ABSTRACT

AN EXPLORATION OF THE ECONOMICS OF NOSTALGIA IN THE VIDEO GAME MARKET

by Morgan Alaric Otto

An old, signed baseball mitt or your first tickets to a concert often hold more personal value than you originally spent on them. Nostalgia is a powerful force that can drive a consumer to purchase a product for the sole purpose of remembering a past time. This paper posits that one of the ways businesses in the video game market can utilize nostalgia is by timing the release of remakes. Using observational data on video game sales with information on genre, sequels, and remakes for each observation, I estimate that the length of wait time that generates the most sales for the release of a remake is between 9 and 20 years.

AN EXPLORATION OF THE ECONOMICS OF NOSTALGIA IN THE VIDEO GAME MARKET

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Table 1.a - Genre Statistics

	North American		Japanese	
	Avg. Sales	% of dataset	Avg. sales	% of dataset
Action	406,577	15.31%	158,116	17.15%
Adventure	221,158	2.88%	96,283	8.07%
Fighting	471,004	5.09%	251,451	6.79%
Misc.	449,495	10.11%	243,913	6.92%
Platformer	754,819	6.13%	521,593	5.78%
Puzzle	357,331	3.29%	380,068	3.17%
Racing	357,977	9.77%	259,061	4.56%
Role-Playing	371,044	9.15%	345,551	20.90%
Shooter	532,903	11.09%	99,858	7.56%
Simulation	334,568	5.27%	256,584	4.33%
Sports	396,084	18.80%	244,833	11.56%
Strategy	210,036	3.11%	155,733	3.21%

Table 1.b - Sequel and Remake Breakdown

		North American		Japanese	
		Avg. Sales	% of dataset	Avg. sales	% of dataset
Sequels					
	Crossovers	444,088	2.61%	197,785	4.78%
	Expansions	382,018	2.07%	352,500	0.95%
	Regular	482,049	95.32%	270,926	94.27%
Remakes					
	First game	375,989	18.61%	249,627	26.43%
	Sequels	383,158	15.98%	205,897	25.84%
	Game Compilation	425,241	65.40%	144,258	47.73%

Table 1.c - Likelihood a Game Gets a Sequel or a Remake

	North American		Japanese	
	Avg. Sales	% of dataset	Avg. sales	% of dataset
First game in a series .	309,603	31.47%	210,322	25.19%
Remake	411,289	10.62%	186,331	11.00%
Sequels	482,007	57.91%	268,042	63.81%
Likelihood game gets a sequel	30.66%		42.90%	
Likelihood game gets a remake	5.56%		7.64%	
Likelihood game does not get remade or has a sequel	63.78%		49.46%	

Table 2 - Sales By Quartile

	North America	Japan	Global
Sales at 1st percentile	0	0	10,000
Sales at 25th percentile	10,000	0	80,000
Sales at 50th percentile	90,000	0	210,000
Sales at 75th percentile	290,000	50,000	590,000
Sales at 99th percentile	3,360,000	1,560,000	6,910,000
Percent sequels	0.6018878	0.6751606	0.6116132
Percent remakes	0.1026097	0.1055675	0.100955
Percent ports	0.3458079	0.2029979	0.3194065
Percent game compilation	0.0735147	0.054818	0.0649727
Percent game crossover	0.0152138	0.032334	0.0148363
Percent expansion	0.0121044	0.006424	0.0125341

Notes: Sales were measured in millions and did not give values of less than 0.01 which is equivalent to 10,000 sales. Notice that .602+.103+.346 = 1.051, this is because sequels, remakes, and ports are not mutually exclusive. In addition compilations, crossovers and expansions represent a very small portion of the dataset.

Table 3 - Linear Regression

	(1) NAlogsales	(2) NAlogsales	(3) NAlogsales	(4) NAlogsales
Yearsbetweensequel	-0.0294***		-0.0297***	
	(-4.89)		(-4.73)	
Yearsbetweenremake		0.0152***		-0.00197
		(3.31)		(-0.39)
g1			-0.0168	-0.321**
			(-0.21)	(-2.61)
g2			-0.651***	0.535***
			(-4.37)	(3.49)
g3			0.159	-0.785***
			(1.55)	(-4.65)
g5			0.426***	0.279
			(4.12)	(1.82)
g6			-0.341**	-0.301
			(-2.64)	(-0.85)
g7			-0.208*	-0.328
			(-2.36)	(-0.94)
g8			-0.206*	-0.147
			(-2.30)	(-0.90)
g9			0.0746	-0.685***
			(0.79)	(-3.69)
g10			-0.174	-1.437***
			(-1.73)	(-3.36)
g11			-0.0363	-1.068**
			(-0.50)	(-2.81)
g12			-0.712***	-1.238***
			(-5.32)	(-4.16)
_cons	-1.519***	-1.956***	-1.459***	-1.537***
	(-63.44)	(-25.51)	(-22.29)	(-14.07)

Notes: t statistics are in parentheses (* p<0.05 **p<0.01 ***p<0.001)

Table 4 - Linear Regression with Sales of Previous Game

	(1) NAlogsales	(2) NAlogsales
Yearsbetweensequel	-0.0442***	
	(-6.26)	
SalesofprequelNA	0.183***	
	(5.82)	
Yearsbetweenremake		-0.00937
		(-1.90)
SalesofOGNA		0.198***
		(4.44)
g1	0.0543	-0.449***
	(0.69)	(-3.75)
g2	-0.635***	0.393*
	(-4.58)	(2.51)
g3	0.227*	-0.739***
	(2.31)	(-4.50)
g5	0.382***	0.0906
	(3.91)	(0.66)
g6	-0.411**	-0.510
	(-3.25)	(-1.67)
g7	-0.142	-0.314
	(-1.67)	(-0.89)
g8	-0.103	-0.172
	(-1.19)	(-1.13)
g9	0.168	-0.781***
	(1.83)	(-4.68)
g10	-0.0744	-1.469**
	(-0.76)	(-3.17)
g11	0.0345	-1.068**
	(0.47)	(-2.97)
g12	-0.602***	-1.167***
	(-4.61)	(-3.96)
_cons	-1.601***	-1.613***
	(-23.87)	(-13.57)

Notes: t statistics are in parentheses (* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

Table 5 - Quadratic Regression

	(1) NAlogsales	(2) NAlogsales	(3) NAlogsales	(4) NAlogsales
logSalesofprequelNA	0.396***		0.397***	
	(25.91)		(25.68)	
Yearsbetweensequel	-0.0640***		-0.0580***	
	(-3.94)		(-3.55)	
YearssequelSq	0.00116		0.000924	
	(1.12)		(0.92)	
logSalesofOGNA		0.457***		0.455***
		(14.56)		(14.88)
Yearsbetweenremake		0.0729***		0.0478*
		(4.51)		(2.55)
YearsemakeSq		-0.00317***		-0.00261***
		(-6.26)		(-4.53)
g1			0.0496	-0.190
			(0.61)	(-1.52)
g2			-0.508***	0.138
			(-3.80)	(0.75)
g3			0.185	-0.207
			(1.88)	(-0.97)
g5			0.136	0.112
			(1.45)	(0.99)
g6			-0.313**	-0.600*
			(-2.72)	(-2.18)
g7			-0.138	-0.119
			(-1.63)	(-0.42)
g8			0.0780	-0.0802
			(0.85)	(-0.47)
g9			0.190	-0.540**
			(1.94)	(-3.12)
g10			0.0992	-1.663***
			(0.91)	(-3.35)
g11			0.162*	-0.669*
			(2.21)	(-2.23)
g12			-0.428**	-0.163
			(-3.07)	(-0.46)
_cons	-0.831***	-1.585***	-0.897***	-1.271***
	(-21.77)	(-13.50)	(-12.62)	(-8.40)

Notes: t statistics are in parentheses (* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

