} \tag{4}$$

While I observe exit bids for all bidders whose values are higher than the reserve price, I use only the highest two exit bids, namely B^2 and B^3, in the estimation. On the one hand, this step simplifies the likelihood function and reduces the computational burden. On the other hand, the assumption of $V^j = B^j$ is less vulnerable to nonstandard bidding behavior bias for higher-value bidders, especially for jump bidding behavior. : when a jump bid occurs, the lower-valued bidder's bid could be hidden by a jump bid. Thus, his maximum valuation might be underestimated. For example, if a jump bid raises the current price from 99 to 101 before a bidder could bid her valuation of 100, then I would not be able to observe this bidder's exit bid of 100, and conclude that her valuation is 99. Such a jump bid is less likely to happen if fewer bidders remain in the auction. For more analysis regarding nonstandard bidding behavior, see section E.4.

To conduct the MLE estimation, I would need to express the likelihood of observed data $\hat{B}^2, \hat{B}^3, \hat{R}$ as a function of the probability densities of f_X, f_W, f_U, f_{U^2} that I want to estimate. The joint distribution of $\hat{B}^2, \hat{B}^3, \hat{R}$ can be rewritten as follows:

$$\begin{aligned} P(\hat{B}^2 = b^2, \hat{B}^3 = b^3, \hat{R} = r) &= \int P(\hat{B}^2 = b^2, \hat{B}^3 = b^3, \hat{R} = r) f_X(x) dx && (5) \\ &= \int P(U^2 = b^2 - x, U^3 = b^3 - x, W = r - x) f_X(x) dx && (6) \\ &= \int P(U^2 = b^2 - x, U^3 = b^3 - x) P(W = r - x) f_X(x) dx && (7) \end{aligned}$$

The first step uses the law of iterated expectation. The second step comes from equation 3 and equation 1, and the third step comes from the independence between W, U, X. Thus the likelihood function can thus be written as:

$$l(B^2 = b^2, B^3 = b^3, R = r) = \int f_{U^2|U^3}\left(b^2 - x \mid b^3 - x\right) f_{U^3}\left(b^3 - x\right) f_W(r - x) f_X(x) dx \quad (8)$$

Where $f_{U^2|U^3}$ follows equation 4.

I estimate the probability density of f_x, f_w, f_u by maximizing the log-likelihood function. The MLE estimation is performed using both the parametric and nonparametric methods. For the parametric method, I assume X, U, W to be all normally distributed. For the nonparametric method, I approximate the densities of f_U, f_W, f_X with 4th-degree Hermite polynomials.

$$f_U(u) \approx \frac{1}{\sigma_U}\left(\sum_{m=1}^{M=4} \theta_m^U \left(\frac{u - \mu_U}{\sigma_U}\right)^{m-1}\right)^2 e^{-\left(\frac{u-\mu_U}{\sigma_U}\right)^2} \quad (9)$$

The nonparametric estimation results are presented in appendix B. The estimated nonparametric distribution of the valuation is close to the normal distribution. Thus in the rest of the paper, I only present the parametric estimation result with the assumption that X, U, W follows the normal distribution.

Appendix D discusses the case when the third highest bidder's valuation is below the reserve price. For this paper, I only estimate the model with a sample where the reserve price is not binding.

4.4 Estimation results

Table 8 summarizes the parametric estimation result. I estimated the auction model separately for the eight different asset types.

Panel A summarizes the estimation for the appraisal price informativeness α, the parameter showing how much bidders rely on the appraisal price relative to their common expertise and idiosyncratic value in forming their valuation for the asset. This parameter ranges from 0.88 to 1 for tangible assets, showing that appraisal price is more informative for tangible assets like consumption goods, real estate, and PPE. Intangibles and financial assets, on the other side, are incorporated by only around 50%. The ratio for debt is only 17% because of private debts, especially account receivables.

Panel B illustrates the estimation results for the remaining auction parameters. x shows the common valuation bias that (1) matters for the auction results and (2) the appraiser fails to capture. μ_x shows the average size and $_x$ shows the variation. μ_x is negative across all types of assets, suggesting that there are negative common frictions that the appraisers fail to recognize overall. This suggests that overall, regardless of asset types, the appraisers tend to overestimate the common valuation. Such a negative specialty is especially big for intangible and financial assets, nearly doubling to tripling the size of tangible assets. The standard deviation σ_u is bigger for financial assets, again doubling to tripling the standard deviation of tangible and intangible assets, suggesting that the negative common valuation bias ignored by appraisers is more asset-specific for financial assets. This means that for financial assets, adjusting back the negative common valuation bias is more difficult because it is case-specific.

u, the bidder-specific value component, is connected to asset specificity, or how much the asset's value differs across different bidders. For assets with high variation, the cost of misallocation, i.e., not selling to the highest-valued bidder, is high. The estimation result shows that asset specificity is the highest for intangible assets, whose standard deviation of .279 nearly doubles that of the remaining asset types. The following two types are consumption goods (.156) and equity (.148).

5 Illustration of the information structure

In the previous section, I estimated the information structure and showed the heterogeneity across asset types. In this section, I will map the estimated information structure to several empirical practices, including text analysis using a transformer-based model (BERT), bidder behavior analysis, and liquidation friction analysis (studying frictions in the bankruptcy liquidation literature). Through these practices, I illustrate how information structure is reflected in data and what factors contribute to such heterogeneity.

5.1 The informativeness of appraisal report

The auction model has shown that tangible assets have a more informative appraisal price, while for intangible assets and financial assets, the appraisal price is less relevant for the bidders' valuation. In this subsection, I will illustrate why this is the case by showing what public information is disclosed, how such information is used to form the appraisal price, and if it differs from how auction participants price these information components. For a typical auctioned asset, an asset description and several other supporting documents, including the appraisal report, are disclosed in the auction. The supporting documents typically have, on average, 5021.96 words. Given the large sample size, analyzing the text data without shrinking the dimensionality of the text data is difficult. To better understand the information in the appraisal reports, I perform unsupervised topic modeling using the BERT method (Devlin et al., 2018). Topic modeling METHODS rely on the co-occurrences of word patterns to identify clusters of word patterns ("topics"). BERT (Bidirectional Encoder Representations from Transformers) is a model based on the self-attention mechanisms of transformers. It has three advantages in terms of topic modeling. First, as a transformer-based model, the attention mechanism allows the model to incorporate contexts in the target text representation. Second, the model is pre-trained by Wikipedia and BooksCorpus, which allows it to understand the language structures better and thus can efficiently parse out important topics of specific text content.[11]

Using the text analysis results, I first answer why appraisal price informativeness differs across asset types. The appraisal report has very different quality across different asset types. Table 9 summarizes the quality of appraisal reports by summarizing the average number of words in an

[11] While currently the most popular transformer-based model is GPT, I use BERT for two reasons. First, there is no consensus that GPT outperforms BERT in topic modeling. BERT has the advantage over GPT in that it is bidirectional: it uses both previous and post texts to form the context and analyze the structure of the sentences, unlike GPT, which only uses one direction and thus has an advantage in text-generating. As a side evidence, here is the suggested answer from GPT 3.5 about the difference between BERT and GPT: "BERT is trained using a masked language modeling objective, where it learns to predict missing words in a sentence. It understands bidirectional context by considering both the left and right context of a word. This makes BERT suitable for various NLP tasks, including text classification, named entity recognition, and question-answering. GPT models, on the other hand, are trained using an autoregressive language modeling objective. They generate text one word at a time based on the preceding context, allowing them to generate coherent, contextually relevant text. GPT models are primarily used for text generation tasks, such as chatbots, content generation, and creative writing." Secondly, the API for GPT is costly, while BERT can be applied free of charge. Given the text size for my data (around 200k samples, with an average 5000 characters per sample), BERT is a more cost-efficient text analysis method.

appraisal report and the number of overall topics covered by given asset types. The results show that tangible assets, on average, have longer appraisal reports and cover more topics overall. A further look at the topic words illustrates that tangible assets have better quantifiable metrics. For example, the appraisal report covers detailed descriptive topics of consumption goods (electronics and automobiles) and PPEs (equipments), including the manufacturer, brand, type, size, material, current usage, and asset condition. For real estate, the topics include size, architectural structure, facilities, location, transportation, and peripheral facilities (peripheral business centers, hospitals, schools, etc). As a comparison, the appraisal report for intangible assets (patent and brand) covers its industry, the patent/brand expiration date, and the current owner of the asset. It discusses less about the asset's current quality and usability. Similarly, for financial assets, the report covers the basic information about the issuing company, some of its coarse ownership, and, very rarely, its operating metrics. Overall, appraisal reports for tangible assets cover more topics, which are also more concrete and comparable.

