Section 1: Introduction

Like many other entities, it is typical for a sports league to want to maximize the profits

earned from producing and selling access to the competitions the league sanctions. As discussed

in classic fashion by Neale (1964), a league not only has to find ways to create compelling

matches but also has to create more compelling matches than other sports leagues. Fans have

only so many resources to devote to watching sporting events, and, like firms in non-sports

related industries, leagues often feel compelled to tinker with their product in order to continue to

captivate consumers.

The Association of Tennis Players (ATP) has historically granted players unlimited time

between points and no penalty was enforced for stalling. USTA spokesman Chris Widmaier

acknowledged that "pace of play is a major issue in sports today. We recognize that and we want

to be ahead of it" (Kovalchik, 2018). In April of 2018, the US Open announced it would display

a 25-second serve shot clock that year, though adherence to the clock was not required at this

time. In 2020, the serve clock became present at all Grand Slams and tournaments on the ATP

tour, with the first violation resulting in a warning and the second being a lost first serve. In a

tennis game, the serve is, "the only stroke that is self-generated, hit irrespective of the opponent"

(Wertheim, 2010). Thus, the pace of a match at any point in time is solely dictated by the player

who is serving and limiting this time re-introduces offensive excitement to the game.

The clock allows the league to preserve competitive balance by mitigating unfair

advantages between players that limit the uncertainty of outcome. In a match between two

players of differing physical abilities, the more fit player could restrict the returners' rest time

between points as the server and sustain a faster paced game than his opponent. However,

without the league's offensive restriction, the less fit player could supplement his lack of physical skill by taking increased rest time when in the serving position.

Looking at the variability in time taken between points across players, it is clear that the league was in need of stricter regulation. Rafael Nadal, a player who enjoys toweling off and performing his serving ritual, averaged 26.1 seconds between points, compared to the average player at 19-20 seconds, and faster players like Kyrgios and Federer at 16-17 seconds (Kovalchik, 2018). Andy Murray commented that he believed "the clock could have shaved more than 20 minutes," off of his first-round match in the 2018 US Open (Rothenberg, 2018).[1] The vast range of preparation times across players makes it unclear what the effect of the clock will be on the length of matches in totality, but we do anticipate the clock will have an effect on the way we think about the relative abilities between tennis players.

Rule changes like the serve clock are quite common in organized sport, as league organizers have had to find ways to react to changes in technology and society that alter demand for certain sporting contests. In 1954, the National Basketball Association implemented the shot clock to eliminate teams adopting stall tactics as a way to offset talent differences across opponents and rebound fan attention to the game (Surdam, 2012). In 1969, Major League Baseball lowered the height of the pitching mound to mitigate pitchers' advantages over hitting, thereby generating increases in run scoring (Bogage, 2019). The National Football League in 1994 adopted harsher constraints on contact between defensive backs and receivers in hopes of providing more opportunities for teams to pass (Craft, 2014).

Rule changes such as these alter the way sports are played by competitors and watched by interested spectators. Additionally, betting markets that exist to predict outcomes of these

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[1] See commentary from different players on the serve clock:
https://www.nytimes.com/2018/08/12/sports/tennis/serve-clock.html

contests have to adjust correctly to rule changes or risk a loss of profits. This purpose of this paper is to analyze the relative efficiency of betting markets' pricing decisions after the introduction of the serve clock.

Our findings suggest that the physical characteristics of youth and height were better served in the post-rule change world of professional tennis, as players who possessed those characteristics became more likely to win matches than before the clock was used. Critically, we find evidence of betting markets being somewhat slow to synthesize efficiently information in the near term about how tennis match results would be affected by the rule change. We use information was readily available to bookmakers about players' performance statistics, rankings, injury reports, and head-to-head statistics, but bookmakers were slow to react to the way professional tennis changed after the serve clock was installed, thus providing a window of opportunity for bettors to earn larger than normal returns from betting on professional tennis. To illustrate these increased possible returns, we use a reasonable betting algorithm to show how betting opportunities changed in the knowledgeable bettor's favor following the implementation of the serve clock, resulting in 30% increased returns in the eight months or so after the rule change.

This paper is organized in the following manner: In the second section, we offer a review of related and previously published studies on markets' abilities to respond efficiently to disruptions that forced pricing strategies to be altered. In the third section, we outline the methods we use to study how well tennis betting markets responded to the implementation of the serve clock. Here we describe the data we use to conduct the study, the hypotheses we generate from the data, and the empirical methods we employ to test these hypotheses. In the fourth section, we present our findings on how tennis changed with the implementation of the serve

clock and how betting markets were somewhat slow to capture these changes. Here we illustrate how returns to betting on tennis might have increased after the rule change for the knowledgeable. Finally, in the fifth section, we offer conclusions.

Section 2 - Related Literature

Our literature review starts with studies of how one is successful in professional tennis. We draw on a number of studies of tennis and what parts of the game correlate to winning or losing professional matches. Chief among these works is Klaassen and Magnus (2014), which touches on nearly every aspect of this paper as it pertains to our analysis of what occurs on the court. Ovaska and Summell (2014) analyzed court surface, tournament caliber, round of play, monetary incentives, and physical abilities to determine how these impact players of different ranks, and Barnett and Clarke (2005) looked at how break-point conversions affect win probabilities. Corral and Prieto Rodriguez (2010) found that models using past performance yielded the greatest accuracy in predictions as to who wins the match. Finally, Walker and Wooders (2011) research on the Minimax Hypothesis confirmed that win rates of serve players are consistent with mixed-strategy play, indicating that the serve has real implications for dictating whether a player wins the point, and, consequently, the match. Effectively, the benefit of winning an additional serve point over one's opponent has increasing marginal returns as this player will have a greater probability of winning his service games.

With regards to betting markets, it is not a newsflash for us to say that much of what we are discussing in this paper relates directly to Fama (1970), which provides evidence that supports the idea that asset markets react to information shocks in an economically efficient manner. Scores of papers have used an analytical framework similar to what was used in this

seminal paper to analyze how well entities were able to reconfigure pricing estimates after information shocks.

The ideas from Fama (1970) have spread to many fields other than asset pricing, and Corrado (2010) offers an excellent review of studies that have been conducted and the methods used in many studies published since Fama (1970).

Within studies of sports betting markets, Sauer (1998) discusses several aspects of betting markets, including the relative efficiency of the participants in the market. This influence of this study and the rise of easily obtained data have created a constellation of papers that have used gambling odds to answer various questions related to sports economics. One set of studies attempts to explore the Uncertainty of Outcome Hypothesis, as first discussed in Rottenberg (1956). For instance, Humphrey and Micela (2019), Mills and Fort (2013), Salaga and Tainsky (2015) show evidence of larger TV ratings of a college football bowl game and the pre-game odds of the game.

With regards to betting market efficiency, evidence in Sauer, Waller, and Hakes (2010) concludes that live betting markets of baseball games behave efficiently because live odds adjusted to in-game events in ways that were consistent with the Efficient Market Hypothesis.