Table 6 - Sales Impact on Release Timing

	(1) Yearsbetweensequel	(2) Yearsbetweensequel	(3) Yearsbetweenremake	(4) Yearsbetweenremake	(5) Yearsbetweensequel	(6) Yearsbetweenremake
NA_Sales	-0.0737*	-0.101**	0.772*	-0.452*		
	(-2.37)	(-3.23)	(2.05)	(-2.06)		
SalesofprequelNA					0.167***	
					(3.42)	
SalesofOGNA						0.391***
						(3.49)
g1		1.413***		-9.601***	1.431***	-9.532***
		(8.87)		(-13.68)	(8.99)	(-13.66)
g2		1.379***		-9.719***	1.448***	-9.520***
		(6.11)		(-10.48)	(6.42)	(-10.39)
g3		1.546***		-10.70***	1.563***	-10.17***
		(7.49)		(-16.12)	(7.57)	(-15.14)
g5		1.982***		-4.531***	1.825***	-5.093***
		(7.73)		(-5.19)	(7.13)	(-5.79)
g6		1.350***		-0.834	1.267***	-1.055
		(4.27)		(-0.58)	(4.40)	(-0.76)
g7		0.713***		-12.51***	0.729***	-12.24***
		(4.79)		(-10.05)	(4.92)	(-9.72)
g8		2.403***		-11.27***	2.459***	-10.98***
		(12.40)		(-19.13)	(12.65)	(-18.45)
g9		1.367***		-11.72***	1.374***	-11.65***
		(7.73)		(-17.44)	(7.78)	(-17.61)
g10		0.950***		-12.23***	1.013***	-12.02***
		(4.75)		(-11.17)	(5.05)	(-10.91)
g11		-0.151		-15.30***	-0.104	-14.92***
		(-1.25)		(-18.40)	(-0.85)	(-17.83)
g12		1.598***		-12.99***	1.680***	-12.28***
		(5.64)		(-15.25)	(5.92)	(-13.94)
_cons	2.740***	1.736***	10.18***	17.28***	1.587***	16.74***
	(64.24)	(15.03)	(36.36)	(42.19)	(13.36)	(42.20)

Notes: t statistics are in parentheses (* p<0.05 **p<0.01 ***p<0.001)

Table 7 - Log Sales Impact For Sequels and Remakes Quadratic Relationship of Years Between Releases

	Panel A: Sequels log(Sales)		
Years between	-0.0640***	-0.0580***	0.161*
	(-3.94)	(-3.55)	(-2.33)
Years between SQ	0.00116	0.000924	-0.00656*
	(-1.12)	(-0.92)	(-2.46)
	Panel B: Remakes log(Sales)		
Years between	0.0729***	0.0478*	0.0485**
	(-4.51)	(-2.55)	(-2.71)
Years between SQ	-0.00317***	-0.00261***	-0.00243***
	(-6.26)	(-4.53)	(-4.07)
Genre FE		✓	✓
Logged Previous Sales Control	✓	✓	✓
Year FE			✓

Notes: *** p<0.01, ** p<0.05, * p<0.10.

Table 8 – Quadratic Relationship of Years Between by Sales Groups

	(1) NAlogsales	(2) NAlogsales	(3) NAlogsales
logSalesofOGNA	0.0609	0.0164	0.332***
	(1.89)	(0.99)	(9.02)
Yearsbetweenremake	-0.0323*	0.0353***	-0.0322
	(-2.04)	(4.57)	(-1.48)
YearsemakeSq	0.000985	-0.000911***	0.000581
	(1.95)	(-3.81)	(0.71)
g1	-0.199	0.0519	-0.289*
	(-1.64)	(1.04)	(-2.07)
g2	0	0.453***	-0.747***
	(.)	(8.46)	(-4.09)
g3	0.113	-0.246	-0.155
	(0.81)	(-1.43)	(-0.65)
g5	0.275***	0.0418	-0.314**
	(4.49)	(0.53)	(-2.88)
g6	-0.376	0.0713	-0.506
	(-1.44)	(0.67)	(-1.62)
g7	-0.166	-0.0733	0.114
	(-0.80)	(-0.61)	(0.93)
g8	-0.126	0.337***	-0.353*
	(-0.81)	(4.33)	(-2.13)
g9	-0.0799	0.211*	-0.308
	(-0.73)	(2.51)	(-1.85)
g10	0.504***	-0.0732	-0.0766
	(4.20)	(-0.58)	(-0.91)
g11	-0.620**	-0.104	-0.941**
	(-2.74)	(-0.54)	(-2.80)
g12	-0.790***	0.304**	-0.657
	(-6.21)	(2.70)	(-1.72)
_cons	-2.810***	-2.088***	0.127
	(-19.81)	(-33.19)	(0.80)

Notes: t statistics are in parentheses (* p<0.05 **p<0.01 ***p<0.001)

Table 9 - Sales Impact For Sequels and Remakes Linear Relationship of Years Between Releases

	Panel A: Sequels Sales			
Years between	-0.0294***	-0.0297***	-0.0442***	-0.0181***
	(-4.89)	(-4.73)	(-6.26)	(-5.44)
	Panel B: Remakes Sales			
Years between	0.0152***	-0.00197	-0.00937	-0.00558*
	(-3.31)	(-0.39)	(-1.90)	(-2.45)
Genre FE		✓	✓	✓
Linear Previous Sales Control			✓	✓
Year FE				✓

Notes: *** p<0.01, ** p<0.05, * p<0.10.

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Figure 1 - Data Histograms

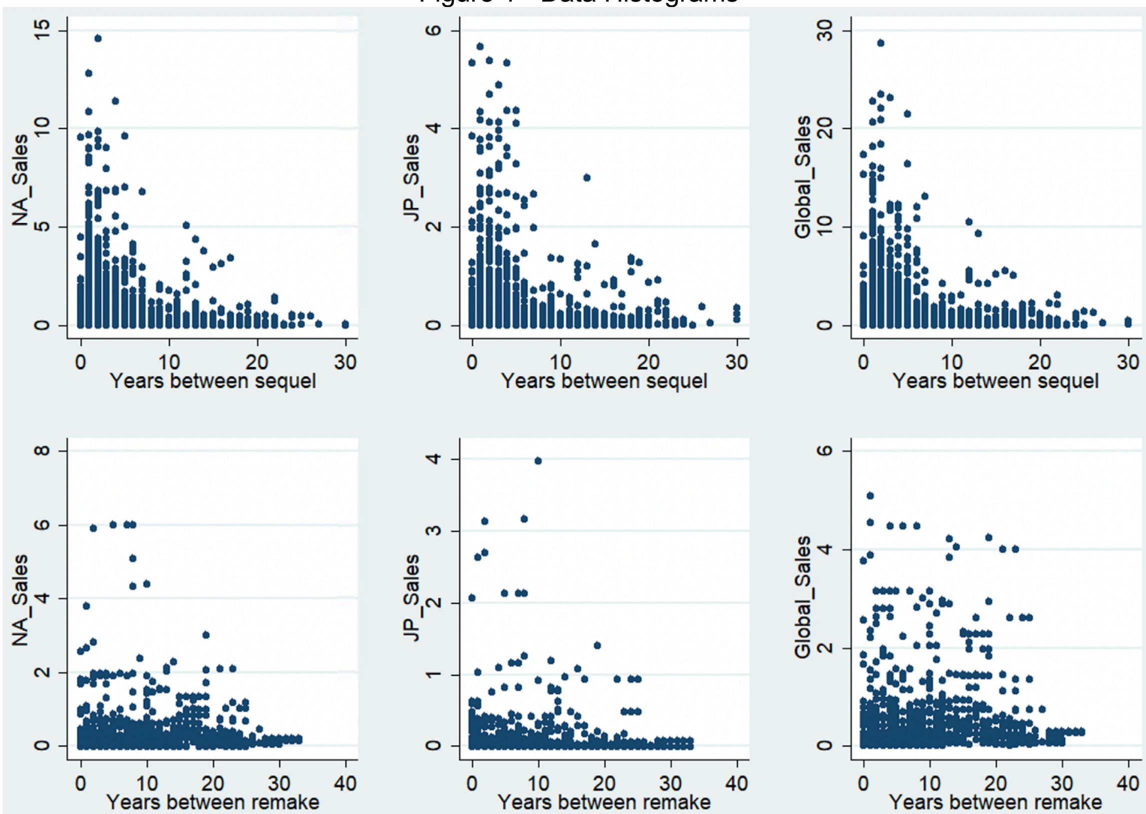
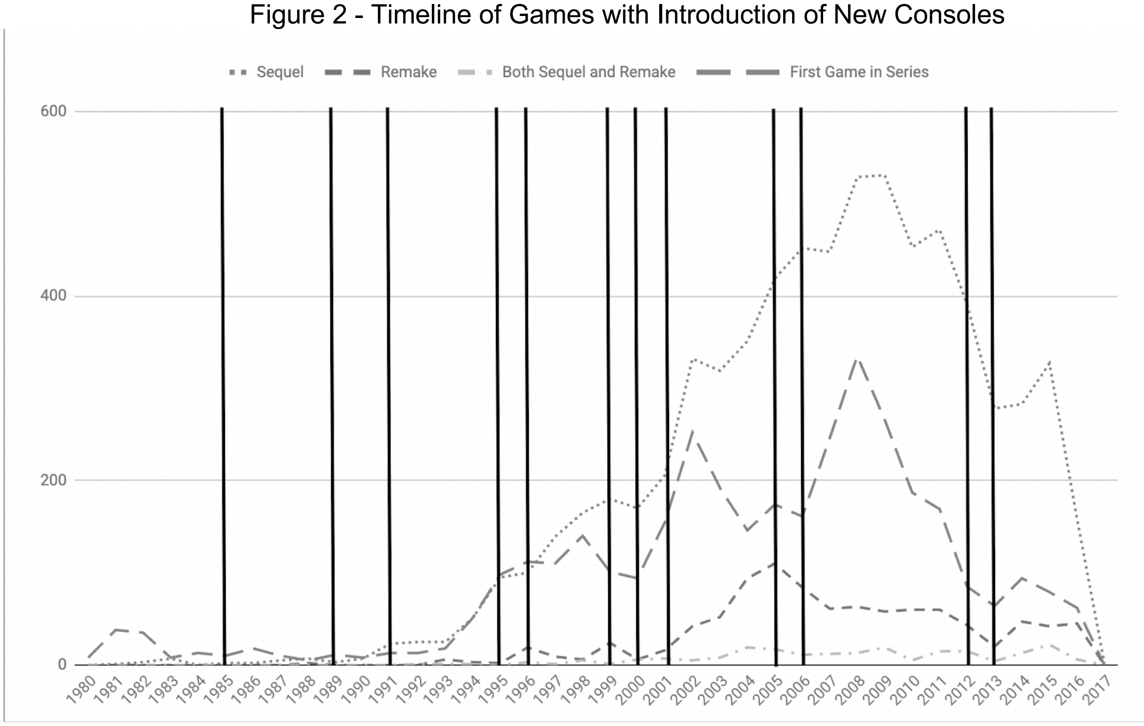