In addition to the lack of topics covered, the appraisal reports for intangible and financial assets mention more frequently possible issues that might lead to appraisal failure than tangible assets. For example, for financial assets, such failure could be operating metrics not being audited. One common failure topic for account receivables (debt) is that the account receivables are not verifiable. The reports would specifically mention the "litigation risk" in account receivables: the issuer of the account receivable might not recognize the account receivables, and the receivables might not be collectible.[12]

5.2 What topics and frictions are not captured and why

As a second step to understanding the information structure, in this section, I run several analyses to study what topics and frictions affecting the auction results are not captured by the appraisers. At the end of this section, I will provide speculations on why the appraisers fail to capture these

[12]Trustee in this case typically are not able to provide administration document proving the account receivable obligation, either due to lack of documentation, or due to cross-account receivable relations (This refers to the case that firm A holds account receivable of firm B, and firm B also holds account receivable of firm A. When Firm B files for bankruptcy, there is controversy about whether the account receivable it holds from Firm A should be canceled out with Firm A's account receivables or not).

frictions.

I identify topics and frictions not captured by the appraisers through the following practice: For item i and factor j, I run the following two regressions and obtain coefficients α_1 and α_2:

$$log(P_i^{Appraisal}) = \beta_{1,j} * Factor_{ij} + FE(Province, Time, Firm, Assettype) \tag{10}$$

$$log(P_i^{Sale}) = \beta_{2,j} * Factor_{ij} + FE(Province, Time, Firm, Assettype) \tag{11}$$

For topics the appraisers fail to capture, $\beta_1 = 0$ while $\beta_2 \neq 0$. This means that while such a factor affects the sale price of the asset, it does not affect the appraisal price. For topics the appraiser fails to price correctly, $\beta_1 \neq 0$, $\beta_2 \neq 0$, and $\beta_1 \neq \beta_2$.

The topics and frictions are created by combining the topics identified through the BERT model and the literature on bankruptcy liquidation and corporate assets.

The first topic not captured by the appraisers is the relocation cost. This refers to the time, labor, and monetary cost of transferring the asset from the seller to the bidder. For tangible assets, such fee includes the uninstallation, transportation, and reinstallation fee. For intangibles and financial assets, such fees include the registration cost with the government.

Another such friction is the industry condition. Industry distress negatively affects the liquidation results for two reasons. First, industry distress affects the profitability of the asset and, thus, the intrinsic value of the asset. In addition, industry distress could also affect the financial health of industry insiders, who are typically the asset's highest-value buyers. When the best alternative users of an asset are financially constrained, the asset would more likely be bought by industry outsiders, which leads to misallocation and an economy-wide welfare loss. Following this logic, I define industry distress at the industry-province-quarter level as the ratio of deregistered firms to newly registered firms. Table 12 summarizes the result. One standard deviation increase in distress (0.14) leads to an approximately 7.28% decrease in the sale price, but it does not lead to a statistically significant or economically big change in the appraisal price.

5.3 Why do appraisers fail to capture these frictions?

Why do appraisers fail to capture these frictions in their appraisal results? I provide three explanations. First, the appraisers do not specialize in providing appraisals for bankruptcy liquidations. The appraisers typically provide services specializing in geographic location and asset types, and most of their businesses come from providing collateral appraisals for banks.[13] This means they have less experience estimating frictions related to bankruptcy sales. The second explanation is that some frictions are difficult to predict. For example, for geographic industry distress, since the appraisals are conducted 3 to 6 months before the auction, the appraisers cannot incorporate such distress in their appraised price. The third explanation is time constraints. It is common for bankruptcy liquidations to be conducted under strict time constraints, given the nature of the firesale emergency of bankruptcy liquidations. Limited appraisal time leads to compromised appraisal results.

For example, one of the most common appraisal methods is matched-to-market, where the appraisers use the previous transaction results of similar assets to determine the appraisal price. Why does matched-to-market fail to capture certain frictions? The first explanation says the appraisers do not specialize in appraising liquidation-related frictions, and in the case of matched-to-market, it means that instead of using only the previous liquidation auction results, they benchmark all secondary markets to evaluate the valuation. The first evidence is in the appraisal report: they describe their appraisal methodology to follow the above strategy without a special focus on the bankruptcy liquidation market. The second evidence is that, years after the auction platform was introduced, the quality of appraisals did not improve. If anything, the appraisal quality, as measured by sale price over appraisal price (SAV), has declined significantly. This is an example of how appraisers do not match only to liquidation market results. The second explanation, on failing to predict industry distress, also applies here. When conducting the valuation based on historical prices, they cannot adjust for future industry conditions.

[13] I interviewed several bank loan managers and distressed asset investors to get this intuition. In addition, I obtained one of the banks' collaborative appraiser lists and found that it is a superset of the qualified appraiser list disclosed by Chinese Supreme Court.

5.4 Bidder-specific private value and bidder strategic behavior

The result estimation result can be cross-checked with the result from the bidder behavior analysis. Specifically, I look at jump bidding, increasing the current price more than the minimum allowed amount. The literature on jump bidding (Fishman, 1988; Hirshleifer and Png, 1989) has established that jump bidding is only observed when there is a private value, and the reason why a bidder would engage in jump bidding, instead of the incremental bidding strategy is to signal their high private value to their competitor, reducing the competitors' estimation of winning probability, and thus reduce competition from the competitors. Table 10 summarized the ratio of jump bidders by asset types. Consistent with the estimation results, intangible assets have the highest ratio of jump bidders, followed by equity and consumption goods.

5.5 Pooled assets

A special group of assets is classified as "Pooled assets", where multiple items are pooled as an asset bag and sold together. Panel A shows that 95.1% of the appraisal price is incorporated in the valuation, and panel B shows that the bidders' downward valuation adjustment is as small as 0.24. The results show that for bundled assets, the bidders generally rely more on the appraisal result than their knowledge of their asset valuation. This can result from selection: the trustee choose only sell the assets that can be grouped together as a pool.

Implication for optimal market designs The information structure analysis provides rich policy suggestions for ex-post bankruptcy procedures, ex-ante bank lending, and firm financing decisions. In this section, I use the model results to simulate counterfactual scenarios and provide policy recommendation based on these calculation practices.

5.6 Cost of misallocation, limited competition, and uncertainty

A major difference across asset types is how important is their private value, which has important implications for the cost of misallocation, limited competition, and uncertainty. Private value is the value that is bidder-specific. A high private value component first indicates failing to sell the asset to its highest valued buyer will generate a higher loss both in terms of profit to the seller (or debt recovery for creditor) and in terms of welfare to the economy (because the asset is not used by its optimal user). This is particularly costly for bankruptcy liquidations given that the optimal buyers of the asset, or industry insiders, are more likely to be financially constrained when the firm is liquidated during industry downturns, so they could not bid for the asset up to their true valuation of the asset (Shleifer and Vishny, 1992). Second, given the nature of the English auction that the highest bidder does not bid for his own valuation, but the second highest buyer's valuation, a high private value component indicates a greater transfer from the seller (ultimately the creditor to the bankruptcy firm) to the final buyer. Lastly, a higher private-valuation component means more unpredictable outcome for the ex-post liquidation market, which in turn means a higher uncertainty for the ex-ante financing market, especially for bank lending and firm financing.

I simulated the model to calculate the difference in valuation between the highest-valued buyer and the second-highest-valued buyer. This practice (1) estimates the lower bound for the welfare cost of misallocation if the asset is not sold to the optimal buyer, (2) estimates the surplus lost due to limited competition in an English auction by the seller because the highest bidder pays the valuation of the second highest seller, and (3) estimates the lower bound of potential uncertainty ex-ante bankruptcy and lending decision makers face regarding the potential recovery results. The results are shown in table 11. The median cost is as high as 16.9% for intangible assets, while only 5.6% to 7% for tangible assets and 5% to 9% for financial assets. The results suggest that the cost of misallocation, limited competition, and uncertainty are high for intangibles, nearly doubling to tripling the size for other asset types. Thus ex-post when designing the optimal liquidation market for intangibles, the asset should be liquidated through market mechanisms that minimize the search friction and allow matching with the optimal buyer. Such a process might request a longer liquidation period, which is usually less possible when the firm is under liquidation pressure. This suggests room for distress investment specializing in intangibles, which can be both profitable and welfare-improving. Ex-ante, when making lending decisions using intangibles as collateral, the higher uncertainty for intangible assets means that they should have a higher haircut because the nature of debt instruments makes creditors more vulnerable to high uncertainties. Taking one step further, when innovative firms are financing for intangible assets, they should finance them with equity-like instruments to avoid such higher financing costs. The second implication comes from the fact that there are high negative common expertise for both intangible assets and financial assets that are not captured by general appraisers. The implication is that such assets should be financed by investors with relative expertise in these assets. This is observed in real-world practices: receivables are often financed through special bank branches and fintech companies specializing in accounts receivable financings. Yu (2022) shows that account receivable finance providers specialize in screening the quality of account receivables; Innovative firms investing in intangibles are mostly financed by VCs specializing in the relative industry.

