What is the effect of the corporate marriage of Disney and Pixar on their films' image quality?

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Abstract

This paper estimates the impact of Disney's acquisition of Pixar on the image quality of Disney's animated feature films. Image quality is one of the explicit measurements for the product's key attributes. Better image quality, signifies that another innovation has been created to make technology cheaper and more competitive. Although visual attributes in the animated films are the critical factor for the decision-making of the firm's production, previous literature describes them as unobservable. This paper uniquely adopts to quantify image quality using a modern image quality assessment technique Blind/Referencelss Image Spatial Quality Evaluator (BRISQUE). Demand elasticity of quality and diversion ratios are computed to show how the quality matters to the market share of Disney and consumer's choice. To find the impact on quality improvement following the merger, this paper conducts an empirical analysis using the Synthetic Control Method. In this studies, the best set of possible predictors is chosen by applying the out-of-sample (OOS) model selection technique. The pre-treatment period is split into two parts: the first training set is used to build control units among all possible models, and the second testing set is then used to evaluate the performance of each model. The best optimal set of predictors is selected by the smallest root mean squared prediction error in the evaluation part. Our empirical findings from the SCM imply that the merger between Disney and Pixar has improved the image quality of Disney's animation since the transaction in 2006.

Keywords: Synthetic Control Method, Model Selection, Image Quality Assessment.
JEL Classification: C8, L1

1. Introduction

The entertainment and media industries have actively increased mergers and acquisitions (M&A), which have become an important industry growth strategy over two decades (Kumar (2012)). The purposes of business acquisition are an integration and expansion strategy of the industry, either vertically or horizontally. Companies want to consolidate their market positions and intensify their competitiveness not only in their domains but also in other domains. In the case of Disney, mega-mergers were with Pixar (7.4 billion USD, 2006), Marvel (4.4 billion USD, 2009), Lucasfilm (4.05 billion USD, 2012), and 21st Century Fox (71.3 billion USD, 2019). The acquisitions of each company have somewhat different rationales. For instance, Disney bought Lucasfilm to gain the copyrights of the Star Wars series, and the purchase of 21st Century Fox was to enter the streaming service market. Despite the significant financial performance implications (Vedd and Liu (2011)), the impact of M&A on product quality remains an unanswered question. Product quality has been a focal point within the movie industry, influencing aspects such as advertising, critical reviews, box office revenue, and ultimately, trade patterns (Ginsburgh and Weyers (1999); Elliott and Simmons (2008); Tang et al. (2018)). This paper contributes to the existing literature by empirically estimating the effects of Disney's acquisition of Pixar on the product quality of Disney's animated feature films.

Movies are considered experience goods characterized by both observable and unobservable heterogenous attributes. Observable attributes include reviewers' ratings from premiers or Oscar nominations, while unobservable attributes may encompass the visual or audio quality of the movie. In animated films, the visual quality of animation often stands out, given that they comprise sequences of moving images captured by a camera or synthesized through computer graphics. The assessment of image quality serves as a fundamental metric for evaluating key attributes of animation. Visual elements, such as images or text, are crucial components of consumer's objective recognition, and producers consider them as primary variables in their decision-making process. Despite the significance of these visual attributes, quantifying such unstructured characteristics can be challenging. Images, for instance, contain infinite information, making them difficult to capture in a dataset. Within the movie industry literature, various empirical studies have defined movie quality using two primary aspects through proxy variables: (1) artistic excellence assessed using the critical reviews and star power (2) commercial success gauged through market buzz and box office revenues (Elberse (2007); Suárez-Vázquez (2011); **?**); Addis and Holbrook (2018)). In other industry studies, a few papers have employed the number of patents as a measure of product quality improvement resulting from M&A (Cloodt et al. (2006); Giovanni (2012)). However, it is acknowledged that patents offer a second-best solution for capturing product quality. It is hard to claim that the quality of films is based on the growth in the number of patents. Not all companies pursue acquisition to exploit the increase in patents. Some firms are involved in M&A to increase market power, or gain entry into new markets, not for technological innovation only (Zhao (2009)). Once we quantify unstructured data (visual attributes in this paper), it is possible to identify the effect of the merger on quality improvement.

Today Disney's animated films are highly acclaimed in outstanding storytelling and emotional resonance. As they release a new animated film, it consistently ranks at the top ten highest-grossing movies. However, Disney faced increasing competition, when in the late 1990s, their box office performances were not always stellar. For example, Pixar and DreamWorks incorporated their developed technology such as computer-generated sequences into their films. Disney had no striking computer graphics technology compared to other companies, but they had proficiency in the movie industry. While Pixar had an innovative software program, for example, RenderMan, they had no distribution channel. From this merger, Disney expected to reboot their image quality and take back the throne, whereas Pixar anticipated expanding its market power or reducing financial risk. The reason to improve image quality is not only to provide a better product to consumers, but also companies want to trim their costs. The animation used to be laborintensive, but become a computing-intensive task in a digital environment. The technical director of Pixar once said at VentureBeat's Transform 2020 conference that the modern digital animation industry faces time-consuming and high costs in rendering animation (server costs are high). They try to improve the image quality to reduce the workload and costs[1]. Better image quality means creating another innovation to make technology cheaper and more efficient. Disney's effort makes leeway to improve product quality. Historically, purchasing established firms could reduce costs than internalizing growth, according to Singh, Harbir and Montgomery, Cynthia A. (1987)

This paper conducts a causal analysis of how the acquisition affected Disney's animation quality improvement before and after the merger using the Synthetic Control Method (SCM). Disney only acquired Pixar among animated studios between 1996 to 2016. The SCM is the perfect method to estimate the effect of a single aggregate unit that is exposed to an interest of event at period T_0. However, it is always an unclear question of which variables should be included to find the synthetic controls. This paper adopts the model selection method in the SCM, which uses out-of-sample techniques. From the candidate non-nested models, one model is selected based on the lowest root mean squared prediction error (RMSPE) and finally, it produces the synthetic Disney. This is the first empirical paper using the model selection approach in this SCM literature.

Another main challenge is quantifying the image quality. No other paper measures the effect on the image quality from the acquisition. Instead, Zhang et al. (2017) estimate the effects of property images on demand for AirBnb. They brought up the word "image quality" but only used the number of images posted on the website as an indicator. This indicator is not an appropriate measurement for image quality. Previously, the image qual-

[1]In the conference, he said that "at least 50 CPU hours to render one frame at 2K resolution." Each individual frame has to be rendered to integrate all the moving parts using a tremendous server. Those companies try to make rendering cheaper through innovation for the high rendering times in the digital animation industry. Pixar adopted a Generative Adversarial Network (GAN) to improve quality, so they can make the rendering system cheaper through innovation.

ity is measured subjectively, called Mean Opinion Score (MOS)[2]. To objectively measure perceptual image quality, this paper employs Blind Referenceless Image Spatial Quality Evaluator (BRISQUE), a widely recognized technique in the engineering fields developed by Anish et al. (2012). The correlation between the MOS and BRISQUE's predictive performance is computed to assess how well BRISQUE aligns with human opinions of signal quality. Notably, BRISQUE demonstrates a strong correlation with subjective measurements of perceived image quality. This distinguishing method operates without the need for a reference image[3], where it evaluates an image as it is distorted. To illustrate a new practical application of the BRISQUE in economics, this paper delineates the process and elucidates how quality is gauged. The fundamental concept behind image quality assessment stems from the recognition that images encompass statistical characteristics. Unknown features of the images are extracted from the Natural Scene Statistics (NSS). Subsequently, the Support Vector Machine (SVM) is exploited to assign a quality score to the image by feeding the features. The noteworthy aspect of BRISQUE lies in its capacity to reduce the number of unknown feature parameters from infinite to finite. This paper quantifies the image quality of animated films in each studio and uses it as the dependent variable in our analysis.

The SCM is well-suited to estimate the effects of the merger between Disney and Pixar. This paper estimates that Disney's acquisition of Pixar notably improved Disney's animated films' image quality with the gap between Disney and Synthetic Disney. An average image quality increased by 18 points more than the value it would have not acquired Pixar after 2006. Placebo studies are carried out to evaluate the credibility of our results. Permutation distribution is set by pooling the effect iteratively by applying the same method to the control units in the donor pool and putting the treated unit

[2]The MOS is a numerical value used to represent the average subjective assessment from a group of people regarding the quality of image. The MOS is obtained through subjective evaluation where individuals rate the quality of the content based on their personal opinions with restricted scales.

[3]A reference image denotes a very good non-distorted quality image that other image quality assessment techniques used to require.

into the donor pool. Note that the placebo studies have been conducted for all animated studios. The results show that post-acquisition divergence in Disney is visibly larger than any of the divergences in the other studios.

2. Background

2.1 Development of the animation technology

Animation is the procedure of bringing inanimate objects into moving objects via motion pictures. Animation techniques manipulate drawings and the movement of images, and then present those combined images with a narrative on screen. The history of animation extends from hand-drawn methods to computer graphics technology. The industrialization of the animation industry was established in New York around 1914, when American cartoonist Winsor McCay drew the first short animation, *Gertie the Dinosaur*. This animation involved the key elements of animation techniques such as keyframes, registration points, a tracing paper, and animation loops [4]. It influenced the Fleischer brothers and Walt Disney who are known as the next generation of animators.

Walt Disney Studio was founded in 1923 by brothers Walt and Roy Disney. They refined and developed the previous animation techniques, concentrating on quality. Toward the end of the 1920s, Walt Disney put the sound in cartoons, thus building on their huge success. Walt Disney's first short animated film is *Steamboat Willie* in 1928, popularizing Mickey Mouse. Disney's studio relocated from Kansas City to Hollywood with the rest of the movie industry in 1930. Disney's core competency was making characters express emotion and working with detailed realism. Disney Studio released the first feature-length animation movie, *Snow White and the Seven Dwarfs*, in 1937. The traditional animation process, the inclusion of two-dimensional

[4] Keyframe is an animator's signpost, which directs the animation software to know the movement of the images. Keyframes are used to mark the start and end of an action. The registration point is the native center $(0, 0)$ at all times of the object. Animation loop causes an animation to repeat.

visuals on a transparent sheet of celluloid, was introduced in this film. This technique is called a cel animation process. The cel animation is known as 2D, paper-drawn, or traditional animation technique. Animators produce a sequence of drawings in celluloid, and a movie camera photographed sequentially over a background. Rather than redrawing from scratch each time, it was possible to transfer illustrations between frames from the cel animation technique. *Snow White* was a monumental success around the world in that period, and became the highest-grossing film that year.

Disney's main competitor was Fleischer Studios in the 1930s. Brother Max and Dave Fleischer founded an American animation studio in 1929. This studio used the rotoscope process which creates animated sequences with live-action footage frame by frame. Animators can create realistic characters by using this technique, but is time-consuming. The Fleischers were a premier producer of animated cartoons with Disney Studio in the 1930s until Paramount Pictures acquired ownership in late 1941. The other Disney competitor was Warner Bros. Warner Bros. movie studio was founded in 1921, and its animation studio was opened in 1928. Warner Bros. developed characters in zany, exaggerated, and extreme styles. They created enduring cartoon characters, such as *Bugs Bunny, and Road Runner*.

A rising production costs delayed the investment in feature-length animation until two developments were boosted in the 1980s. Disney Studio discovered the musical could be revived in the cartoon form, when they released *The Little Marmaid* in 1989. The second was the development of computer animation technology. The cel animation had developed inside a computing environment in the digital age, but the cel animation was superseded by computer graphics[5]. Editing, compositing, and motion tracking had been prohibitively expensive. The advent of the new technology in the animation industry greatly reduced costs. In the 1980s, many people began

[5]The computer graphics was implemented by scientists and researchers in the 1940s. In the 1940s, John Whitney built a custom computer device, that produced precise lines and shapes. Saul Bass, with the assistance of Whitney, animated the opening title sequence of *Vertigo* using this device. *Vertigo* is the movie by Alfred Hitchcock in 1958, considered to be one of the first live-action films by computer graphics.

using computer graphics as an art form so graphic design tools had evolved energetically. From 2D images to virtual 3D objects, animators have figured out how to move, shade, and light objects before rendering them as animation frames. Superior software compressed the previous animation process and helped to produce animation.

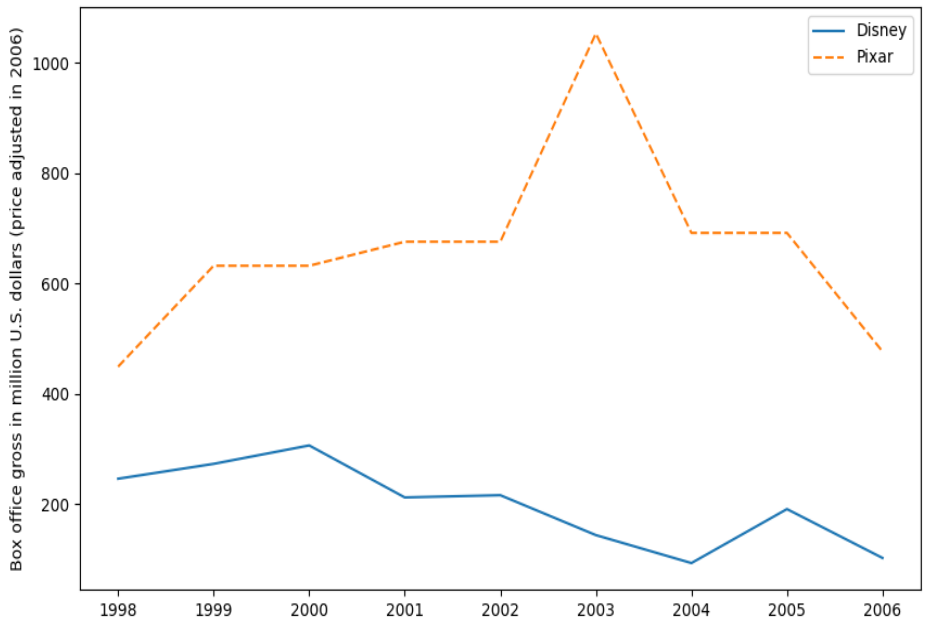
3D animation utilizes 3D computer graphics in productions. As the computer became smaller and faster in the 1970s, the idea of 3D animation are developed. Researchers at the University of Utah created an algorithm that implemented the hidden surfaces to be rendered as 3D surfaces. Up to this point, a technician was able to draw lines using computer graphics, but Ed Catmull achieved texture mapping close to realistic in 1974. Many of the basic techniques were used to make 3D animation a viable commercial industry in the 1980s (Beane (2012)). John Lasseter cofounded the Pixar studio with Steve Jobs and Ed Catmull in 1986[6]. Not only Pixar, but many animation studios were founded in the 1980s including Lucasfilm and Pacific Data Images(which became DreamWorks[7] later).

