Abstract

Settlements are instruments to expedite case resolution. Though most civil cases are settled, these settlements are often achieved after long periods of expensive litigations, causing avoidable inefficiencies. In this paper, I examine these inefficiencies and the decisions that produce them.

First, I construct a tractable and flexible bargaining model with time-varying flow costs and endogenous delays. Second, I estimate this structural model with a proprietary Cornerstone Research dataset. In this process, I devise robust strategies to account for unobserved heterogeneities. Third, I quantify the inefficiencies caused by settlement delays. Fourth, I evaluate welfare improvements associated with accelerated court judgements.

My key finding is that settlement delays create significant welfare losses which government policies about court acceleration can do little to mitigate.

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1 Introduction

Justice does not come cheaply in civil courts. In 2001, shareholders of the Enron Corporation went to court over the company’s fraudulent accounting practices. After losing billions in investments, claimants spent seven years and nearly seven hundred million dollars in legal fees to argue their case—only to settle out of court. Significant settlement delays in the Enron case are indicative of a larger paradox in the American legal system.

As instruments that expedite case resolution, settlements are generally considered welfare enhancing for both the plaintiff and defendant (Prescott and Spier, 2016). However, although a vast majority of cases end in settlements, cases rarely settle before long periods of costly litigations. Existing literature fails to adequately explain these delays and quantify the associated inefficiencies. In this paper, I address these shortcomings in four ways.

First, I construct a tractable and flexible bargaining model with time-varying flow costs and endogenous settlement delays. Second, robustly accounting for unobserved heterogeneities, I estimate this structural model with a proprietary Cornerstone Research dataset. Third, I quantify the inefficiencies caused by settlement delays. Fourth, I evaluate welfare improvements associated with accelerated court judgements.

I base my model on the tenets of Abreu and Gul’s (2000) influential reputational bargaining game. Because the contexts of the AG model and litigations are not fully compatible, I make comprehensive modifications to capture the following dynamics: monetary transfers between parties (in the form of settlements and court judgments), time-varying flow costs, time-varying outside options, and court judgments.

What results is a rich bargaining model which, despite the numerous variables it encapsulates, is highly tractable and very well suited to be structurally calibrated. My estimation strategy is based on converting this structural model into a random effects

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1Case information is based on the reporting by Stanford Law School’s Securities Class Action Clearinghouse http://securities.stanford.edu/filings-case.html?id=102098
2To be very precise, the number of cases that are settled is significantly larger than the number of cases that go to trial. Many other cases get dropped or dismissed.
3A more detailed explanation of my adjustments are as follow. First, agents in the original model negotiate over windfall gains while litigants negotiate over transfers between themselves. Second, the agents in the Abreu and Gul (AG) model negotiate over fixed pies while litigation settlement surplus pies are time-varying. Third, the original model has no flow costs while litigations are very expensive affairs. Fourth, the AG model is an infinite horizon game while litigations are finite horizon games: at some point, (unless the case is dropped) a judge will surely rule on the dispute.
model where factors like costs appear as unobserved heterogeneities. I pay special attention to avoiding restrictive statistical assumptions.

I estimate my model in quartiles of data ranked by case size (defined as the alleged monetary damages). This strategy allows me to approximate dependence between case size and unobserved factors like costs without needing to assume exact statistical relations. Then, within every subgroup, instead of directly assuming density functions of latent variables, I employ flexible mixture models to approximate those unknown densities.

Ultimately, I estimate the average inefficiencies for a typical case to be $14M. (For context, the typical settlement is $15M.) I also conclude that litigation costs are back-loaded, meaning that most costs (in the form of legal fees and business disruption) come at the end of the litigation process.

Moreover, implementing counterfactual analyses, I find that accelerated court judgments have muted effects on inefficiency. For the Cornerstone sample, I calculate that a one-month reduction in the judgement period generates an expected welfare improvement of $209M on average. However, even after this reduction, total inefficiency is more than $12.1B.

1.1 Literature Review

The literature has developed many explanations to the paradox of settlement failures and some for settlement delays. This paradox is especially striking in the American legal system where parties are not awarded their legal costs even when they win their cases in court (Chopard, Cortade, and Langlais, 2010).

These explanations can mostly be categorized into two groups. The first relies on well-known game-theoretic conclusions about how imperfect information can cause breakdowns in negotiations (Kennan and Wilson, 1993). Bebchuk (1984) presents one of the earliest examples of private information in lawsuit models. In this model, only the defendant knows her true odds at a successful court judgement. Hence, she might fail to coordinate a settlement with a plaintiff who misestimates the true probability of her success. Another example is Wang, Kim, and Yi’s (1994) model where only the plaintiff knows her true damages, which causes settlement delays and breakdowns. There are many more models that permute information asymmetries and derive settlement breakdowns and delays. However, the validity of these asymmetries is questionable.

From depositions to complaint filings, parties communicate intensely with each other
from the very start of the legal process. For this reason, it seems unlikely that information asymmetries can exist for a significant amount of time.

The second category of explanation relaxes standard assumptions about rationality to solve the paradox. An example is Vasserman and Yildiz’s (2019) model, populated by optimistic lawyers who delay settlements. In the model, lawyers acquire information about their true odds at a successful court judgement over time. Optimistic lawyers overestimate the probability of receiving favorable information in the future and thus might choose to delay settling. However, it is once again not clear whether assumptions on systematic optimism are valid. It seems more likely that lawyers are feigning optimism than systematically misunderstanding case fundamentals (e.g., probability of success in court).

On the technical side, many of the existing models abstract away from the time dimension in the negotiation phase. For example, Sieg’s (2000) article (a rare example of structural estimation in the literature) tries to statistically recover litigation costs without modeling a time dimension. However, the timing of settlements greatly impacts costs (Hannafor-Agor and Waters, 2013). Abstractions like these were likely done for tractability purposes, as many models with time dimensions (e.g., Cooter, Marks and Mnookin, 1982) do not have closed-form solutions.

In addition to theoretical problems, the literature is also constrained by a dearth of data. Under many circumstances, it is not mandatory that information on settlements be publicly released (Gibeaut, 1998). Therefore, data on settlements are uncommon. Securities class actions are an important exception because the disclosure of these settlements is mandatory. Class actions of this type are filed by shareholders who claim losses due to their company executives’ alleged misconduct.