As for tangible assets, it is shown that their value is generally well summarized by appraisal prices and are less susceptible to misallocation costs. The bankruptcy literature (Franks et al., 2022) has shown that tangible assets are more vulnerable to quality impairment due to poor management and lack of labor. This is also illustrated by my text-analysis results: tangible assets mention more about quality concerns in their appraisal reports (which are appropriately reflected by the appraisal prices), and quality-related topic words are more common when the industry is distressed. It is thus suggested that tangible assets will benefit from a prompt liquidation process.

6 Information asymmetry

The parameters from the auction model suggest that for intangible and financial assets, the buyers' valuation relies less on the appraisal report, but more on their own private information. To show the source of such heterogeneity, in this section, I analyze what information is provided in the appraisal report, and why .

6.1 Asset specificity and fire sale discount

In this section, I test the idea that high asset specificity leads to fire sale distress when the economy is going through distress. To test the idea, I first estimate the asset specificity measure using the methodology developed in this paper. I calculate asset specificity for all 90 asset-class-industries pairs. Then I run the following regression:

$$Y_{icpt} = \beta_1 Distress_{pt} + \beta_2 AssetSpc_{ic} + \beta_3 Distress_{pt} * AssetSpc_{ic} + FE_{province,year*month,assetclass,firm} \tag{12}$$

Where i stands for industry, c stands for the asset class, p stands for the province, and t stands for time. The fixed effects include the fixed effect for province, time (year-month), asset classes, and firm. Distress is defined as the ratio of the number of firm closures and the number of new firm registrations. This distress is measured at the province-quarter level. The theory predicts that assets with high specificity should face higher fire sale distress when sold in economic distress. i.e., the theory predicts β_3 to be negative.

The regression result is summarized in table **??**. The results are very interesting in that they partially confirm the theory by showing assets whose value is more dispersed among bidders (i.e., whose value is more specific) face higher illiquidity in distress. This result only exists when the economy is in real recession, in my sample post-2020 (including 2020) when COVID induced recession economy-wide. The results, however, are very different for prices. Given the asset is sold, assets sold in distress with higher variation receive higher recovery than similar assets sold with a lower variation. The results indicate that the alternative-buyer-also-under-distress story only brings illiquidity to the market but does not create downward price pressure.

7 Conclusion

This paper provides the first systematic documentation of the bankruptcy liquidation market across various industry-asset pairs while examining the information structure through the market microstructure. I show that there is a heterogeneity in the information structure across asset types, with tangible, financial, and intangible assets each having a relatively higher weight on appraisal price, common valuation, and bidder-specific valuation. I combined a transformer-based topic-modeling exercise, bidder behavior analysis, and bankruptcy-related liquidation friction analyses to show that such heterogeneity in information structure comes from the difference in information production and the relative importance of private valuation. Using the estimated results, I provide policy implications for ex-post bankruptcy and ex-ante lending and financing decisions.

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Figure 1: Screenshot of the online auction platform, https://sf.taobao.com/

Figure 2: Home page of the auction platform

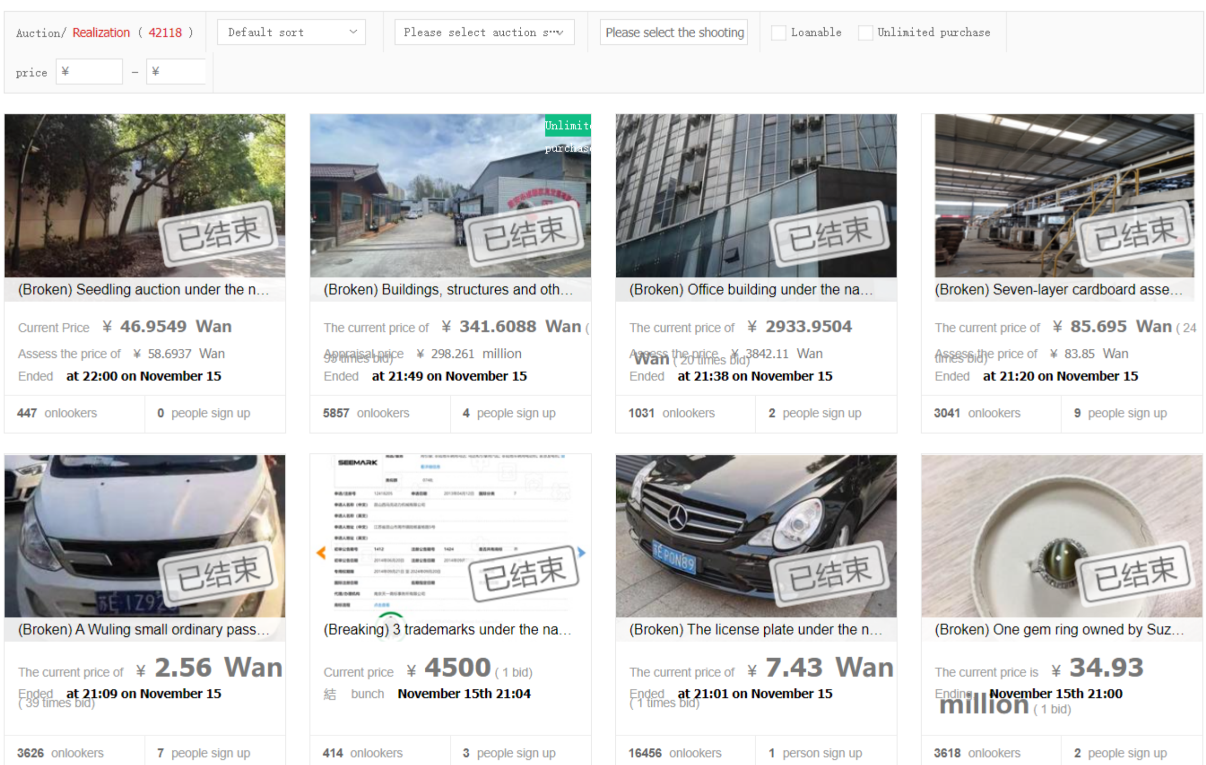
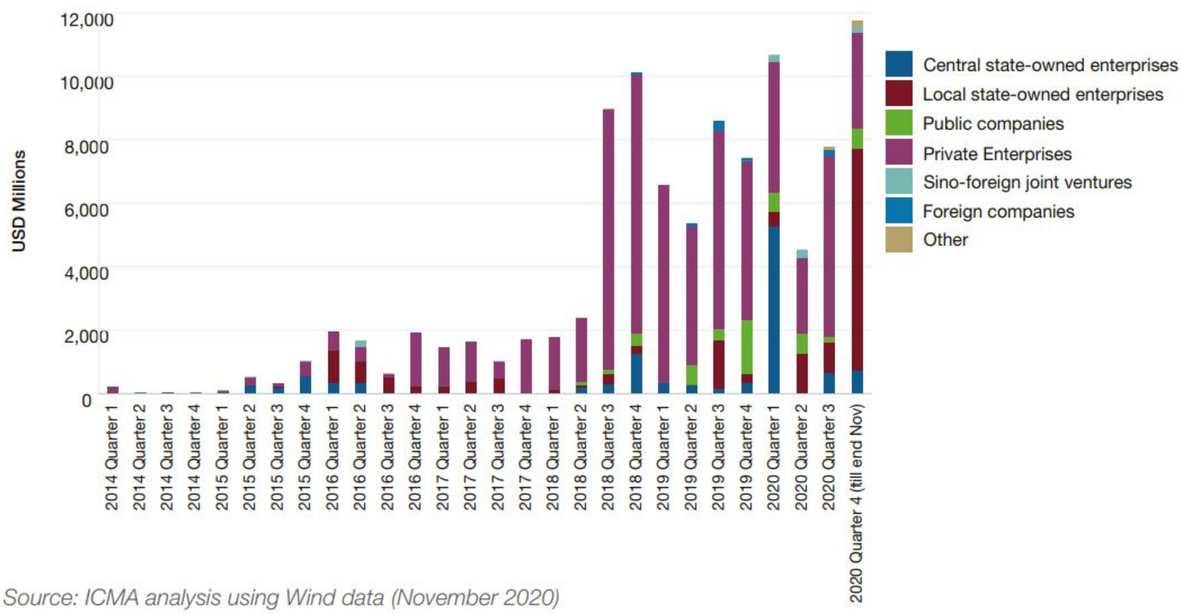