Prior literature has provided ambiguous conclusions as to how bettors wager money specifically in professional tennis markets. Forrest and McHale (2007) examined the relationship between odds and returns using data from men's professional tennis matches and found that longshot bias exists. Angelini, Candila, and Angelis (2022) similarly conclude that the expected returns from different betting strategies as predicted by the Elo and WElo models was consistent with the longshot bias. Opposingly, Newall and Cortis (2021) argue that markets presenting gambles limited to only two possible outcomes (winning or losing) often produce favorite bias as

these types of gambles attract skewness loving bettors. Following this logic, they assert that longshot bias is more likely to present itself with a range of possible outcomes where there is no "sure bet" because these bettors look to maximize returns amongst competing longshots (i.e. placing a bet on the exact score of a football game). Tennis tournaments are structured such that the highest seeded players face opponents increasing in skill as they move to the later tournament rounds. It is realistic for either bias to present itself in these markets as gambles in earlier rounds typically have a surer option, while later stages of tournaments are expected to produce competitions between players of relatively similar skill.

Our work joins a few other studies that focused on how sports or betting markets responded to rule changes, without which we would have nothing to analyze. McCannon (2011) shows that three-point shooting success by men's college basketball players did not change following the rule change that lengthened the distance for such a shot. McFall and Treme (2011) show that PGA Tour golfers were able to alter their strategies in such a way that scoring did not change meaningfully following a rule change that limited the types of grooves allowed on club faces. Finally, Linna, Moore, Paul, and Weinbach (2014) find betting lines did not respond appropriately to rule changes made before the 2006 college football season. Scoring fell by more than markets expected, and bettors had chances to exploit the miscalculation by wagering that teams would score fewer points following the rule change. As far as we can tell, we are the first paper to consider the implications of betting market efficiency after rule changes to professional tennis.

Section 3 - Data and Methodology

We collected data from https://github.com/JeffSackmann, which sources data from the official ATP website on professional tennis matches. This paper uses panel data preceding the

rule change (2017 and 2018) and the time period following it (2021, 2022, and the former half of 2023). Information about the tournament level, round, and surface are provided, as well as the players' demographics, physical characteristics, current ranking, and in-match tennis-specific statistics. Round-robin tournaments and incomplete matches were excluded from the sample.[2] The final dataset has 11338 matches, 534 players, and 292 tournaments.[3]

We collected betting data from http://www.tennis-data.co.uk/, which lists the latest odds reported at the start of a match by individual bookmakers on oddsportal.com.[4] Our research refers to the odds provided by Bet365 as they cover the greatest number of matches included in the initial dataset and are regarded as the world's highest revenue sportsbook.[5] In cases where the market has priced both players equally, the model defaults to the average odds across all individual bookmakers listed.

We use these data in two different ways. Our equation 1 has the purpose of showing it is possible to create a model that reasonably successfully predicts which player wins a given match. Our equations 2 and 3 are set up to imagine how a bettor might use the data to choose which player is going to win a given match so that we can compare how successful our hypothetical betting models are to the market's rate of successful predictions. In both instances, our models allow for us to examine the likelihood of winning a match before and after the serve clock was implemented. Previous research on tennis has led us to believe that we must consider a multitude of skill factors while considering the probability of a player winning the match.

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[2] Round-robin tournaments do not follow a single-elimination structure, thus incentives to win are not homogenous. Incomplete matches are instances when a player does not complete the match (usually due to injury) and the winner is determined by forfeit.

[3] N < 11339 in model specification due to missing data on player height.

[4] These bookmakers are considered were: Bet365, Expekt, Ladbrokes, and Pinnacle Sport.

[5] See listings from https://bestonlinebookmakers.com/largest-bookmakers.html

Our basic regression model, which follows the structure of many previous event studies is:

(1) *Prob(betting favorite wins$_{jt}$) = β_0 + Physical Characteristics$_{jt}$*Ω + Tennis Skills$_{jt}$*T + Match Information$_{jt}$*Λ + δ_{rule}(β_0 + Physical Characteristics$_{jt}$*Ω + Tennis Skills$_{jt}$*T + Match Information$_{jt}$*Λ) + ε_{jt}*

We assign a value of one to the dependent variable for matches that the betting favorite won, and zero if not. *Physical characteristics* is a vector that contains information about relative physical characteristics of each player, like the height ratio and age ratio of the players, in match j at time t. *Tennis Skills* is a vector that contains information about how each player performed in match j at time t.[6] These characteristics include information presented in relative fashion on the various facets of the game of tennis, like serving or defending against or converting break points. For instance, in one specification we use the relative percentage of first-serve points won in a match. If the favored player won 60% of his first-serve points and the underdog only 30%, then the value of the variable *ratio % 1st-serve won* is two. The vector *Match Information* contains particulars pertinent to the match itself, like the round in a tournament the match occurred, the type of tour on which the match was played, the surface on which the match was played, and if the match is one of the four Grand Slam events is found in this vector.[7] We included the dummy variable, Big Three, when Nadal, Federer, or Djokovic played in the match. Of the 509 matches in our dataset that include one of these players, 88% of the matches were won by the Big Three player. The variable δ_{rule} takes on the value of 0 for matches that occurred before the change and 1 for post-rule change matches. Finally, the ε_{it} is a mean-zero error term.

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[6] Information about aces and double faults was not used in model specification as these discrete differences were highly correlated with other predictors and skewed regression results.

[7] We follow the work of Ovaska and Summell (2014) who determined that exogenous factors to ability such as prize money, round of play, and tournament level matter in estimating the probability of winning, and McHale and Morton (2011), whose forecasting model was 2.3% more accurate at predicting player rankings when court surfaces were treated uniquely.

We provide descriptive statistics for these variables in Tables 1 and 2. (About 56% of matches in our dataset occurred after the rule change.) The positive mean values of all the serve variables support Walker and Wooders (2011) empirical research in game theory stating that the serve is a critical aspect in determining who wins the match.