Due to immediate implications of securities class actions on corporate governance and financial economics, many empirical studies have focused on repercussions to executives, market prices, firm financial health, etc. (See Arena and Julio (2015); McTier and Wald (2011); Bai, Cox, and Thomas (2010) for some recent examples.) A parallel research field has also emerged, analyzing the consequences of government’s enforcement suits against public companies. (See Karpoffa, Leeb, and Martinb (2008) for an analysis of government-initiated lawsuits after the 2008 financial meltdown.) However, data on securities class actions could be useful for other purposes as well: specifically, studying

\[\text{https://www.uscourts.gov/about-federal-courts/types-cases/civil-cases}\]

\[\text{With the passage of Private Securities Litigation Reform Act of 1995, it is difficult to seal settlement amounts in securities class actions. https://www.law.cornell.edu/uscode/text/15/78u-4}\]
settlement decisions, as I do in this paper.

In other parts of the empirical literature, it is well established that litigation costs affect settlement decisions and amounts (Glover, 2012). However, data on costs are generally hard to collect. Some studies try to recover costs from aggregate insurance company financial data (e.g., Towers Watson, 2011). Other studies analyze fees awarded to plaintiffs’ lawyers (e.g., Fitzpatrick, 2010). Still others have relied on survey results (e.g., Hannaford-Agor and Waters, 2013).

However, these measures do not fully characterize the costs that parties bear. Litigants also incur implicit costs such as business disruption. Presumably, these implicit costs have significant effects on settlement decisions as well. Therefore, I evaluate a much more holistic cost metric in this paper.

Cognizant of empirical and theoretical gaps in the literature, I utilize securities lawsuits data to shed light on settlement decisions. I model costs as more holistic than legal fees and as potentially time-varying. Ultimately, settlement delays in this model persist because of an intuitive dynamic: Neither party wants to show her cards first.

1.2 Roadmap

Section 2 builds a game theoretical bargaining model that serves as the foundation for this paper’s analysis. Section 3 reports the data used for estimation. Section 4 presents the estimation strategy. Section 5 reports estimation results and considers policy solutions. Finally, Section 6 concludes.

2 Model

A risk-neutral plaintiff $P$ and risk-neutral defendant $D$ are locked in a civil dispute. At the beginning of the game ($t = 0$), both parties simultaneously make demands regarding settlement surplus allocations ($s_P$ and $s_D \in [0, 1]$). If the demands are compatible (i.e., $1 \geq s_D + s_D$), $P$’s and $D$’s demands are implemented with equal probability.

If the game does not end immediately (i.e., incompatible demands), settlement offers are redeemable until the terminal period $T \in \mathbb{R}_+$, at which point the court rules on the case. The court orders $D$ to compensate $P$ for her alleged damages $\omega \in \mathbb{R}_+$ with
probability $\rho \in (0, 1)$. With probability $1 - \rho$, the court rules against $P$, and no transfers are made. The game ends with the court’s judgement.

At all times $t \in [0, T)$, if a party has not yet conceded, her counter-party decides whether to concede (and thus end the game) or to continue litigating. For every moment agents continue litigating, they expend flow costs. Agents’ (individual) cumulative flow costs at time $t \in [0, T]$ is $K(t) = T \cdot c \cdot \left(\frac{t}{T}\right)^\kappa$, where $c \in \mathbb{R}_+$ is the average flow cost per agent per unit of time and $\kappa \in (0, \infty)$ parameter determines the timing and not the total size of litigation costs. $\kappa > 1$ represents back-loaded costs, $1 > \kappa$ represents front-loaded costs, and $\kappa = 1$ represents uniform costs across time. Note that, at time $T$, the cumulative cost is $T \cdot c$ (i.e., the duration of a full litigation times the average flow cost of litigating), and thus $\kappa$ does not affect the total size of costs. Finally, note that both agents know the values of $T$, $\rho$, $\omega$, $c$, and $\kappa$ when strategizing about offers and concessions.

2.1 Agent Types and Causes for Delays

The model is populated by two types of agents: flexible and stubborn. Flexible agents maximize their expected monetary gains in the one-shot game and are willing to compromise to reach a mutually beneficial deal. Stubborn agents are unwilling to make a deal that gives positive surpluses to their counter-parties. They do not compromise even if their insistence is against their own financial interests. This behavior can be caused by many factors. Some examples could be (1) vindictiveness, (2) monetary considerations outside the one-shot game, (3) significant unrealistic optimism about the strength of their case, or (4) other reasons for irreconcilable disagreements on parties’ prospects. I do not take a position on what causes stubbornness in agents.

Agents know that $z \in (0, 1)$ portion of all agents are stubborn. Moreover, they know model’s terminal periods are not stochastic like Fanning’s (2016) set-up, which uses terminal period uncertainty to induce deadline effects. My model ends up exhibiting deadline effects under certain circumstances.

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8Levin (2004) presents some attrition models with flow costs, but those costs are uniform across time. The model presented in this paper allows for time-varying costs.

9Abreu and Gul (2000) call these types rational and irrational, respectively. Fanning (2016) calls them behavioral and non-behavioral, respectively. To better reflect the way many people might think about litigations, I change the labels.

10This specification is analogous to the one behavirol-type model in Fanning (2016) if it is initialized with $\alpha_i = 1$.

11Note that if disagreements are small relative to case size, parties might still be able to settle.
whether they themselves are stubborn. However, they do not know whether their counter-
parties are stubborn. This information asymmetry allows flexible agents to posture as
if they are stubborn to try to force their counter-parties to capitulate. This attrition
process is the main driver of delays. The important point is that the model predicts
significant settlement delays even when $z$ is very small.