In the 1990s, Hollywood noticed the commercial success of 3D animation as a new technique for film making (Beane (2012)). In 1995, Pixar released its first full-length computer graphics movie, *Toy Story*, which was a huge success, grossing $3.3 billion worldwide. In the 2000s, more technology was being created to reinforce 3D animation, and there seemed to be competition in the animation industry (Beane (2012)). Animation studios were trying to outstrip previous 3D animations with better graphics and visuals. In 2001, Pixar showed the realistic fur in 3D in *Monster Inc.*. *Monster Inc.* box office score was twice as great as the animated movie released by

[6] Pixar aimed to develop 3D animation. Pixar became a world leader in the field of computer animation, and its groundbreaking work advanced the animation industry. One famous CG software program is RenderMan, which creates complex, high quality photorealistic imagery (Raghavachary (2006)).

[7] DreamWorks was formed in 1994 by Steven Spielberg, David Geffen, and Jeffrey Katzenberg, three of the entertainment industry's biggest names. They have focused on computer-generated imagery (CGI) since 2003. The combination of comedy and high-quality technology appealed to adults as well as children, such that DreamWorks became one of the most successful animation studios, and in 2007, it had the top grossing with the movie *Shrek the third*, $7.9 billion.

Figure 1: Disney and Pixar animation annual box office revenue per film



Disney. Figure 1 plots the total box office of Disney and Pixar per movie. It shows that the box office revenue of Disney gradually fell over the past ten years through 2006, a trend poised to continue the fall from the release of Pixar movies. The box office of Disney is smaller than Pixar's as the computer graphics animation was released in the market.

Up to now, 3D animation has evolved with the technology including full-body motion captures, stereoscopic 3D output, and real-time animation, etc. The motion capture is the technique of recording the movement of a real person to be applied to a digital character. Steeroscopic 3D technology creates the illusion of depth on a two-dimensional screen. The real-time animation is the current development of the 3D animation, which asks animators not to wait for character's rig to update. It saves the time to work and refine in real-time. Computer graphics help improve drawing efficiency and accuracy in the animation industry. In 2020, the collective 3D animation industry saw a total value of $264 billion.

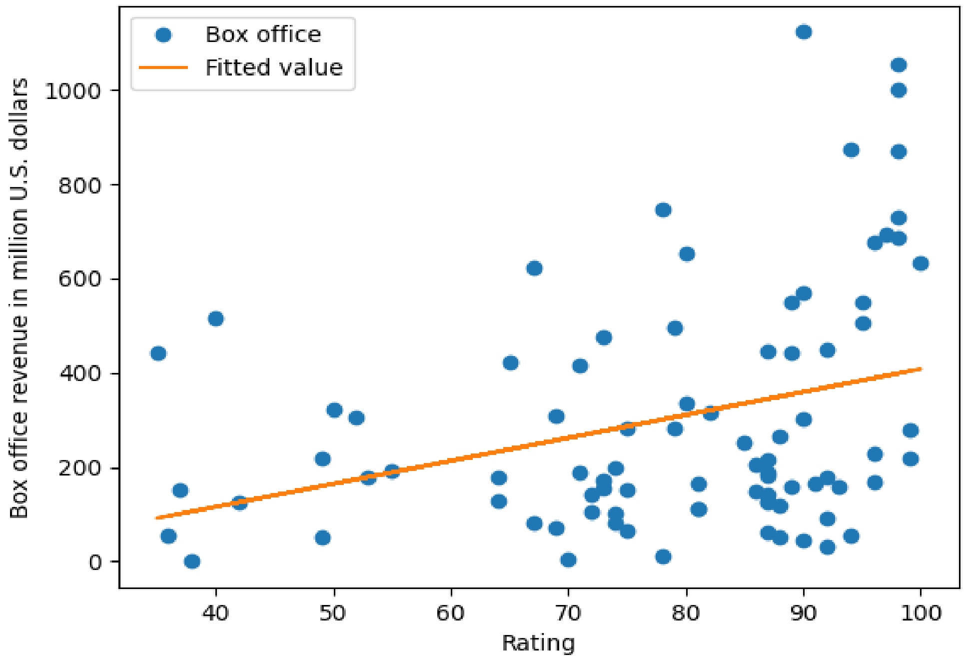
2.2 The mergers and acquisition between Disney and Pixar

Today Disney is renowned for their outstanding storytelling and emotional resonance to moviegoers. Their brand reputation has kept them at the top animation movie making companies for the past decades. In 2010s, they held seven of the top ten highest-grossing animated movies in the US and worldwide. Nevertheless, their box office rankings were not always stellar. Disney started to face a ton of competition in the late 1990s as more animated studios developed their technology based on computer graphics. Disney's hand-drawn method was perceived as outdated to viewers as Pixar and DreamWorks movies were released. The box office performance of Disney dropped in the late 1990s and early 2000s. For example, Hercules was the highest-grossing animated films of 1997. Then, the revenue of Tarzan, which was released in 1999, dropped to 294.7 million USD (adjusted in 2006 price index), and the revenue of Atlantis in 2001 to 212.1 million USD. After all, Disney lost the throne to Pixar in 1998, 1999, and 2001. Even though Disney introduced fully computer animation in 2005, Chicken Little, the movie "won" as the worst animated film in Stinkers Bad Movie Awards and took in only $21,228,878. Previous literature relates the box office performance and the implicit quality using the critic and consumer reviews. Critic and consumer reviews have been used as potential explanatory variables of box office performance to measure the quality of movies (Koschat (2012); Huang et al. (2017); Chiu et al. (2019)). As shown by Figure 2, box-office revenues are positively correlated with animation films' reviews[8].

At that time, Pixar did not outsource its products to others, keeping their technology as their core competency. Still, Pixar and Disney had a solid relationship that Disney funded and distributed Pixar's films. In January 2006,

[8]The reviews are obtained from IMDb and the box office revenues are collected from the Numbers. Data only depict animation movies between 1996 and 2016 of the following studios: Disney, Pixar, DreamWorks, 20th Century, Paramount, Universal, and Sony Pictures.

Figure 2: Movie reviews versus box-office performance



Disney announced they would acquire Pixar at a valuation of 7.4 billion USD, but they decided to keep the animation studio separate. From the business and market side, Pixar wanted to expand their market power or reduce their financial risk in belonging to a parent company.

From M&A, one could expect that the merger of Disney and Pixar would further strengthen the capability of technology and innovation for both companies. If the purpose of M&A were to find a way to reboot Disney's image, one should look on whether the transaction of those companies was successful or not by looking over the image quality improvement.

3. Literature Review

3.1 The merger and acquisition and quality in economies

The broader aspects for the effect of the M&A start from research on the relationship between the market structure and quality. From the market structure, the effect on the product quality differs. Previous papers study the social welfare implications of product quality and product variety and how competition affects them through the structural models (Watson (2009); Matsa (2011); Crawford et al. (2019)). Structural models construct consumer demand and firms' product quality and pricing decisions in the aspect of the market structure change. The consumer demand is usually specified by a discrete-choice demand model. On the supply side, profit maximization is assumed in a Nash Equilibrium/Nash Bertrand Equilibrium. Finally, the simulated counterfactual prices and qualities is used to find for a social welfare maximization. Those values are compared with the qualities offered in the market. In theory, competition results in either an increase or decrease in product quality or variety. Mainly, common findings from the aforementioned papers are that the competition affects the quality which relies on the extent to the internalizing the consumer surplus to the firm's decision behavior. Most relevant research related to this paper is from Katz (2013). Theoretically, he demonstrates that the change of market structure induces a change in the number of providers and leads to change in the quality, holding prices, consumer preferences and technology fixed.

The ambiguity over whether the market structure affects quality is a long-standing debate (Gaynor et al. (2006); Katz (2013)). Two different arguments are: increasing competition provides an incentive to improve the quality which finally affects the increase in the consumer surplus, whereas the decline in the differentiated products through quality control induces a loss in the overall social welfare. In the hospital industry, Kessler and McClellan (2000); Bloom et al. (2013) find out the market concentration affects the death rate where the competition decreases the mortality rate. Gowrisankaran and Town (2003) illustrate the opposite result of the Kessler and McClellan (2000). Recent health industry study extends the question to investigate how competition affects physician's induced demand in the context of utilization the medical device as quality measurement (Ikegami et al. (2021)). Aside from the health industry, Mukamel et al. (2001) find no evidence on the relationship between the industry concentration and the product quality. Mazzeo (2002) figures out that the more competition increases the quality of using the product choice model in the motel industry. Mazzeo (2003) also finds out the same results in the airline flight industry using the probit model. The overall findings of those papers are that more competition, increases quality. Berry and Waldfogel (2001) evaluates the positive correlation between market concentration and quality. Molna and Savage (2017) provide important insights into the relationship with the market structure and quality with actually using the real estimated quality of internet speed. They punctuate the increased competition affecting the quality in the broadband industry. Busso and Galiani (2019) also find out a statistically significant improvement in the service quality with an evidence from a field experiment in the cash transfer program. Aside from the product quality, there are studies on the product variety from the change of market structure.

Limiting the research on the relationship between M&A and quality is also vastly studied in the economics. Chen and Gayle (2019) show theoretically the quality might increase (decrease) due to the competitiveness before the merger. U-shaped relationship in the quality have been found from the pre-merger competition intensity, without the price fixed. Interestingly, in the robustness check, they estimate the effect of merger on the airline service's quality adopting the SCM. The empirical analysis of two airline mergers between the Continental/United and the Delta/Northwest shows the quality change after the merger. Even though the competition intensity is not regarded in the SCM, it is possible to estimate the effect of merger on its routing quality, they added. Fan and Yang (2020) state that reduced competition decreases the product variety. They also simulate the hypothetical merger in the smartphone industry and find out the product variety decreases from the merger. From past theoretical research, it is reasonable to state that the quality might increase or decrease as the competition changes based on the characteristics of the market structure.

Numerous empirical studies have estimated the effects of M&A on firm's performance such as stock price and product quality. The results are widely equivocal. In the financial performance, Bennett and Dam (2018) estimate significant embedded merger premiums in stock prices using both the logit regression and the two-stage fixed-effect method. Dranev et al. (2019) narrow down to see the effect of the fintech industry M&A on the financial sector stock returns. Yang (2018) find the activity decreases market volatility during the interim period. In the entertainment sector, Sweeting (2010) applies the fixed effect to find the product positioning of the music radio industry post M&A. For the effect of Disney's acquisition of 20th Century-Fox, Sergi et al. (2019) and Agnihotri and Bhattacharya (2021) provide case studies of the comparison between pre and post-merger revenue. Still, few papers ask whether the transaction between companies directly improves the quality of their product. Not only considering the firm's performance, Smeets et al. (2016) study the influence on employment with robust matched employer-employee data. The focus on product quality has primarily been on the health industry. The findings are still mixed in which the quality increases or decreases through the firms' consolidation (Vogt and Town (2006)). Fan (2013) simulates the impact of the acquisition in the newspaper market on the price and quality.

Previous reduced form papers use various methods to find the effect of M&A. Especially for comparative case studies, Kessler and McClellan (2000), Lehto and Böckerman (2008), and Di Guardo et al. (2016) analyze the firm's employment and the performance from M&A using difference-in-difference (DiD). Prince and Simon (2017) estimate how mergers affect quality provision in the airline industry using the DiD, and the results demonstrate that airline mergers have minimal effects on airline quality performance. The strategy of using DiD in those papers is to control for confounding factors that may be affecting the outcome of interest. Moreover, it helps to identify the effect of merging itself, holding other factors constant. However, DiD may not be suitable for estimating the effect of M&A if the transaction involves significant changes in the structure or operation of the firm[9]. Whereas, Giovanni (2012) first uses the synthetic control method (SCM) to explore the effect of M&A on the patenting quantity. Zohrehvand et al. (2021) exploit the synthetic control method to find the effect of Dollar Tree-Family Dollar acquisition on shareholder returns. Berger et al. (2021) study deregulation, which allows the transaction between companies using SCM. They argue mergers create value for the firm and its shareholders. In the mathematics literature, the SCM is also applied to estimate the effect of M&A on the consulting engineering companies' financial performance (Albuquerque Junior et al. (2021)).