Figure 2 - Timeline of Games with Introduction of New Consoles



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I Introduction

People tend to look back on the past with rose colored glasses, even if that time was not special itself. People long for the ways they spent their youth. The market reflects this desire for the past as an increase in demand for products that people were fond of in their childhood. A prime example of this phenomenon is reflected in the video game industry with sequels, remakes, and ports. In the 1980s and 1990s, video games were marketed to children at an impressionable age. Today those people are now adults, some with children themselves. As the technology improves, many of the games people grew up loving have aged poorly. Graphical issues, technical limitations, and outdated game design philosophy that were emblematic of video games when they were released hold these games back from the quality of a modern gaming experience. However, many of these problems can be alleviated by the use of the modern HD remake, and this paper posits that the timing of those releases can be adjusted to match the fluctuations in the market caused by nostalgia.

Due to the fact that this research is descriptive, this paper examines both the producer side and consumer side. It should be predicted that consumers' demand for nostalgic products would naturally wax and wane throughout their lifecycle with demand for products within specific times in the past matching up with high demand for products from those specific times in their future. An example of consumer-focused perspective is illustrated when parents buy a Mario game for their child at roughly the same age they were when they got their first Mario game. Following this logic to its conclusion, a parent might mimic their own childhood by buying products for their child at the same ages they received those products. The producer wants to be able to accurately forecast when demand will be highest for the nostalgic good in question in order to maximize sales. In addition, one could expect a remake would be less work than a sequel because the game was already made once, thus only needs to be "updated." For this reason, the research focuses on the difference between remakes and sequels.

Additional research is required to answer the broader research question: when should a producer release any nostalgic good? The scope of that question falls outside the bounds of this paper. The focus instead is on the smaller question: what is the best time to release a sequel or remake in the video game industry to generate the most sales? By using a term for years between games in a series and a squared term for years between games in a series, I find that the best time to release a remake is between 9.15 to 11.5 years. Under the most naive regression that leaves out all genre and market shock controls, the best time to release a remake is 11.5 years. Under the most stringent regression specification the best time to release a remake is 10 years. These numbers, however do not match my generational story. Another story that the 10 years could tell is that I was nostalgic for a game from my childhood, and now that I am a young adult I have the funds to purchase this game for myself when I am feeling nostalgic for the game in question. This research is beneficial to consumers because they receive a nostalgic good exactly when they want it most in their consumption life cycle. Essentially, the product is released at a point in time where the marginal benefit is largest for that good. Given the nostalgic good, video game companies also benefit from larger sales, and in the case of remakes, lower costs.

The literature in economics focusing on nostalgia is thin and does not delve deeply into the subject. Because there is not much literature on the economics of nostalgia, there is not an agreed upon meaning of the economics of nostalgia. This paper uses nostalgia as a mechanism for why such sequels and remakes exist and I evaluate the presence of nostalgia by estimating the success of such products. From this perspective, the ultimate determiner of nostalgia is the consumer, because they make the final purchasing decision. The natural question is what is the difference between the economics of nostalgia and the economics of repeat purchasing. Crémer, in his 1984 paper, investigates repeat buying from a monopolist by looking at a two period system of changing prices for a product to capture more profit. Crémer both looks at a monopolist who can easily differentiate between repeat buyers and monopolists who cannot identify repeat buyers. In his model consumers cannot identify the exact utility from a product and therefore buy the product in the first period to understand their own taste, and the quality of the product. In the second period they may choose to repeat buy the product, and the price that is charged is lower. The main difference between my work and Crémer's is that he is concerned with dynamic pricing and I am concerned with the timing of release. Other research has been done into repeat buying on more seasonal factors like purchasing gifts (Palma, Hall, & Collart, 2011).

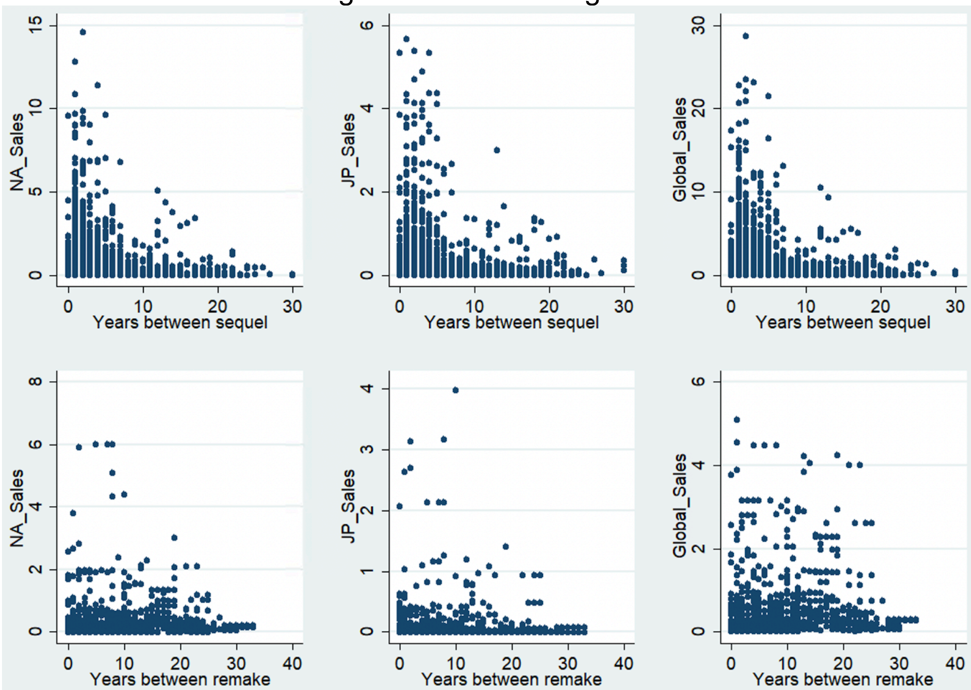
This paper began with the question of how nostalgia impacts sales. When researching the literature on nostalgia's impacts on economies and other product markets, one finds very little information. Investigating similar topics like repeat buying (Crémer 1984 and Palma, Hall, & Collart, 2011) or upgrade, tradein or buyback purchasing (Fudenberg & Tirole 1998) one can see that the focus of the discussion is on pricing and not the timing of release. It is possible that there is huge untapped potential in understanding the economics of nostalgia for four reasons: one, consumers benefit from nostalgia most if the products they feel nostalgic for are released at just the right time to match with the natural waxing and waning of demand for nostalgic goods. Two, producers benefit because understanding nostalgia will help the businesses release those nostalgic goods at just the right time to reach the most consumers and drive optimal sales. Three, a well-timed remake or a port will be much lower cost for the producer while meeting the nostalgic needs of the consumer. Finally, contributing to the economic literature, and opening up new avenues for future research.