2.2 Surplus

Surplus of a settlement amount $a \in \mathbb{R}_+$ can be derived by referencing agents’ outside
options. $P$’s outside option at time $t$ (i.e., her expected gains from not settling at $t$ and
instead litigating to reach court judgement) is worth

$$\pi_P(t) = \rho \cdot \omega - \left[ K(T) - K(t) \right].$$  \hspace{1cm} (1)

Similarly, $D$’s outside option is worth

$$\pi_D(t) = -\rho \cdot \omega - \left[ K(T) - K(t) \right].$$  \hspace{1cm} (2)

Then, agents’ combined surplus from settling for $a$ is

$$\pi(t) = \left[ \pi_P(t) - a \right] + \left[ \pi_D(t) - a \right],$$

$$= 2 \cdot \left[ K(T) - K(t) \right].$$ \hspace{1cm} (3)

It is important to note that $\pi(t)$ (i.e., total surplus) is equal to parties’ combined savings
in future litigation costs. Therefore, as settlements get delayed, surplus will decrease
because more flow costs will be sunk.

Intuitively, expected court judgement does not appear in total surplus because court
judgements are zero-sum. However, litigation costs are irrecoverable and are a drain on
both agents. Therefore, by avoiding paying more costs, both parties benefit.

Finally, note that, regardless of $a$, the total surplus is the same. However, no agent
would accept a settlement amount that is worse to them than taking their outside option.
Therefore, without loss of generality, $a$ can be considered as bounded above by $-\pi_D(t)$
and below by $\pi_P(t)$.

In this region, negotiating over $a$ is analogous to negotiating over surplus distribution.
For mathematical tractability, I choose to solve the equilibrium in terms of surpluses
rather than in terms of settlement amounts.
2.3 Equilibrium

2.3.1 Offers

Stubborn agents demand the entire surplus pie, as explained before. Flexible agents’ best response is to mimic stubborn agents and also demand the entire surplus pie. If a flexible agent does not make the same request as a stubborn agent, she exposes herself as flexible. Once she is exposed, her counter-party has every incentive to posture as stubborn herself and wait-out the exposed party until capitulation. Considering that there is a positive chance that her counter-party is stubborn, the outed party’s best course of action is to concede immediately. Therefore, the flexible party’s optimal strategy is to make the demand that a stubborn agent would make. That is, \( s^* = 1 \). This part of the model is analogous to AG where the rigorous mathematical proof of this fact is provided. Hence, I do not repeat the proof in this paper.

2.3.2 Concession

Stubborn agents never concede. However, flexible agents concede strategically. In this section, I solve for flexible agents’ optimal concession strategies. Let probability density function (PDF) \( f_j \) (defined on \([0, T]\)) and cumulative density function (CDF) \( F_j \) represent the concession strategy of agent \( j \). Assuming \( F_j \) is absolutely continuous, agent \( i \)'s utility from conceding at time \( t \) is\(^{12}\)

\[
U_i(t) = \int_0^t \left[ \pi(s) - K(s) \right] f_j(s) \, ds + \left[ 1 - F_j(t) \right] \cdot \left[ -K(t) \right].
\]

Solving for agent \( j \)'s strategy that makes agent \( i \) indifferent to concede across time implies a hazard rate,

\[
\lambda_j(t) = \frac{f_j(t)}{1 - F_j(t)} = -\frac{1}{2} \cdot \frac{T^\kappa}{t^{\kappa}} \cdot \left[ \frac{\beta}{T^\kappa} \right]^{\frac{\kappa}{\kappa - 1}}.
\]

This hazard rate can be translated into the concession CDF for agent \( j \),

\[
F_j(t) = 1 - e^{-\int_0^t \lambda_j(s) \, ds} = 1 - \left( \frac{T^\kappa}{T^\kappa - t^\kappa} \right)^{-\frac{1}{\kappa}}.
\]

\(^{12}\)Note that simultaneous concession has zero probability though it is still in the sample space. I exclude it from the formula because it does not have a positive probability of occurring.
Note that \( F_j \) is not conditioned on \( j \)'s type. At this point, close attention has to be paid to how \( i \) updates her beliefs about \( j \)'s type. The probability of \( j \) having been initialized as stubborn conditional on not conceding by time \( t \) is

\[
\bar{z}_j(t) = \frac{z}{1 - F_j(t)}. \tag{7}
\]

At \( t^* = F_j^{-1}(1 - z) = (1 - z^2)\frac{1}{\kappa} \cdot T \leq T \), \( j \)'s reputation as stubborn reaches 100\%, and she will certainly not concede thereafter (because all the flexible agents would have conceded before that point). Recall that stubborn-types never concede. Therefore, the following adjustment produces flexible \( j \)'s strategy\[13\]

\[
\bar{F}_j(t) = \frac{1 - (\frac{T^\kappa}{T^\kappa - t^\kappa})^{-\frac{1}{2}}}{1 - z}. \tag{8}
\]

At \( t^* \), \( \bar{F}_j \) hits 1. The flexible-type agent \( j \)'s concession PDF is

\[
\bar{f}_j(t) = \frac{\kappa \cdot t^\kappa - 1 \cdot T^\kappa \cdot (\frac{T^\kappa}{T^\kappa - t^\kappa})^{-\frac{3}{2}}}{(T^\kappa - t^\kappa)^2 \cdot (1 - z)}. \tag{9}
\]

and is defined on \([0, t^*]\). By the symmetries of flexible \( i \) and flexible \( j \)'s strategies, the combined concession strategy of two flexible types is

\[
\bar{F}(t) = 1 - \left[ (\frac{T^\kappa}{T^\kappa - t^\kappa})^{-\frac{1}{2}} - \frac{z}{1 - z} \right]^2, \tag{10}
\]

and the corresponding PDF is

\[
\bar{f}(t) = \frac{\kappa \cdot t^\kappa - 1 \cdot T^\kappa \cdot (\frac{T^\kappa}{T^\kappa - t^\kappa})^{-\frac{3}{2}} \cdot (\frac{T^\kappa}{T^\kappa - t^\kappa})^{-\frac{1}{2}} - z}{(T^\kappa - t^\kappa)^2 \cdot (1 - z)^2}. \tag{11}
\]

The model is now closed\[14\]

### 2.3.3 Preparation for Estimation

Considering the model is ultimately fit on settlement data, PDFs in line (9) and in line (11) are not ready for estimation. Note that although settlements are observed, types

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\[13\] This correction is in line with Levine (2004).

\[14\] Because agents are ex-ante symmetric, neither party has to concede with positive probability at time \( t = 0 \) like in the Fanning (2016) model.
of agents are not observed in the dataset. Hence, the settlement PDF conditional on eventual settlement is

\[ f_{t|T}(t|T, \kappa, z) = \frac{(1 - z)^2 \cdot \bar{f}(t) + 2 \cdot z \cdot (1 - z) \cdot \bar{f}_j(t)}{1 - z^2}, \]

\[ = \frac{\kappa \cdot t^\kappa - 1 \cdot T - \kappa}{1 - z^2}. \tag{12} \]

This PDF is formed by adjustments based on probabilities of one and both agents being flexible. Then, the PDF is scaled up to adjust for the probability of neither agent being flexible (because a settlement would not have occurred with two stubborn litigants). The resulting PDF is highly tractable.