Figure 3: Listed items in the auction

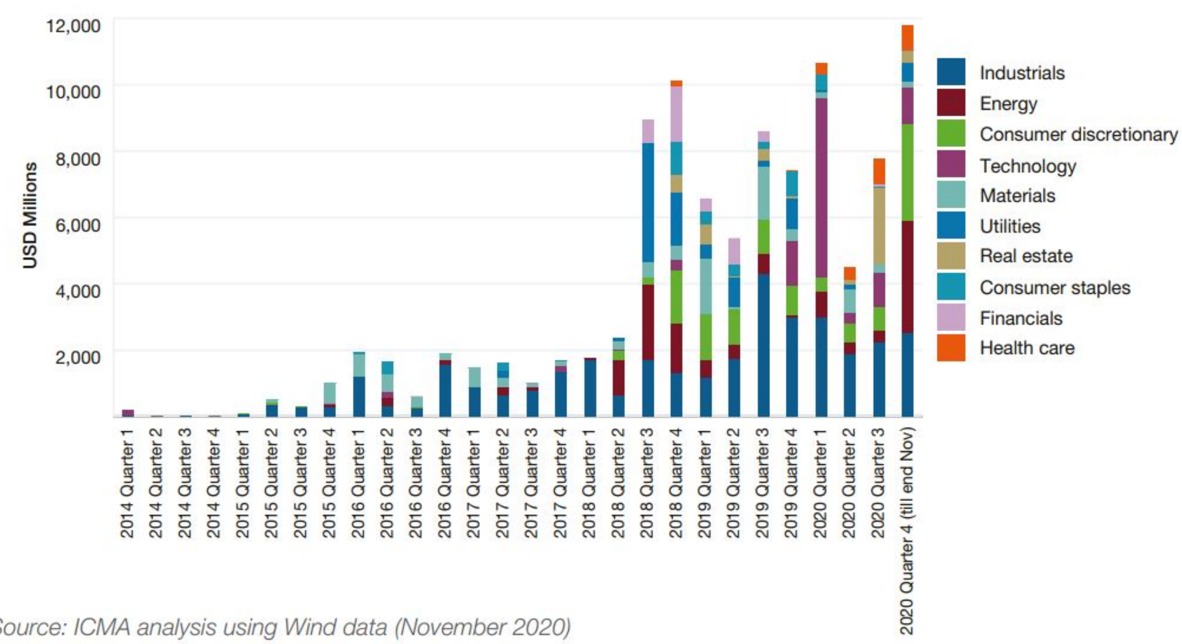
Figure 4: Bond default in China

Figure 15: Onshore credit bond defaults by issuer type since 2014



Source: ICMA analysis using Wind data (November 2020)

Figure 16: Onshore corporate bond defaults by sector since 2014



Source: ICMA analysis using Wind data (November 2020)

Figure 5: The number and value of auctions listed and completed for online bankruptcy liquidation auctions

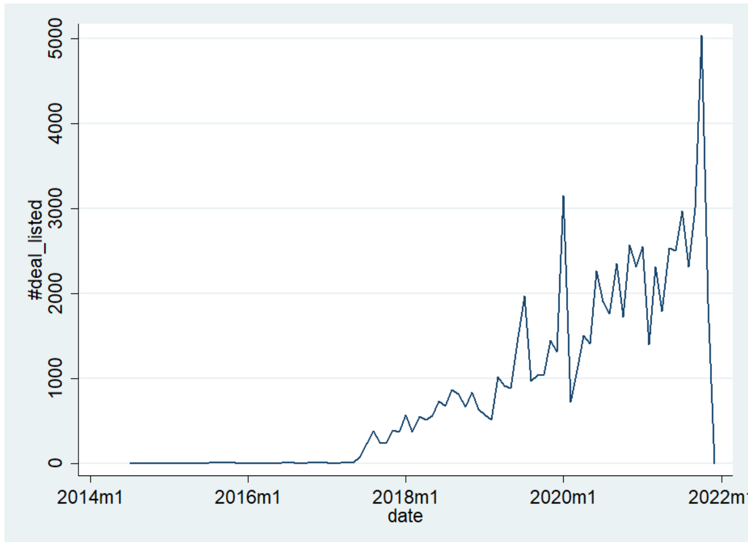


Figure 6: Number of auctions listed

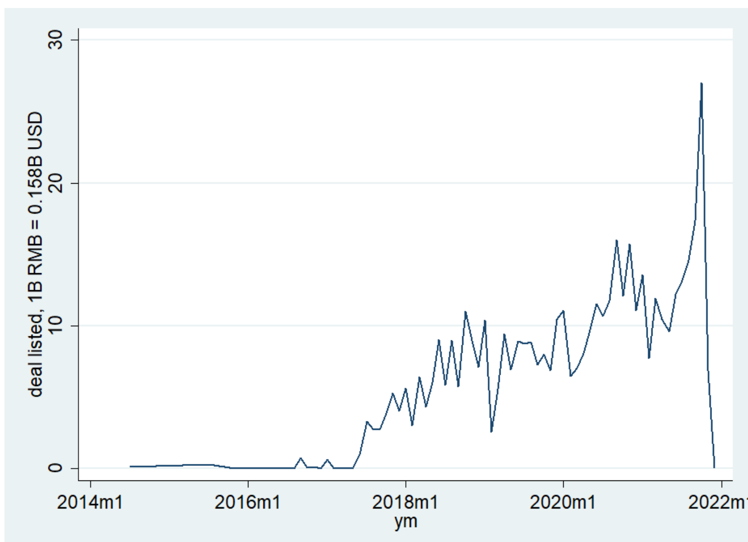


Figure 7: RMB value of auction listed

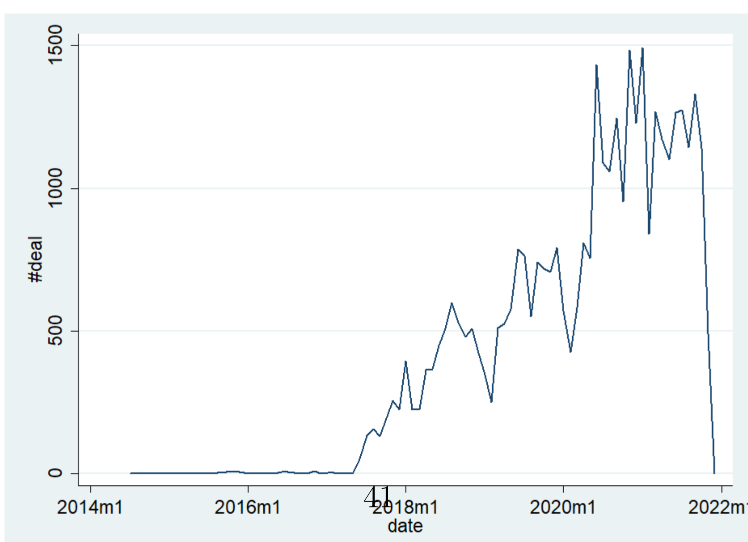


Figure 8: Number of deals made

Figure 10: Screenshot of the bidding record

STATUS	ID	BID
成交	T2809	420,000
出局	F7238	410,000
出局	T2809	400,000
出局	Q5193	390,000
出局	T2809	380,000
出局	Q5193	370,000
出局	T2809	360,000
出局	Y3039	350,000

This figure shows the screenshot of a bidding record. The record shows the bidding id, the bid, the time the bid is submitted, and the final status of the bid (won/lose). For each auction, a bidder is randomly assigned an id like "T2809". The same bidder will have different digital IDs across different auctions. For this auction, there are four bidders. The minimal increment is 10,000 RMB.

Figure 11: The number of covid cases in Chinese provinces

Figure 12: Estimation result for the auction model, offline inspection: no vs yes