		(1)	(2)	(3)	(4)	(5)
Table 1: Summary Statistics Before Rule Change						
Variable Type	Variable Name	Mean	SD	Min	Max	N
Dependent Variable (binary)	Betting Favorite won (favorite = 1)	0.632	0.2	0	1	4,988
Physical Characteristics	Ratio of Age	1.046	0.256	0.483	2.069	4,988
	Ratio of Height	1.01	0.054	0.806	1.224	4,981
	Big Three	0.062	0.241	0	1	4,988
Tennis-Specific Skills	Ratio of % 1st Serves Made	1.024	0.181	0.494	2.06	4,988
	Ratio of % 1st Serves Won	1.111	0.226	0.462	2.917	4,988
	Ratio of % 1st Serves Missed	1.028	0.305	0.142	3.769	4,988
	Ratio of % 2nd Serves Made	1.038	0.327	0.148	3.891	4,988
	Ratio of % 2nd Serves Won	1.215	0.641	0.137	11.189	4,988
	Difference in Break Points Saved	-0.955	4.144	-20	22	4,988
	Difference in Break Points Faced	-2.015	5.398	-25	26	4,988
	Ratio of Rank	0.432	0.274	0.004	0.994	4,988
Match Information	Time of Match (min)	110.22	39.774	36	396	4,958
Court Type	Grass	0.125	0.331	0	1	4,988
	Clay	0.314	0.464	0	1	4,988
	Hard	0.56	0.496	0	1	4,988
Tournament Level	Grand Slam	0.194	0.395	0	1	4,988
	Masters 1000	0.22	0.415	0	1	4,988
	ATP 500	0.167	0.373	0	1	4,988
	ATP 250	0.419	0.494	0	1	4,988
Round of Play	1st Round	0.451	0.498	0	1	4,988
	2nd Round	0.289	0.453	0	1	4,988
	3rd Round	0.067	0.251	0	1	4,988
	4th Round	0.019	0.136	0	1	4,988
	Quarter Finals	0.1	0.3	0	1	4,988
	Semi Finals	0.05	0.217	0	1	4,988
	The Final	0.025	0.156	0	1	4,988

Notes: Table 1 lists the descriptive statistics for the primary variables of interest in the logit models. All tennis-specific skills and physical characteristics are computed as relative ratios between the favorite and underdog, except for break point variables which are computed as differences. Court type, tournament level, and round variables are binary variables that take on the value of 1 if the condition is true for that match.

Table 2: Summary Statistics After Rule Change

Variable Type	Variable Name	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Dependent Variable (binary)	Betting Favorite won (favorite = 1)	0.624	0.199	0	1	6,346
Rule Change (binary)	Match Occurred After Rule Change	0.56	0.5	0	1	6,350
Physical Characteristics	Ratio of Age	0.994	0.236	0.453	2.3	6,350
	Ratio of Height	1.01	0.051	0.825	1.212	6,296
	Big Three	0.031	0.175	0	1	6,350
Tennis-Specific Skills	Ratio of % 1st Serves Made	1.032	0.171	0.435	2.174	6,350
	Ratio of % 1st Serves Won	1.108	0.232	0.422	2.945	6,350
	Ratio of % 1st Serves Missed	1.009	0.290	0.251	3.637	6,348
	Ratio of % 2nd Serves Made	1.017	0.309	0.206	3.383	6,349
	Ratio of % 2nd Serves Won	1.191	0.610	0	9.706	6,348
	Difference in Break Points Saved	-0.91	4.195	-23	16	6,350
	Difference in Break Points Faced	-1.995	5.454	-27	19	6,350
	Ratio of Rank	0.434	0.275	0.0008	0.993	6,350
Match Information	Time of Match (min)	116.99	41.1	31	345	6,350
Court Type	Grass	0.120	0.325	0	1	6,350
	Clay	0.341	0.474	0	1	6,350
	Hard	0.539	0.499	0	1	6,350
Tournament Level	Grand Slam	0.193	0.395	0	1	6,350
	Masters 1000	0.224	0.417	0	1	6,350
	ATP 500	0.141	0.348	0	1	6,350
	ATP 250	0.442	0.497	0	1	6,350
Round of Play	1st Round	0.444	0.497	0	1	6,350
	2nd Round	0.291	0.454	0	1	6,350
	3rd Round	0.072	0.258	0	1	6,350
	4th Round	0.022	0.145	0	1	6,350
	Quarter Finals	0.097	0.297	0	1	6,350
	Semi Finals	0.05	0.217	0	1	6,350
	The Final	0.025	0.156	0	1	6,350

A scan across these first two tables show the ways in which the widespread use of the serve clock started to alter the way tennis was played. For instance, the ratio of the percent of first-serves made increased after the rule change, but the percentage of first-serve points won fell. These two summary statistics taken together tell a story of favored players being unable to leverage small relative accuracy gains on first-serve attempts in their favor because they

determined they were not able to hit serves with the same force as they could when they had longer time to recover between points.

The biggest change, though, can be attributed to age across the two time periods. Before the rule change was universally applied, the age ratio of the favored to underdog player was 1.046, meaning older players tended to be favored over their younger counterparts. Youth, however, has been served in the time of the serve clock, as the age ratio of the favored player to the underdog fell below 1.0. Younger legs have been able to withstand the rigors of the more quickly paced matches, and markets recognized this (eventually) by shifting toward younger players when anointing favorites.

We take two approaches for examining changes to the game of tennis and to betting market efficiency brought about by the rule change. First, we imagine bettors placing wagers on the basis of the players' relative physical and/or playing characteristics, which we model with Equation 2.[8] This equation attempts to replicate the strategy of a sophisticated bettor who collects information about the physical and/or playing characteristics of the players involved in the match. To this end, we average playing data from the last five matches in which each player competes and relate those observations against each other. The variable Past Performance$_{jt-n}$ is a vector that contains this information.

(2) *Prob(betting favorite wins$_{jt}$) = β_0 + Physical Characteristics$_{jt}$*Ω + Past Performance$_{jt-n}$*M + Match Information$_{jt}$*Λ + δ_{rule}(β_0 + Physical Characteristics$_{jt}$*Ω + Past Performance$_{jt-n}$*M + Match Information$_{jt}$*Λ) + ε_{jt}.*

Summary statistics for variables used in equation 2 are shown in Tables 3 and 4.

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[8] Summary statistics for physical characteristics and dummy variables are listed in Table 1 only as they are used in all regression models and the values remain constant whether past performance is considered or not.

Table 3: 5-Match Profile Summary Statistics Before Rule Change

Explanatory Variables	(1) Mean	(2) SD	(3) Min	(4) Max	(3) N
Ratio of % 1st Serves Made	1.017	0.12	0.61	1.654	4,988
Ratio of % 1st Serves Won	1.039	0.113	0.645	2.046	4,988
Ratio of % 1st Serves Missed	1.003	0.192	0.425	2.27	4,988
Ratio of % 2nd Serves Made	1.009	0.198	0.35	2.41	4,988
Ratio of % 2nd Serves Won	1.052	0.258	0.095	5.05	4,988
Ratio of Break Points Saved	1.078	0.77	0	13.333	4,972
Ratio of Break Points Faced	1.0006	0.597	0	12	4,981
Ratio of Serve Games Won	1.115	0.393	0.167	9.6	4,988
Ratio of Serve Games Lost	0.991	0.693	0	16	4,958
Ratio of Matches Won	1.294	0.783	0	5	4,540

Notes: Explanatory variables represent the ratio of performance between the favorite and the underdog over the past 5 matches, as they enter a match in time period t. When we do not have previous data (i.e. a player's first match in the dataset) we take the average of the player's performance on that tennis-specific skill for all matches in the dataset. Where $1 < t < 6$, profiles are constructed for a match in time t such that: $t=2T=5nt/(t-1)=(n1+n2+...+nt-1)/(t-1)$

