Statistical Evaluation of Tommy John

Surgery

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Tommy John surgery is a growing issue happening with this new evolution of baseball. Velocity has become such an integral part of being a successful major league pitcher but it has its costs. The ulnar collateral ligament is a sensitive ligament that suffers from the motion of pitching a baseball. A "Tommy John" injury consists of rupturing this ligament due to overuse, not from one throw or one bad pitch. The number of these injuries appears to be going up exponentially every year. This could be due to a number of reasons but increased velocity in MLB pitchers can rapidly degrade the ligament in question. Others hypothesize that specializing in baseball too young and poor youth sports coaches are leading factors to this growing issue. Regardless of the cause it is possible, and in fact common, to come back and pitch in the major leagues after suffering this injury. This led us to our research question; How does the performing surgeon in a Tommy John surgery impact the postoperative pitching statistics and outcomes of major league baseball pitches? There are a lot of doctors who specialize in this specific surgery and we wanted to see who was the best. We hypothesized that the surgeon wouldn't matter and that all surgeons would provide the same outputs.

This study's literature review and data was collected from multiple sources with two sources used very heavily. Those sources were baseballsavant.com and a Google Sheet maintained by baseball writer Jon Roegele, which documents professional baseball players who have undergone Tommy John surgery. The data gathered from Baseball Savant comprises a list of pitching metrics deemed important for the study, including strikeout percentage, walk percentage, average exit velocity of balls in play, hard-hit percentage, fastball rotations per minute, fastball velocity, earned run average, and walks plus hits per innings pitched.

Additionally, information sourced from the Tommy John Google Sheet includes details such as a pitcher's age at the time of surgery, the surgeon involved, and the recovery time between surgery and returning to Major League Baseball.

Each data group collected included the MLB ID number for each player, enabling the merging of the two groups into one using SQL. Moreover, rows of data lacking key information,

such as surgeon and recovery time, were promptly excluded from the dataset, ensuring the analysis was conducted on clean, complete data. Following this, the data was exported to Excel for additional cleaning. This involved refining the dataset to include only the statistics of each pitcher from the year before their surgery and their return year from surgery. Subsequently, the statistics from the year before surgery were subtracted by those after surgery, resulting in 35 distinct rows representing 35 different pitchers. When looking at the data we also wanted to examine potential statistical differences between pitchers who have had Tommy John surgery and those who haven't. Baseball Savant's website was used again to compile an Excel sheet of 35 non-Tommy John pitchers. Differences between the two seasons were also taken from these pitchers to compile data. We hypothesized that the Tommy John pitchers would have a worse difference than non-Tommy John pitchers.

The initial methodology identified that age and surgeon would be good y variables used to build models where the x variables would be the differences between seasons of strike out percentage, walk percentage, average exit velocity, how often they are hit hard, fastball velocity and rpm, ERA, Whip, and recovery time. We chose to use age in order to see if that was affecting the statistics and not the surgeon being used. Regression models 1-9 show the relationship between the surgeon used and the 9 pitching statistics. Three surgeon categories were identified based on the 2 most used surgeons (Andrews and Elattache) with an "other" column used for the other surgeons. Regression models 10-18 would be the age of the pitcher predicting the difference in season-long variables from the season before injury to the season after. A regression output and bar graph were then created to amplify the statistically significant findings of our initial model output.

OLS Regression Results								OLS Regression Results					
Dep. Varial Model: Method: Date: Time: No. Observe Df Residua Df Model: Covariance	Mo ations: ls:	Least Squar n, 15 Apr 20 22:35:	LS Adj. F es F-stat 24 Prob (12 Log-Li 35 AIC: 32 BIC:	red: squared: -istic: F-statistic kelihood:):	0.024 1.413 0.258 -99.710 205.4	Dep. Varia Model: Method: Date: Time: No. Observ Df Residua Df Model: Covariance	rations: rls:	bbpercen OL- Least Square Mon, 15 Apr 202 22:35:1 3 3	S Adj. S F-sta 4 Prob 3 Log-L 5 AIC: 2 BIC:	ared: R-squared: tistic: (F-statistic ikelihood:):	0.030 -0.030 0.5024 0.610 -91.857 189.7 194.4
========	coef	std err	t	P> t	[0.025	0.975]		coef	std err	t	P> t	[0.025	0.975]
const andrews neal	-2.8706 2.8563 2.1706	1.060 1.962 1.691	-2.709 1.455 1.284	0.011 0.155 0.208	-5.029 -1.141 -1.274	-0.712 6.854 5.615	andrews	0.3412 -1.5697 -0.5230	1.568	0.403 -1.001 -0.387	0.690 0.324 0.701	-1.384 -4.764 -3.275	2.066 1.624 2.229
Omnibus: Prob(Omnib Skew: Kurtosis:	us):	0.2 0.9 -0.0 2.4	03 Jarque 47 Prob(3			0.410 0.815	Omnibus: Prob(Omnib Skew: Kurtosis:	us):	0.69 0.70 0.07 2.31	7 Jarqu 2 Prob(2.456 0.711 0.701 3.32