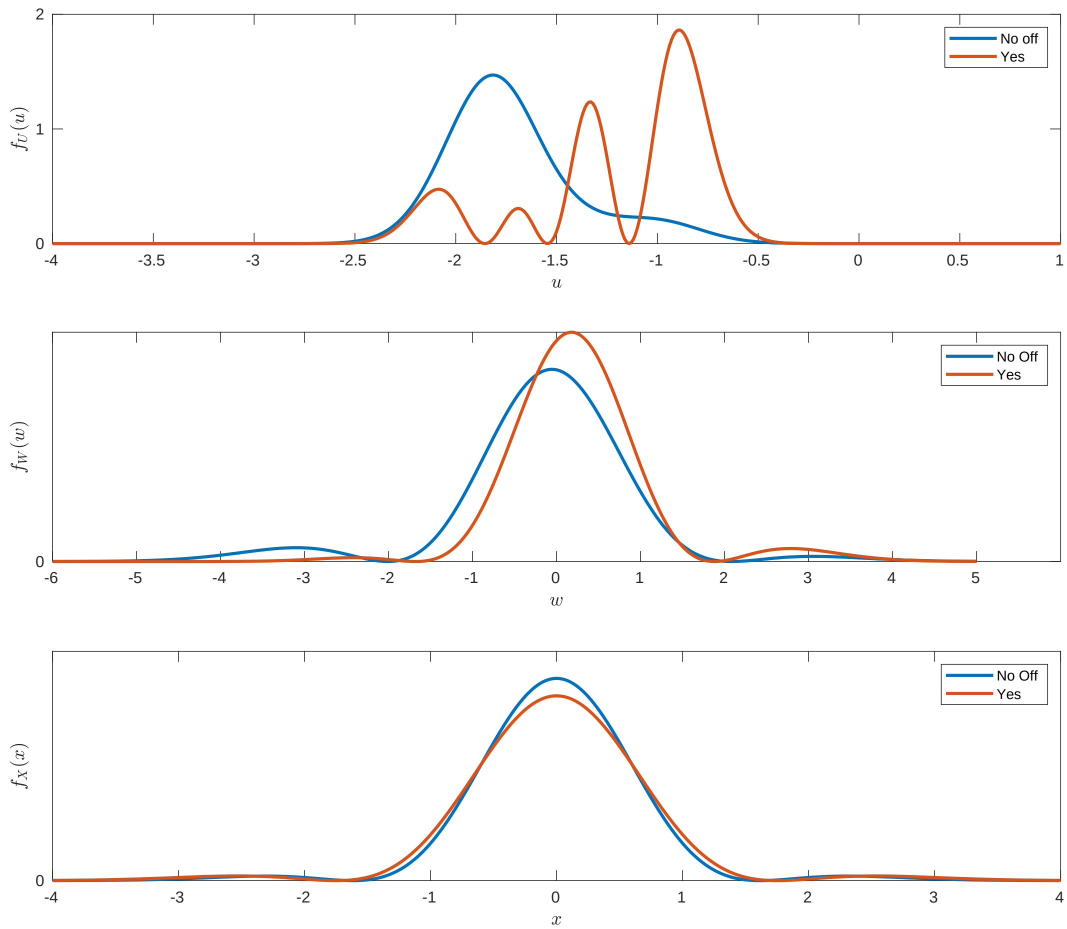


Table 1: Summary statistics: number of firms by industry type

Industry	# Firms	Pct(%)
Accommodation and Food Services	174	1.39
Administrative, Support, Waste Managmt and Remediation	32	0.26
Agricultural, forestry, fishing	161	1.29
Arts, Entertainment, and Recreation	75	0.6
Construction	312	2.5
Education	2	0.02
Finance	43	0.34
Health Care and Social Assistance	13	0.1
Information	141	1.13
Manufacture	4,347	34.76
Mining	54	0.43
Other services	71	0.57
Professional, Scientific, and Technical Services	826	6.61
Real Estate	586	4.69
Rental and Leasing	1,044	8.35
Retail	4,402	35.2
Transportation and warehousing	184	1.47
Utilities	37	0.3

This table describes the industry composition for my sample which consists of 13266 firms liquidated through online judiciary auctions on the Taobao and JD platforms.

Table 2: Summary statistics: number of assets liquidated by industry

This table describes the asset-by-industry composition for my sample which consists of 137697 unique assets liquidated through online judiciary auctions on the Taobao and JD platforms from Jan 2017 to Feb 2022. *Consump.* refers to consumer goods including office supplies, electronics, auto vehicles, and collectibles. *RealEst.* includes business real estate, industrial real estate, residential real estate, and land. *PPE* includes equipment (including industrial vehicles), materials, and unfinished projects. *Intan* are mainly patents and brands. *Equity* refers to equity ownership for other companies held by the bankrupt firm. Debt refers to debt-like ownership for other companies held by the bankrupt firm. These are mostly account receivables. *Pooled* refers to multiple assets bundled to be sold together. *Else* refers to assets difficult to classify with the current classification algorithm.

Industry	Consump.	RealEst.	PPE	Intan	Equity	Debt	Pooled	Else	Total
Accommodation and Food Services	171	1,941	52	47	17	19	151	23	2,421
Administrative, Support, Waste Managmt, Remediation	33	19	16	1	3	2	40	171	285
Agricultural, forestry, fishing	107	630	131	90	37	40	152	87	1,274
Arts, Entertainment, and Recreation	24	142	34	67	14	7	53	44	385
Construction	413	1,008	255	59	152	254	110	82	2,333
Education	0	0	0	0	0	0	2	0	2
Finance	498	207	29	29	46	18	54	28	909
Health Care and Social Assistance	13	2	47	2	1	1	3	0	69
Information	68	57	43	307	59	11	35	34	614
Manufacture	4,576	4,893	4,487	2,622	1,272	670	3,099	2,044	23,663
Mining	50	54	59	1	6	26	68	18	282
Other services	88	1,844	25	7	4	9	39	42	2,058
Professional, Scientific, and Technical Services	634	910	834	1,580	294	196	491	386	5,325
Real Estate	746	17,356	184	216	112	60	323	659	19,656
Rental and Leasing	6,967	12,742	620	740	1,059	397	1,511	1,270	25,306
Retail	5,369	15,524	3,515	2,997	1,627	727	4,379	1,991	36,129
Transportation and warehousing	1,143	332	125	47	95	40	114	143	2,039
Utilities	40	142	22	0	4	12	25	14	259

Table 3: Summary statistics: liquidation result by asset type

This table describes the liquidation results of the auctions by asset type. *item_listed* describes the total amount of assets listed. *item_sold* describes the total amount of assets sold. *sold_pct* is the ratio between asset listed and sold. *SAV* is the sale-price-to-appraisal-price ratio. *Sale Price* is the transaction price of the asset, the unit is thousand RMB. *n_bid* is the number of bids placed in the auction. *n_bidder* is the number of bidders placing a bid in the auction.

AssetClass	item_listed	sold_pct	P_sale/P_appraisal			Price, 10^3		n_bid	n_bidder
	count	%	p50	mean	sd	p50	mean	mean	mean
Consumptions	21977	62%	1	1.31	1.11	19	106	14.38	4.15
RealEstate	68834	32%	0.81	0.89	0.49	748	5297	15.36	2.78
PPE	11248	48%	0.81	1.15	1.17	82	2139	14.00	3.89
Intan	9087	50%	1	1.92	2.24	4	136	16.34	3.88
Equity	5123	43%	0.74	0.99	1.34	100	5046	16.34	4.16
Debt	2707	29%	0.08	0.28	0.8	81	1731	16.26	5.42
Pooled	11253	36%	0.8	1	0.99	330	10519	11.14	3.15

Table 4: Summary statistics: liquidation result by industry

This table describes the liquidation results of the auctions by industry. *item_listed* describes the total amount of assets listed. *item_sold* describes the total amount of assets sold. *sold_pct* is the ratio between asset listed and sold. *SAV* is the sale-price-to-appraisal-price ratio. *Sale Price* is the transaction price of the asset, the unit is thousand RMB. *n_bid* is the number of bids placed in the auction. *n_bidder* is the number of bidders placing a bid in the auction.

Industry	item_listed count	item_sold count	sold_pct %	sav p50	sav mean	sav sd	Price p50	Price mean	n_bid mean	n_bidder mean
Accommodation and Food Services	2421	446	18%	1.02	1.74	1.78	93	4730	6.83	4.35
Administrative and Support	285	118	41%	0.8	0.83	0.59	13	3915	5.47	2.24
Agricultural, forestry, fishing	1274	601	47%	0.7	1.02	1.29	43	2194	7.25	2.54
Arts, Entertainment, and Recreation	385	166	43%	0.9	1.52	1.93	31	1814	15.15	4.26
Construction	2333	1106	47%	0.97	1.35	1.39	97	3043	12.61	3.65
Education	2	1	50%	1	1		59279	59279	0.50	1.00
Finance	909	269	30%	1	1.38	1.28	17	1882	7.17	4.25
Health Care and Social Assistance	69	32	46%	0.94	1.08	0.78	39	639	11.42	3.84
Information	614	364	59%	1	1.43	1.67	8	1356	23.30	4.59
Manufacture	23663	11975	51%	0.84	1.15	1.14	56	5173	16.73	3.86
Mining	282	115	41%	0.94	1.14	1	394	5583	8.66	3.09
Other services	2058	1605	78%	0.85	0.89	0.28	112	881	14.33	2.75
Professional, Scientific, and Tech	5325	2430	46%	0.85	1.23	1.38	22	3226	15.32	4.08
Real Estate	19656	5741	29%	0.8	0.9	0.66	378	2538	5.11	2.61
Rental and Leasing	25305	8557	34%	0.81	1.06	0.81	8	2482	6.02	3.08
Retail	36128	15002	42%	0.88	1.12	1.08	69	3614	12.99	3.73
Transportation and warehousing	2039	1095	54%	0.9	1.14	1.02	47	2653	14.60	3.62
Utilities	259	135	52%	0.94	1.26	1.21	180	3987	17.24	3.81

Table 5: Summary statistics: mean SAV by asset type, industry

This table summarizes the mean SAV (SalesPrice-to-AppraisalPrice ratio) by asset-type-industry. *Consump.* refers to consumer goods including office supplies, electronics, auto vehicles, and collectibles. *RealEst.* includes business real estate, industrial real estate, residential real estate, and land. *PPE* includes equipment (including industrial vehicles), materials, and unfinished projects. *Intan* are mainly patents and brands. *Equity* refers to equity ownership for other companies held by the bankrupt firm. Debt refers to debt-like ownership for other companies held by the bankrupt firm. These are mostly account receivables. *Pooled* refers to multiple assets bundled to be sold together. *Else* refers to assets difficult to classify with the current classification algorithm.