Table 4: 5-Match Profile Summary Statistics After Rule Change

VARIABLES	(1) Mean	(2) SD	(4) Min	(5) Max	(3) N
Ratio of % 1st Serves Made	1.021	0.113	0.628	1.658	6,350
Ratio of % 1st Serves Won	1.039	0.115	0.633	2.314	6,350
Ratio of % 1st Serves Missed	0.995	0.187	0.425	2.35	6,350
Ratio of % 2nd Serves Made	0.999	0.196	0.37	2.792	6,350
Ratio of % 2nd Serves Won	1.044	0.251	0.252	3.116	6,350
Ratio of Break Points Saved	1.072	0.741	0	12.5	6,339
Ratio of Break Points Faced	0.997	0.606	0	17.5	6,350
Ratio of Serve Games Won	1.107	0.389	0.234	11.2	6,350
Ratio of Serve Games Lost	0.99	0.693	0	14	6,344
Ratio of Matches Won	1.345	0.821	0	5	5,828

We use the information from the regression results of equations 2 and 3 to create the variable *predict$_{ji}$,* the likelihood of the betting favorite winning match jt. We then use the

information from *predict$_{jt}$* and the market odds in two different ways to identify how the rule change might have impacted tennis itself and how much market inefficiency the rule change introduced. First, we identify the number of matches in which our model or the market odds identified instances in which the winner of the match was the predicted favorite of the match and compare the number of those instances across different time periods that relate to the rule change. Second, we use a simple algorithm that identifies matches in which the likelihood of a winner diverges across the models by five or 10 percentage points, which enables us to imagine matches that were ripe for betting. With this thought experiment, we can gain an idea of how returns to betting on tennis might have changed with the rule change. As we will show, our model, which consists of easily obtained data available in live fashion on the ATP site, predicted better the match winners throughout the time we analyze, especially so in time periods immediately following the rule change.

Section 4 - Results

Predicting Who Wins

In this section, we start by evaluating the results of the logit regressions pertaining to equation 1. We consider tennis-specific skill metrics and physical characteristics in isolation, as well as taken together to obtain the true effects. Table 5 presents the results of the logit regressions.

Table 5: Logit Models of Betting Favorite Winning

Explanatory Variables	(1) 1st & 2nd Serve + PC	(2) Tennis-Specific Skills	(3) Break Points	(4) Physical Characteristics
Ratio of % 1st Serves Made	9.421***	4.320***		
	(0.318)	(0.692)		
Ratio of % 1st Serves Won		17.83***		
		(0.617)		
Ratio of % 1st Serves Missed		-8.262***		
		(0.750)		
Ratio of % 2nd Serves Made		0.215		
		(0.562)		
Ratio of % 2nd Serves Won	4.515***	7.058***		
	(0.150)	(0.306)		
Difference Break Points Faced			-1.981***	
			(0.0661)	
Difference Break Points Saved			1.975***	
			(0.0694)	
Ratio of Age	-0.0750		-0.211	-0.162
	(0.145)		(0.241)	(0.121)
Ratio of Height	4.286***		-0.726	1.249***
	(0.565)		(0.857)	(0.425)
Match Time (min)	-0.00422***	-0.000107	9.44e-05	-0.00994***
	(0.00113)	(0.00181)	(0.00220)	(0.000927)
Ratio of Ranks	-0.645***	-0.109	-0.0999	
	(0.146)	(0.217)	(0.248)	
Grand Slam	0.690***	0.360	0.00497	1.052***
	(0.142)	(0.223)	(0.287)	(0.120)
ATP 250	0.0695	0.0907	-0.0361	-0.0314
	(0.105)	(0.156)	(0.170)	(0.0869)
ATP 500	0.0854	0.178	-0.0637	0.146
	(0.126)	(0.189)	(0.206)	(0.104)
Clay	-0.00971	-0.0230	-0.105	0.208*
	(0.128)	(0.188)	(0.218)	(0.107)
Hard	0.0292	0.0272	-0.194	0.194*
	(0.120)	(0.175)	(0.202)	(0.101)
Round 2	-0.0766	-0.106	0.0247	0.0224
	(0.0918)	(0.136)	(0.152)	(0.0747)
Round 3	-0.0842	0.137	0.132	-0.0186
	(0.165)	(0.246)	(0.283)	(0.138)
Round 4	0.0400	0.0289	0.713	0.0763
	(0.299)	(0.429)	(0.481)	(0.262)
Quarter Final	-0.102	-0.180	-0.00131	-0.0823
	(0.133)	(0.194)	(0.217)	(0.109)
Semi Final	-0.183	-0.340	-0.403	-0.0127
	(0.177)	(0.259)	(0.298)	(0.150)
Final	-0.466*	-0.497	-0.471	-0.373*

	(0.247)	(0.391)	(0.417)	(0.204)
Big Three	0.659***	-0.162	0.269	1.245***
	(0.215)	(0.325)	(0.344)	(0.186)
Rule Change * 1st Serves Made	-0.123	-0.138		
	(0.387)	(0.517)		
Rule Change * 1st Serves Won		1.081		
		(0.813)		
Rule Change * 1st Serves Missed		-0.105		
		(0.962)		
Rule Change * 2nd Serves Made	-0.152	-0.250		
	(0.182)	(0.763)		
Rule Change * 2nd Serves Won		-0.0171		
		(0.405)		
Rule Change * Break Points Faced			-0.187**	
			(0.0944)	
Rule Change * Break Points Saved			0.177*	
			(0.0982)	
Rule Change * Age	-0.363*		0.0415	-0.454***
	(0.206)		(0.349)	(0.171)
Rule Change * Height	0.995*		0.277	0.627**
	(0.546)		(0.596)	(0.254)
Rule Change * Time	-0.00100	-0.00116	-0.00398	0.000291
	(0.00148)	(0.00241)	(0.00294)	(0.00121)
Rule Change * Rank	-0.311	-0.393	-0.332	
	(0.195)	(0.297)	(0.338)	
Rule Change * Grand Slam	-0.0591	-0.199	0.220	-0.0978
	(0.192)	(0.307)	(0.400)	(0.164)
Rule Change * ATP250	-0.168	-0.217	-0.0290	-0.0812
	(0.138)	(0.210)	(0.231)	(0.114)
Rule Change * ATP500	-0.0423	-0.296	-0.0930	0.0150
	(0.173)	(0.265)	(0.292)	(0.143)
Rule Change * Clay	-0.0171	7.28e-05	0.250	-0.0814
	(0.173)	(0.259)	(0.299)	(0.144)
Rule Change * Hard	-0.00117	-0.0865	0.362	-0.150
	(0.160)	(0.237)	(0.273)	(0.135)
Rule Change * Round 2	0.0635	-0.108	-0.0571	0.0616
	(0.124)	(0.188)	(0.212)	(0.101)
Rule Change * Round 3	-0.0452	-0.384	-0.356	0.0726
	(0.219)	(0.331)	(0.391)	(0.183)
Rule Change * Round 4	-0.303	-0.127	-1.276*	-0.120
	(0.386)	(0.565)	(0.652)	(0.336)
Rule Change * Quarter Final	0.114	0.0289	-0.256	0.103
	(0.178)	(0.269)	(0.300)	(0.147)
Rule Change * Semi Final	-0.0382	0.00797	0.278	-0.118
	(0.236)	(0.348)	(0.396)	(0.197)
Rule Change * Final	0.311	0.262	0.755	0.453*
	(0.328)	(0.518)	(0.563)	(0.273)
Rule Change * Big Three	-0.101	0.227	0.812	-0.0965
	(0.326)	(0.484)	(0.581)	(0.285)