For the assessment of the firm's quality improvement, previous literature, in contrast to this analysis, mostly uses the number of patents in their portfolios to measure knowledge and show the increase of the number of patents (Cloodt et al. (2006); Giovanni (2012))[10]. They use the random effects regression model and Poisson regression. In the animation industry, some firms have animation-related patents such as generating 3D animation sequences or editing 3D videos and images. After its acquisition of Pixar, Disney increased the number of patents and diversified its animation related to its patent portfolio (Insights (2022)). It is explicit that patents provide the second-best solution to the resulting problem of finding the effect of M&A on quality improvement.

However, Zhao (2009) argues that firms engaging in acquisition activities are less innovative and show declines in technological innovation. The patent confers to an inventor the sole right for production. However, not all companies pursue the acquisition to exploit the increases in patents for this purpose. Not acquiring these inputs for technical innovation, some firms involved in this form of transaction acquire access to distribution channels, raise market power, or gain entry into new markets. Thus, a limitation of us-

[9]It is hard to apply DiD in the case of Disney and Pixar. Beforehand, two companies operated largely independent each other even though they used to be a longstanding partnership. After buying Pixar, Disney's operation has been changed by a more collaborative work with Pixar and producing intense in computer graphic animated film.

[10]Only Molna and Savage (2017) use the actual quality of the product through observing the speed of the Internet.

ing the number of patents exists. For example, it is unclear which movie in the specific period paves the way for the application for patents as it takes time to apply and get acceptance. Usually, the patent application takes up to 18 months to be approved.

This paper argues that, for the animation assessment, the image quality assessment approach is a more explicit measure to estimate the firm's transaction effect directly. Perhaps the only example of this type of inquiry, Han et al. (2021) signify to use unstructured data, which represents the product differentiation to analyze the business decision. They apply the design characteristics of fonts to investigate the effect of the M&A on font companies' design change. Font shapes are also comprised of an infinite number of parameters. They quantify font shapes by using a word embedding method from a neural network technique to transform font shapes into low-dimensional vector.

3.2 Image Quality Assessment

This paper is the first study applying image quality assessment techniques in economics. Image Quality Assessment (IQA) evaluates the perceptual quality of an image close to human vision. As human vision is subjective, it provides a better objective measure of the image. Studying image quality is desirable because it provides the necessary guidance to optimize, construct, or manage business decisions. Unstructured data such as images do not adhere to conventional data models, where it is more challenging to interpret and parse the hidden characteristics. The technical method for assessing image quality has been researched in the computer science and engineering fields. IQA is undergoing increasing popularity in the field of image processing. IQA algorithms capture an arbitrary image as input and produce a quality index as output. IQA measures can be divided into three types: full-reference (FR), reduced-reference (RR), and no-reference (NR). The main distinction between the three measures is whether one needs a distorted image or not. A distorted image is the original image that is distorted by noise, color transformation, geometric transformations, etc. FR needs a relatively clean, non-distorted, image to measure the level of distortion in the quality of distorted image. RR does not have a reference image but needs some selective information to compare and measure the quality of the distorted image. NR does not require a base image, the only information that the algorithm receives is a distorted image that is being gauged. Previous literature about NR requires it to be distortion-specific where image distortion is known beforehand (Ferzli and Karam (2009)). Another method based on the Natural Scene Statistics (NSS) is proposed to use statistical model approaches in the wavelet domain (Moorthy and Bovik (2011)) and the DCT domain (Saad et al. (2012)). The reason why previous literature uses the wavelet domain and the DCT domain is to capture the change of image through a given frequency. Compared to these two studies, Anish et al. (2012) demonstrate that BRISQUE is exceedingly adequate to use as it does no require the transformation of image frequency in the computational process. In other words, even BRISQUE does not require mapping to a different coordinate domain, it provides a better ability to predict the quality.

4. Theoretical motivation: why the quality matters?

The movie industry is a competitive market, with a vast number of films released in a week t, but the feature-length animated film by a studio is produced once or two per year. Those animation studios compete with non-animated movies released in a given week. Consumers have access to a wide range of options and can easily compare the quality of different movies by watching trailers even before going to a theater. This creates an incentive for firms to produce high-quality films that stand out from the competition. Furthermore, as the animation industry continues to evolve and advance with the advent of technology, firms are constantly raising the bar for quality. This intense competition drives the industry forward and pushes firms to improve quality of their productions consistently. This section introduces a simple model for the argument that competition induces quality improvement in the animation industry. This paper analyzes the effectiveness of quality in explaining consumers' taste heterogeneity from aggregate data and cross-demand elasticities in the Appendix D and E.

Consider a market that each animation firm's quality is measured by a scalar, with z_i denoting the quality of firm i and the vector z_{-i} denoting all other firms' qualities. The quantity demand for firm i is

$$d_i(z_i, z_{-i}) = s_i(z_i, z_{-i})X(z_i, z_{-i}) \tag{1}$$

where s_i denotes firm i's market share and X denotes the industry output level. Firm i's profits are

$$\Pi_i(z_i, z_{-i}) = s_i(z_i, z_{-i})X(z_i, z_{-i})[\bar{p} - c(z_i)] \tag{2}$$

where $\bar{p}$ is the fixed price because the film's price is equal to all other firms as it is distributed in the movie theater, and $c(z_i)$ denotes the cost of firm i providing the quality z_i. For simplicity, the fixed cost F is set to zero. Assume that the quality and the market share has a positive relationship.

The first-order condition for firm i's choice of quality is

$$\begin{aligned}[\bar{p} - c(z_i)]\Big(X(z_i, z_{-i})\frac{\partial s_i(z_i, z_{-i})}{\partial z_i} + s_i(z_i, z_{-i})\frac{\partial X(z_i, z_{-i})}{\partial z_i}\Big) \\ -s_i(z_i, z_{-i})X(z_i, z_{-i})\frac{\partial c(z_i)}{\partial z_i} = 0\end{aligned} \tag{3}$$

Say firm i is a monopolist, then $s_i \equiv 1$ and the first term in equation (3) is zero. For a competitive firm, $\frac{\partial s_i}{\partial z_i}$ is positive by the assumption, then the first term in equation (3) is positive. Then, $X(z_i, z_{-i})\frac{\partial s_i(z_i, z_{-i})}{\partial z_i} + s_i(z_i, z_{-i})\frac{\partial X(z_i, z_{-i})}{\partial z_i}$ is larger with competitive firms than with a monopolist which means that the competition pushes a stronger quality incentives.

The quality elasticities of market demand and market share are denoted as η_X and η_h which equation (3) can be written as

$$z_i = \frac{[\bar{p} - c](\eta_X + \eta_h)}{c_z} \tag{4}$$

where c_z denotes the first derivative of cost with respect to the quality. The firm i's quality is increasing in the elasticity of demand with respect to quality, the elasticity of market share regarding quality, and the marginal cost of quality (the cost function is decreasing as the quality increases from the assumption relative to the animation market). Thus, the profit-maximizing choice of quality depends in part on the elasticities of demand with respect to both quality and market shares. If we presume that a rise in competition induces a fall in market shares and demand more elastic, then quality will increase. The overall effect on quality will rely on the direction and size of the change in the elasticity of quality.

5. Methodology

5.1 Estimating the Impact of M&A with the Synthetic Control Method

The paper compares companies affected by the interest of event (in our case, M&A) to a group of unaffected companies. We have units indexed by $j = (1, \cdots, 12)$ observations on periods $t = 1996, ..., 2016$. Unit 1 (Disney) is exposed to the intervention during periods $T_0 + 1, ..., T$ that we say j=1, "treated unit". The remaining j are untreated units, $j = 2$ to $j = 12$ where we say "donor pool". Let Y_{jt}^1 be the outcome that would be observed for unit j at time t of the intervention. Let Y_{jt}^0 be the potential outcome that would be observed for unit j at time t in the absence of the intervention.

The aim of comparison case studies is to estimate the effect of Disney purchasing Pixar on Disney's image quality $\alpha_{1t} = Y_{1t}^1 - Y_{1t}^0$ for $t > T_0$. However, it is impossible to observe the Y_{1t}^1 and Y_{1t}^0 simultaenously. The observed outcome is $Y_{jt} = d_{jt}Y^1_{jt} + (1 - d_{jt})Y^0_{jt}$, where $d_{jt} = 1$ if unit j is treated at time t and $d_{jt} = 0$ for otherwise. The first unit has been treated since $T_0 + 1$, hence $Y_{jt} = Y^1_{1t}, t > T_0$ and $Y_{jt} = Y^0_{jt}$ for $j = 2, ..., J + 1$ and $t = 1, \cdots, T$. Y^1_{1t} is observable so that the challenge is to predict the counterfactual outcome Y^0_{1t}.

Abadie and Gardeazabal (2003) introduce the weights that characterize the synthetic controls by the combination of weighted control units to build a counterfactual outcomes for the treated unit in the absence of treatment. To choose weights $W = (w_2, \cdots, w_J)$, first let X_1 be a $(k \times 1)$ vector of pre-intervention characteristics (predictors) of the treated unit, where k is the number of predictors. Let X_0 be $(k \times J)$ matrix of containing the same variables for the untreated units. Abadie and Gardeazabal (2003) and Abadie et al. (2010) propose to minimize the distance between the characteristics of untreated (X_0) and the characteristics of treated (X_1),

$$||X_1 - X_0W|| = \sqrt{(\sum_{h=1}^{k} v_h(X_{h1} - w_2X_{h2} - \cdots - w_{J+1}X_{hJ+1})^2} \tag{5}$$

subject to the restriction with the sum of weights to one and weights to be non-negative. W denotes weights for a potential synthetic controls and V is weights of predictors (relative importance of obtaining a good match between X_1 and X_0) given by the nonnegative diagonal matrix. The selection of the weights of predictors (V) are chosen from using the bi-level optimization. This optimization problem contains nested optimization problem as a constraint when a subset of variables is constrained to be a solution of a given upper optimization. Abadie et al. (2010) choose V by minimizing the mean squared prediction error (MSPE) of pre-treated outcome (Y_{1t}) to the MSPE of the synthetic control outcomes $((Y_0 = \{Y_{2t}, \ldots, Y_{J+1t}\})$ prior to the treatment period,

$$\sum_{t \in \mathcal{T}_0}(Y_{1t} - w_2(V)Y_{2t} - \cdots - w_{J+1t}(V)Y_{J+1})^2 \tag{6}$$

for set $\mathcal{T}_0 \subseteq \{1, 2, \dots T_0\}$ of pre-treatment period.

What predictors are used affect the selection of synthetic controls. However, there is no consensus about which variables should be included in predictors. For most of the studies, they use the simple average of the outcome variable for the pre-treatment periods, or include covariates for the precise estimation. Abadie and Gardeazabal (2003); Abadie et al. (2015) use the mean of all pre-treatment outcome values and additional covariates, Abadie et al. (2010) pick Y_{j,T_0}, Y_{j,T_0-8} and Y_{j,T_0-13}, and Bohn et al. (2014); Gobillon and Magnac (2016) use all pre-treatment outcome values only. Abadie et al. (2010) emphasizes the need of the model selection technique to provide a good fit for the treatment outcome. In practice, however, Ferman et al. (2020) pose a problem of a lack of guidance on the selection of predictors. No references on predictors will create specification-searching opportunities. Researchers will look for specifications that generates better results by the inclusion or exclusion of variables.

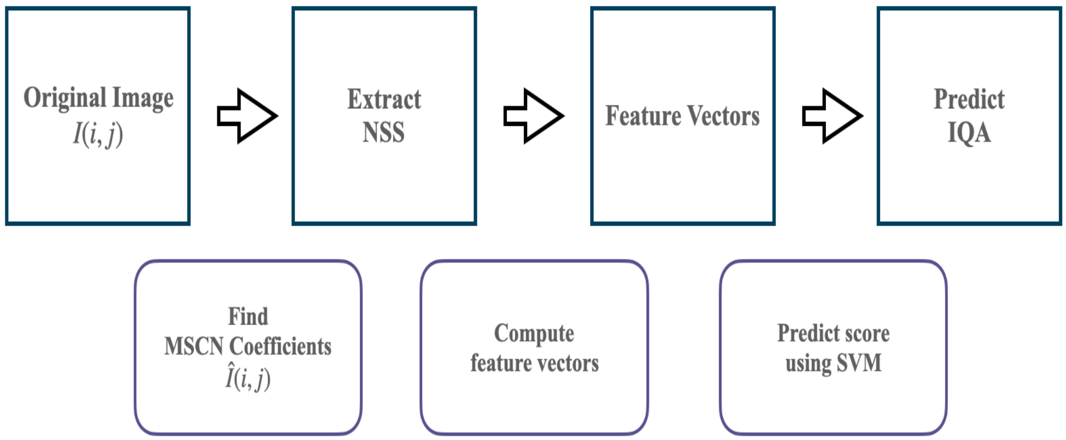
To ensure the accuracy of the counterfactual outcome, the selection of the correct set of predictors is crucial. Choi (2022) involves incorporating the out-of-sample (OOS) forecasting technique into SCM to identify the best set of predictors. This approach enables the predictions of the counterfactual outcome beyond the sample period used for creating the synthetic controls. If it is evaluated using the same data set such as in-sample prediction, it tends to show high performance, potentially leading to an overly optimistic assessment of its performance. The paper uses sample splitting to estimate the synthetic controls and evaluate the performance of those weights.The synthetic controls are found from the first set of samples and evaluates the predictive power of each candidate model from the rest set of samples to find the best set of predictors. The goal of sample splitting is to evaluate the performance of the model through the data that it has never used before and check whether the synthetic controls predict the counterfactual outcome from the evaluation sample.