Industry	Consump.	RealEst.	PPE	Intan	Equity	Debt	Pooled	Else	Total
Accommodation and Food Services	2.34	0.97	0.79	4.84	3.05	0.08	1.23	1.15	
Administrative and Support	1.19	0.99	1.10		0.57		0.73	0.56	
Agricultural, forestry, fishing	1.47	0.67	0.91	1.29	1.02	0.08	0.76	2.47	
Arts, Entertainment, and Recreation	1.19	0.73	0.87	3.29	1.18	0.08	1.10	2.50	
Construction	1.45	0.99	1.55	1.75	1.73	0.16	0.99	2.26	
Finance	1.76	0.80	0.77	0.73	0.66	0.53	0.88	1.33	
Health Care and Social Assistance	1.06	0.87	1.17				0.41		
Information	1.56	0.72	2.14	1.75			0.72	0.71	
Manufacture	1.34	1.01	1.14	2.19	0.94	0.30	0.99	0.85	
Mining	1.05	1.04	1.69	0.49	0.59	0.32	0.97	1.07	
Other services	1.18	0.87	1.25	0.52	0.90	0.32	1.08	0.80	
Professional, Scientific, and Technical Services	1.27	0.86	1.09	1.49	0.49	0.15	0.99	2.22	
Real Estate	1.50	0.85	1.43	2.08	1.34		0.90	1.34	
Rental and Leasing	1.28	0.82	1.01	1.85	0.90	0.41	0.90	0.94	
Retail	1.25	0.93	1.09	1.69	1.11	0.30	1.04	1.44	
Transportation and warehousing	1.18	0.99	0.96	4.39	0.42	0.16	1.31	1.06	
Utilities	1.67	0.95	1.29		1.49	0.12	0.80	3.69	

Table 6: Summary statistics: mean Prob(Sale) by asset type, industry

This table summarizes the mean Probability of sale by asset-type-industry. *Consump.* refers to consumer goods including office supplies, electronics, auto vehicles, and collectibles. *RealEst.* includes business real estate, industrial real estate, residential real estate, and land. *PPE* includes equipment (including industrial vehicles), materials, and unfinished projects. *Intan* are mainly patents and brands. *Equity* refers to equity ownership for other companies held by the bankrupt firm. Debt refers to debt-like ownership for other companies held by the bankrupt firm. These are mostly account receivables. *Pooled* refers to multiple assets bundled to be sold together. *Else* refers to assets difficult to classify with the current classification algorithm.

Industry	Consump.	RealEst.	PPE	Intan	Equity	Debt	Pooled	Else	Total
Accommodation and Food Services	0.84	0.08	0.31	0.77	0.53	0.53	0.41	0.43	
Administrative and Support	0.79	0.75	0.40	0.00	1.00	0.00	0.60	0.26	
Agricultural, forestry, fishing	0.72	0.43	0.45	0.73	0.59	0.18	0.32	0.57	
Arts, Entertainment, and Recreation	1.00	0.07	0.56	0.81	0.36	0.57	0.58	0.43	
Construction	0.73	0.37	0.63	0.75	0.51	0.11	0.50	0.83	
Finance	0.24	0.15	0.52	0.76	0.28	0.39	0.65	0.93	
Health Care and Social Assistance	0.85	0.50	0.34	1.00	1.00	0.00	0.33		
Information	0.76	0.54	0.67	0.53	0.51	0.27	0.64	0.97	
Manufacture	0.64	0.38	0.50	0.59	0.45	0.34	0.48	0.55	
Mining	0.58	0.26	0.42	1.00	0.67	0.15	0.40	0.61	
Other services	0.70	0.81	0.52	0.71	0.50	0.75	0.51	0.23	
Professional, Scientific, and Technical Services	0.74	0.25	0.43	0.40	0.50	0.33	0.55	0.67	
Real Estate	0.50	0.29	0.56	0.09	0.40	0.13	0.23	0.21	
Rental and Leasing	0.53	0.20	0.46	0.47	0.40	0.26	0.19	0.72	
Retail	0.74	0.29	0.45	0.48	0.40	0.34	0.31	0.63	
Transportation and warehousing	0.59	0.32	0.58	0.51	0.51	0.33	0.37	0.81	

Table 7: Summary statistics: liquidation result by appraisal method

This table describes the liquidation results of the auctions by appraisal methods. *item_listed* describes the total amount of assets listed. *item_sold* describes the total amount of assets sold. *sold_pct* is the ratio between asset listed and sold. *SAV* is the sale-price-to-appraisal-price ratio. *Price* is the transaction price of the asset, the unit is thousand RMB. *n_bid* is the number of bids placed in the auction. *n_bidder* is the number of bidders placing a bid in the auction.

Appraisal Method	item_listed count	item_sold count	sold_pct %	sav p50	sav mean	sav sd	Price p50	Price mean	n_bid mean	n_bidder mean
Cost Based	3017	2097	69.51%	1.00	1.31	1.32	299.4078	11305.69	28.73	4.35
DCF	1636	652	39.85%	0.76	0.82	0.60	624	7399.084	9.75	2.53
Matched to Market	3141	1909	60.78%	0.81	1.03	0.98	124.5	3473.193	15.03	3.08
NA	129856	52311	40.28%	0.85	1.08	1.07	72.94	2958.284	10.65	3.46

Table 8: Model estimation result

This table shows the parameter estimated from the auction model. Column (1) shows the estimation results for the whole sample. Column (2) to (9) estimate the result separately for the corresponding asset type. In Panel A, I show the estimation for α, the loading on appraisal price. α is derived through truncated regression $B_ij = \alpha A_i + u_ij$, where B_ij is truncated from below by R_i. In Panel B, I show the estimation result for mean and standard deviation for the rest of model parameters: x (common part), w (seller-private) and u (bidder-private). μ_u is 0. These parameters are estimated by MLE method from likelihood function 8

	(1) Consum.	(2) RealEstate	(3) PPE	(4) Intan	(5) Equity	(6) Debt	(7) Pooled
Panel A: Truncated Reg parameter							
α (App. Informativeness)	0.886	1.004	0.893	0.478	0.499	0.171	0.951
	(0.027)	(0.012)	(0.011)	(0.049)	(0.076)	(0.078)	(0.024)
Observations	30883	102392	17209	4253	3969	3219	18070
Panel B: auction parameter							
mu_x (Common Expertise ex. App)	-0.299	-0.483	-0.354	-0.879	-0.954	-0.514	-0.240
	(0.093)	(0.146)	(0.045)	(0.144)	(0.109)	(0.022)	(0.036)
sig_x (Common Expertise ex. App)	0.571	0.370	0.763	1.105	2.475	1.650	0.874
	(0.03)	(0.028)	(0.01)	(0.03)	(0.008)	(0.019)	(0.005)
sig_u (Bidder Specific Value)	0.156	0.132	0.123	0.279	0.148	0.096	0.103
	(0.023)	(0.023)	(0.005)	(0.021)	(0.011)	(0.006)	(0.004)
mu_w (Seller Specific Value)	-0.358	-0.133	-0.414	-1.069	-2.186	-4.695	-0.325
	(0.007)	(0.004)	(0.02)	(0.07)	(0.186)	(0.42)	(0.032)
sig_w (Seller Specific Value)	0.609	0.190	0.844	1.525	3.333	4.782	1.097
	(0.044)	(0.014)	(0.073)	(0.109)	(0.161)	(0.173)	(0.112)

Table 9: Appraisal report quality: summary statistics

This table summarizes the quality of appraisal reports regarding how much detail they cover. #Words counts the average number of words in an appraisal report. #Topics counts the total number of topics covered by all appraisal reports that fall into this asset type category.

AssetClass	Consumption	RealEstate	PPE	Intan	Equity	Debt	Pooled
#Words	3731	5666	5237	3347	7355	3997	6462
#Topics	325	618	275	158	103	52	165

Table 10: Asset specificity: evidence from ratio of jump bidders

This table summarizes the ratio of jump bidders and jump auctions for a given type of asset. A jump bid is defined as a bid that satisfies $B_t - B_{t-1} > MinimalIncrement$. $MinimalIncrement$ is the minimum amount that must be bid above the current bid to become the new highest bid. A jump bidder is a bidder who has at least submitted one jump bid in an auction. A jump auction is an auction where there has been at least one jump bid.