Constant	-17.31***	-21.39***	1.427	0.372
	(0.669)	(1.197)	(0.879)	(0.436)
Observations	10,999	11,055	10,999	10,999

Standard errors in parentheses

*** p<0.01, ** p<0.05, *p<0.1

The first aspect of these results on which we want to focus is how consistent the return of tennis-specific skills are with prior studies of what increases the likelihood of a player being successful in professional tennis matches. The second aspect is on the post-rule change coefficient estimates that capture changes to the returns on skills or characteristics that have occurred to the sport since the serve clock was implemented. We want to leverage this information later in this paper, when we highlight inefficiencies in post-rule change betting markets.

First, note that the first three columns of Table 5 results are consistent with previous studies of tennis. For instance, in column 1, the coefficient estimates on relative percent of first-serves made and relative percent of second-serve points won are positive and highly significant, thus matching and reasonable a priori estimates of how success in those parts of the game would change the probability of winning a match. The coefficient estimates on tennis-specific skills shown in columns 2 and 3 are not surprising in the context of tennis. In column 2, the sign on the coefficient estimates of the five tennis-specific skills are consistent with reasonable predictions of how relative success in these parts of the game change the likelihood of a player winning. For example, we would expect that the coefficient estimate on the relative percent of first serves missed is less than zero, as it is not a favorable position for the server to have to play more points off of the second serve.

As for returns to success in the post-rule change world, our findings suggest no tennis-specific skill has increased in value. None of the coefficient estimates in which skills are interacted with the rule change indicator variable are statistically significant. Instead, our results suggest that players' physical characteristics have become more important for predicting who will win matches. To illustrate this point, we evaluate the marginal effect of a change in relative age and height at the means of those variables with the estimates in column 4 and find that the changes observed are significant at less than the 1% level. When the age ratio decreases by one percent in the post-serve clock era, the favorite's likelihood of winning increases by 9.7 percentage points over the same change in the pre-serve clock era. Similarly, as the height advantage of the favorite to the underdog increases by one percent, the favorite is 13.4 percentage points more likely to win after the rule change than before the clock was implemented. These two findings suggest that younger players and taller players have gained an advantage since the serve clock was universally adopted and corroborate the conclusion of Ovaska and Summell (2014), that height is a significant advantage in tennis, and further confirm Magnus and Klaassen (1999) finding that stronger servers, as defined by the taller player, hold their advantage throughout the duration of matches. As seen by the negative coefficients of relative age in columns 1 and 4, our results align with Ovaska and Summell (2014) that the younger player holds the advantage. However, it appears that age was not considered to be a key identifier in predicting matches before the rule change as these effects are not significant. As we will show, the betting markets undervalued the advantages that physical characteristics hold in tennis and this was exploited with the implementation of the serve clock.

In the context of tennis, the results in column 3 are consistent with findings from Forrest and McHale (2007), which highlights the importance of breaking opponents' service games and

holding serve. The marginal effect of break points saved implies that for every additional break point saved, the favorite is 14.3 percentage points more likely to win the match, and this effect is significant at less than the 1% level. The inverse relationship between break points faced and the favorite winning does not come as a surprise per Barnett and Clarke (2005) empirical findings that converting on break points is of critical importance to maintaining a competitive position in the match.

For illustrative purposes, we consider a match before the rule change in which relative tennis-specific skills depict the outcome. In a best-of-three sets Masters 1000 match at the Miami Open in 2017, Rafael Nadal, who was 30 years old at the time of the match, defeated his 24-year-old opponent, Pablo Sock, in straight sets. Nadal made 69% of his first serves compared to Sock's 56%, and he won 71% of his first-service points compared to Sock's 63%. Nadal warded off six of seven break points that he faced. Sock was a competitive player ranked #17 in the world and the odds were not long against him; Sock still had a 33% chance to win. Thus, we can say this was not a "Nadal given win," but he earned it with his skills.

Now consider a match in 2023 between Nadal (36) and Borna Coric (25) at the Western and Southern Open (also a 1000 event). Although the market odds quoted Nadal with an 87% chance of winning and he may have outplayed his opponent on paper, the 152nd ranked Coric closed the deal on this match. Nadal made 55% of his first serves (Coric with 49%) and won 84% of first service points (Coric with 82%). Additionally, both players only faced two break points, and each saved one of them. Nadal fell short in a grueling first-set tiebreak, and though reclaiming the second set, he was unable to close out the match in his typical fashion. If a seemingly young nobody and a serve clock can throw Nadal off his feet like that, we are not surprised to see the returns to youth increasing in the serve clock era.

Forecasting Models

Now that we have established that our data has power in terms of predicting match outcomes, we turn our attention to imagining ways in which this data could have been used by bettors or sportsbooks to forecast match outcomes. Table 6 shows results of estimates of permutations of equation 2. The results in the first column show results of a logit regression from the estimation of equation 2, featuring only playing skills. Column 2 uses information about aggregate serving ability. Column 3 uses physical characteristics in addition to information about how well players defended or converted break points. Column 4 uses the players' relative number of match wins and losses approaching the current match, a technique that was used in the work of Angelini, Candila, and Angelis (2022) to better forecast match outcomes using WElo models, in which previous match outcomes were weighted based on the number of games (or sets) won to account for skill level. Column 5 adds physical characteristics to the information used in column 4. We consider the inclusion of previous match performance in the model to make up player j's "profile", as he enters a match in time t.

	(1)	(2)	(3)	(4)	(5)
Table 6: Five-Match Profile Logit Models					
Explanatory Variables	Tennis-Specific Skills	Serve Games	Break Points	Match Wins	Match Wins & PC
Ratio of % 1st Serves Made	1.268*				
	(0.658)				
Ratio of % 1st Serves Won	0.874***				
	(0.296)				
Ratio of % 1st Serves Missed	-0.283				
	(0.628)				
Ratio of % 2nd Serves Made	0.0513				
	(0.511)				
Ratio of % 2nd Serves Won	0.528***				
	(0.205)				
Ratio of Serve Games Won		0.00522			
		(0.0771)			
Ratio of Serve Games Lost		-0.156***			
		(0.0453)			
Ratio of Break Points Saved			0.0140		