The rest of the paper is broken up into sections pertaining to my research. Section II describes the data and the methods used to make the data usable for regression analysis. Section III will go over the first linear regression and the implications we can draw from the observational data collected. Section IV will go over the quadratic version of the problem. Finally, Section V will show the main results and check the robustness of said results while section VI will go over the conclusion and possible extensions to this research.

II Data

This project uses a large time series video game dataset with sales for every game which is scraped off the internet from VGChartz.com. The data set is from 2017 with video games that sold at least 10,000 copies after the year 1980. However, these sales units are in millions of sales, so in the dataset, a video game that sold 10,000 copies is written as 0.01 sales. In addition to sales, the game's original title at release, the genre, the platform/console the game was released under, and the publisher of the game are listed. Sales are also broken down into three regions: North America, Japan, and Europe, as well as an aggregate global sales variable. Although global sales are included in the dataset and have more non zero values (there are some games that read as having no sales in any region, but still have sales globally), it would be unwise to use that variable as the dependent variable in any of the regressions due to the difficulty in separating possible average cultural differences in nostalgic effects.

Figure 1 - Data Histograms



Here, I provide histograms (without controls) that highlight the variation in the years between when a remake or a sequel occurs. This suggests that my research question is valid and that I may be able to better understand the time of release of a video game for a company. The complete dataset includes over 11,000 unique video game observations with at minimum sales recorded globally. The histograms also show evidence that sequels make more sales than remakes do on average. There is clear variation in the length of time of second game release as the data set goes from the 80's to the late 2010's. From that information alone, it is impressive to see that some of the oldest games recorded by the data set are still getting sequels and remakes 20 or 30 years down the line.

My dataset also includes detailed information on the genre of each game, which can be broken down into 11 genres and one catch-all category to capture games that don't fit into the strict genre system most other games adhere to. Many genres are targeted towards specific demographics or age ranges. Shooter games tend to be rated for older children or even for adults, while platforming games tend to be rated for a younger audience. These clues led me to believe that nostalgic effects would work differently for different genres of games. An incredibly helpful measure would be the age rating scale for the video game in each observation. Rating systems are different across the globe and are controlled by the government of each country that has one, as well as the belief systems of each country and what they would deem an appropriate rating for an older audience. Besides genres, my dataset also has information on the publisher of each video game. I thought that a publisher's reputation may have an impact on the sales of video games produced by that publisher, but the effects are negligible.

After the data scraping and the first round of data cleaning was complete, I started adding information that would be important to the data set. The information included is:

dummies on if the game was a sequel[1], remake[2], port[3], if the game was a sequel to a game not in the data set, if the game was part of a video game compilation, if the game was the sequel to multiple games, if the game was a video game crossover, and finally, if the game was a pure expansion[4]. I also included other data fields pertaining to the previous game in the series, like what the game was ported from, what the name of the previous game in the series was, and what the original name before the game was remade was. The last bits of information I was able to calculate were: the years between a sequel or a remake (this is the most important variable), and the sales of the previous game in the series (remake or sequel).

Fans of a series and executives might not agree on what constitutes a sequel, but what we really care about is what the consumer has to say because the consumer determines what they call nostalgia. I trust the consumer's opinion more than the producer, because the nostalgia impacts the consumer, not the producer. The most dedicated fans of the franchise are the most likely to be editing and creating websites with specific information on remakes and sequels. These websites are generally open to editing from the public, but if incorrect information were to be inputted, then the more dedicated fans would change that information to be more accurate. I used many of these fan websites to determine specific information about the sequels and remakes[5][6][7][8].

[1] This paper defines a sequel as a game in a franchise or series that did not start that franchise or series that also isn't a direct copy of a previous game in that franchise or series. In addition, a sequel could be spiritual successor to a series as long as the fans of that series agree. It is also important to say what a sequel is not as well: A sequel does not need to be a direct continuation of a story. A sequel does not need to be published or developed by the same company, nor does it need to be the same genre or even feature the same characters.

[2] This paper defines a remake as a new version of an old game with mostly technical improvements, such as graphical upgrades or updating the frame rate. A remake is usually created as a result of the release of a new console, and the company producing the remake may update one or two of its gameplay features to fit the updated console. In the category of remakes, there lies a larger game containing multiple old games on one disc, these are called game compilations.

[3] This paper defines a port as a game similar to a remake in that almost nothing would change for a port, but a port isn't an update. A port is a copy of a game produced for consoles other than the console where the game was initially released. In addition, because the port is on a different console, the game might not be perfectly replicated. For those reasons, I mostly ignore ports.

[4] This paper defines a pure expansion as a very small sequel that requires that the consumer already owns the original game it is a sequel to.

[5] https://segaretro.org/Sakura_Taisen_Hanagumi_Tsuushin

[6] https://nintendo.fandom.com/wiki/Kururin_Paradise

[7] https://guiltygear.fandom.com/wiki/Guilty_Gear_XX

[8] https://advancewars.fandom.com/wiki/Advance_Wars:_Days_of_Ruin

Table 1.a - Genre Statistics

	North American		Japanese	
	Avg. Sales	% of dataset	Avg. sales	% of dataset
Action	406,577	15.31%	158,116	17.15%
Adventure	221,158	2.88%	96,283	8.07%
Fighting	471,004	5.09%	251,451	6.79%
Misc.	449,495	10.11%	243,913	6.92%
Platformer	754,819	6.13%	521,593	5.78%
Puzzle	357,331	3.29%	380,068	3.17%
Racing	357,977	9.77%	259,061	4.56%
Role-Playing	371,044	9.15%	345,551	20.90%
Shooter	532,903	11.09%	99,858	7.56%
Simulation	334,568	5.27%	256,584	4.33%
Sports	396,084	18.80%	244,833	11.56%
Strategy	210,036	3.11%	155,733	3.21%

To help show that this research question is worthy of answering, I analyzed the section of the video game market revealed in this dataset, including the data on the Japanese market for comparison. All categories of Table 1 give the average sales and the percent of the dataset with non-zero sales observed. I specify non-zero sales here, because some games are only sold, or only have sales over 10,000, in certain places in the world. Although there are 11,000 observations with year information, there are less observations with non-zero values for sales in America.

Table 1.a analyzes games by genre. Interesting things to note in Table 1.a are that for the most part there are similar percentages of genre in the dataset in Japan than there are in America in all categories but four: the genres of role-playing, adventure games, racing, and miscellaneous games. This is due to Japan having two types of games that are not seen in American markets. These games are Japanese role-playing games (JRPGs), which fall under the role-playing genre and dating simulation games, which fall under the adventure genre.

The story told so far is that a consumer who liked a game in their youth will want to purchase the game as close to their perfect time to maximize the utility they receive from the game in the current period, but the problem with this thinking is that the consumer does not decide when the game is released. Ignoring possible costs associated with waiting to release a game, a company using the economics of nostalgia perfectly would release their games at a frequency to maximize their sales. Another commonly used strategy by large companies is to expose the potential consumers to the product at all times. I think of the Pokémon franchise with a new game every couple of years across different genres, a television show that has been running for 25 years, and card sales for about 25 years as well. Another alternative approach to the one just described would be sports games that release every year along with the new roster for the season that sports game is associated with. It is important to control for different genres of video games in my regressions, because of the sports genre and other genres that behave in similar ways. The genre may be the main reason why a video game series has a certain release schedule.