2.4 Comments

**Proposition 1.** All else equal, as costs become more back-loaded (i.e., larger \( \kappa \)), average settlement delays of flexible types increase.

The intuition is as follows. An important dynamic of the model is the interplay between flow costs incurred by delaying and the possibility of the counter-party’s concession during that delay. Therefore, the timing of flow costs (the \( \kappa \) parameter) is essential to agents’ strategies. Intuitively, back-loaded costs allow agents to avoid settling quickly because they do not face the bulk of their costs until later into the litigation.

**Proof.** Recall

\[ \bar{F}_j(t) = \frac{1 - \left(1 - \left(\frac{t}{T}\right)^\kappa\right)^\frac{1}{2}}{1 - z}. \tag{13} \]

The partial is

\[ \frac{\partial \bar{F}_j(t)}{\partial \kappa} = \frac{\frac{1}{2} \cdot \left(\frac{t}{T}\right)^\kappa \cdot ln \left(\frac{t}{T}\right)}{(1 - \left(\frac{t}{T}\right)^\kappa)^\frac{1}{2} \cdot (1 - z)}, \tag{14} \]

which is negative because \( T > t \). Hence, for \( \kappa' > \kappa \), \( \bar{F}_j(t|\kappa') \) first-order-stochastic dominates \( \bar{F}_j(t|\kappa) \).

**Proposition 2.** All else equal, under front-loaded costs (\( 1 > \kappa \)), conditional on not settling early, flexible agents’ concessions might exhibit deadline effects (i.e., the PDF might have a “U” shape).
Front-loaded costs incentivize quick settlements to avoid paying expensive premiums to continue litigating (proposition 1 showed this mechanic mathematically). However, over time, the incentive to delay could actually increases because future flow costs decay. Therefore, one might expect significant settlements delays conditional on the front-loaded case not settling early. Of course, the probability of such a case not settling early could be low. The boundary conditions for $\kappa$ does not have tractable analytical solutions. Therefore, this point is demonstrated numerically. Observe the following simulations where the flexible agent PDFs have “U” shapes.

**Figure 1:** Example 1

![Concession Density](image1)

**Figure 2:** Example 2

![Concession Density](image2)

**Proposition 3.** All else equal, when the stubborn population decreases (i.e., smaller $z$), average settlement delays of flexible agents increase.

Flexible agents posture as stubborn agents in their offer strategies, but unlike actually stubborn types, they concede with positive probability on every time interval. Therefore, every moment agent $i$ does not concede, agent $j$’s expectation on $i$’s stubbornness increases. How long should a flexible $i$ keep up her delaying tactic? The answer not only depends on $\kappa$ but also depends heavily on $z$.

The mechanism works through $i$’s expectation of $j$’s type. If there are a lot of stubborn types and a long time has already passed in the game, $i$ might see it best to concede soon because the probability that she is facing a stubborn type is considerable. However, if the stubborn population is small and a lot of time has passed, $i$ could continue delaying as she believes the probability of her counter-party’s stubbornness is not large enough yet. The passage of time increases the odds of $j$’s stubbornness. However, if $z$ is very small, the increased likelihood of $j$’s stubbornness might still be small. Therefore, a flexible agent’’s expected concession timing is longer when the stubborn population is smaller.
Proof. The partial of the appropriate CDF is
\[ \frac{\partial \bar{F}_j(t)}{\partial z} = 1 - \left(1 - \frac{t}{\bar{T}}\right)^{\frac{1}{\kappa}} \left(1 - z\right)^2, \]
which is positive. Hence, for \( z' > z \), \( \bar{F}_j(t|z) \) first-order-stochastic dominates \( \bar{F}_j(t|z') \). \( \square \)

3 Data

Empirical analyses in this project are based on two primary sources: a proprietary Cornerstone Research dataset and the CRSP database. The Cornerstone data include every SEC Rule 10b-5 securities class action settled between 2009 and 2018. The data report defendant names, relevant court dates, relevant stock information, and settlement amounts.

This dataset is merged with CRSP data on stock market volumes. The matched dataset consists of 601 cases. The aggregate information on the full and the matched datasets is provided in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Settlement Amount ($M, Full)</th>
<th>Settlement Timing (Mo., Full)</th>
<th>Settlement Amount ($M, Matched)</th>
<th>Settlement Timing (Mo., Matched)</th>
</tr>
</thead>
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<tr>
<td>count</td>
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<td>676</td>
<td>601</td>
<td>601</td>
</tr>
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<td>25.341</td>
<td>147.124</td>
<td>25.275</td>
</tr>
<tr>
<td>min</td>
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<td>0.275</td>
<td>12.267</td>
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<tr>
<td>25%</td>
<td>3.137</td>
<td>27.950</td>
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</tr>
<tr>
<td>50%</td>
<td>8.375</td>
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<tr>
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<tr>
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<td>226.067</td>
<td>2425.000</td>
<td>226.067</td>
</tr>
</tbody>
</table>

The descriptive statistics between the full and the matched datasets are very close. Therefore, the likelihood of a selection bias in matching seems low. Histograms of settlement data are provided in Figures 3 and 4.

\footnote{Cases with damages that are estimated as zero are also excluded from the matched dataset. There are 29 such cases.}
Lastly, qualitative information on the five cases that went through a full trial (since 2009) was taken from a 2016 report by another consulting company, NERA (Boettrich and Starykh 2017, NERA). More recent reports do not provide updated trial lists, most likely implying that no securities cases have been ruled by judges since 2016.