				(0.0759)	
Ratio of Break Points Faced				-0.235**	
				(0.109)	
Ratio of Matches Won				0.124***	0.130***
				(0.0432)	(0.0448)
Ratio of Age				-0.322***	-0.274**
				(0.123)	(0.129)
Ratio of Height				0.503	1.261***
				(0.445)	(0.453)
Match Time (min)	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Ratio of Ranks	-0.858***	-0.920***	-0.930***	-0.812***	-0.797***
	(0.122)	(0.118)	(0.122)	(0.122)	(0.128)
Clay	0.210*	0.153	0.174	0.104	0.149
	(0.108)	(0.104)	(0.108)	(0.107)	(0.114)
Hard	0.191*	0.136	0.158	0.0739	0.109
	(0.102)	(0.0966)	(0.102)	(0.0995)	(0.108)
Grand Slam	0.931***	0.918***	0.925***	0.894***	0.902***
	(0.121)	(0.121)	(0.121)	(0.126)	(0.126)
ATP 250	0.00778	-0.0357	-0.00237	-0.0373	-0.00286
	(0.0878)	(0.0856)	(0.0877)	(0.0872)	(0.0910)
ATP 500	0.106	0.0748	0.101	0.0582	0.0934
	(0.105)	(0.103)	(0.105)	(0.105)	(0.109)
Round 2	-0.0970	-0.132*	-0.121	-0.0888	-0.0757
	(0.0774)	(0.0764)	(0.0774)	(0.0795)	(0.0809)
Round 3	-0.0827	-0.113	-0.117	-0.0655	-0.0610
	(0.139)	(0.138)	(0.139)	(0.139)	(0.141)
Round 4	-0.0162	-0.0509	-0.0622	0.0263	0.0318
	(0.262)	(0.262)	(0.262)	(0.262)	(0.263)
Quarter Final	-0.0561	-0.0877	-0.0928	-0.0397	-0.0394
	(0.151)	(0.151)	(0.151)	(0.152)	(0.153)
Semi Final	-0.136	-0.160	-0.153	-0.112	-0.103
	(0.111)	(0.111)	(0.111)	(0.113)	(0.113)
The Final	-0.388*	-0.406**	-0.407**	-0.375*	-0.354*
	(0.205)	(0.206)	(0.206)	(0.206)	(0.206)
Big Three	0.932***	0.962***	1.045***	0.971***	1.059***
	(0.188)	(0.186)	(0.188)	(0.187)	(0.189)
Rule Change * 1st Serves Made	0.0987				
	(0.300)				
Rule Change * 1st Serves Won	-0.200				
	(0.662)				
Rule Change * 1st Serves Missed	0.00371				
	(0.393)				
Rule Change * 2nd Serves Made	0.419				
	(0.657)				
Rule Change * 2nd Serves Won	0.0588				
	(0.279)				
Rule Change * Serve Games Won			0.113		
			(0.0976)		
Rule Change * Serve Games Lost			0.0408		
			(0.0588)		
Rule Change * Break Points Saved				0.0978	

			(0.110)		
Rule Change * Break Points Faced			-0.0993		
			(0.153)		
Rule Change * Matches Won				0.0630	0.0385
				(0.0554)	(0.0588)
Rule Change * Age				-0.282	-0.401**
				(0.173)	(0.181)
Rule Change * Height				0.504*	0.587**
				(0.276)	(0.294)
Rule Change * Time	-0.000619	-0.000143	-0.000384	-0.000517	-0.000941
	(0.00123)	(0.00110)	(0.00122)	(0.00110)	(0.00127)
Rule Change * Rank	-0.191	-0.129	-0.106	-0.0999	-0.126
	(0.164)	(0.153)	(0.164)	(0.159)	(0.171)
Rule Change * Clay	-0.0885	-0.00337	-0.0323	0.0572	0.00272
	(0.147)	(0.134)	(0.146)	(0.137)	(0.152)
Rule Change * Hard	-0.135	-0.0462	-0.0927	0.0151	-0.0519
	(0.137)	(0.123)	(0.137)	(0.123)	(0.143)
Rule Change * Grand Slam	-0.0425	-0.00195	-0.00907	0.0360	0.0166
	(0.165)	(0.164)	(0.165)	(0.170)	(0.171)
Rule Change * ATP250	-0.0658	0.000863	-0.0390	-0.00741	-0.0479
	(0.116)	(0.110)	(0.116)	(0.111)	(0.120)
Rule Change * ATP500	0.0138	0.0810	0.0217	0.112	0.0469
	(0.144)	(0.138)	(0.144)	(0.140)	(0.149)
Rule Change * Round 2	0.0168	0.0546	0.0446	0.0851	0.0534
	(0.104)	(0.101)	(0.105)	(0.105)	(0.109)
Rule Change * Round 3	0.0391	0.0776	0.0424	0.118	0.0620
	(0.186)	(0.183)	(0.186)	(0.184)	(0.188)
Rule Change * Round 4	-0.164	-0.144	-0.158	-0.0961	-0.129
	(0.337)	(0.336)	(0.338)	(0.336)	(0.339)
Rule Change * Quarter Final	0.0552	0.0665	0.0671	0.123	0.102
	(0.149)	(0.148)	(0.150)	(0.151)	(0.153)
Rule Change * Semi Final	-0.167	-0.131	-0.145	-0.0788	-0.109
	(0.199)	(0.199)	(0.200)	(0.200)	(0.202)
Rule Change * Final	0.387	0.405	0.394	0.486*	0.437
	(0.275)	(0.276)	(0.277)	(0.276)	(0.277)
Rule Change * Big Three	-0.339	-0.331	-0.146	-0.365	-0.149
	(0.284)	(0.283)	(0.290)	(0.283)	(0.291)
Constant	-0.716	2.110***	1.942***	1.751***	0.635
	(1.073)	(0.139)	(0.470)	(0.124)	(0.466)
Observations	11,056	11,020	10,945	10,104	10,079

This table shows results of logit estimations in which the dependent variable is a binary variable set to 1 when the higher-ranked player in a match wins. Independent variables are relative tennis-specific collected over the past five matches in which the players competed, as well as relative physical characteristics. Results with *** show estimates significant at less than 0.01 level, ** at 0.05 level, and * at 0.1 level. Standard errors are in parentheses.

The results from the profile models allow us to do two things: we define the aspects of

tennis performance that are necessary to make informed betting decisions, as well as detect the

updated set of information to set odds efficiently after the league's structural change. First, note that the tennis-specific skills of importance to winning matches are consistent with results from equation 1 as well as prior literature. The significant and positive estimates of relative matches won in columns 4 and 5 confirm the work of Angelini, Candila and Candelis (2022) that previous match outcomes matter in predicting current matches. We are not surprised to see that players who have faced more break points leading up to a match are at a disadvantage per previous literature illustrating how win probabilities are impacted by break point opportunities (e.g. Barnett & Clarke, 2005). The increased probability of the favorite winning as a result of winning more first and second points is significant at less than the 1% level, a finding that is consistent with research in game theory by Walker and Wooders (2011) asserting the serve has real implications in determining win probabilities.