The out-of-sample forecasting technique is conducted by splitting the pre-treatment period into two parts: 1) the initial 70% for the training set and 2) the subsequent 30% period for the testing set. The proportions are decided according to the size of the sample and type of the data. More data in the training set will likely to give better accuracy and avoid the over-fitting issue. In this application, 30% of test set is well enough to provide good accuracy of the selected model and the predicted synthetic controls resemble the counterfactual outcome with lowest risk. The training set is used to build the synthetic controls in each candidate model. Afterwards, the testing set is used to evaluate the predictive power of each model by minimizing the root mean squared prediction error (RMSPE) of the outcome. The number of candidates model is non-nested $2^K - 1 = 2^9 - 1 = 511$, where the number of plausible predictors is k=9. The case where all predictors are not included is excluded. Finally, the smallest RMSPE among all possible models is selected as the optima model for the estimation.

5.2 Blind/Referenceless Image Spatial Quality Evaluator

Human beings can capture the image as it is, but a computer needs the value to perceive it is an image. As we input an original image into the computer, the computer starts to segment the image into the smallest indivisible segments unit, a pixel. Pixel intensity is the first collection of information of pixels. Since a few metrics have been developed to measure image quality using the information of pixel intensities, the BRISQUE is the newest automatic spatial NR IQA model that image processing literature and research actively uses. It is a powerful tool, which provides a single score for the entire image quality. The technique relies on NSS, analyzing the image quality through a statistical process. Figure 3 shows the steps of arriving at the image quality assessment. First, we need to compute the locally normalized luminescence via local mean subtraction and divide it by the local deviation to find mean subtracted contrast normalized (MSCN) coefficients. The reason for computing MSCN is it provides a good normalization for pixel intensities. Next, we compute feature vectors from the given MSCN. Feature in an image is the information of the image such as edges, lines, the change in pixel values through blurring or noise, etc. Quality of image is a feature

Figure 3: Proccess of BRISQUE



for image that valuation discovered. These features affect image quality. We need to form a set of features to capture image quality to feed to an SVM. Finally, we predict IQA using the SVM. The SVM is trained using those features extracted from images in the previous step and provide an information of visual quality.

Extracting Natural Scene Statistics in the Spatial Domain

The first step of the BRISQUE process normalizes the image intensity to find the amount of distortion of the image. The main idea in this step is that the natural image possesses specific regular statistical properties, whereas the distorted image deviates from the regular statistical properties. Distribution of the natural image's pixel intensity differs from the distribution of the distorted image's pixel intensity. As we normalize the pixel intensities and compute the distribution over these normalized intensities, the resulting discrepancy from the regularity of natural statistics helps to design the image quality assessment without needing any reference image. The pixel intensity is represented by height $i \in 1, \cdots, M$ and width $j \in 1, \cdots, N$, $I(i,j)$.

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \tag{7}$$

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j) \tag{8}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l}(I_{k,l}(i,j) - \mu(i,j))} \tag{9}$$

where K, L is the maximum value of height and width[11]. Equation (7) is the formula of MSCN where equation (8) and equation (9) are local mean and local deviation, and $C = 1$ is a constant value to avoid the denominator to be zero. Here $w_{k,l}$ is a Gaussian filter of size (K,L) to apply the Gaussian filter to the image. In order to extract features from the image, we use filter technique where we call filter as window, mask, or kernel. Gaussian filter is used to blur images and reduce noise, which uses Gaussian function.

Pixel intensities of natural images follow a Gaussian Distribution after normalization. As we compute MSCN, it is possible to know the relationship of the pixel since it is smoothly connected with neighboring pixels. Even though MSCN coefficients are definitely homogenous for pristine images, there would be disturbance from the distortion to the sign of the adjacent coefficients. The BRISQUE technique provides a model to capture the properties of neighboring pixels; it is called the empirical distribution of pairwise products of neighboring MSCN coefficients, namely: Horizontal (H(i,j)), Vertical(V(i,j)), Left-Diagonal (D1(i,j)), and Right-Diagonal (D2(i,j))[12]. Anish

[11] In the implementation, Anish et al. (2012) set $K = L = 3$.

[12]

$$H(i,j) = \hat{I}(i,j)\hat{I}(i,j+1) \tag{10}$$

$$V(i,j) = \hat{I}(i,j)\hat{I}(i+1,j) \tag{11}$$

$$D1(i,j) = \hat{I}(i,j)\hat{I}(i+1,j+1) \tag{12}$$

$$D2(i,j) = \hat{I}(i,j)\hat{I}(i-1,j+1) \tag{13}$$

et al. (2012) find that the MSCN coefficients are distributed as a Generalized Gaussian Distribution (GGD) and the pairwise products of neighboring coefficients are distributed as Asymmetric Generalized Gaussian Distribution (AGGD). The Appendix A presents the GGD and AGGD to capture a broader spectrum of image statistics.

Calculating Feature Vectors and Predicting IQA

We have just derived one MSCN and four pairwise products of MSCN, which help to calculate a feature vector. MSCN is the distribution of pixel intensity which contains the information for an image. From MSCN, we need to capture features of the image, or the feature vector. In the original image, we could think of any dimension where the number of features is infinite. This is very high computational load to find those features. The compelling part is that this method reduces the number of parameters into finite numbers against the unknown infinite number of parameters.

In this method, the size of the feature vector is 36×1. The first two elements of the feature vector are calculated by fitting the MSCN image to a GDD, where it has two parameters - shape and variance. Each pairwise product element is calculated by fitting it into an Asymmetric for of Generalized Gaussian Fitting, which has four parameters: shape, mean, left and right variance. 36 features are used to identify distortions of the image and to perform distortion-specific quality assessment. Some might wonder why one needs to find 36 features instead of 18. As we discriminate the scale into two – original image scale and reduced resolution – we need 36×1 feature vector. In order to fit the unknown finite parameters, Lasmar et al. (2009) use maximum likelihood estimation, but having computational inefficiency, Anish et al. (2012) exploit moment-generating function. After fitting the parameters, it is possible to know the features of images.

In the final step, SVM is used to find IQA from the feature vector. SVM is one of the Machine Learning techniques implemented mostly in image recognition problems. It is one of the methods that predict the category of the new example. This method aims to classify data based on statistical information extracted from pristine images. In image recognition, previous papers adopt SVM to assess image quality (Ferzli and Karam (2009); Narwaria and Lin (2010)). Like Anish et al. (2012), this paper also exploits the LIBSVM package provided by Chang and Lin (2011). The Appendix B explains the training data in the SVM.

From SVM, one finally predicts IQA. The IQA index is inversely proportional to image quality so smaller IQA values indicate low levels of image distortion whereas higher values indicate high levels of image distortion. For more a detailed explanation of the technique, see Anish et al. (2012).

In the merger analysis, the outcome of interest is the image quality. The goal of using BRISQUE in this paper is to extract the information of image quality of animation firms to measure the effect of M&A on image quality. IQA is computed by taking an average of each IQA for all movies created by companies j in period t.

6. Data

To estimate the effect of M&A on image quality, this paper considers 12 samples, where the treated unit is "Disney" and the control units are the animation studios that produced animations from 1996 to 2016: Shin-Ei, Asatsu, Toei, Ghibli, 20th Century, DreamWorks, Paramount, TMS, OLM, Universal, Sony. When one studio produced at least more than two animated films, we take the average of those films. For the case where one firm did not produce in a given year, the average between before and after is taken. The starting point is 1996, ten years prior to the 2006 merger, and the impact up to ten years later (2016) is measured.

This paper collects the images of the animations in the Internet Movie Database, IMDb. IMDB is the world's most popular online database of information about films. They provide the film's related features and still cuts of the film. For IQA, the first steel-cut image of the feature-length movie is chosen provided by IMDb. The candidates for predictors were all collected manually from IMDb and Anime News Network. Anime News Network is a number of English-language news sources that provide information on Japanese animation.

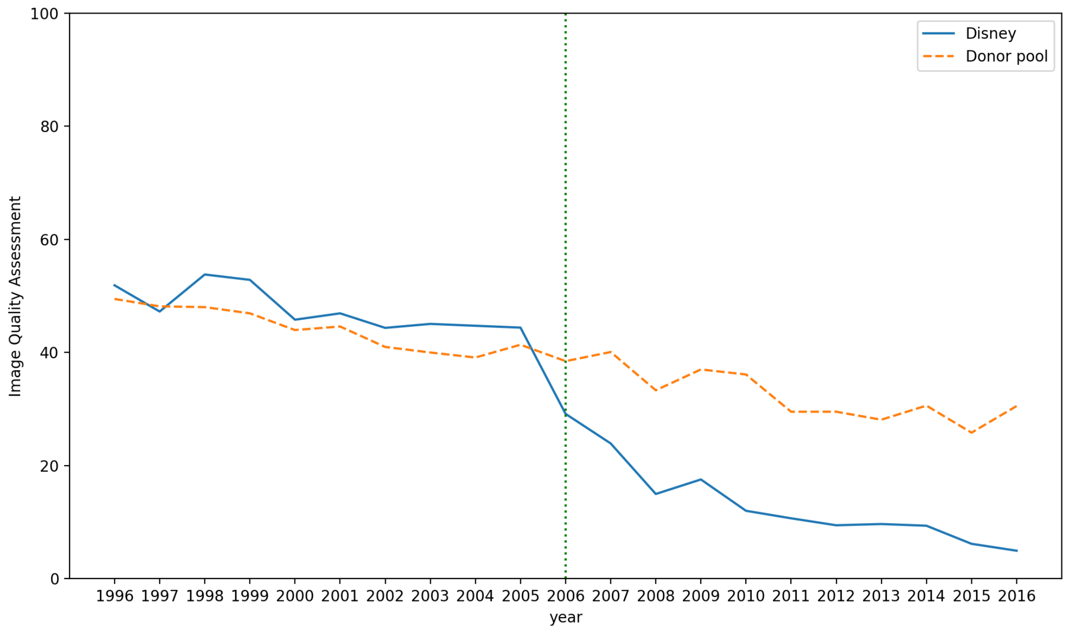
Possible variables used for predictors are the pre-treatment period of IQA, country of origin (dummy variable whether it is produced in the United States or Not), budget (measured in 2006 dollars), length of the film (minutes), the number of producers, the number of film editors, the number of staff of the art, visual, and animation department. The number of staff involved in the production line provides a solid indicator of how the company focuses on image quality.

From the storyboard to the final frame of animated films, each film takes an average of three to five years to create (WaltDisney (2022)). The duration of the creation of each animated film is a possible variable to consider. However, some famous movies were possible to obtain this information, but it is hard to obtain data for all movies that I consider in this analysis. Thus, the duration of the creation period is excluded as the predictor.

7. Results

Directly comparing the dynamic of IQA between Disney and other companies could produce disparities in their effect if the treated outcome and the counterfactual outcome differ before the event of interest. Figure 4 plots the trends of IQA of Disney and the average of the rest of the animation companies. The vertical dotted green line denotes the year of Disney acquired Pixar. The dashed orange line represents the average of IQA of units in the donor pool. As the figure shows, the rest of the companies may not provide a suitable comparison group to study the effects of M&A on image quality. Before M&A between Disney and Pixar, Disney and other companies show different trajectories in image quality. Levels of the image quality in Disney start to diverge with the advent of the technology of 3D animation in 2005, the period when Chicken Little was released. In 2006, the year M&A was accomplished, Disney adapted to the technology change and acquired new 3D animation techniques to improve the image quality.

Figure 4: Trends in IQA: Disney and other animation companies



Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

The synthetic Disney is constructed by the convex combination of companies that most closely resembled Disney in terms of possible values of image quality improvement predictors. Table 1 displays the comparison between Disney, Synthetic Disney and the average of other companies for the 1996-2016 period. The average of other companies does not seem to provide a suitable control group for Disney. In particular, the number of staff in the three departments is dissimilar. Further, the budget average of other companies was substantially lower than Disney's average, prior to the M&A between Disney and Pixar. In contrast, the synthetic Disney reproduces the values of budget almost the same as Disney. Table 1 underscores the predictors to consider in estimating the effect of M&A on image quality. As a researcher, there are various candidate predictors to be considered. For example, a movie's length would affect the image quality, so it is included in the subset of predictors. As a movie's length becomes longer, image quality

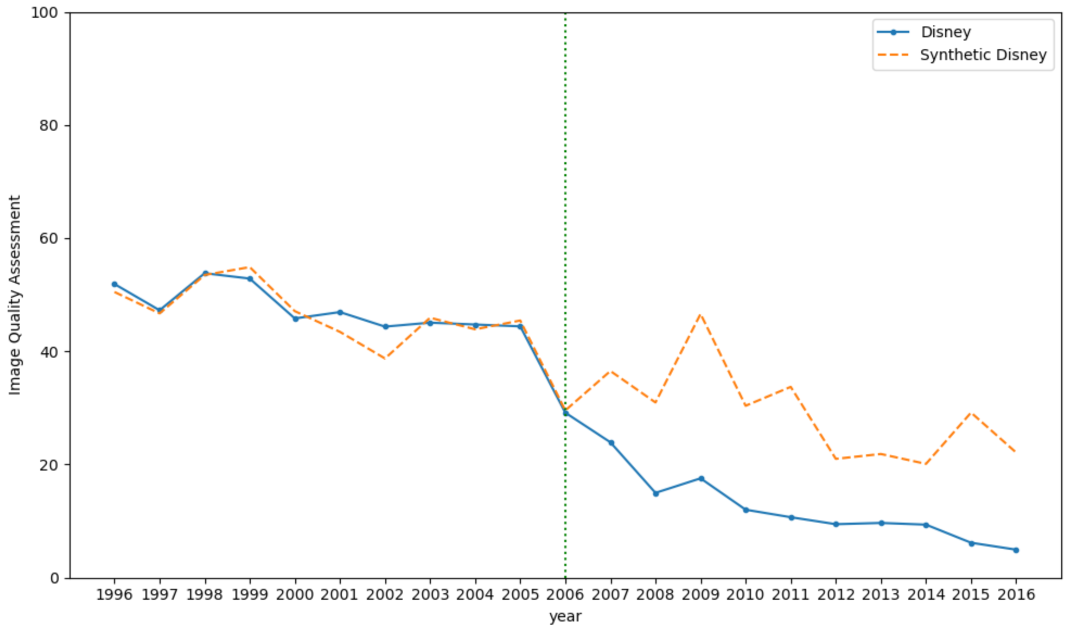
Table 1: Average of predictor values

Variables	Disney	Synthetic	Average of others
IQA	49.92	46.21	43.75
Length of the movie	90.87	91.34	90.01
Budget	103,760,477	97,317,241	37,754,153
The number of producers	3.13	6.01	6.89
The number of film editors	1.55	2.10	1.78
The number of staff in the art department	43.27	43.42	17.15
The number of staff in the visual department	111.46	167.90	44.76
The number of staff in the animation department	261.64	214.97	116.91

becomes poorer. However, the average length of a movie is similar in Disney and other companies. It means companies follow the rule that animation should be about 90 minutes long. WaltDisney (2022) also stresses that feature-length films are approximately 90 minutes, so this variable will not be an important factor for the quality. Thus, it is important for a researcher to test the performance of predictors before putting everything into a jar or cherry-picking the variables.