Figure 1: Regression output surgeon predicting strikeout percentage (left) and walk percentage (right)

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Dep. Variable: Model: Method: Date: Time: No. Observatio Df Residuals: Df Model: Covariance Typ	Mo ns:	-	Adj. R F-stat Prob (3 Log-Li 5 AIC: 2 BIC:	red: k-squared: istic: F-statistic kelihood:):	-0.039 0.3697 0.694 -220.00	Dep. Varia Model: Method: Date: Time: No. Observ	ble: Mo vations: uls:	hardhi OL Least Square n, 15 Apr 202 22:35:1 3 3	t R-squ S Adj. s F-sta 4 Prob 3 Log-L 5 AIC: 2 BIC:			0.091 0.034 1.599 0.218 -112.40 230.8 235.5
	coef	std err	t	P> t	[0.025	0.975]		coef	std err	t	P> t	[0.025	0.975]
andrews neal -	-3.4118 43.4118 11.2246	32.952 61.015 52.573	-0.104 0.711 -0.214	0.918 0.482 0.832	-70.532 -80.871 -118.312	63.709 167.695 95.863		0.3294 -4.5008 -3.1567	1.523 2.820 2.430	0.216 -1.596 -1.299	0.830 0.120 0.203	-2.773 -10.245 -8.106	3.432 1.244 1.793
Omnibus: Prob(Omnibus): Skew: Kurtosis:		19.49 0.00 -1.14 8.02	3 Durbin 10 Jarque 16 Prob(J			1.720 44.455 2.22e-10 3.32	Skew:	ous):	4.87 0.08 -0.56 4.03	8 Jarqu 7 Prob(,-		1.906 3.450 0.178 3.32

Figure 2: Regression output surgeon predicting fastball rpm (left) and hard hit percentage (right)

	OLS Regression Results										
Dep. Variable:	fastvelo	R-squared:		0.077	Variable	:	exitvel	R-squa	ared:		0.110
Model:	0LS	Adj. R-squared:		0.020	:l:		OLS	5 Adj. I	R-squared:		0.055
Method:	Least Squares	F-statistic:		1.344	od:		Least Squares	s F-stat	tistic:		1.984
Date: M	on, 15 Apr 2024	Prob (F-statistic):	:	0.275	12	M	on, 15 Apr 2024	4 Prob	(F-statistic):		0.154
Time:	22:35:13	Log-Likelihood:		-73.038	12		22:35:13	3 Log-L	ikelihood:		-65.797
No. Observations:	35	AIC:		152.1	Observati	ons:	35	5 AIC:			137.6
Df Residuals:	32	BIC:		156.7	esiduals:		32	2 BIC:			142.3
Df Model:	2				lodel:			2			
Covariance Type:	nonrobust				riance Ty	pe:	nonrobust	t			
					========	=======		- 			
coef	std err	t P> t	[0.025	0.975]		coef	std err	t	P> t	[0.025	0.975]
const 0.2471	0.495	0.499 0.621	-0.760	1.255	it	0.5471	0.402	1.360	0.183	-0.272	1.366
andrews 1.0815	0.916	1.181 0.246	-0.784	2.947	'ews	-1.1899	0.745	-1.598	0.120	-2.707	0.327
neal -0.5289	0.789 -	0.670 0.508	-2.136	1.079		-1.0652	0.642	-1.660	0.107	-2.372	0.242
Omnibus:	17.133	Durbin-Watson:		1.344	bus:		0.690	a Durbi	n-Watson:		2,231
Prob(Omnibus):	0.000	Jarque-Bera (JB):		24.807	(Omnibus)	•	0.708		e-Bera (JB):		0.377
Skew:	-1.263	Preb(JB):		4.10e-06	r:		-0.25				0.828
Kurtosis:	6.260	Cond. No.		3.32	osis:		2.97				3.32

Figure 3: Regression output surgeon predicting fastball velocity (left) and average exit velocity (right)