Table 1.b - Sequel and Remake Breakdown

		North American		Japanese	
		Avg. Sales	% of dataset	Avg. sales	% of dataset
Sequels					
	Crossovers	444,088	2.61%	197,785	4.78%
	Expansions	382,018	2.07%	352,500	0.95%
	Regular	482,049	95.32%	270,926	94.27%
Remakes					
	First game	375,989	18.61%	249,627	26.43%
	Sequels	383,158	15.98%	205,897	25.84%
	Game Compilation	425,241	65.40%	144,258	47.73%

Table 1.b is provided with information that breaks down sequels and remakes into some smaller categories. The top section provides average sales and the percentage of those sequels that are crossovers, expansions and neither. Looking at this section, a very small percentage of sequels made are crossovers or expansions in this dataset. Many modern games come out with expansions, however the majority of these expansions are sold through the online stores that are associated with the console they are released on. This means that my dataset will capture a very small portion of the actual expansion sales, only those expansions that are purchased in a physical store. One can see that, in America, games that are not crossovers or expansions actually make more sales on average. The bottom section of Table 1.b focuses on remakes, and breaks them down into the categories of a remake of the first game in a series, a remake of a sequel, and a remake that is a game compilation. It may be interesting to note that the majority of remakes are game compilations, and they make more sales on average than the other two categories in the United States.

The main outcome of interest in this research is the log of North American sales (referred to now as logsales). The reason logsales are used over just sales is twofold; one, because the log helps account for heterogeneous results, and two, because logsales are more understandable than just sales as they may be interpreted as a percentage change rather than a linear increase.

Table 1.c - Likelihood a Game Gets a Sequel or a Remake

	North American		Japanese	
	Avg. Sales	% of dataset	Avg. sales	% of dataset
First game in a series .	309,603	31.47%	210,322	25.19%
Remake	411,289	10.62%	186,331	11.00%
Sequels	482,007	57.91%	268,042	63.81%
Likelihood game gets a sequel	30.66%		42.90%	
Likelihood game gets a remake	5.56%		7.64%	
Likelihood game does not get remade or has a sequel	63.78%		49.46%	

Table 1.c includes ports for the calculation for the percent of games that are remakes, sequels, and the first game in the series. The other important thing to note in the data set is that, for the American market, both remakes and sequels make more sales than the first game in the series. I have used my data to calculate the likelihood that a game will get a sequel, a remake, or will get neither in my dataset. This number is different from the percent of the dataset that is a sequel or a remake. The percent of the dataset that is a remake is calculated by taking the number of games that are a remake and dividing that number by the total number of games in the dataset, while the percent of the dataset that is a sequel is calculated by taking the number of games that are sequels and not also remakes and dividing that number by the total number of games in the dataset. The likelihood that a game gets a sequel is calculated by taking the number of games in the dataset that get a sequel by the total number of games in the dataset. Many games that get sequels get more than one sequel. This is where the idea of multiple series spinning off from one game in a franchise comes from. The opposite is true for remakes, because if a game is influential enough to warrant a remake, that likely means it is influential enough to warrant another remake a couple of years later.

It is not likely that games randomly get a sequel or a remake in reality. Rather a game getting a sequel or a remake is dependent on how well the previous game in the series sells and the fanbases created surrounding that game series. In addition, the console the game is made for, the producer of the game, or developers who worked on the game factor into whether or not a game can get a sequel or a remake. If a producer owns the rights to a franchise or a series, but cannot fund a sequel or a remake, then it does not matter that a game has a suitably large enough fan base, or the previous game made enough sales, or the timing is just right to release the next game in the series. Developers can influence these odds because the consumer can decide that a game made by a specific developer on the team that made the original game is actually a spiritual sequel. Remakes really have to be made by someone who owns the intellectual property of the original game. In reality, whether or not a game gets a sequel or a remake is a lot more complicated than simply stating there is a 30.66% likelihood that a game will get a sequel and a 5.56% likelihood a game gets a remake.

As previously mentioned, there is also information on European and Japanese video game sales included in the dataset. I am less equipped to understand the video game markets in those places, and a broad “European” market will likely have many different nostalgic effects at play throughout the continent. In addition, there are less recorded sales in the European market or the Japanese market than there are in the American market for this dataset. The global sales have more listed sales than any other group and the nostalgic effect would be hard to find for the same reason that the European market’s nostalgic effect would be hard to find.

Table 2 - Sales By Quartile

Table 2- Summary Statistics

	North America	Japan	Global
Sales at 1st percentile	0	0	10,000
Sales at 25th percentile	10,000	0	80,000
Sales at 50th percentile	90,000	0	210,000
Sales at 75th percentile	290,000	50,000	590,000
Sales at 99th percentile	3,360,000	1,560,000	6,910,000
Percent sequels	0.6018878	0.6751606	0.6116132
Percent remakes	0.1026097	0.1055675	0.100955
Percent ports	0.3458079	0.2029979	0.3194065
Percent game compilation	0.0735147	0.054818	0.0649727
Percent game crossover	0.0152138	0.032334	0.0148363
Percent expansion	0.0121044	0.006424	0.0125341

Note: Sales were measured in millions, and did not give values of less than 0.01 which is equivalent to 10,000 sales

Summary statistics in Table 2 are provided with information on sales at different percentiles and the proportion of the dataset that is a sequel, remake, port, or any subcategory or combination of those. In addition, this dataset treats each port of a game as another game observation, which is why the percentages numbers do not add up exactly to the numbers from Table 1.c. Looking at either North America or Japan, the lowest 25% of sales are all listed 0, and in Japan that percentile of 0 sales increases to 50%. In addition to sales at different percentiles, I also include the proportion of the games within the dataset that are sequels, remakes, ports, and other specific classifications of those three. Here, you can see that being a remake, a sequel, or a port is not mutually exclusive. That being said, due to the trimming methods used (not including games with zero recorded sales), more smaller games that are the first in their series ended up getting dropped from the dataset. The final piece of note from Table 2 is the high prevalence of sequels. The majority of all games made are now sequels, and remakes are only becoming more popular over time. In addition, the low prevalence of crossovers and expansions helps explain the negligible impacts of a game being an expansion or a crossover.

It is important to note that there is no quasi experiment nor any natural experiment used in this paper. Observational data is used to measure the effect of nostalgia on sales. This is good for our data set because it captures the entire time frame with which video games have been popular up to 2017, but bad for causal identification because there will be little causal conclusions that can easily be drawn from this data. Therefore, my empirical strategy can only pick up correlations and not any causal effect.

The movie product market can muddle the product nostalgia influence of when we think the consumer first experienced the media, by having different dates for when the movie becomes available for box office sales as well as the date the movie is released for streaming or DVD. Television takes this problem to the extreme, because we would have even less information on the day the consumer first experienced this media. Essentially, the consumer could have started watching the show in season 3 episode 16 after the show had been running for four years. To combat this problem in the video game dataset, all movie-based video games and all television-based video games have been removed from the data set. To be clear, a movie or television-based video game is a video game that came out directly because of a television show or a movie.

III Linear Estimation

In this section, I present several sets of results investigating the relationship between the length of time between video games releases in a series and the sales of video game sequels and remakes. Equation (1) is the linear specification for the question of the relationship between the length of time between video games releases in a series and the sales. $Sales_{igt}$ indicates the sales for video game *i* with the specific genre *g* in the year *t*. The most important variable YrsBetween is a simple linear term of years between releases in a series. This variable is equal to zero in the case that the remake or sequel is made within the same year that the previous game in the series is made. SalesPrev is a control variable to account for some variation in the sales of the current game given the sales of the previous game in the series. This variable is equal to zero in the case that the previous game in the series sold less than ten thousand copies in North America. I also included time effects δ_t control for time specific shocks to a particular video games sales such as a recession.

$$\ln(Sales_{igt})=\beta+\gamma*YrsBetween_i+\alpha*SalesPrev_i+\delta_t+\mu_{igt} \quad (1)$$