Figures 5 and 6 represent trends of IQA for Disney and its synthetic counterpart from 1996 to 2006. Figure 5 clearly shows that Disney Synthetic resembles its actual counterpart prior to the transaction. After the treatment, the IQA of Disney start to decrease, which means the quality of the image improved. Again, the lower IQA index means better image quality. Furthermore, the goal of this paper is to select the best model among the alternative set of predictors. One tries to select the model with the highest predictive power under the smallest number of predictors. It shows trends of IQA be-

Figure 5: The number of staff in art and animation departments and the image quality assessment are included.

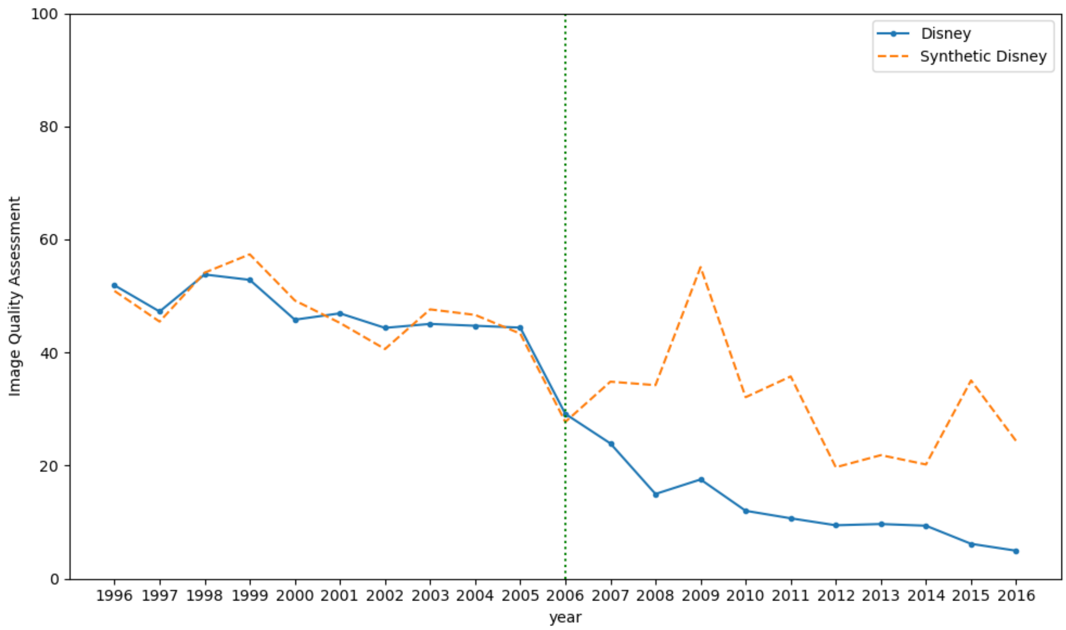


Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

tween Disney and Synthetic Disney estimated by using only three predictors: budget, the number of film editors, and the number of staff in the visual departments. This model gets the smallest RMSPE among all possible candidate models at 0.806. However, Figure 6 depicts trends of IQA between Disney and Synthetic Disney computed by including all possible variables this paper considered: budget, the number of producers, the number of film editors, the number of staff in the visual and animation departments, and the average of IQA; here, RMSPE is 1.508. Instead of finding the synthetic Disney using all possible variables, a limited number of predictors are found to produce better prediction ability.

For comparison, Figure 7 and Figure 8 show the examples of trajectories of IQA for Disney and its synthetic but computed using other candidate models. In Figure 7, RMSPE is 3.388, and three variables are included to find synthetic groups. In Figure 8, RMSPE is 4.393, but six variables are in-

Figure 6: All variables are included.

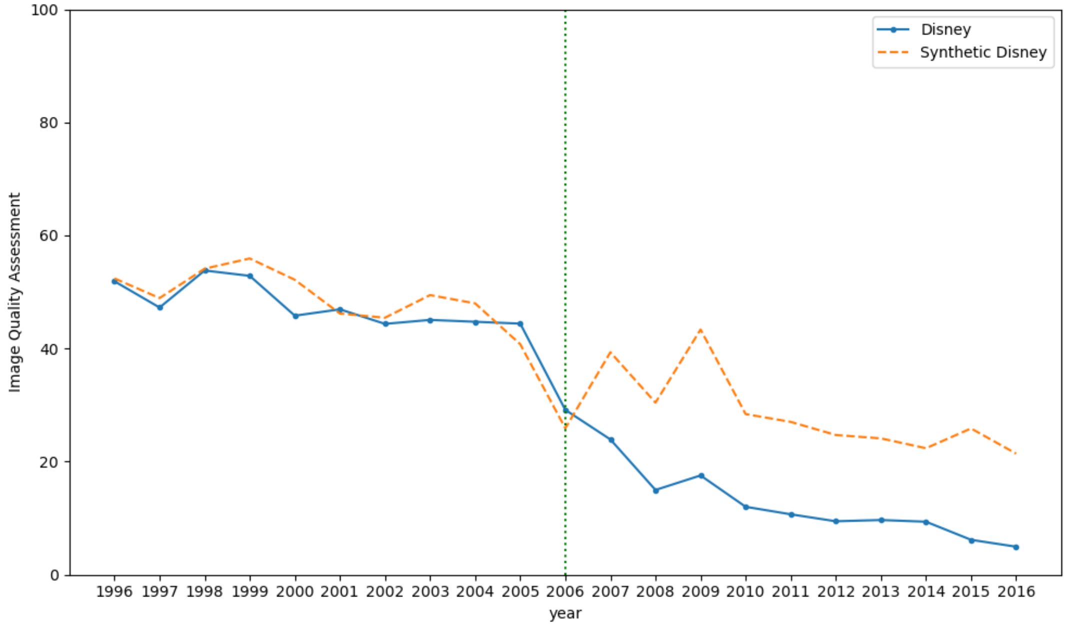


Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

cluded. Figures 7 and 8 demonstrate that the weights of each company differ as the set of predictors changes in the estimation process. Different models demonstrate different synthetic controls, which will influence on the treatment effect. Interestingly, the selected control units differ by alternative sets of predictors. If researchers do the specification searching, they might obtain different results from the other sets of control units. As selecting the control units is crucial in the causal analysis, the SCM is touted as obvious in selecting control units. These findings suggest implementing the model selection before reporting the final results to be transparent in the selection of control units.

Table 2 displays the weights of each company in the synthetic Disney. The weights reported indicate that a combination of Toei (0.275), DreamWorks (0.703), and Paramount (0.022) best produces IQA. In contrast, other combinations of control units in the donor pool comprise the synthetic con-

Figure 7: The country of origin, budget, and the number of film editors are included.

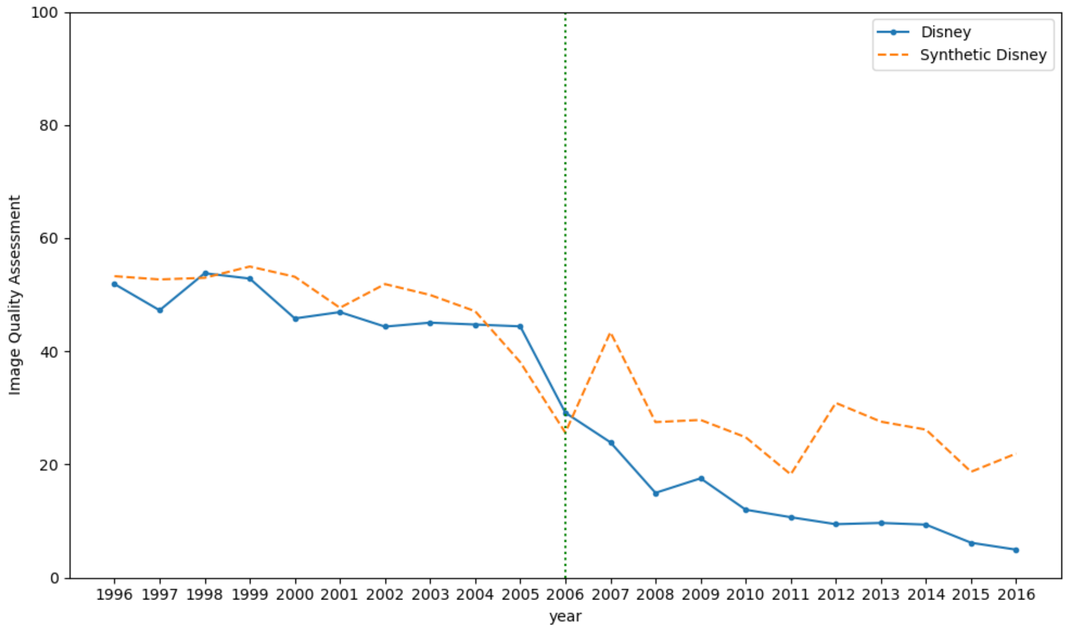


Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

trols in the other possible model. The second column of Table 5 shows the weights of control units where we use all candidates of predictors. Here, DreamWorks is only selected as a control unit. Different models put the weights to different control units in columns 3 and 4. All other companies in the donor pool are assigned zero weights.

This paper shows the effect of M&A of Disney and Pixar on image quality. After M&A was accomplished, IQA plummeted, meaning the image quality performed better than in the previous period. Figure 9 plots the yearly gaps in IQA between Disney and its synthetic counterpart. It suggests that the firms' transaction hugely affected image quality, and this impact increased over time. Usually, the animation film takes three to five years to produce. The IQA of Disney decreases notably and is stable post 2009. The magnitude of the estimated effect after the treatment is crucial in the empirical analysis. The results provide evidence that the image quality improved at an average

Figure 8: The country of origin, length, budget, the number of film editors, the number of staffs in the visual department, and IQA are included.



Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

of almost 18 points for the entire 2006 to 2016 period than the value it would have been no transaction between these two companies in 2006.

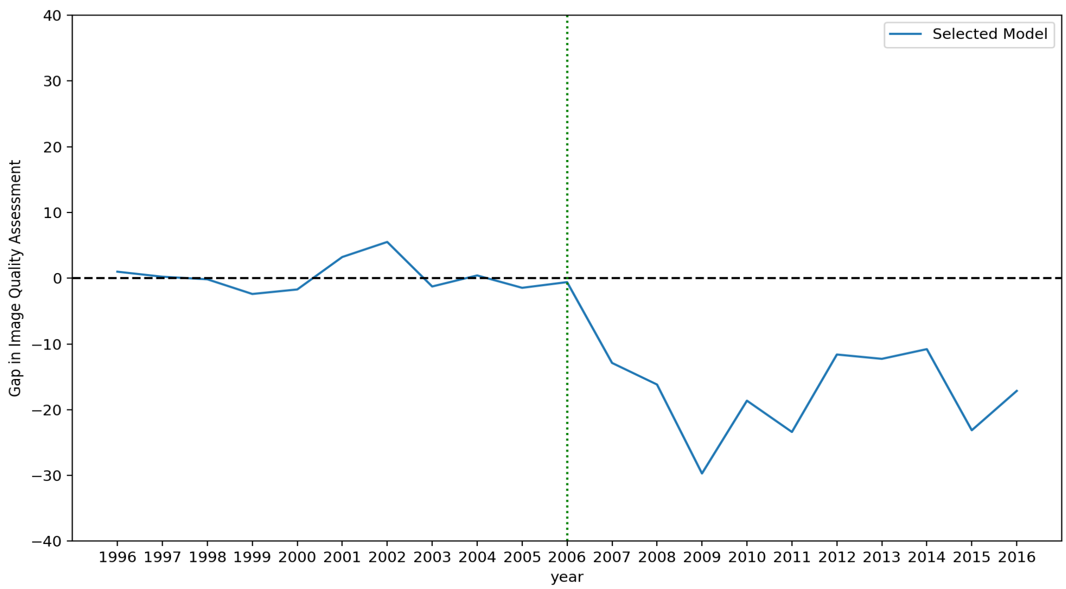
Figure 10 illustrates the IQA gaps between Disney and synthetic Disney under the selected and full model. The degree of the estimated effect after Disney's acquisition of Pixar shows the 20 point of increase in IQA under the full model (all predictors are included). Interestingly, the full model captures more treatment effects, which leads to misjudgment of the findings. It is highly recommended to conduct model selection to avoid excessive or minor treatment effects.