Note that some legal disputes settle before the litigation process starts. Because I can only track disputes where a case is filed with the court, I cannot comment on side-deals that resolve disputes without litigations. However, I doubt many securities cases are settled preemptively. Note that these cases are class actions because many investors suffer from the alleged actions of defendant companies. Hence, without a lead plaintiff who represents all class members, coordinating an exhaustive settlement with multiple parties with different stakes would be incredibly difficult.

4 Estimation

The key to this paper’s estimation strategy is recognizing that the game theoretical model can be translated into a random effects model. In this environment, parameters like $T$ and $c$ become unobserved heterogeneities. In the econometrics literature, some methods to estimate unobserved heterogeneities have been developed (see Heckman and Singer 1984 for an example). I use flexible mixture models to approximate $T$ and $c$ distributions. Moreover, to approximate dependence between unobserved heterogeneities, I estimate the structural model separately for every quartile of data as ranked by case size.

Estimations are implemented over three stages. First, propensity of stubborn types ($z$) is identified by analyzing the number of cases that do not settle. Second, terminal period distribution ($T$) and cost timing parameter ($\kappa$) are identified from settlement timing data. Third, the mean litigation cost ($c$) is identified from settlement amounts.
4.1 Type Propensity

Propensity of stubborn agents \((z)\) has a discernible impact on flexible agents’ settlement timings. Therefore, \(z\) could be fit in Stage 2 with settlement timing data. However, there is a more direct path to \(z\)’s estimation: namely, focusing on the cases that went to trial. Recall that the structural model posits that if both parties are stubborn, then neither accepts her counter-party’s settlement offer. So, the dispute cannot be resolved with a settlement, and thus the court eventually rules on the case.

Let \(x_i \in \{0, 1\}\) represent whether case \(i\) was settled \((x_i = 0)\) or was fully tried \((x_i = 1)\). The discrete distribution of \(x_i\) is Bernoulli with \(z^2\) probability of \(x_i = 1\) and \(1 - z^2\) probability of \(x_i = 0\). Then the likelihood function is

\[
L(\{x_i\}_{i=1}^N | z) = \prod_{i=1}^N (z^2)^{x_i} \cdot (1 - z^2)^{1-x_i},
\]

where \(N\) is the sample size, including all the cases that were settled or tried. This function is maximized by

\[
\hat{z}_{ML} = \sqrt{\bar{x}},
\]

where \(\bar{x} = \frac{1}{N} \cdot \sum_{i=1}^N x_i\), i.e., the fraction of tried cases. A closed-form estimate of the asymptotic variance of \(z_{ML}\) can also be derived by the quotient of the negative log-likelihood function’s second derivative. Hence, the asymptotic variance of the ML estimator is

\[
\hat{\text{Var}}(z_{ML}) = \frac{1 - \bar{x}}{4 \cdot N}.
\]

4.2 Trial Duration and Cost Timing

The settlement timing PDF derived in Section 2.3.3, \(f_{t|T}(t|T, \kappa, z)\), is comprised of three factors: propensity of stubborn types \((z)\), the realization of terminal period \((T)\), and the cost timing \((\kappa)\). Having already estimated \(z\) in the first stage, now \(T\) and \(\kappa\) can be estimated with data on settlement timing. Note that the following procedure is applied to every quartile of the data (ranked by case size) individually.

First, the PDF needs to be \textit{unconditioned} on the realization of \(T\), which researchers cannot observe and is unique to each cases. That is, \(T\) is an unobserved heterogeneity, which is required to be marginilized out of the PDF. Let the function \(g_T\) with a domain on \(\mathbb{R}_+\) represent \(T\)’s PDF.
Note that if a settlement take place at time $t$, it is immediately known that realization of $T$ must not have been smaller than $t$. If it were, the court would have already ruled on the case, and there could not be a settlement at time $t$. More precisely, line (7) implies that the smallest possible $T$ is $\bar{t} = \frac{t}{(1-z^2)^{\kappa}}$. Hence, the unconditioned settlement timing PDF is

$$f_t(t|\kappa, z, \theta_g) = \int_{\bar{t}}^{\infty} f_{t|T}(t|T, \kappa, z) \cdot g_T(T|\theta_g) \, dT,$$  \hspace{1cm} (19)$$

where $\theta_g$ represents the $T$ distribution’s parameters.

There is no economic or statistical rationale for assuming a particular heterogeneity distribution. For decades now, labor economists who attempt to estimate unemployment duration models have faced an analogous problem (Heckman and Singer 1984). To cope with this problem, my estimation approach is based on approximating the $T$ distribution with a flexible framework. I use a weighted combination of $K$ (truncated) gaussian distributions for approximation. The resulting mixture model can be represented as

$$f_t(t|\kappa, z, \theta_K) = \sum_{k=1}^{K} p_k \cdot \int_{\bar{t}}^{\infty} f_{t|T}(t|T, \kappa, z) \cdot \frac{\phi\left(\frac{T-\mu_k}{\sigma_k}\right)}{1 - \Phi\left(-\frac{\mu_k}{\sigma_k}\right)} \, dT,$$  \hspace{1cm} (20)$$

where $\theta_K$ is the collection of weights ($p_k$), (untruncated) means ($\mu_k$), and (untruncated) standard deviations ($\sigma_k$) of $K$ latent truncated gaussian distributions. These approximations are especially accurate if the $T$ distribution is smooth and has peak(s). Estimations suggest that the $T$ distribution is indeed well-behaved.

The likelihood function can be constructed as

$$L(\{t_i\}_{i=1}^{N} | z, \kappa, \theta_g) = \prod_{i=1}^{N} \sum_{k=1}^{K} p_k \cdot \int_{\bar{t}_i}^{\infty} f_{t|T}(t_i|T, \kappa, z) \cdot \frac{\phi\left(\frac{T-\mu_k}{\sigma_k}\right)}{1 - \Phi\left(-\frac{\mu_k}{\sigma_k}\right)} \, dT,$$  \hspace{1cm} (21)$$

where $t_i$ is the $i$’th case’s settlement timing. For a given $K$, this likelihood function can be optimized via the expectation maximization algorithm (EM). Note that, with more components (i.e., larger the $K$ gets), approximations get (weakly) better. Hence, there is no straightforward way of selecting the number of components as the likelihood function

\[16\] This approach is inspired by approximation theorems reviewed by Nguyen and McLachlan (2018).