		OLS Regr	ession Re				[1] Stalla		assi	OLS Regr		Results	e e11013	13 (011661)
Dep. Variable: Model: Method: Date: Time: No. Observatio Df Residuals: Df Model: Covariance Typ	Mo	whi OL Least Square n, 15 Apr 202 22:35:1 3 nonrobus	S Adj. s F-sta 4 Prob 3 Log-L 5 AIC: 2 BIC:	ared: R-squared: tistic: (F-statistic ikelihood:):	0.131 0.077 2.422 0.105 -3.0036 12.01 16.67	Dep. Varial Model: Method: Date: Time: No. Observ. Df Residua Df Model: Covariance	ations: ls:	Mor	er OL Least Square n, 15 Apr 202 22:35:1 3 3	S Adj s F-s 4 Prol 3 Log 5 AIC 2 BIC			0.149 0.096 2.795 0.0761 -64.252 134.5 139.2
	coef	std err	t	P> t	[0.025	0.975]		co	ef	std err	t	P> t	[0.025	0.975]
	0.1494 -0.2351 -0.1803	0.067 0.124 0.107	2.234 -1.899 -1.690	0.033 0.067 0.101	0.013 -0.487 -0.398	0.286 0.017 0.037	const andrews neal	0.75 -0.96 -1.39	96	0.385 0.713 0.614	1.963 -1.361 -2.280	0.058 0.183 0.029	-0.029 -2.421 -2.650	1.539 0.482 -0.149
Omnibus: Prob(Omnibus): Skew: Kurtosis:		4.06 0.13 0.59 3.64	1 Jarqu 5 Prob(n-Watson: e-Bera (JB): JB): No.		2.236 2.672 0.263 3.32	Omnibus: Prob(Omnib Skew: Kurtosis:			0.24 0.88 0.11 2.50	6 Jar 0 Proi 0 Con	bin-Watson: que-Bera (JB): b(JB): d. No.		2.203 0.435 0.804 3.32

Figure 4: Regression output surgeon predicting Whip (left) and Era (right)

OLS Regression Results						
Dep. Variab	 le:	recov	/ R–squ	 ared:		0.194
Model:		0L9	Adj.	R-squared:		0.144
Method:		Least Squares	F-sta	tistic:		3.854
Date:	Mo	on, 15 Apr 2024	Prob	(F-statistic	:):	0.0316
Time:		22:35:12	2 Log-L	ikelihood:		-127.31
No. Observa	No. Observations: 35 AIC:					260.6
Df Residual	Df Residuals: 3					265.3
Df Model:		2	2			
Covariance ¹	nonrobust	:				
========						
	coef	std err	t	P> t	[0.025	0.975]
const	20.0588	2.332	8.601	0.000	15.308	24.809
andrews	9.3697	4.318	2.170	0.038	0.574	18.166
neal	-3.3316	3.721	-0.895	0.377	-10.911	4.248
Omnibus:		14.669	Durbi	 n-Watson:		1.845
Prob(Omnibus	s):	0.001	l Jarqu	e-Bera (JB):		18.040
Skew:		1.174	Prob(JB):		0.000121
Kurtosis:		5.619	Cond.	No.		3.32

Figure 5: Regression output surgeon predicting recovery time

The results of our initial methodology considering surgeons predicting differences in statistics went how we expected it to for the most part. The surgeons did not seem to have a significant impact on statistics. As seen in figures 1-4 the p values of the first 8 models were all greater than 0.05 showing the surgeon performing the surgery didn't impact the statistics. We did find that the era and whip p values were closer to 0.05 which caused us to explore a second question. Figure 5 shows the only thing statistically significantly impacted by the performing

surgeon of the Tommy John surgery. Dr. Neal ElAttrache was shown to reduce recovery time by 3 months when compared to other surgeons. This was validated as being statistically significant as seen by a p-value of 0.03. This conclusion was validated by an output table and a box plot which can be seen in Figures 6 and 7 below.

[12]:		count	mean	std	min	25%	50%	75%	max
	surgeon								
	Dr. Christopher Ahmad	1.0	15.000000	NaN	15.0	15.0	15.0	15.0	15.0
	Dr. David Altchek	5.0	22.400000	8.502941	16.0	17.0	20.0	22.0	37.0
	Dr. George Paletta	3.0	17.666667	3.055050	15.0	16.0	17.0	19.0	21.0
	Dr. James Andrews	7.0	29.428571	17.775049	9.0	18.0	25.0	38.0	60.0
	Dr. Keith Meister	5.0	20.600000	11.036304	14.0	14.0	16.0	19.0	40.0
	Dr. Neal ElAttrache	11.0	16.727273	3.495452	13.0	14.0	15.0	20.0	22.0
	Dr. Timothy Kremchek	3.0	19.333333	6.027714	13.0	16.5	20.0	22.5	25.0

Figure 6: Output table showing surgeons statistics as it pertains to recovery time.