The merger of Disney and Pixar has led to increased creative output. Pixar contributes its technological expertise to enhance the quality of Disney's animation. The success of Disney and Pixar merger is evident in the substantial profits generated by both companies. For instance, Pixar movie's box office revenue in 2004 was 591 million USD, but following the merger,

Table 2: Company Weights in the synthetic Disney

Company	Selected Model	Full Model	Comparison Model 1	Comparison Model 2
Toei	0.275	-	-	-
Ghibli	-	-	0.418	-
20th Century	-	-	0.582	0.75
DreamWorks	0.703	0.999	-	-
Paramount	0.022	-	-	0.25

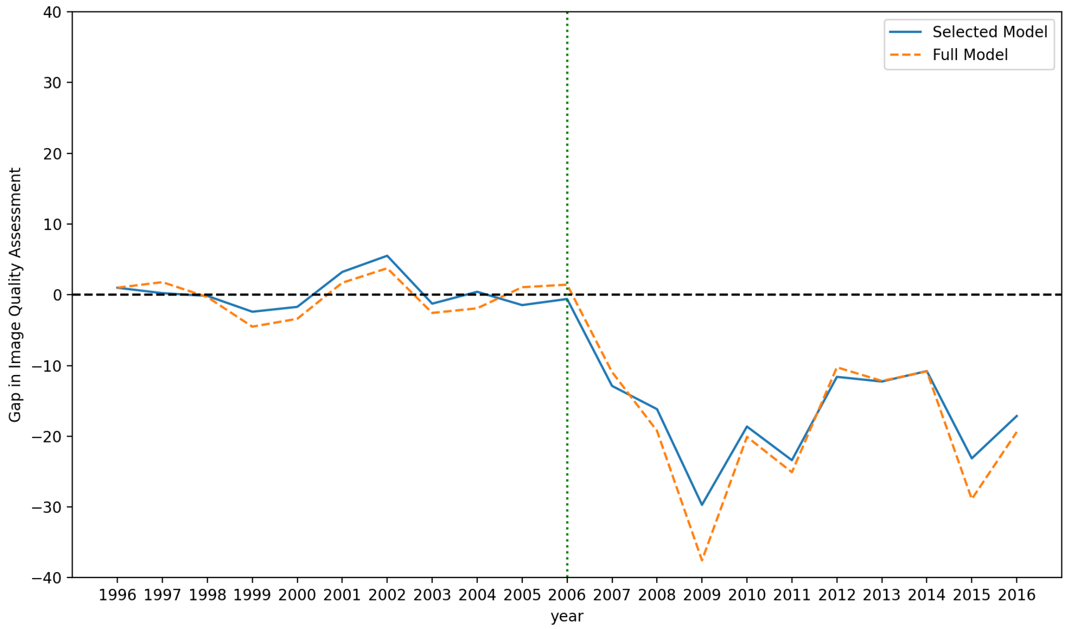
Figure 9: IQA gaps between Disney and synthetic Disney of the selected model



Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

it rose to 638 million USD. In the Appendix C, Figure 13 shows the rank of the highest-grossing film for Disney and the other four representative studios in a given year. Animation movies from Dream Works, Paramount, or

Figure 10: IQA gaps between Disney and synthetic Disney: Selected Model vs Full Model



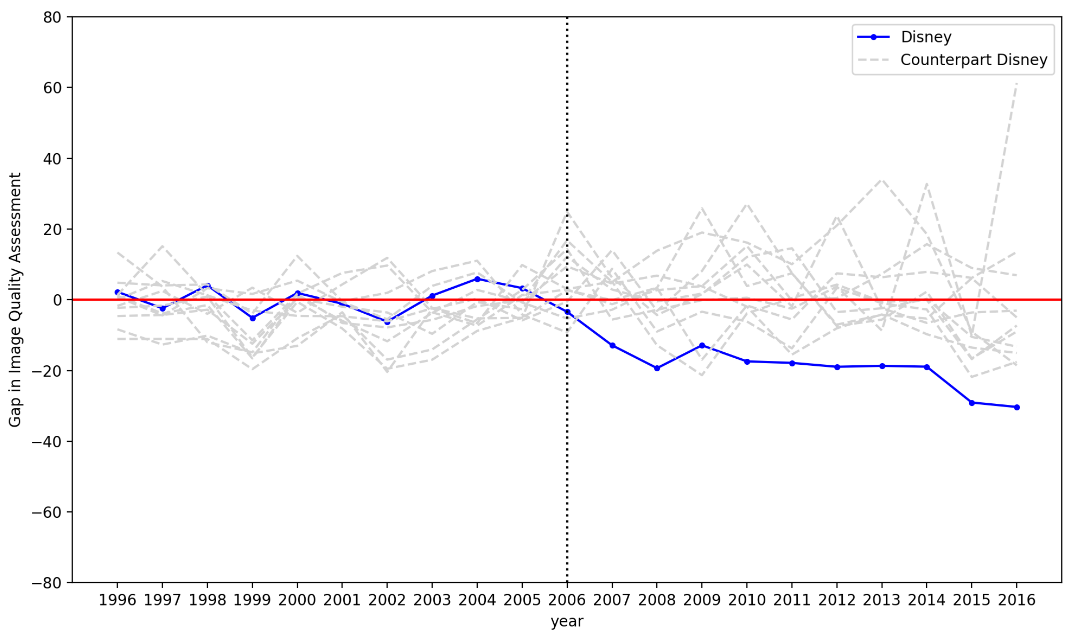
Pixar used to seize the market power of the animation industry between 2006 and 2012. Although Disney struggled to be the highest-grossing film after the merger, they took back the throne in 2013 from *Frozen*. Disney finally knew how to create hits on their hands by mixing their hand-drawn method with computer-animated techniques. *Frozen*, released in 2013, is the perfect blend of these techniques that Disney admitted. They were aware that their animation quality had returned to a satisfactory level (Kara (2019)). From the Disney's acquisition of Pixar,

8. Inference about M&A

To assess the significance of our estimates, we conduct the same placebo studies that Abadie et al. (2010) used in previous studies. The treatment of interest is reassigned to companies different from Disney. Other companies are being reassigned as treated and Disney is shifted to the donor pool. The synthetic control method is used iteratively to estimate the effect of M&A and to check estimated gaps for other companies where no intervention took place. If the effect of M&A on image quality shows a large difference relative to the distribution of placebo effects, then we will consider the effect to be significant.

Figure 11 represents the results for the placebo test. The dashed gray

Figure 11: IQA gaps in Disney and Synthetic Disney and placebo gaps in all companies of the selected model

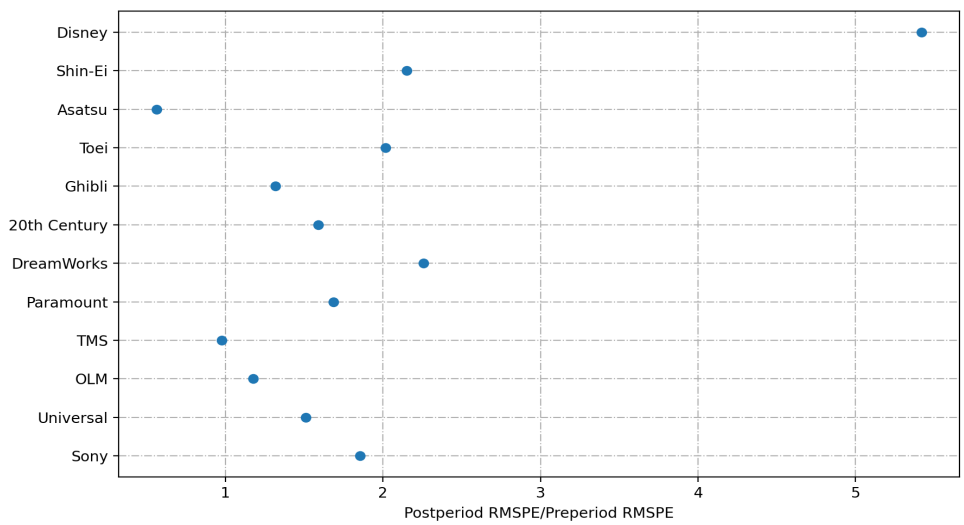


Note: The vertical dotted green line denotes the year of Disney acquired Pixar.

lines are the gap associated with each of the 11 runs of the test. This denotes IQA difference between mock treated companies and their respective synthetic versions. The bold blue line emphasizes the gap estimated for Disney. Before the merger, gaps between each mock company and its synthetic counterpart show a larger gap, whereas change in Disney is nearly zero which doesn't show much change. That is, our placebo Disney has no noticeable effect in contrast to the actual Disney. As Figure 11 exhibits, the estimated gap for Disney over the post-treatment period is large relative to the distribution of the gaps for the companies in the donor pool.

Figure 12 reports the ratios between the post M&A RMSPE ($R_j(T_0+1,T)$)

Figure 12: Ratio of Post M&A RMSPE to pre M&A RMSPE: Disney and other companies



and the pre M&A RMSPE ($R_j(1,T_0)$) for Disney and for all the companies in the donor pool. The ratio is

$$r_j = \frac{R_j(T_0+1,T)}{R_j(1,T_0)} \tag{14}$$

which measures the quality of the fit of synthetic control for unit j in the post-treatment period, relative to the quality of the fit for unit j in the pre-treatment period. Disney is prominent as the company with the highest ratio between post and pre treatment period. The post-treatment gap is about 5 times larger than the pre-treatment gap on average. These results demonstrate that our estimated treatment effects for Disney are largely significant relative to that obtained when we conduct the same application to the firms in the donor pool.

9. Conclusion

This paper estimates the effect of Disney's acquisition of Pixar on Disney's image quality applying the synthetic control method. Economists are confronted with the question of which variables to use in the SCM. This paper adopts an out-of-sample technique to select the optimal model in the SCM. Among all possible candidate sets of models, synthetic controls were selected using the first 70% of the pre-treatment period. Then, this analysis selected the smallest RMSPE of models computed using the 30% of the pre-treatment period. The empirical findings is the image quality improved 18 points after the merger compared to the pre-treatment period. Moreover, the estimated results using all predictors show more change in the magnitude of the quality improvement, which alerts researchers to take notice of the interpretation of the treatment effect after the interest.

In addition, this paper introduces a modern image quality assessment technique currently used in engineering literature to measure image quality. Even though these visual attributes are the crucial part of the decision behavior of the firm's production, they are deemed to be unobservable attributes in the economic literature. As this paper quantifies the image quality, it is now possible to measure the quality improvement from the M&A. This paper finds that the merger between Disney and Pixar enhances the image quality of Disney's films after its acquisition in 2006. It actually supports the argument that Disney developed their strategy to reboot their image quality and finally took back their throne in 2013 with *Frozen*.

The limitation of this paper is that it does not consider all images in the feature-length animated movie analyzed. It is too time-consuming and expensive to measure all the scenes in a movie, so it is impossible to quantify the quality of all the images. Nevertheless, the IQA score closely resembles that of other steel-cut images in the film. For instance, the chosen image's

IQA score for *The Hunchback of Notre Dame* is 51.889, while other images score 56.9 and 55.5, indicating comparable quality assessments. Moreover, Abadie et al. (2010) and Ferman et al. (2020) propose using a longer pre-treatment period of time for a good synthetic control fit. However, there are few companies that produced animation over 20 years before the treatment period. For this reason, we only select 10 years ahead of the treatment for the estimation. This paper obtains a good measurement of fit with 10 years prior to the 2006 merger, so we have shown that the SCM works well in the short-term period.

There is still an unanswered question from the acquisition how Pixar's market entry affected their power in the movie industry or their financial performance. Nevo (2000) estimates the effects of the mergers with differentiated products. He estimates the effect of the horizontal merger to the cereal industry concentration. One can extend his research to the vertical merger between Disney and Pixar on the industry concentration of Disney or Pixar. This case, the price is fixed, while Nevo (2000) did not. All animated studios have the same market price of their films (except movies provided through streaming service), because the ticket price of a movie in the theatre is stable. Besides the price, it is possible to think only about the cost side. Berry and Waldfogel (2010) assume that the marginal cost is constant in quantity but increases in quality, and study the effect on the market size. The movie industry might be distinctive to apply this theorem because the cost of producing animation decreases as the quality increases. Thus, it might be interesting to observe the change in the producer welfare as the cost of production decreases but quality increases for further research.

Lastly, the automated image quality assessment can be applied to other fields in economics. These techniques have been highly applied to epidemiological and clinical pathology studies in recent days. For example, several factors, such as movements in an organ will degrade the image quality while taking an image of ultrasonic waves or magnetic resonance imaging. That is why those fields adopt IQA techniques to detect symptoms better quality of an image. It is so far an interesting field of research in the healthcare industry to use the IQA. Even though the quality of healthcare is a significant concern, previous economic studies show that mergers can positively or negatively impact healthcare quality in the health industry (Kessler and McClellan (2000); Gaynor (2004); Bloom et al. (2013). Future studies may be extended to investigate the quality improvement of health by using the IQA index. This may contribute to the research to find other findings in the M&A literature of the healthcare industry. Not only restricted to the healthcare industry, IQA can also address questions in economics, such as understanding changes in consumer behavior in the online market when they encounter high image quality products on the website.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "Synthetic Control Methods for Comparative Case Studies : Estimating the Effect of California ' s Tobacco Control Program," *Journal of the American Statistical Association*, 2010, *105* (490), 493–505.