Table 3 - Linear Regression

	(1) NAlogsales	(2) NAlogsales	(3) NAlogsales	(4) NAlogsales
Yearsbetweensequel	-0.0294***		-0.0297***	
	(-4.89)		(-4.73)	
Yearsbetweenremake		0.0152***		-0.00197
		(3.31)		(-0.39)
g1			-0.0168	-0.321**
			(-0.21)	(-2.61)
g2			-0.651***	0.535***
			(-4.37)	(3.49)
g3			0.159	-0.785***
			(1.55)	(-4.65)
g5			0.426***	0.279
			(4.12)	(1.82)
g6			-0.341**	-0.301
			(-2.64)	(-0.85)
g7			-0.208*	-0.328
			(-2.36)	(-0.94)
g8			-0.206*	-0.147
			(-2.30)	(-0.90)
g9			0.0746	-0.685***
			(0.79)	(-3.69)
g10			-0.174	-1.437***
			(-1.73)	(-3.36)
g11			-0.0363	-1.068**
			(-0.50)	(-2.81)
g12			-0.712***	-1.238***
			(-5.32)	(-4.16)
_cons	-1.519***	-1.956***	-1.459***	-1.537***
	(-63.44)	(-25.51)	(-22.29)	(-14.07)

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

Table 3 is provided above and was the starting point in trying to understand the relationship of time between releases and sales for a sequel or a remake. This regression table leaves out all year fixed effects as well as the control for the sales of the previous game. The most naïve regressions are in columns 1 and 2. In each of these regressions there are no controls and columns 1 and 2 simply look at the relationship between the length of time it takes to release a sequel or a remake. The way these coefficients can be understood is if we take the length of time between the release of the original game and its sequel or remake we would expect sales to increase or decrease by the YrsBetween * γ * 100%. From column 1, if a producer waited a year to release a sequel we would expect that the sequel would make 1*-0.0294*100% = 2.94% less sales than a sequel that was released the same year as its predecessor on average holding all else constant. The constant term, β, (listed at the bottom as _cons) is a little bit harder to understand, as it involves using the logic of the natural log. The average level of log sales can be interpreted in levels to be e^(β). The first column of Table 3 would imply that the longer you wait to release a sequel the less sales it will make, and the average level of logged sales for a sequel that releases the same year as its predecessor will be $e^{-1.519}$ which is equal to 2190 sales. Column 2 of Table 3 implies that there is a more complicated relationship of length of time of release and sales for remakes, as the positive 0.0152 coefficient for years between suggests that there is some benefit to waiting to release a remake. Column 3 of Table 3 looks at sequels again, and after adding in genre controls the coefficient becomes slightly more negative than column 1. Looking at Column 4 of Table 3 with the genre controls being added to the equation for remakes we find that YrsBetween is negative, but very close to zero, and not statistically significant. This is in contrast to column 2 which is both positive and statistically significant.

Table 4 - Linear Regression with Sales of Previous Game

	(1) NAlogsales	(2) NAlogsales
Yearsbetweensequel	-0.0442***	
	(-6.26)	
SalesofprequelNA	0.183***	
	(5.82)	
Yearsbetweenremake		-0.00937
		(-1.90)
SalesofOGNA		0.198***
		(4.44)
Action	0.0543	-0.449***
	(0.69)	(-3.75)
Adventure	-0.635***	0.393*
	(-4.58)	(2.51)
Fighting	0.227*	-0.739***
	(2.31)	(-4.50)
Platformer	0.382***	0.0906
	(3.91)	(0.66)
Puzzle	-0.411**	-0.510
	(-3.25)	(-1.67)
Racing	-0.142	-0.314
	(-1.67)	(-0.89)
Role-Playing	-0.103	-0.172
	(-1.19)	(-1.13)
Shooter	0.168	-0.781***
	(1.83)	(-4.68)
Simulation	-0.0744	-1.469**
	(-0.76)	(-3.17)
Sport	0.0345	-1.068**
	(0.47)	(-2.97)
Strategy	-0.602***	-1.167***
	(-4.61)	(-3.96)
_cons	-1.601***	-1.613***
	(-23.87)	(-13.57)

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

Columns 3 and 4 in Table 3 include controls for different genres. One could easily expect that different genres would sell differently and these regressions reinforce that idea. The miscellaneous genre is used as the base case (g4, Misc. games). Looking at g2, Adventure games, we can see that remakes and sequels behave differently. A sequel adventure game sells worse than a miscellaneous game by 65.1% on average, while a remake of an adventure game will sell better than a miscellaneous game by 53.5% on average. Many genres perform at basically the same level, as the difference between the base case and many genres is statistically insignificant. Table 4 has replaced the g1 through g12 naming convention for ease of viewing. The action genre corresponds to g1 through the strategy genre corresponding to g12.

Moving on to Table 4, *SalesPrev* has been added into the equation used for Table 3 columns 3 and 4 (SalesofprequelNA for sequels and SalesofOGNA for remakes) to control for quality of the previous games, as well as size of fanbase for a series. Sales of the previous game are also used as a control for the quality of the previous game. Essentially a positive correlation between price and quality makes sense, because higher-quality products are more costly to produce, so that signaling distorts upward the price of newly introduced high-quality products (Bagwell & Riordan 1991). For remakes more than sequels this metric is a better determiner of quality and fanbase as in a sort of experience good(Bergemann & Välimäk 2006). In remakes a consumer who has already bought the original game has more information on the exact quality of the remade version of the game. SalesofprequelNA and SalesofOGNA also act in a way that would be expected, as it is a fair idea to assume that the better a previous game in a series does, the better we would expect the next game to sell. SalesofpreINA is statistically significant and has a positive coefficient of 0.183. This can be interpreted as, for every million sales that the previous game makes in a series, the next games sales will increase by 18.3% on average, holding all else equal. The previous sales of a game in a remake is also statistically significant, but has a larger effect. The SalesofOGNA coefficient can be interpreted as, for every million sales the previous game makes in a series, we would expect that the next games sales will increase by 19.8%. Comparing column 1 of Table 4 to column 3 of Table 3 YrsBetween is statistically significant in both columns, but Table 4 is more negative and more statistically significant. The same comparison can be made for column 2 of Table 4 and column 4 of Table 3.

IV Quadratic Estimation

In Table 5, I have included a years between squared term, $YrsBetween^2$, to represent a waning of nostalgia or a lack of relevance, while the old years between term now represents the growth of nostalgia. In the case of sequels the $YrsBetween^2$ term is insignificant.

$$\ln(Sales_{igt})=\beta+\gamma*YrsBetween_i+\theta*YrsBetween_i^2+\alpha*\ln(SalesPrev_i)+\delta_t+\mu_{igt} \qquad (2)$$

The squared years between term is insignificant in all sequel cases for Table 5, making equation 2 into a version of equation 1. In addition to the years between squared term, sales of the previous game are now log sales to keep all sales in logs. Looking first at column 2 of Table 5, the years between squared term is statistically significant with a value of -0.00317 and the regular years between term is positive at 0.0729 and is statistically significant. Using the coefficients from Table 5, we can calculate the right time to wait to release a remake using the equation 0.0729 = 2 * -0.00317 * x. This equation is found by taking the derivative of equation 2 with respect to *YrsBetween* and setting the resulting equation to zero to maximize sales from years between. When solving for x, I find the right time to wait to release to be 11.5 years. Moving onto column 4 of Table 5, genre terms controls are added and using this same equation with new coefficients for that column, I found that the perfect time of release was 9.16 years. Table 5 columns 2 and 4 share the positive coefficient with Table 3's column 2. In addition, in all columns in Table 5 the *SalesPrev* term shares the sign with every previous *SalesPrev* in Table 4. Table 5 columns 1 and 3 the YrsBetween term is negative and statistically significant just like in Table 4 and Table 3.