AssetClass	Consumption	RealEstate	PPE	Intan	Equity	Debt	Pooled
%JumpBidder	12.20%	7.40%	13.33%	17.48%	16.94%	12.03%	9.80%
%JumpAuction	12.89%	5.07%	9.60%	12.97%	8.46%	4.63%	6.41%

Table 11: Asset specificity: implication for the cost of limited competition

This table summarizes the cost of limited competition induced by the fact that the final buyer pays less than his true valuation in an English auction. The cost of limited competition is defined as $\frac{B_1}{B_2} - 1$, where B_i refers to the valuation for i-th highest valuation bidder.

AssetClass	Consumption	RealEstate	PPE	Intan	Equity	Debt	Pooled
Mean	0.106	0.077	0.087	0.242	0.126	0.070	0.087
Std.	0.097	0.070	0.076	0.256	0.123	0.064	0.078
Median	0.078	0.056	0.065	0.169	0.091	0.052	0.068

Table 12: Friction not captured: economic distress

This table illustrates the fact that economic distress, an important factor affecting final liquidation valuation, is not captured by appraisal prices. Distress is defined as the ratio of the number of closed businesses over the number of opened businesses in the province-industry combination. All prices in the regressions are log prices. Mean(logsale) = 10.91, mean(losapprs) = 11.44, mean(distress) = 0.25, sd(distress) = 0.14.

	(1) log(Sale)	(2) log(Apprs)	(3) log(Sale)	(4) log(Apprs)
distress	-1.21***	-0.16	-0.54*	-0.09
	(-4.00)	(-0.43)	(-2.47)	(-0.33)
log(reserve)			0.50***	0.54***
			(193.39)	(160.97)
Firmm, Time*Province, AstCls FE	Yes	Yes	Yes	Yes
R2	0.80	0.82	0.90	0.91
N	45975	32926	45975	32926

Table 13: Auction model parameter, by appraisal method

This table shows the parameter estimated from the auction model by different appraisal methods. Column (1) uses the cost-based method. Column (2) uses the discounted cash flow method (DCF). Column (3) uses the market-based method. In Panel A, I show the estimation for α, the loading on appraisal price. α is derived through truncated regression $B_ij = \alpha A_i + u_ij$, where B_ij is truncated from below by R_i. In Panel B, I show the estimation result for mean and standard deviation for the rest of model parameters: x (common part), w (seller-private) and u (bidder-private). μ_u is 0. These parameters are estimated by MLE method from likelihood function 8

	(1) CostB	(2) DCF	(3) Mkt
Panel A: Truncated Reg parameter			
α	0.938	0.977	0.917
	(0.003)	(0.008)	(0.004)
Observations	9186	1680	6199
Panel B: auction parameter			
mu_x (Common value)	0.741	0.848	0.407
	(0.099)	(0.024)	(0.047)
mu_w (Seller private)	0.656	0.927	0.564
	(0.024)	(0.018)	(0.026)
sig_u (Bidder private)	0.113	0.093	0.139
	(0.013)	(0.003)	(0.011)
sig_x (Common value)	0.938	0.368	0.477
	(0.091)	(0.075)	(0.035)
sig_w (Seller specific)	0.884	0.664	0.771
	(0.024)	(0.018)	(0.022)

Table 14: How do bidders react to information friction

This table studies how bidders behave differently under different information regimes by regressing auction results on dummies of access to information. The regression equation is $Y = AccesstoInfo + Controls + FE$. Specifically, the LHS variable flg_bid is a dummy variable that equals to one if the asset is sold (i.e. has at least one bidder bidding on the asset). $sd(ExitBid)$ is the standard deviation of the participants' exit bids, illustrating how much do bidders disagree upon the value of the asset. SAV is the sale price to appraisal price ratio. n_bidder is the number of bidders participating in the auction. The two types of information are $Is_{I}nspection_{o}ffl$ if the offline inspection is canceled due to a temporary covid lockdown, and $Is_{A}ppraisal$ if there is an appraisal price benchmark. Details of these two measures are introduced in section **??**. I additionally control for the reserve price and deposits prior to the auction. I control for province-year-month fixed effect, firm fixed effect, and asset type fixed effect. The sample size is smaller than the descriptive statistics because I define exogenous shock to offline inspection specifically at the June 2020 to 2021 period.

	(1) flg_bid	(2) sd(ExitBid)	(3) SAV	(4) n_bidder
Is_Inspection_lkd	0.028***	-0.064**	0.143*	0.624***
	(0.010)	(0.027)	(0.082)	(0.215)
Is_Appraisal	0.049***	-0.029*		
	(0.007)	(0.017)		
ln_reserve	-0.029***	-0.050***	0.001	-0.091***
	(0.001)	(0.003)	(0.006)	(0.019)
ln_deposit	-0.012***	-0.015***	-0.119***	-0.208***
	(0.001)	(0.004)	(0.008)	(0.024)
Constant	0.626***	0.929***	1.989***	5.608***
	(0.013)	(0.031)	(0.090)	(0.233)
Observations	93564	12129	14396	14396
FE	ProvMonthYear, Firm, Asset Type			

A Appraiser incentives: no bunching around the kinks in the commission function

Antill (2021) shows that when a trustee's commission follows a kinked function of the total liquidation proceeds ("sales"), the bunching around the discontinuous kink point implies that the trustee is exerting suboptimal effort. In my setting, the appraiser commission follows a kinked regime: when the appraisal price is below 1,000 RMB (between 1,000 and 5,000/between 5,000 and 10,000/between 10,000 and 100,000/ above 100,000), the commission is 0.5% (0.2%/0.15%/0.05%/0.01%) of the appraisal price. If the appraiser manipulates the price to increase their commission, there will be significant bunching around the kink point where the commission-to-appraisal price changes. The reasoning is as follows: suppose we compare the appraiser's incentive to manipulate the price around 1,000 RMB. He faces the following trade-off: increasing 1 RMB of price gives him a .2% RMB of monetary earning. On the other hand, manipulating the appraisal price away from the fair value by 1 RMB increases the risk of loss of credibility by x%. At the kink point, the monetary incentive has a discontinuous drop from .2% to .15%. As long as x does not change discontinuously around the kink point, appraisers whose risk of loss of credibility ranges between .15% to .2% will choose to manipulate the appraisal price to just 1,000 RMB[14].

I plot the histogram of appraisal price around the kink points. As is shown in the picture, although there is slight bunching of frequencies around the kink point of 1,000 RMB and 5,000 RMB, such bunching can be mostly explained by bunching around real number.

[14]If he reduces the appraisal price by 1 RMB, the reduced monetary loss will be greater than the reduction in credibility risk of x%. Thus it is not optimal for him to reduce the appraisal price. Similarly, he will also not be interested in increasing the appraisal price by 1 RMB.

Figure 13: Histogram of appraisal price, no evidence of bunching around the compensation kink point