— , — , and — , "Comparative Politics and the Synthetic Control Method," *American Journal of Political Science*, 2015, *59* (2), 495–510.

— and Javier Gardeazabal, "The economic costs of conflict: A case study of the Basque Country," *American Economic Review*, 2003, *93* (1), 113–132.

Addis, Michela and Morris B. Holbrook, "Is movie success a judgment device? When more is not better," *Psychology and Marketing*, 2018, *35* (12), 881–890.

Agnihotri, Arpita and Saurabh Bhattacharya, "Dynamics of the Disney – Fox Merger," *SAGE Business Cases*, 2021.

Albuquerque Junior, Marcos, José António Filipe, Paulo de Melo Neto, and Cristiano da Silva, "The study of events approach applied to the impact of mergers and acquisitions on the performance of consulting engineering companies," *Mathematics*, 2021, *9* (2), 1–21.

Anish, Mittal, Anush Moorthy, and Alan Bovik, "No-reference image quality assessment in spatial domain," *Advances in Intelligent Systems and Computing*, 2012, *21* (12).

Beane, Andy, *3D animation essentials*, John Wiley Sons, Incorporated, 2012.

Bennett, Benjamin and Robert A. Dam, "Merger Activity, Stock Prices, and Measuring Gains from MA," *SSRN Electronic Journal*, 2018, (February), 1–64.

Berger, Elizabeth A., Alexander W. Butler, Edwin Hu, and Morad Zekhnini, "Financial integration and credit democratization: Linking banking deregulation to economic growth," *Journal of Financial Intermediation*, 2021, *45* (January 2020), 100857.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Berry, Steven T and Joel Waldfogel, "Do Mergers Increase Product Variety ? Evidence from Radio Broadcasting," *The Quarterly Journal of Economics*, 2001, *116* (3), 1009–1025.

_ and _ , "Product Quality and Market Size," *The Journal of Industrial Economics*, 2010, *58* (1), 1–31.

Bloom, Nicholas, Carol Propper, Stephan Seiler, and John Van Reenen, "The impact of competition on management quality: Evidence from public hospitals," *Review of Economic Studies*, 2013, *82* (2), 457–489.

Bohn, Sarah, Magnus Lofstrom, and Steven Raphael, "Did the 2007 Legal Arizona Workers Act Reduce the State's Unauthorized Immigrant Population?," *Review of Economics and Statistics*, 2014, *96* (2), 258–269.

Busso, Matias and Sebastian Galiani, "The causal effect of competition on prices and quality: Evidence from a field experiment," *American Economic Journal: Applied Economics*, 2019, *11* (1), 33–56.

Chang, Chih Chung and Chih Jen Lin, "LIBSVM: A Library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, 2011, *2* (3), 1–40.

Chen, Yongmin and Philip G. Gayle, "Mergers and product quality: Evidence from the airline industry," *International Journal of Industrial Organization*, 2019, *62*, 96–135.

Chen, Yuan, Yang Zhao, Li Cao, Wei Jia, and Xiaoping Liu, "Learning Deep Blind Quality Assessment for Cartoon Images," *IEEE Transactions on Neural Networks and Learning Systems*, 2021, *30* (9), 3282–3288.

Chiu, Ya Ling, Ku Hsieh Chen, Jying Nan Wang, and Yuan Teng Hsu, "The impact of online movie word-of-mouth on consumer choice: A comparison of American and Chinese consumers," *International Marketing Review*, 2019, *36* (6), 996–1025.

Choi, Youngeun, “Model Selection for the Synthetic Control Method,” *Working paper*, 2022.

Cloodt, Myriam, John Hagedoorn, and Hans Van Kranenburg, “Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries,” *Research Policy*, 2006, *35* (5), 642–654.

Conlon, Christopher and Jeff Gortmaker, “Best practices for differentiated products demand estimation with PyBLP,” *RAND Journal of Economics*, 2020, *51* (4), 1108–1161.

_ and Julie Holland Mortimer, “Empirical Properties of Diversion Ratios,” *NBER Working Paper*, 2018, *24816.*

Crawford, Gregory S., Oleksandr Shcherbakov, and Matthew Shum, “Quality overprovision in cable television markets,” *American Economic Review*, 2019, *109* (3), 956–995.

Di Guardo, Maria Chiara, Kathryn Rudie Harrigan, and Elona Marku, “Quantity at Expense of Quality? The Effects of “Successful” MA on Innovation Performance,” *Academy of Management Proceedings*, 2016, *2016* (1), 16182.

Dranev, Yury, Ksenia Frolova, and Elena Ochirova, “The impact of fintech MA on stock returns,” *Research in International Business and Finance*, 2019, *48* (February), 353–364.

Einav, Liran, “Seasonality in the U.S. motion picture industry,” *RAND Journal of Economics*, mar 2007, *38* (1), 127–145.

Elberse, Anita, “The power of stars: Do star actors drive the success of movies?,” *Journal of Marketing*, 2007, *71* (4), 102–120.

Elliott, Caroline and Rob Simmons, “Determinants of UK box office success: The impact of quality signals,” *Review of Industrial Organization*, 2008, *33* (2), 93–111.

Fan, Ying, “Ownership Consolidation and Product Characteristics : A Study of the US Daily Newspaper Market,” *American Economic Review*, 2013, *103* (5), 1598–1628.

— and Chenyu Yang, “Competition, Product Proliferation, and Welfare,” *American Economic Journal: Microeconomics*, 2020, *12* (2), 99–134.

Ferman, Bruno, Christine Pinto, and Vitor Possebom, “Cherry Picking with Synthetic Controls,” *Journal of Policy Analysis and Management*, 2020, *39* (2), 510–532.

Ferreira, Fernando, Amil Petrin, and Joel Waldfogel, “Trade, Endogenous Quality, and Welfare in Motion Pictures,” 2012, (February), 0–38.

Ferzli, Rony and Lina J. Karam, “A no-reference objective image sharpness metric based on the notion of Just Noticeable Blur (JNB),” *IEEE Transactions on Image Processing*, 2009, *18* (4), 717–728.

Gaynor, Martin, “What Do We Know About Competition and Quality in Health Care Markets ? Martin Gaynor What Do We Know About Competition and Quality in Health Care Markets ? Abstract,” *CMPO Working Paper Series*, 2004, (06).

— , Carol Propper, Ray Rees, Lise Rochaix, Patrick Romano, Bill Sage, Alain Trannoy, and Mike Vita, “What Do We Know About Competition and Quality in Health Care Markets?,” *NBER Working Paper Series*, 2006, *12301.*

Ginsburgh, Victor and Sheila Weyers, “On the perceived quality of movies,” *Journal of Cultural Economics*, 1999, *23* (4), 269–283.

Giovanni, Valentini, “Measuring the Effect of MA on Patenting Quantity and Quality,” *Strategic Management Journal*, 2012, *33*, 336–346.

Gobillon, Laurent and Thierry Magnac, “Regional policy evaluation: Interactive fixed effects and synthetic controls,” *Review of Economics and Statistics*, 2016, *98* (3), 535–551.

Gowrisankaran, Gautam and Robert J Town, “Competition, Payers , and Hospital Quality,” *Health Service Research*, 2003, *12* (38), 1403–1422.

Han, Sukjin, Eric H. Schulman, Kristen Grauman, and Santhosh Ramakrishnan, “Shapes as Product Differentiation: Neural Network Embedding in the Analysis of Markets for Fonts,” *Working paper*, 2021, pp. 1–38.

Huang, Jianxiong, Wai Fong Boh, and Kim Huat Goh, "A Temporal Study of the Effects of Online Opinions: Information Sources Matter," *Journal of Management Information Systems*, 2017, *34* (4), 1169–1202.

Ikegami, Kei, Ken Onishi, and Naoki Wakamori, "Competition-driven physician-induced demand," *Journal of Health Economics*, 2021, *79* (May), 102488.

Insights, "What's Inside Disney Patent Portfolio?," *GREYB*, 2022.

Kara, Hedash, "Frozen: Disney Admitted Their Drop In Quality In The Movie's Trailer," *SCREENRANT*, 2019.

Katz, Michael L., "Provider competition and healthcare quality: More bang for the buck?," *International Journal of Industrial Organization*, 2013, *31* (5), 612–625.

Kessler, Daniel P. and Mark B. McClellan, "Is hospital competition socially wasteful?," *Quarterly Journal of Economics*, 2000, *115* (2), 577–615.

Koschat, Martin A., "The Impact of Movie Reviews on Box Office: Media Portfolios and the Intermediation of Genre," *Journal of Media Economics*, 2012, *25* (1), 35–53.

Kumar, B. Rajesh, *Mega Mergers and Acquisitions*, Palgrave Macmillan, 2012.

Lasmar, Nour Eddine, Youssef Stitou, and Yannick Berthoumieu, "Multiscale skewed heavy tailed model for texture analysis," *Proceedings - International Conference on Image Processing, ICIP*, 2009, (1), 2281–2284.

Lehto, Eero and Petri Böckerman, "Analysing the employment effects of mergers and acquisitions," *Journal of Economic Behavior and Organization*, 2008, *68* (1), 112–124.

Leung, Tin Cheuk, Shi Qi, and Jia Yuan, "Movie Industry Demand and Theater Availability," *Review of Industrial Organization*, 2020, *56* (3), 489–513.

Matsa, David, "Competition and product quality in the supermarket industry," *The Quarterly Journal of Economics*, 2011, *126* (3), 1539–1591.

Mazzeo, Michael J., "Product Choice and Oligopoly Market Structure," *The RAND Journal of Economics*, 2002, *33* (2), 221.

__ , "Competition and service quality in the U.S. airline industry," *Review of Industrial Organization*, 2003, *22* (4), 275–296.

Molna, Gabor and Scott Savage, "Market Structure and Broadband Internet Quality," *The Journal of Industrial Economics2*, 2017, *65* (1), 73–104.

Moorthy, Anush Krishna and Alan Conrad Bovik, "Blind image quality assessment: From natural scene statistics to perceptual quality," *IEEE Transactions on Image Processing*, 2011, *20* (12), 3350–3364.

Mukamel, Dana B, Jack Zwanziger, and Kennethj Tomaszewski, "HMO Penetration, Competition, and Risk-Adjusted Hospital Mortality," *Health Service Research*, 2001, *12* (3), 38.

Narwaria, Manish and Weisi Lin, "Objective image quality assessment based on support vector regression," *IEEE Transactions on Neural Networks*, 2010, *21* (3), 515–519.

Nevo, Aviv, "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry," *The RAND Journal of Economics*, 2000, *31* (3), 395.

Raghavachary, Saty, "A brief introduction to RenderMan," *Association for Computing Machinery*, 01 2006, p. 2.

Saad, Michele A., Alan C. Bovik, and Christophe Charrier, "Blind image quality assessment: A natural scene statistics approach in the DCT domain," *IEEE Transactions on Image Processing*, 2012, *21* (8), 3339–3352.

Sergi, Bruno S., James Owers, and Alison Alexander, "Valuation changes associated with the fox/disney divestiture transaction," *Economics and Sociology*, 2019, *12* (2), 36–47.

Shapiro, Carl, "Mergers with Differentiated Products," *Antitrust*, 1996, *10*, 23–30.

Singh, Harbir and Montgomery, Cynthia A., "Corporate Acquisition Strategies and Economic Performance," *Strategic Management Journal*, 1987, *8* (4), 377–386.

Smeets, Valerie, Kathryn Ierulli, and Michael Gibbs, "An Empirical Analysis of Post-Merger Organizational Integration," *Scandinavian Journal of Economics*, 2016, *118* (3), 463–493.

Suárez-Vázquez, Ana, “Critic power or star power? The influence of hallmarks of quality of motion pictures: An experimental approach,” *Journal of Cultural Economics*, 2011, *35* (2), 119–135.

Sweeting, Andrew, “The effects of mergers on product positioning: Evidence from the music radio industry,” *RAND Journal of Economics*, 2010, *41* (2), 372–397.

Tang, Yihong, Jing Yan, and Feng Yu, “Multi-product firms, heterogeneous quality and exporting behaviour: product-level evidence from the movie industry,” *Applied Economics*, 2018, *50* (54), 5920–5934.

Vedd, Rishma and David Liu, “The Effect of Cultural Integration on Financial Performance Post-Merger,” *Global Journal of Business Research*, 2011, *11* (1), 1–25.

Vogt, Claudia and Robert Town, “How has hospital consolidation affected the price and quality of hospital care ?,” *Research Synthesis Project Report No.*, 2006, (9).

WaltDisney, Animation Studios, “Filmmaking Process,” 2022.

Watson, Randal, “Product Variety and Competition in the Retail Market for Eyeglasses,” *The Journal of Industrial Economics*, 2009, *57* (2), 217–251.

Yang, Louis, “Predicting Stock Market Returns with an Accounting Factor,” *SSRN Electronic Journal*, 2018.

Zhang, Shunyuan, Dokyun Lee, Param Vir Singh, and Kannan Srinivasan, “How Much is an Image Worth? Airbnb Property Demand Analytics Leveraging A Scalable Image Classification Algorithm,” *SSRN Electronic Journal*, 2017, p. NA.

Zhao, Xinlei, “Technological innovation and acquisitions,” *Management Science*, 2009, *55* (7), 1170–1183.