Table 5 - Quadratic Regression

	(1) NAlogsales	(2) NAlogsales	(3) NAlogsales	(4) NAlogsales
logSalesofprequelNA	0.396***		0.397***	
	(25.91)		(25.68)	
Yearsbetweensequel	-0.0640***		-0.0580***	
	(-3.94)		(-3.55)	
YearssequelSq	0.00116		0.000924	
	(1.12)		(0.92)	
logSalesofOGNA		0.457***		0.455***
		(14.56)		(14.88)
Yearsbetweenremake		0.0729***		0.0478*
		(4.51)		(2.55)
YearsemakeSq		-0.00317***		-0.00261***
		(-6.26)		(-4.53)
g1			0.0496	-0.190
			(0.61)	(-1.52)
g2			-0.508***	0.138
			(-3.80)	(0.75)
g3			0.185	-0.207
			(1.88)	(-0.97)
g5			0.136	0.112
			(1.45)	(0.99)
g6			-0.313**	-0.600*
			(-2.72)	(-2.18)
g7			-0.138	-0.119
			(-1.63)	(-0.42)
g8			0.0780	-0.0802
			(0.85)	(-0.47)
g9			0.190	-0.540**
			(1.94)	(-3.12)
g10			0.0992	-1.663***
			(0.91)	(-3.35)
g11			0.162*	-0.669*
			(2.21)	(-2.23)
g12			-0.428**	-0.163
			(-3.07)	(-0.46)
_cons	-0.831***	-1.585***	-0.897***	-1.271***
	(-21.77)	(-13.50)	(-12.62)	(-8.40)

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

Table 6 - Sales Impact on Release Timing

	(1) Yearsbetweensequel	(2) Yearsbetweensequel	(3) Yearsbetweenremake	(4) Yearsbetweenremake	(5) Yearsbetweensequel	(6) Yearsbetweenremake
NA_Sales	-0.0737*	-0.101**	0.772*	-0.452*		
	(-2.37)	(-3.23)	(2.05)	(-2.06)		
SalesofprequelNA					0.167***	
					(3.42)	
SalesofOGNA						0.391***
						(3.49)
g1		1.413***		-9.601***	1.431***	-9.532***
		(8.87)		(-13.68)	(8.99)	(-13.66)
g2		1.379***		-9.719***	1.448***	-9.520***
		(6.11)		(-10.48)	(6.42)	(-10.39)
g3		1.546***		-10.70***	1.563***	-10.17***
		(7.49)		(-16.12)	(7.57)	(-15.14)
g5		1.982***		-4.531***	1.825***	-5.093***
		(7.73)		(-5.19)	(7.13)	(-5.79)
g6		1.350***		-0.834	1.267***	-1.055
		(4.27)		(-0.58)	(4.40)	(-0.76)
g7		0.713***		-12.51***	0.729***	-12.24***
		(4.79)		(-10.05)	(4.92)	(-9.72)
g8		2.403***		-11.27***	2.459***	-10.98***
		(12.40)		(-19.13)	(12.65)	(-18.45)
g9		1.367***		-11.72***	1.374***	-11.65***
		(7.73)		(-17.44)	(7.78)	(-17.61)
g10		0.950***		-12.23***	1.013***	-12.02***
		(4.75)		(-11.17)	(5.05)	(-10.91)
g11		-0.151		-15.30***	-0.104	-14.92***
		(-1.25)		(-18.40)	(-0.85)	(-17.83)
g12		1.598***		-12.99***	1.680***	-12.28***
		(5.64)		(-15.25)	(5.92)	(-13.94)
_cons	2.740***	1.736***	10.18***	17.28***	1.587***	16.74***
	(64.24)	(15.03)	(36.36)	(42.19)	(13.36)	(42.20)

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Table 6 looks at the relationship between sales and years between releases in reverse with the years between term as the independent variable. It is generally accepted that if a game makes more sales it was likely a higher quality game. In the case that a video game company does not have the luxury to wait to release their video games, and instead must release those games the moment that those games are good enough quality to provide to consumers. Table 6 attempts to address this idea that the release of a sequel is correlated to the quality of a game. Column 1 of Table 6 states that as the sales increase for a sequel the years between the sequel and its predecessor decreases. This idea is in line with Table 5, Table 4 and Table 3 which state that there will be less sales as a company waits longer to release a sequel. This idea holds in column 2 as genre controls are added. Column 3 of Table 6 mimics the result in Table 3 column 2 with a statistically significant and positive relationship between years waiting for release and sales. In addition, the constant term is larger, around 10 years, and this could be indicating that remakes are made not as close to the original game's release as sequels are on average. This in itself could be evidence that remakes have a perfect time of release. Column 4's coefficient on sales is negative in contrast to the previous column. Finally, columns 5 and 6 look at the relationship of the predecessor video game's sales and the *YrsBetween*. Interesting results occur where regardless of if a game is a remake or a sequel the sales of the previous game in the series positively impact the length of time video game companies wait to release the next game in the series.

V Results

In this section, I show that my main results are robust to adding in controls for other exogenous factors impacting the video game market and different sample restriction choices. The next table shows the quadratic impact of years between on log sales for both sequels and remakes.

Table 7 - Log Sales Impact For Sequels and Remakes Quadratic Relationship of Years Between Releases

	Panel A: Sequels log(Sales)		
Years between	-0.0640***	-0.0580***	0.161*
	(-3.94)	(-3.55)	(-2.33)
Years between SQ	0.00116	0.000924	-0.00656*
	(-1.12)	(-0.92)	(-2.46)
	Panel B: Remakes log(Sales)		
Years between	0.0729***	0.0478*	0.0485**
	(-4.51)	(-2.55)	(-2.71)
Years between SQ	-0.00317***	-0.00261***	-0.00243***
	(-6.26)	(-4.53)	(-4.07)
Genre FE		✓	✓
Logged Previous Sales Control	✓	✓	✓
Year FE			✓

Notes: *** p<0.01, ** p<0.05, * p<0.10.

This table puts the main coefficients of interest in one space to compare. Regardless of controls used, remakes behave in a similar way. This is evidence that these regressions accurately identify the relationship between time and sales of a video game. Even including a year fixed effects that could account for some of the variation caused by the release of a new console, the release of a market changing game, or a shock to the market like a recession. Although sequels do not behave in a similar fashion regardless of controls used, sequels do respond in a similar way to remakes under the right conditions.

Many new issues appeared while trying to find the answer to the question of when the perfect time to release a video game based around nostalgia and time to maximize sales. One of the main questions was "what sorts of games do people feel nostalgic for?" A main concern was if video games of different qualities or different sized fan bases had nostalgic fans who behaved in the same ways or if they behaved in different ways. It would not be hard to believe that video games needed to meet a minimum threshold of sales to even capture a fanbase that enjoys a series enough for any of them to buy the remakes of any of the games they have already played. It may also be possible that games that make too many sales are more a product of the fans of the company purchasing the games rather than having any relation to nostalgia or any time of release component. It may also be possible that if too many people buy the previous game in a series that those fans were more jumping on the bandwagon than actually enjoying the game and becoming a long-term nostalgic fan. The next table will investigate regressions in which that are broken up into different sales groups to represent the sizes of the fanbases around a video game.

Table 8 - Quadratic Relationship of Years Between by Sales Groups

	(1)	(2)	(3)
	NAlogsales	NAlogsales	NAlogsales
logSalesofOGNA	0.0609	0.0164	0.332***
	(1.89)	(0.99)	(9.02)
Yearsbetweenremake	-0.0323*	0.0353***	-0.0322
	(-2.04)	(4.57)	(-1.48)
YearsemakeSq	0.000985	-0.000911***	0.000581
	(1.95)	(-3.81)	(0.71)
g1	-0.199	0.0519	-0.289*
	(-1.64)	(1.04)	(-2.07)
g2	0	0.453***	-0.747***
	(.)	(8.46)	(-4.09)
g3	0.113	-0.246	-0.155
	(0.81)	(-1.43)	(-0.65)
g5	0.275***	0.0418	-0.314**
	(4.49)	(0.53)	(-2.88)
g6	-0.376	0.0713	-0.506
	(-1.44)	(0.67)	(-1.62)
g7	-0.166	-0.0733	0.114
	(-0.80)	(-0.61)	(0.93)
g8	-0.126	0.337***	-0.353*
	(-0.81)	(4.33)	(-2.13)
g9	-0.0799	0.211*	-0.308
	(-0.73)	(2.51)	(-1.85)
g10	0.504***	-0.0732	-0.0766
	(4.20)	(-0.58)	(-0.91)
g11	-0.620**	-0.104	-0.941**
	(-2.74)	(-0.54)	(-2.80)
g12	-0.790***	0.304**	-0.657
	(-6.21)	(2.70)	(-1.72)
_cons	-2.810***	-2.088***	0.127
	(-19.81)	(-33.19)	(0.80)

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

Table 8 is shown above and each column uses a subset of the original dataset containing only a portion based around the percentile of sales the games made. Games in the lowest 25th percentile are all zero sales such that a regression of the lowest 25th percentile of games against years between would result in all coefficients being zero, including the sales of the previous game in the series. This is not saying that all zero sales have been ignored, as many zero sales are meaningful. If a game is a sequel or remake to a game with zero sales, then that game's information is contained in the log sales of the previous game in the series. Column 1 of Table 8 uses the 25th percentile to the 50th percentile of games. Both the years between and the squared years between coefficients having little statistical significance could be evidence that smaller companies that make smaller games release those games as soon as they possibly can. If video game companies are put in a time crunch to get a video game done as soon as possible, they might not have the luxury to wait to release their games to reap the maximum benefit. Column 2 of Table 8 uses the 50th percentile to the 75th percentile of game sales, and the result of the perfect time to release a game to maximize sales occures. Calculating the perfect time of release for column 2 is 19.37 years. This is an interesting number, as the results are similarly statistically significant and have higher total results for the perfect time of release of a remake. This could give evidence of my original argument, implying that parents who played the game as a child would purchase the remakes of games they care about for their children when they are old enough to enjoy those games. Finally, column 3 of Table 8 contains 75th percentile of game sales up to the 100th percentile. The perfect timing of release is not present in the 3rd column.