\[17\] Note that truncation changes the actual means and standard deviation of resulting distributions. However, because the analytic formulas are still based on the untruncated gaussians’ means and standard deviations, for mathematical tractability, $\mu_k$ and $\sigma_k$ are the location and scale parameters of the $k$th distribution had it not been truncated.
is always (weakly) improved by adding a new component. For $K$ selection, I employ the Bayesian information criterion (BIC), commonly used in the K-means machine learning algorithm as the metric penalizes the number of parameters.$^{18}$

### 4.3 Case Fundamentals and Costs

Let $\eta_{D,i} = 1$ denote $D$’s concede and $\eta_{P,i} = 1$ denote $P$’s concede. Based on the structural model, a settlement amount can be decomposed as

$$s_i = \rho_i \cdot \omega_i + c_i \cdot T_i \cdot \left[1 - \left(\frac{t_i}{T_i}\right)^\kappa\right] \cdot (\eta_{D,i} - \eta_{P,i}).$$  

(22)

In expectation, $\eta_{D,i} - \eta_{P,i}$ equals 0, so the average cost cannot be recovered with regressions. Parametric stipulations have to be made such that the average can be derived from higher moments.$^{19}$ Note that the following procedure is applied to every quartile of the data (ranked by case size) individually.

#### 4.3.1 Estimating Damages

Damage (i.e., $\omega$) estimation is a critical part of trials. Plaintiffs and defendants often hire consultant to estimate damages. There are a couple of difficulties in establishing losses. First, only the stocks bought during the “class period” are eligible. This period is the timeframe that the alleged misconduct of the defendant took place. The first day of the class period is when the alleged fraud starts and the last day of the period is the last trading day before a so-called “corrective disclosure” is made by the company.$^{20}$ Second, stocks purchased in the class period must not have been sold before the class period’s end. The lead-plaintiff merely represents everyone who could be eligible. However, until the case is over and compensation is distributed, no one actually knows exactly how many investors can benefit from the court award/settlement.

Consulting firms like Cornerstone use “volume reduction assumptions” in their models to estimate how many shares are eligible (Bulan, Ryan, and Simmons 2018, a Cornerstone

$^{18}$https://jakevdp.github.io/PythonDataScienceHandbook/05.12-gaussian-mixtures.html
$^{19}$This statement implicitly assumes that the chosen distribution will have at least a finite variance.
$^{20}$Sometimes this period is not lined up so cleanly. Some information might leak before the disclosure. And, some lawsuits are filed before the corrective statement is even made. However, these events are rather uncommon.
I follow a standard two-trader model to estimate the size of the eligible pool from daily trading volume data as presented by Gkatzimas, Li, and Voetmann (2017, a Brattle Group report). Moreover, I appropriately discount daily volumes to not double count trades (due to factors like market maker activity) as prescribed by Simmons and Ryan (2006, a Cornerstone Report).

Once the eligibility pool is established, the actual investor loss has to be calculated. I use a “constant dollar value line” that designates the price decline on the corrective disclosure as shareholder losses (Bulan, Ryan, and Simmons 2017, a Cornerstone report). Calculating this loss is also a laborious process as market participants use everything from simply looking at price decline to event studies. I did some early testing with simple price declines and event studies. Headline results did not seem to change significantly. Therefore, I use the Disclosure Dollar Loss (DDL) index provided in the Cornerstone dataset, which is simply the price decline from right before the corrective disclosure to right after. DDL is known to be highly correlated with settlement amounts, which is also borne out in this study’s dataset.

4.3.2 Estimating Distributions

Let \( v_i = c_i \cdot T_i \cdot \left[ 1 - \left( \frac{T_i}{t_i} \right)^\kappa \right] \) denote remaining costs (i.e., future costs saved) at the time of settlement \( i \). I assume a beta distribution for \( \rho_i \). Beta distribution’s support is (0,1), making it a natural candidate for the probability of success. Moreover, this distribution is already very flexible as it can exhibit peaks or it can be strictly monotonic.

I approximate \( v_i \) similarly to \( T_i \)’s approximation. The only difference is that I employ exponential distributions to form the basis of the approximation for \( v_i \). This modification is made because when gaussian distributions were used, the optimum \( \mu \) parameters were negative. That is, the truncated gaussians only exhibited decay, similar to exponential distributions. Hence, I choose to model exponential distributions directly for computational reasons.

It is not surprising that \( v_i \) has a decaying shape because settlement, damage, and remaining trial duration (i.e., full litigation duration minus settlement timing) have decaying distributions.

Settlement amount random variable is a convolution of \( \rho_i \cdot \omega_i \) and \( v_i \). Therefore, the settlement amount PDF can be constructed as follows. Suppose, in case \( i \), the defendant

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21 The report explains the necessity to make assumptions in the endnotes.
22 Details of discounting are in the endnotes of this report.
conceded (i.e., \( \eta_{D,i} = 1 \)). This concession implies that \( v_i = s_i - \rho_i \cdot \omega_i \). Note that settlement amounts cannot be negative; therefore, the boundary condition on the probability of success is \( \frac{s_i}{\omega_i} \geq \rho_i \). Then, the probability of observing \( s_i \) given \( \omega_i \), \( \eta_{D,i} = 1 \), and number of approximation components \( K \) is

\[
Pr(s_i | \omega_i, \eta_{D,i} = 1, \alpha_\rho, \beta_\rho, \lambda_\omega) = \sum_{k=1}^{K} p_k \cdot \int_{0}^{\min\{1, \frac{s_i}{\omega_i}\}} Pr_{\rho}(\rho_i | \alpha_\rho, \beta_\rho) \cdot Pr_v(s_i - \rho_i \cdot \omega_i | \lambda_{v,k}) \, d\rho_i,
\]

(23)

where \( Pr_{\rho}(\cdot) \) is the PDF of the beta distribution, \( Pr_v(\cdot) \) is the PDF of the exponential distribution, \( \lambda_\omega \) is collection of parameters \( \lambda_{v,k} \) of exponential distributions while \( \alpha_\rho \) and \( \beta_\rho \) are the parameters of the beta distribution.