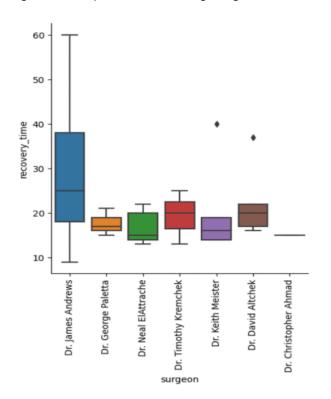
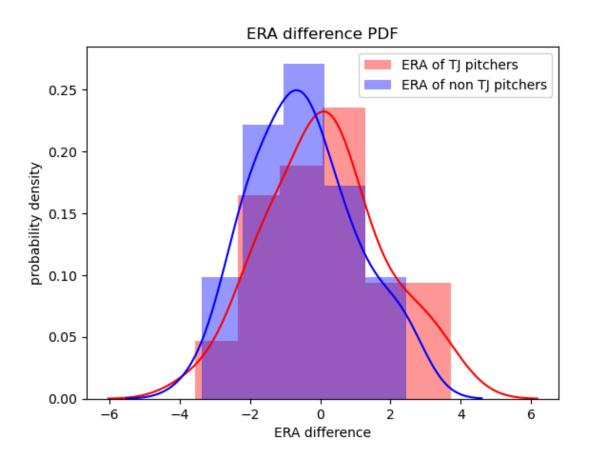


Figure 7: Box plot of output table

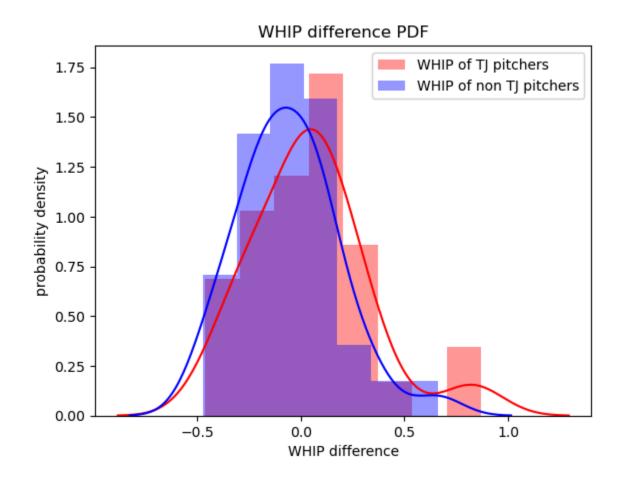
Both figures 6 and 7 confirm that Dr. Neal is the best surgeon to pick if you want to recover the fastest. He has treated the most patients (11) and still has the lowest mean recovery time of almost 17 months. His standard deviation is also one of the smallest which is impressive given the number of patients treated. Interestingly Dr. James Andrews has one of the highest means in part due to his extremely high standard deviation.

The study's second research question aimed to investigate whether there exists a statistically significant difference between the statistics of pitchers who underwent Tommy John surgery and those who did not. Given that the most significant disparity was observed in the difference between a pitcher's ERA and WHIP from the year before surgery to their return year, conducting a test to compare non-Tommy John pitchers with those who underwent the surgery was important for the study's objectives. To achieve this, two independent t-tests were conducted to identify any statistical significance. Test number one involved comparing a list of Tommy John pitchers' ERA differences with a list of non-Tommy John pitchers' ERA differences. The second test is the same but performed on WHIP instead of ERA. The results of these tests are as follows.



T-Test Result: statistic=1.591418198901537, p value=0.11615403130184827, df=68.0

The result of the ERA T-Test shows no statistical significance because of the p-value greater than 0.05. However, by analyzing the graph of the normal distribution of the two data sets it is an interesting observation that pitchers post-Tommy John appear to be improving in performance more than pitchers without the surgery.



T-Test Result: statistic=1.6424610891642755, p value=0.10511137950195451, df=68.0

The result of the WHIP T-Test also indicates no statistical significance, with a p-value greater than 0.05. However, similar to the ERA T-Test, the observation remains consistent: pitchers post-Tommy John surgery seem to exhibit greater performance improvement compared to pitchers without the surgery.