Figure 2 - Timeline of Games with Introduction of New Consoles

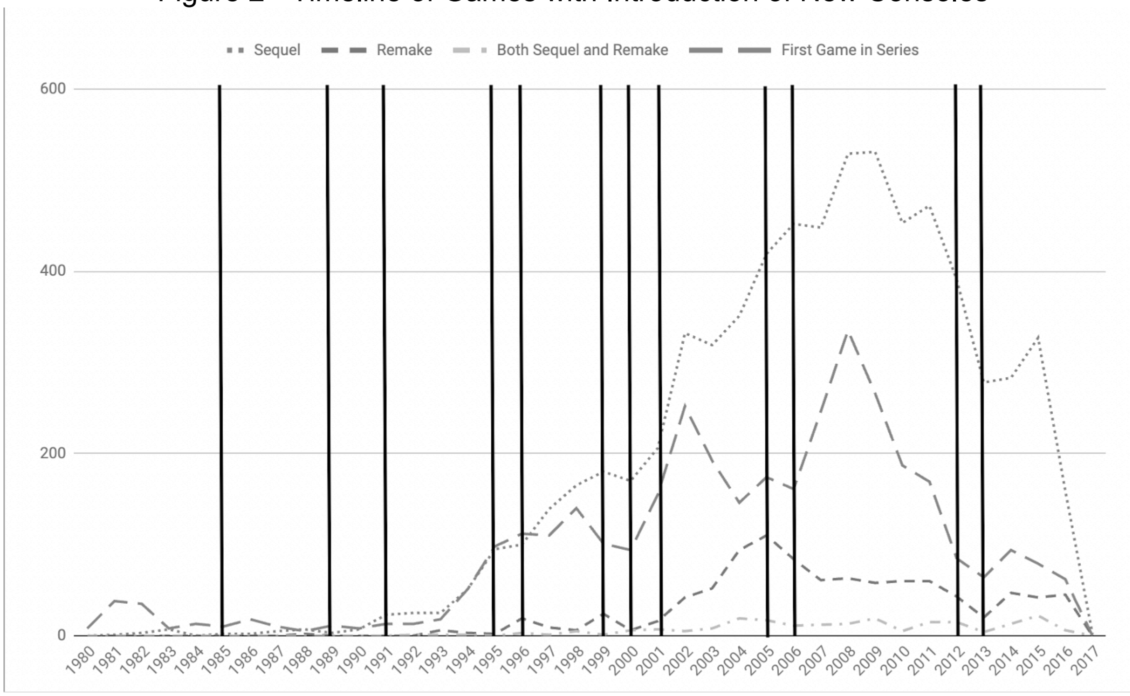


Figure 2 is a timeline and shows a count of sequels, remakes to the first game in a series, remakes to a sequel, the first game in a series on the y-axis, and the year a game was produced on the x-axis. In addition, it provides a marker line indicating the introduction of new major home consoles. Figure 2 tries to investigate the relationship between producers of games and producers of new consoles. The question was asked, “How do game developers respond to a new console being released? Does the release of a new console lead producers to make more sequels, or could there be a rise in remakes as game technology has advanced and producers want to revisit old titles that sold well and improve the technical aspects with an updated console?” Possibly neither of these things happen, but rather producers use new game consoles as an excuse to come up with new franchises that they hope will spin off sequels and remakes of their own on the new console. Too few games are actually recorded in the earlier years of video games during the release of the Nintendo Entertainment System (1985), the Sega Genesis (1989), and the Super Nintendo Entertainment System (1990) to notice a notable change in the quantity of games released. There is almost always a spike in both new series and sequels after the release of newer game consoles, PlayStation (1995), the Nintendo 64 (1996), Sega Dreamcast (1999), the PlayStation 2 (2000), the X-Box (2001), the X-Box 360 (2005), the Wii (2006), and the PlayStation 3 (2006). There is even a spike in remakes the year the X-Box 360 is released, although the number of remakes had been rising in the years before the release of the new X-Box console. There is, again, less data for the release of even newer consoles, WiiU (2012), the PlayStation 4 (2013), and the X-Box One (2013). It is relatively inconclusive whether there is a direct relationship between the release of a new console and the release of sequels, remakes, or new games from this timeline.

The best possible extension to this research would be a way to watch individual consumers' purchases and decisions over their life with information on when a consumer became enamored with a brand. In the case of this research specifically, a good extension would be a way to differentiate between better and worse games. It may be the case that only games that are rated highly by fans even make remakes. Another example of a good extension would be including games that have constantly changing consumer bases. If we could track each consumer as to when they choose to play the game, we can track how long it takes for the consumer to go back to the game, ergo find the perfect length of time to wait to release a game for nostalgia to be at its highest. One variable that is sorely missing from the data set is a variable to differentiate franchises, franchise crossovers, and spin offs within a franchise but not on the main series. We would expect that all of the games under the Mario franchise to behave in similar ways, at least in comparison to other franchises. A set of variables to determine franchise effect would be a series of variables relating *all* previous games sales in a franchise to the game. My regressions currently operate under the assumption that how well this game sells depends only on how well the last game in the series sold, the length of time between release of just the last game and this one, and the games genre, and that is a ridiculous assumption.

VI Conclusion

Rosy retrospection is a psychological descriptor, describing the false fondness people tend to look on the past with (Coleman 2018). The target of this backwards looking fondness is often the childhood of the person in question. This paper provides some evidence that the market tends to reflect this desire for the past as an increase in demand for products, specifically video games, that people were fond of in their childhood. The most evidence for this phenomenon occurs in the video game remake market. In the early years of video games popularity, many games made massive sales and attracted a large and dedicated fanbase that would care about those games for many years. Today, many of those people are now adults, some with children themselves, and these parents may want to show their children the activities they enjoyed, or come back to a game they enjoyed earlier in their life. This paper posits that the timing of those releases can be adjusted to match the fluctuations in the market caused by nostalgia.

Much of the literature in economics involving intertemporal purchases of products from one supplier focus on the concept of repeat buying. The basic idea is that it is more economical for the firm to keep a customer than to acquire a new one (Reichheld and Sasser 1990; Ryals and Knox 2001). However, when researching the literature on nostalgia's impacts on economies and other product markets, one finds very little information.

When is the best time to release a remake in the video game market to capitalize on nostalgia to maximize sales? This is the question core to my research, and the answer seems to be somewhere between 9 and 20 years depending on specification. The years between term represents a nostalgic term that grows larger as the fans wait longer for a release. This could be due to increasing the amount that those individuals are willing to spend because they make more money later in life. I believe the nostalgia term is likely more complicated than that, with a sort of cyclical pattern that may grow over time slowly. I have included a years between squared term to represent a waning of nostalgia or a lack of relevance. When I solved the equation for the perfect time of release in Table 5, I found the right time to wait to release a remake to be 10 years under the preferred regression.

I have identified other variables that matter in determining the success of a game other than nostalgia, or the length of time between releases. It may be that nostalgia has very little impact in determining the success of a video game or any other product, but I do not think that is the case. Businesses already use nostalgia for their benefit, but also for the benefit of the consumer. I believe that many businesses already have tasks dedicated to maximizing the benefit of nostalgia, but there are no papers that explore that idea economically in depth.

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