Now, suppose that the plaintiff conceded (i.e., \( \eta_{D,i} = 0 \)), implying that \( v_i = -(s_i - \rho_i \cdot \omega_i) \) and \( \rho_i \geq \frac{s_i}{\omega_i} \). Then, the corresponding likelihood is

\[
Pr(s_i | \omega_i, \eta_{D,i} = 0, \alpha_\rho, \beta_\rho, \lambda_\omega) = \sum_{k=1}^{K} p_k \cdot \int_{0}^{1} Pr_{\rho}(\rho_i | \alpha_\rho, \beta_\rho) \cdot Pr_v(-(s_i - \rho_i \cdot \omega_i) | \lambda_{v,k}) \, d\rho_i.
\]

(24)

Note that the realization of \( \eta_{D,i} \) is not observed in the settlement data. Therefore, the likelihood of observing a specific settlement amount has to be unconditioned on \( \eta_{D,i} \),

\[
Pr(s_i | \omega_i, \alpha_\rho, \beta_\rho, \lambda_\omega) = Pr(\eta_{D,i} = 1) \cdot Pr(s_i | \omega_i, \eta_{D,i} = 1, \alpha_\rho, \beta_\rho, \lambda_\omega) + Pr(\eta_{D,i} = 0) \cdot Pr(s_i | \omega_i, \eta_{D,i} = 0, \alpha_\rho, \beta_\rho, \lambda_\omega)
\]

\[
= \frac{1}{2} \sum_{k=1}^{K} p_k \cdot \int_{0}^{1} Pr_{\rho}(\rho_i | \alpha_\rho, \beta_\rho) \cdot Pr_v(|s_i - \rho_i \cdot \omega_i| | \lambda_{v,k}) \, d\rho_i.
\]

(25)

Hence, the sample likelihood function is

\[
L(\{s_i, \omega_i\}_{i=1}^{N} | \alpha_\rho, \beta_\rho, \lambda_\omega) = \prod_{i=1}^{N} \prod_{k=1}^{K} p_k \cdot \int_{0}^{1} Pr_{\rho}(\rho_i | \alpha_\rho, \beta_\rho) \cdot Pr_v(|s_i - \rho_i \cdot \omega_i| | \lambda_{v,k}) \, d\rho_i.
\]

(26)

This system is optimized with the EM algorithm and the optimal number of approximating components are selected via their BIC scores. Once the \( v_i \) distribution is fit, the average \( c \) can be recovered by assuming independence between \( c \) and \( T \),

\[
E[c_i] = \frac{E[v_i]}{E[T_i] - E[T_i \cdot \left(\frac{T_i}{T}\right)^\kappa]}.
\]

(27)

Note that multiplying the likelihood function by a constant does not change the values of parameters that maximize the likelihood function. Therefore, I omit multiplying by \( \frac{1}{2} \) for every observation.
5 Results

5.1 Parameter and Inefficiency Estimates

Distributional fits are tight both numerically and visually. For visual analysis, I simulated 5,000 settlement timings and amounts from my distributional estimates. These simulations are compared to the Cornerstone data below.

![Figure 5: Settlement Timing Comparison Between Estimation and Data](image1)

![Figure 6: Settlement Amount Comparison Between Estimation and Data](image2)

Below, I summarize my findings. Greater detail can be found in the appendix sections A and B.

First, I estimate the fraction of stubborn agents ($z$) as 8.6% (with a standard deviation of 1.8%). Second, in all quartiles (as ranked by case size), I estimate the cost timing parameter ($\kappa$) to be between 3.78 and 5.06. In more intuitive terms, monthly costs are below average for the first 62% to 67% of the full litigation duration. In the tail-end, costs rise above the average. Hence, the model predicts that costs are generally back-loaded. Survey evidence aligns with the findings on back-loaded costs (Hannaford-Agor and Waters 2013).

Third, I estimate that the average duration until court judgements varies between 47 and 73 months, depending on the case’s size. This trend implies that larger cases take longer to litigate. Intuitively, larger cases could be generally more complex and hence require more time for the judge to rule. Fourth, these terminal period estimates imply that, with settlements, cases conclude 9 to 16 months before the court’s judgement on average.

Fifth, court judgement duration distribution is right-skewed. This shape implies that, although many cases have similar durations, some cases take significantly longer. Sixth, I estimate that average monthly costs vary between $448K and $915K. These costs are
similar for the first three quartiles but increase dramatically in the last quartile. This trend aligns with trends in settlement amounts. In the Cornerstone data, the lower 75% of cases have similar average settlements while those in the top 25% are significantly larger. Intuitively, cases with significant stakes probably require significant resources to litigate, explaining the jump in costs for the top 25% of cases.

Seventh, the average inefficiency (i.e., flow costs expended due to delayed settlements) is between $11M and $15M for the lower 75% of cases. In the top 25%, average inefficiency is $33M. These results are unsurprising, considering that larger cases have higher monthly costs and longer full-litigation durations. Therefore, settlements are delayed for longer and the cost of every month of delay is larger.

Eighth, the average inefficiency in the middle 50% of cases is $14M, with an average settlement of $15. In other words, significant resources are wasted due to settlement delays. Finally, on expectation, in the middle 50% of cases, settlements are reached when monthly costs are $1.4M, which is considerably larger than the average monthly cost of $534K for similar cases. That is, on expectation, settlements tend to be reached when costs exhibit significant non-linear increases due to the back-loaded structure.

5.2 Counterfactual Analysis

Litigants decide when to settle conditional on how long it will take the court to rule. Court durations are determined by a variety of factors ranging from case complexity to the court’s resources. Generally, government policy can play an important role in determining litigation durations. This factor is perhaps most apparent when courts are backlogged due to limited resources. In this section, I analyze the welfare consequences of faster courts. To be clear, I do not examine what types of policies can increase court speeds. I instead analyze how litigants’ settlement decisions would be affected if a policy could reduce court durations without altering other fundamental factors.

The model (and common sense) suggests that faster courts lead to faster settlements (and less inefficiency). However, how large are these gains? I answer this question in two parts: first by analyzing a representative case then by analyzing the population of cases.