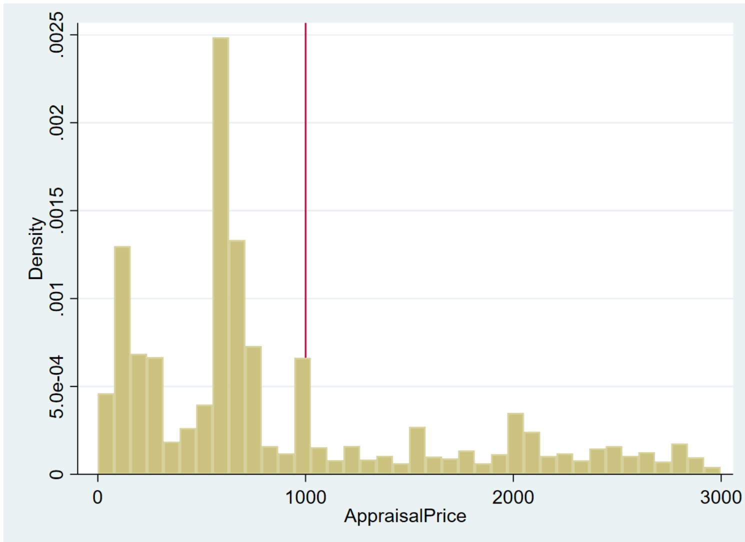


Figure 14: Bunching around 1,000 RMB

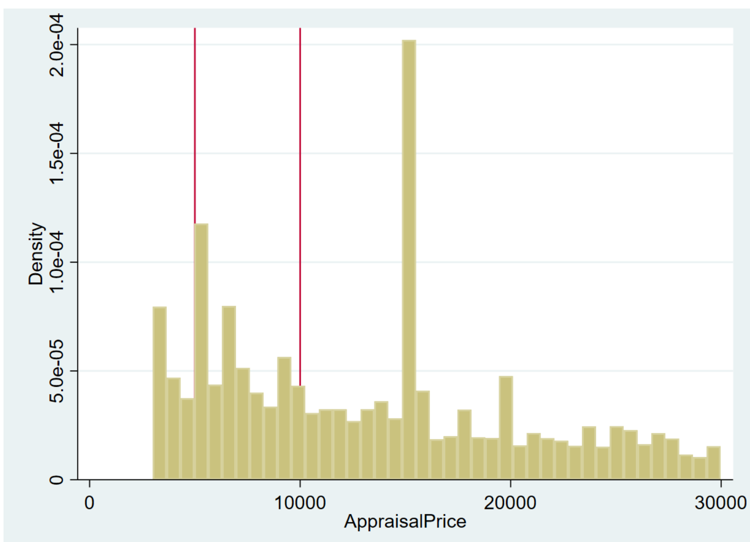


Figure 15: Bunching around 5,000 and 10,000 RMB

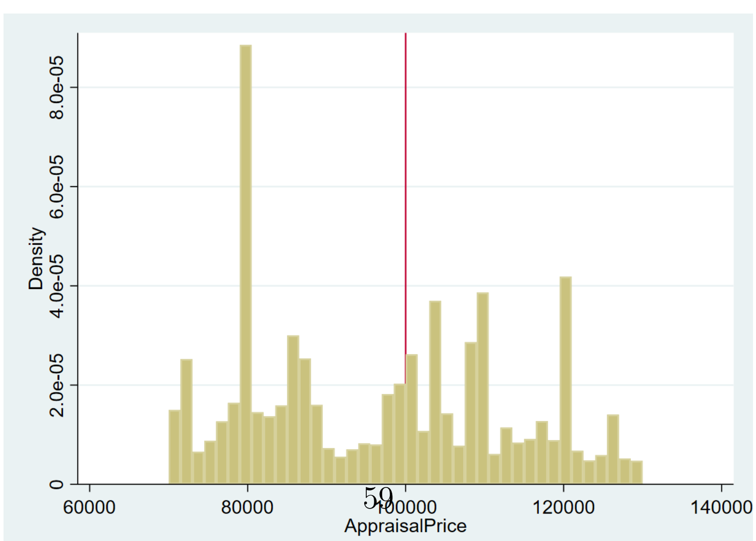


Figure 16: Bunching around 100,000 RMB

B Nonparametric estimation

In this section, I show the nonparametric estimation results. The estimated distribution of the valuation is close to normal distribution. Thus in the rest of the paper, I estimate the valuation with the assumption that the valuation follows normal distribution.

C Optimal reserve price

In this section, I show that simplify the setup: $B = X+U$, the seller has his seller specific preference S, B F_B, and U F_U The optimal reserve price fully incorporate X and satisfy the following structure:

$$\begin{aligned}
R &= X + S + \frac{1 - F_B(R)}{f_B(R)} \\
&= X + S + \frac{1 - F_U(R-X)}{f_U(R-X)} \\
&= X + W \\
Where W &= S + \frac{1 - F_U(W)}{f_U(W)}
\end{aligned}$$

Notice that here F_U is a constant parameter, so it is independent from the realization of U

D Estimation when reserve price is binding

For English auction with a public reserve price, only bidders whose valuation is higher than the reserve price will bid for the item. Define the following scenarios:

$$\begin{aligned}
D_1 &= 1(R > B^2 \geq B^3) \\
D_2 &= 1(B^2 \geq R > B^3) \\
D_3 &= 1(B^2 \geq B^3 > R)
\end{aligned}$$

The likelihood function for no bidder bids for the item, only one bidder bids for the item and more than one bidder bid for the item are:

$$p_1(r) = \int_{-\infty}^{\infty} \int_{-\infty}^{r-x} F_{U^2|U^3}(r - x \mid u_3)\, f_{U^3}(u_3)\, du_3 f_W(r-x) f_X(x) dx \tag{13}$$

$$p_2(r, b_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{r-x} f_{U^2|U^3}(b_2 - x \mid u_3)\, f_{U^3}(u_3)\, du_3 f_W(r-x) f_X(x) dx \tag{14}$$

$$p_3(r, b_2, b_3) = \int_{-\infty}^{\infty} f_{U^2|U^3}(b_2 - x \mid b_3 - x)\, f_{U^3}(b_3 - x)\, f_W(r-x) f_X(x) dx \tag{15}$$

The total log-likelihood function is

$$l_p(\theta, Z_i) = D_1 ln(p_1(R_i)) + D_2 ln(p2(R_i, B_i^1) + D_3 ln(p_3(R_i, B_i^2, B_i^3)) \tag{16}$$

Where $Z_i = (B_i^2, B_i^3, Z_i)$ denotes the data for auction i and $\theta = (f_X, f_W, f_U)$ denotes the parameter.

E Nonstandard bidding behavior

In the major auction model, I assumed that bidders adopt the weakly dominant bidding strategy of increasing their bids gradually until the current price exceeds their valuation. However, in real-world auctions, there might be alternative equilibriums where bidders adopt non-standard bidding practices due to behavioral or strategic incentives. In this section, I examine whether such non-standard behavior exists in my auction setting, the cause of such nonstandard behavior that deviates from the optimal strategies, and how they affect my previous estimation results.

E.1 Collusion

Several studies (Graham and Marshall, 1987; Robinson, 1985; Phillips et al., 2003) have documented that English auctions, especially the ones with repeated auctions and the same group of participants are prone to collusion. The cartel members collude to keep low the prices of assets for sale at auction by not bidding against each other. [15]Collusion is rarely discussed in online auctions due to the anonymity of its bidders and the low cost of entry. This is because both the formation and enforcement of the collusion agreement require identifying auction participants' identities (Zhang, 2022). It will be difficult to form a cartel if bidders do not know who they are bidding against, and even if the cartel is formed, the participants can deviate from the collusion agreement by participating in the auction under a separate anonymous account.

In this online liquidation auction, temporary auction-specific IDs are assigned to the participants (see figure 10), making it difficult to identify the bidders' identities. The cost of entry is low: the median entry deposit is 14,000 RMB (the average annual household income is 29,975 RMB), and the deposit will be returned to the losing bidders after the auction concludes. Unfortunately, this data does not allow for most common tests for collusion like Zhang (2022); Kawai and Nakabayashi (2022); Marmer et al. (2016) because I can not observe the bidder's behavior across auctions.

[15]The collusion can be regarded as a three-step process: pre-auction value revelation, formal auction, and post-auction allocation. In the first phase, members of the carter hold a private auction to decide who has the highest value of the asset, and the winner of the pre-auction is the "designated winner" of the cartel. In the formal auction phase, only the designated winner will actively bid in the auction, whereas the remaining cartel members will not bid against him. In the post-auction phase, the collusion profit shall be divided among cartel members so that it is incentive-compatible for the losing cartel members not to deviate from the collusive strategy.

Game theoretic models of collusion, such as Greene and Porter (1984) frequently require the threat of retaliation from the collusive agreement in order to sustain collusion in equilibrium. If it is more difficult to monitor the actions of other bidders, it will be more difficult to sustain collusive equilibrium via retaliation.

How to test it?

E.2 Conflict of interest and shill bidding

Shill bidding refers to the practice where the seller places bids covertly to artificially inflate the final sale price. If there is shill bidding, the seller captures more surplus in the auction. The 2017 provision regulates that people who work in the following places and their relatives can not participate in the auction: the court, the online auction platform, the appraiser, and all other service providers in the auction. Since the auction participants need to provide their identity to the auction platform when registering, shill bidding is prohibited in the judiciary auction market.

E.3 Snipping

Sniping refers to the practice of placing a bid as late as possible—usually seconds before the end of the auction—giving other bidders no time to outbid the sniper. Snipping is mechanically impossible in the auction because of the auction setting: the auction will be extended for 5 minutes if there is any bid within the last 5 minutes of the auction.

E.4 Jump bidding

Haile et al. (2003) proposed the possibility that losing bids do not necessarily reflect true values because of jump bidding, i.e. the ith highest bidder getting overbid before him being able to bid his exit price. Thus a jump bid would implicate an underestimated exit bid. This would not affect the exit bid for Marmer et al. (2016) argues that this is less likely to be the case for Internet auctions, which conforms more closely to the original "button" model considered in the theoretical literature given the low cost of bidding. On the other hand, the identification strategy that I use builds on only the exit bid of the second and third highest bidder. Second highest bidders are always able to bid their exit bid by English auction design. Thus the only additional assumption is that the third highest bidder could bid their exit bid before quitting the auction.

jump bidding in an ascending-bid auction with affiliated values using a multi-round signaling model. Bidders communicate their private information with one another via the sizes of jump bids. These signals are credible since bidders with lower private information incur a higher ex ante cost for choosing a jump bid with any given size.