When looking at the valued set of information in the serve clock era, we see again there is very little evidence of tennis-specific characteristics having greater importance than before the rule change. The consistent significance of coefficient estimates on youth and age in predicting who wins matches in Tables 5 and 6 supports the idea that the serve clock has created advantages for younger players and taller players. Looking at the results of column 5, the marginal effect of a change in relative age at the means of the variables reveals that as the ratio between players ages decreases by one percent, the favorite player is 8.6 percentage points more likely to win the match in the serve clock era than he was before. With the increased rate of play that players had to adjust to, youthfulness became an increasingly valuable trait to have against one's opponent.

We posit that inefficiencies arise in the markets following the rule change that are directly related to how the Big Three players were impacted in the serve clock era. We explore the power of the dummy variable for Big Three as it relates to the estimate of age using the

model in column 5. The markets historically set odds heavily in favor of the Big Three, for reference, there are only 18 matches in our data set where one of the Big Three were not favored, and in only five of these was the opponent not another member of the Big Three. There is a negative relationship between the ratio of age and the favorite winning the match before the rule change, however the parameter is increasingly closer to zero and no longer significant when Big Three is taken out of the model. We conduct a post-estimation test on the null hypothesis that the difference between the coefficients on relative age in the model with and without the Big Three is zero. The chi-squared value of 35.56 is significant at less than the 1% level. When we take the dominant players of the game out of the picture, it becomes apparent that younger players generally had an advantage over older players that were not named Nadal, Federer, or Djokovic. Pre-serve clock, in an average match with the Big Three player favored, the favorite was more likely to win by 22.7 percentage points if the match included one of the Big Three. This effect does not hold in the serve clock era: younger players still hold the advantage and the favorite (i.e. the Big Three player) is 3.2 percentage points less likely to win when it is a Big Three match, though not significant. This suggests that the serve clock provided difficulties for even the best players in the world, players the gambling markets might have been slow to recognize weaknesses brought about with the serve clock. If the markets failed to detect the difference in how younger players rebounded from the rule change as opposed to the Big Three, this would introduce a world where there are positive returns to longshot bias to the market.

One of the particular challenges that sportsbooks face in tennis compared to any other sport is that traditionally, casual betting has minimally occurred (e.g. Forrest & McHale, 2007). The foundation of wagering markets was studied in horse racing, where the market is flooded with casual bettors that are generally uninformed and wealthy and have influential impacts on the

revenue that bookmakers receive. With a pool of bettors in tennis that are knowledgeable about the game and strategic about placing bets, bookmakers could not afford increased margins of error when setting prices at this time.

Market Efficiency

Now, we use the results of the in-sample forecasting models as a benchmark to assess the accuracy of bookmakers' predictions. In Tables 7 and 8, we show the differences in our predictive models' performances and the sportsbooks' performances of forecasting the winner of a match. Table 7 divides into four time periods the matches we analyze, with two periods before and after, while Table 8 divides the data into six time periods.

First, in each time period, our five-match profile and physical characteristics models outperformed the bookmakers' models in terms of predicting match results. As Levitt (2004) discusses, sportsbooks are trying to maximize operating profits, not results predictions, so our superiority over the sportsbooks in this dimension should be taken with a grain of salt. However, it is hard not to conclude that these differences suggest openings for bettors to outperform sportsbooks.

More to one of the central questions of this paper, though, is that the difference in the two models' predictive powers widens in the period immediately following the implementation of the serve clock. This widening is seen in the third time period of Table 7 and the fourth time period in Table 8. In Table 7, the improvement in our physical characteristics model prediction success was 0.6 percentage points better than the sportsbooks' immediately following the rule change, and 0.7 percentage points for the profiles model respectively, and these findings are significant at less than the 10% level. When we further restrict the time periods in table 8 to thirds, it becomes clearer that both of our models significantly outperformed the sportsbooks immediately

following the rule change. The difference-in-differences of the sportsbooks and physical characteristics models is 1.2 percentage points, while the same difference is 1.1 percentage points between the sportsbooks and five-match profile models, significant at less than the 5% level. Also, note that in Table 7, the physical characteristics model improves predictive ability by 0.5% after the serve clock is introduced, a finding that is significant at less than the 10% level. The strong predictive capacity of this model is a finding that is also seen in Corral and Prieto Rodriguez (2014) work that showed models using player physical characteristics are of greater importance to yield accurate predictions. This further confirms the findings from our logistic regression analysis that physical characteristics are of utmost importance to forecast matches, and this is stressed in the serve clock era.

Finally, for those who are like us and cannot quit the Efficient Market Hypothesis, it is extremely important to note that the improvement in predictive power of our models over the markets that the difference-in-differences suggest only holds for the period of shock after the rule change. As is consistent with the idea of efficient markets, our models' relative success in predicting match outcomes started to falter over the sportsbooks as time lapsed from the structural change and the markets swiftly incorporated the new set of information in the serve clock era. By the end of our dataset, the difference in the predictive capabilities of the models are back to the size observed in the first time period of our analysis.

Table 7: Comparing In-Sample Models to Market Odds: Differences increased immediately after the serve clock

	T1		T2			T3			T4		
	N	Mean	N	Mean	Δ(T2-T1)	N	Mean	Δ(T3-T2)	N	Mean	Δ(T4-T3)
Physical Characteristics Model Odds	2481	0.687	2470	0.682	-0.006**	3008	0.684	0.0008	3040	0.669	-0.015***

	(0.098)		(0.098)	(0.003)	(0.102)	(0.003)	(0.092)	(0.003)
5-Match Profile Odds	2242 0.683	2234	0.677	-0.009***	2763 0.677	0.0005	2793 0.672	-0.006**
	(0.114)		(0.115)	(0.003)	(0.121)	(0.003)	(0.117)	(0.003)
Market Odds	2502 0.638	2482	0.627	-0.012**	3014 0.621	-0.005	3332 0.627	0.006
	(0.207)		(0.192)	(0.006)	(0.198)	(0.005)	(0.199)	(0.005)
Diff-in-Diff (Market Odds - PC Model)	N/A	2469	-0.056	-0.006	3007 -0.062	-0.006*	3037 -0.05	0.012***
			(0.185)	(0.005)	(0.192)	(0.005)	(0.192)	(0.005)
Diff-in-Diff (Market Odds - Profile Model)	N/A	2233	-0.053	-0.002	2762 -0.06	-0.007*	2790 -0.053	0.007*
			(0.18)	(0.006)	(0.187)	(0.005)	(0.187)	(0.005)

Notes: This table shows differences between the success our model and bookmakers' models had in choosing match winners before and after the serve clock was implemented. Each quarter is slightly longer than one calendar year. Differences statistically significant at the 0.01 level are shown with ***, 0.05 with **, and 0.1 with *.