5.2.1 Representative Case

Consider a case that has parameters equal to the averages of the middle 50% of cases. That is, $T = 51.86$, $\kappa = 4.76$, $c = \frac{0.534}{2}$. Let $I$ be the number of months by which the

25https://www.theguardian.com/commentisfree/2012/jul/18/virtual-courts-speed-justice
terminal period is reduced. To judge the effectiveness of the policy, consider the reduction in total costs as a benchmark,

\[ H(I, c) = I \cdot c. \]  

(28)

The actual welfare improvement can be quantified as the expected reduction in costs expended before settling:

\[
M_I(I, T, \kappa, z) = 2 \cdot \int_0^{(T-I)(1-z^2)^{\frac{1}{2}}} f_{\{T|t\}T}(t|T - I, \kappa, z) \cdot K(t, c, \kappa, T - I) \, dt
\]

Expected Inefficiency With Policy

\[
- 2 \cdot \int_0^{T(1-z^2)^{\frac{1}{2}}} f_{\{T|t\}T}(t|\kappa, z) \cdot K(t, c, \kappa, T) \, dt.
\]

Expected Inefficiency Without Policy

(29)

The difference between \( H(I, c) \) and \( M_I(I, T, \kappa, z) \) is that the latter metric accounts for cost non-linearities as well as the exact pass-through of court durations reduction to settlement delay reductions. Discrepancy in actual welfare gains and the benchmark is reported below.

**Figure 7:** Welfare in the Representative Case

Across every \( I \), the actual welfare improvement is approximately 50% of the benchmark. That is to say, inefficiency is reduced by considerably less than total costs are reduced. Note that by settling, litigants avoid paying some litigation costs. Hence, it is
not surprising that $H(I, c) \geq M(I, T, \kappa, z)$. However, pass-through of only 50% benefit raises questions about efficacy of reducing court durations.

5.3 Population

Now, consider the entire case population. Court duration reductions are more difficult to quantify when the entire $T$ distribution is considered. The difficulty is that $T$’s support is non-negative. Hence, if the $T$ distribution were shifted left by $I$, the distribution will have to be truncated and rescaled. After these operations, $T$’s new mean will not simply be the original mean minus $I$. I choose to measure welfare gains for cases that lie on the $[I, \infty)$ region of the $T$ distribution. That is to say, the new metric measures the expected inefficiency reduction of cases for which the court would have taken at least $I$ months to judge without the policy. This new metric is

$$M_P(I, T, \kappa, z) = 2 \cdot \int_I^\infty \left( \int_0^{(T-I)(1-z)^{\frac{I}{\kappa}}} f_{TT}(t|T-I, \kappa, z) \cdot K(t, c, \kappa, T-I) \, dt \right) \, dT$$

For each additional month of terminal period reduction, reduction in inefficiency is the same. Therefore, below, I report the welfare consequences of only a one month shift. For more detailed outputs, see appendix section C.

**Figure 8:** Absolute Reduction  
**Figure 9:** Relative Reduction
Similar to the results from representative cases, actual welfare gains are around 50% of the benchmark for every quartile. Absolute gains are similar for the bottom 75% of cases and significantly larger for the top 25%. However, relative to the total inefficiency of the quartile, gains in the bottom 75% are larger than in the top 25%. That is to say, improvements in court speeds imply larger absolute but lower relative gains for the largest cases.

All in all, welfare gains are modest for all types of cases. From 2009 to 2018, I estimate the expected welfare improvement from a one-month court duration reduction to be $209M over 676 cases. Note that, even after the policy, the total inefficiency is more than $12.1B.

6 Conclusion

This paper develops a highly tractable and flexible bargaining model with endogenous settlement delays and time-varying flow costs. The model relates settlement timing and amounts to factors that are unobservable to outside researchers. These factors include full litigation durations (i.e., how long the case would have taken had a settlement not been reached), costs, and case strength. With structural estimation, I recover these variables and comment on important market conditions like inefficiency.

In my econometric strategy, I make versatile statistical specifications to estimate the densities of and dependence between unobserved heterogeneities. In this process, I identify full litigation duration and timing of costs (i.e., whether costs are front- or back-loaded) from data on settlement timing, and I identify costs from data on settlement amounts.

I estimate that, between 2009 and 2018, total inefficiency (on expectation) was more than $12.3B (over 676 cases). Costs were back-loaded, and inefficiencies were largest in the top 25% of cases (as ranked by case size). Settlements occurred when flow costs far exceeded average monthly costs, which were similar for the bottom 75% of cases. For policy analysis, I conduct counterfactual analyses on welfare consequences of accelerated courts. I do not assess what policies can accelerate courts, but rather assess welfare gains if a policy could accelerate courts without distorting other margins.

The efficacy of policy on welfare is less than one might think. I find that welfare gains are only about 50% of the benchmark welfare metric (constructed as the reduction in total costs). However, if courts were to be accelerated, the model still expects some gains. A one-month reduction in the court judgement time would have increased welfare
by $209M between 2009 and 2018 (over 676 cases).

These gains are felt most strongly in the largest 25% of cases. However, welfare gains relative to the pre-policy inefficiency is the smallest for the top 25%. That is, absolute and relative gains are negatively correlated. This tradeoff is important for policy makers who, due to limited resources, may want to accelerate court judgements for only subgroups of litigations instead of the entire distribution.

Overall, the estimated magnitudes in this paper are about securities class actions in the U.S. More research is required to quantify inefficiencies in different types of litigations. However, though the exact numbers might change, conclusions of back-loaded costs and muted policy effects could be applicable to other types of cases.
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Appendices

A  Estimation Results

A.1  Stage 1

Table 1: Fraction of Stubborn Litigants

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<th>Estimate</th>
<th>St. Dev.</th>
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<td>0.018</td>
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A.2  Stage 2

Figure 1: Optimal No. of Components

Figure 2: \( \kappa \) Estimates

Figure 3: Estimated Average \( T \)

Figure 4: Components of \( T \) per Quartile
**Figure 5:** Estimated $T$ Distribution (Aggregated from Quartiles)

**Figure 6:** Settlement Timing Comparison Between Estimation and Data

**A.3 Stage 3**

**Figure 7:** Optimal No. of Components

**Figure 8:** Estimated Average $\rho$

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**Figure 10:** Components of $\nu$ per Quartile
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**Figure 25:** One Month Court Reduction’s Welfare Effects Between 2009 and 2018

**Figure 26:** Total Inefficiency Between 2009 and 2018