Table 8a: Comparing In-Sample Models to Market Odds
(Pre-Rule Change)

	T1		T2			T3		
	N	Mean	N	Mean	Δ (T2-T1)	N	Mean	Δ (T3-T2)
Physical Characteristics Model Odds	1632	0.688	1651	0.68	-0.008***	1668	0.685	0.005*
		(0.101)		(0.093)	(0.003)		(0.1)	(0.003)
5-Match Profile Odds	1481	0.686	1507	0.672	-0.013***	1488	0.681	0.008**
		(0.116)		(0.111)	(0.004)		(0.116)	(0.004)
Market Odds	1652	0.648	1652	0.621	-.027***	1680	0.629	0.008
		(0.211)		(0.196)	(0.007)		(0.191)	(0.007)
Diff-in-Diff (Market Odds - PC Model)	N/A		1651	-0.06	0.018***	1667	-0.058	0.002
				(0.192)	(0.007)		(0.192)	(0.006)
Diff-in-Diff (Market Odds - Profile Model)	N/A		1507	-0.055	-0.01*	1487	-0.055	0.0004
				(0.187)	(0.007)		(0.178)	(0.007)

Table 8b: Comparing In-Sample Models to Market Odds
(Post-Rule Change)

	T4			T5			T6		
	N	Mean	Δ (T4-T3)	N	Mean	Δ (T5-T4)	N	Mean	Δ (T6-T5)
Physical Characteristics Model Odds	1998	0.69	0.005*	2015	0.671	-0.019***	2031	0.668	-0.003
		(0.101)	(0.003)		(0.095)	(0.003)		(0.094)	(0.003)
5-Match Profile Odds	1851	0.683	0.003	1830	0.67	-0.013***	1871	0.671	0.001
		(0.122)	(0.004)		(0.116)	(0.004)		(0.118)	(0.004)
Market Odds	1998	0.621	-0.007	2015	0.621	0	2031	0.619	-0.003
		(0.202)	(0.007)		(0.192)	(0.006)		(0.197)	(0.006)
Diff-in-Diff (Market Odds - PC Model)	1998	-0.069	-0.012**	2015	-0.049	0.019***	2031	-0.049	0
		(0.195)	(0.006)		(0.186)	(0.006)		(0.191)	(0.006)
Diff-in-Diff (Market Odds - Profile Model)	1851	-0.066	-0.011**	1830	-0.049	0.017***	1871	-0.053	0.004
		(0.192)	(0.006)		(0.181)	(0.006)		(0.187)	(0.006)

We can use the information in Table 7 and Tables 8a-b to imagine how returns to wagering changed across the serve clock rule change. To this end, imagine calculating the returns to a betting algorithm in which our model and the market identify the same player as a match favorite, but our model assigns the favorite a likelihood of winning of five or ten percentage points greater than the market does. On these matches we bet a hypothetical $1, with payouts thus being calculated with market odds.

We find in the quarter immediately preceding the rule change, 69% of matches in which our model and the markets agree on the favorite, with 22% of matches having a prediction difference bigger than five-percentage points and 12% matches with a difference bigger than 10-percentage points. In the quarter following the rule change, we find 433 betting opportunities with prediction windows of five-percentage points (23%), and 230 betting opportunities with prediction windows of 10-percentage points (12%), while two quarters removed we find 290 (19%) and 142 (10%) similar betting opportunities.

Our net winnings in the quarter preceding the rule change would have been $568 on the matches with a five-percentage-point difference and $320 on the matches with a 10-percentage point difference. In the quarter after the rule change, these returns would have been $739 and $409, respectively. In the last quarter of data, returns were $698 and $343 respectively. These returns are consistent with predictions of the Efficient Markets Hypothesis, as it was arguably more profitable for a bettor to place a wager of the same value in the period after the rule change, when temporary disagreements of the implications of rule change were largest, than before.

In total, our net winnings in the quarter preceding the rule change would have been $1583, $1837 in the quarter following the rule change, and $1786 in the most recent time period.

It is worth acknowledging the potential threat of the COVID-19 pandemic to our empirical analysis. While recreational tennis was seen to have grown by approximately 30% in early 2023 according to the Tennis Industry Association, the professional world had to make adjustments to the league operations just as many other sports entities were forced to do during this time (USTA, 2023). In March of 2020, the ATP announced they would institute a rankings freeze in which all rankings points earned from March of 2019 to 2020 were held and future points accrued had no impact on a player's rank.[9] The freeze benefitted players who were impacted by the pandemic restrictions and needed recovery time from injuries as their absence from the league could not be penalized. However, it is easy to pick apart the disadvantages that could have arisen due to the differences in access to resources players had. In an interview with PTPA, Novak Djokovic speaks to the difficulties of making a living off of professional tennis wages for players who are not in the top couple hundred (Zagoria, 2023). For players that were healthy, some had the ability to invest in maximal training practices, while others outside of the

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[9] The rankings freeze lasted a full two years, before returning to its normal 52-week ranking system in August of 2022.

top 100 were punished by this freeze as they continued to compete but received no rankings benefit and reduced compensation, a decision that was justified by the ATP with a lack of gate receipts at this time.

The effect of this rankings freeze was investigated by Sackmann (2020) who assessed the accuracy of the pandemic-adjusted rankings as compared to its typical 52-week cycle. Using information on the top 100 players ranks and Elo ratings, Sackmann discovered that pandemic-adjusted rankings actually outperformed historical data on rankings, suggesting that the freeze instituted a more accurate rankings system explaining player performance. We further investigate the role of rankings in our data by restricting our sample to time periods 4 through 6. The results reveal that as the ratio between relative ranks decreases by one percent, the favorite's likelihood of winning after the rule change is increased 17.9 percentage points, a result that is significant at less than the 1% level. This finding corroborates the analysis of Sackmann and yields evidence that although at a standstill, the ranking system still remained an important predictor of match wins during the pandemic. Additionally, there is sufficient literature that gives credence to the ATP ranking system as an important predictor in forecasting matches and predicting Grand Slam winners (e.g. Corral & Prieto-Rodriguez 2010; Klaassen & Magnus, 2003). Thus, we feel strongly that if the ranking system held up during this time, then this period of tennis should not be considered an anomaly.

Section 5- Concluding Remarks

In 2020, a serve clock was implemented in professional tennis. In this paper, we analyze the implications of this rule change on the way professional tennis competitions changed and on how efficient betting markets were in internalizing the implications of the clock. Using data from professional tennis matches and tennis-betting markets spanning five seasons preceding and

following the serve clock in 2020, we found that the game, which has historically favored players with superior serving skills, has provided new advantages to younger and taller players after the serve clock was introduced. Our results do not indicate that tennis-specific skills have become relatively more valuable in the serve-clock era.

We also use the match-level data to calculate the likelihood of a player winning and compare those predictions to betting markets' likelihoods. Using a simple algorithm to identify matches with significant differences between predictions, we find returns to betting on tennis would have increased about 30% in the nine months after the rule change, suggesting a level of inefficiency bettors could have exploited. However, as is consistent with the Efficient Market Hypothesis, returns to tennis betting with our algorithm would have receded back to pre-clock levels after the bookmakers adjusted to the implications of the rule change.

We consider the findings on inefficiency to be a warning to sportsbooks, because sports leagues will continue to tinker with rules in order to maintain or grow fan interest, so understanding how to manage risk in these instances is important to the bookmakers' survival.

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