Zohrehvand, Amirhossein, Anil Rajnikant Doshi, and Bart Vanneste, “Generalizing Event Studies Using Synthetic Controls: An Application to the Dollar Tree–Family Dollar Acquisition,” *SSRN Electronic Journal*, 2021.

Supplementary for the Image Quality Assessment

A. Generalized and Asymmetric Generalized Gaussian Distribution

The generalized Gaussian distribution can be used to effectively capture the broader spectrum of distorted image statistics where the GGD with zero mean is given by by (Anish et al. (2012)):

$$f(x;\alpha,\sigma^2)=\frac{\alpha}{2\beta\Gamma(1/\alpha)}exp\Big(-\Big(\frac{|x|}{\beta}\Big)^{\alpha}\Big) \tag{15}$$

where

$$\beta=\alpha\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \tag{16}$$

and gamma function Γ is:

$$\Gamma(\alpha)=\int_0^{\infty}t^{\alpha-1}exp^{-1}dt \tag{17}$$

$\alpha>0$ is the shape of the distribution while σ^2 is the variance.

A single parameter from the GDD cannot provide the full information of the image, so the AGGD is used. The AGGD helps to find the features of paired products of the image. The AGGD with zero mode is as following equation.

$$f(x;\nu,\sigma_l^2,\sigma_r^2)=\begin{cases}\frac{\nu}{(\beta_l+\beta_r)\Gamma(1/\nu)}exp\Big(-\Big(\frac{-x}{\beta_l}\Big)^{\nu}\Big), & x<0\\ \frac{\nu}{(\beta_l+\beta_r)\Gamma(1/\nu)}exp\Big(-\Big(\frac{x}{\beta_r}\Big)^{\nu}\Big), & x\geq 0\end{cases} \tag{18}$$

where ν is the shape parameter, σ_l^2 and σ_r^2 are the scale parameters that control the spread of each side of the mode, respectively.

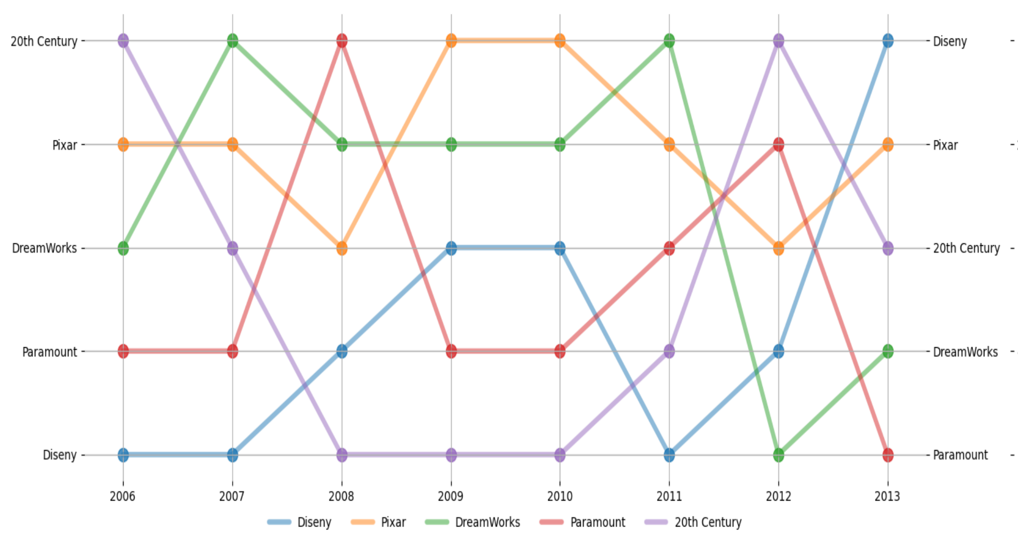
B. Database for the SVM

The BRISQUE approach requires a training procedure to map quality to human ratings via the SVM. In the original paper, the trained data is chosen by taking a set of pristine images from the Berkeley image segmentation database and the similar kinds of distortions in the LIVE IQA database with JPEG 2000, JPEG, white noise, and Gaussian Blur. This paper also selects this set of pristine images from the same database. These database consist of 29 reference images with 7770 distorted images with five different distortion categories - JPEG2000, JEPG compression, additive white Gaussian noise (WN), Gaussian blur, and a Rayleigh fast-fading channel simulation. To correlate human vision, different mean opinion score (DMOS) is used to represent the subjective quality of the image. In the database, each of the distorted images has related discrepancy DMOS.

The limitation of using this database in this paper is that it does not consist of many cartoon or computer graphic images. I admit this limitation, but it is difficult to construct cartoon database for the time constraint and expensive cost. Spearman rank order correlation coefficient (SROCC) is used to evaluate the prediction performance of IQA method. The recent developed technology (Chen et al. (2021)) show better performance than the BRISQUE using the cartoon images. However, this method only considers 2D images, and the performance was 0.8 better than the BRISQUE. This paper sticks to the original method since it considers 3D images and the better performance of the IQA will not matter much to our results.

C. Disney's rank in the box office performance

Figure 13: Five major animated firms ranked by annual highest grossing movie



D. Estimating discrete choice model of image quality

It simply adopts a discrete choice model to explain the quality impact on the demand and marginal costs. Consumers have heterogeneous preferences, with utility from watching a movie being a function of included price, quality of the movie, and other unobserved product characteristics, which include a random, product-specific shock. In each market and time period, consumers choose to watch an animation j or an outside good - that is not an animated movie that consumers may not watch. Consider a market served by animated studios where each offers j movies indexed by $j \in \mathcal{J}$. The indirect utility of consumer i from watching a movie j in t is defined as

$$u_{ij} = -\alpha_i p_{jt} + z_{jt}\beta_i + \xi_{jt} + \epsilon_{ijt} \tag{19}$$

where p_{jt} is the price of movie j in year t, z_{jt} is the observed quality of the product j in year t, and ξ_{jt} is the market level utility of the unobserved characteristic(s), and ϵ_{ijt} is a mean-zero stochastic term with a type I extreme value distribution. The coefficient α_i is the consumer i's marginal disutility of price, and β_i is the column vector of individual-specific taste coefficients for product quality. I follow the assumption of Nevo (2000) that there are no wealth effects from the decision to purchase a ticket.

Breaking down the random coefficients α_i and β_i can be explained by their averages, observed demographics, and unobserved characteristics:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i \tag{20}$$

where D_i is a $d \times 1$ vector of demographic variables in a distribution of demographic variables $\hat{P}_D$, and v_i captures the additional unobserved preferences in parametric distribution of random draws P_v. The matrix Π contains the coefficients which measure the demographics taste. The matrix Σ is defined as the Cholesky root of the preference covariance matrix. It is assumed to be diagonal, limiting the cross-characteristic preference correlation. In this paper, the demographic variables are not included. The set of parameters are θ with $\theta_1 = (\alpha, \beta)$ and θ_2 containing the nonlinear parameters, Π and Σ.

The market-specific product utility averages is denoted as $\delta_{jt} = -\alpha p_{jt} + z_{jt}\beta + \xi_{jt}$ with ξ_{jt} being the structural error term representing the mean market-level utility of the unobserved characteristics. The animated film j's market share in t is computed by the ratio of the movie's box office revenue divided by the ticket price to the U.S. population, which is assumed to be the overall potential market size (Leung et al. (2020)).

Consumer i chooses movie j if selecting the animated film j generates the maximum utility. It is impossible to observe actual consumer preferences, but from a vector of random taste preferences and product-specific errors, the set of consumers choice of product product j in market t is constructed as

$$A_{\{jt\}(z_{.t}, p_{.t}, \delta_{.t}; \theta_2)} = \{(v_i, \epsilon_{i0t}, \ldots, \epsilon_{iJt} | u_{ijt} \geq u_{ikt}, \forall k = 0, 1, \ldots, J\} \qquad (21)$$

The utility of the outside good is normalized to zeros by the standard practice.

To recover the market share, Nevo (2000) integrates over the set to select parameters to find the close predicted market shares to the observed market shares. To solve the endogeniety of price, standard random coefficient models employ an instrumental variables generalized method of moments (GMM) approach. This involves utilizing a matrix of instrument Z_{jt} and weighting matrix W, and this approach minimizes the objective function

$$min_\theta(\frac{1}{N}\sum_{j,t} Z'_{jt}\xi_{jt}(\theta))'W(\frac{1}{N}\sum_{j,t} Z'_{jt}\xi_{jt}(\theta)). \qquad (22)$$

Given an initial value for θ_2, the algorithm estimates δ_{jt} via a contraction mapping, and then the GMM objective function value is computed. The next value of θ_2 for estimation is selected by the nonlinear optimizer and the process repeats until convergence.

For the instrumental variables, this paper uses the number of rival movies shown in a given week when j is released and the market-share weighted average rival weeks-in release, following Einav (2007); Leung et al. (2020). Movie production budgets are also endogenous (Ferreira et al. (2012); Leung et al. (2020)) that the previous year of the total production budgets that studio produced is used as an instrument variable.

On the supply side, studios decide on production, considering their effects on movie quality. Berry et al. (1995) use a marginal cost projection

$$log(mc_j) = w_j\gamma + \omega_j \tag{23}$$

where mc_j is the marginal cost of j, w_j is the observable cost shifters, and ω_j is the unobserved characteristics that affect the marginal cost. In a vector form,

$$p = mc + \Delta(p)^{-1}s(p) \tag{24}$$

where $s(p)$ is the predicted market shares, and $\Delta(p)$ is $J \times J$ matrix of own and demand elasticities. By rearranging this, we can form

$$\omega_j = log(p_j - e'_j\Delta(p)^{-1}s(p)) - w_j\gamma \tag{25}$$

where $e'_j\Delta(p)^{-1}$ is the jth row of $\Delta(p)^{-1}$. For w_j, the number of producers, editors, and staff in the art, animation, and visual departments are used.

Own and cross elasticity with respect to quality

The data employed for estimation is discussed in Section 6, covering the years between 1998 and 2005 in this section[13]. The estimation of the model is conducted using the author's programmed code by Python and `pyblp` by Conlon and Gortmaker (2020), which provides the standard BLP results with optimal instruments. The full sample is 104 markets. The estimated results is provided from the two-stage GMM. The non-linear optimization algorithm utilized is BFGS, with a converge criterion defined as a projected

[13] Only consider the case before the mergers between Disney and Pixar for the demand estimation.

gradient norm (a tolerance less than 1E-4).

Table 3 presents the joint estimation of the demand and pricing equations. The demand estimates include second-stage GMM estimates of $[\theta_1, \theta_2]$ updated after modifying the weighting matrix W and incorporating optimal instruments. Both sets of estimates encompass studio and market fixed effects. The panel of demand-side parameters in the table provides point estimates of the means and standard deviations of the taste distribution of quality and price, respectively. The results show positive and statistically significant estimates on quality, and negative on price. Quality and price are estimated to have a positive and statistically significant effect on the mean and standard deviation of the distribution of utilities. Notably, due to the challenges of collecting individual filmgoer information, variables such as age of viewers and other relevant demographic characteristics are not included in this estimation. In the context of cost-side parameters, the number of producers and staff in the animation department exhibits positive and statistical significant, while the number of editors is negatively statistically significant. Other variables appear to be insignificant. These findings bear relevance to the subsequent results discussed in Section 7, particularly in terms of the effect of the number of staff in the animation department on image quality.

Table 4 presents the median estimates of own and cross elasticities of demand concerning quality by studios. The median own-demand elasticities generally show positive and elastic. Cross-price elasticities are presented in element (i, j), with i indexing rows and j indexing columns, and are derived from the median demand elasticity of i with respect to the quality of j. For example, the cross-elasticity of demand for Disney with respect to Piaxr's quality is -3.328, indicating Disney's high sensitivity to changes in Pixar's quality with respect to their market shares. Conversely, Pixar's cross-elasticity of demand with respect to Disney's quality is -1.1319, suggesting a lower sensitivity to Disney's quality. It shows that the intensity of pre-merger competition between Disney and Pixar matters for the quality effect of Disney. Notably, most companies show elasticity regarding changes in Pixar's

Table 3: Parameters of the Demand and Pricing Equations

Parameters		Parameter Estimate (se)
Demand side parameters		
β	Quality	2.3^{*}
		(0.38)
α	ln(y-p)	-11^{*}
		(0.0008)
Σ		
	Quality	2.3^{*}
		(0.32)
	Price	1.3^{*}
		(0.37)
Cost side parameters (γ)		
	Constant	-2.6^{*}
		(0.075)
	Producer	2.1^{*}
		(0.54)
	Editor	-4.3^{*}
		(0.13)
	Art	-0.023
		(0.15)
	Visual	-0.017
		(0.018)
	Animation	0.062^{*}
		(0.023)

Notes: IQA is inversely proportional to the quality. To make the interpretation easier, Quality is computed (100-IQA)/10. y is income (the real median income in US obtained from Federal Reserve Economic Data) and p is price. Producer is the number of producers, editor is the number of film editors. Art, Visual and Animation mean the number of staff in each department. * indicates significance at the 95% level.

quality, as observed in the last column of Table 4. It is evident that Pixar's entry into the animation industry had a noticeable impact on other companies' market shares, creating increased competition.

Furthermore, Conlon and Gortmaker (2020) support the use of the diversion ratio as an alternative to price elasticity. Calculating diversion ratios is of particular significance for antitrust analysis in horizontal mergers(Shapiro (1996); Conlon and Mortimer (2018)). The diversion ratio provides a more precise description of the substitution pattern across products in response to slight changes in price or other attributes. Specifically, the diversion ratio reflects the proportion of consumers who substitute product i with product j when quality i increases $D_{ji} = -\frac{\partial s_j}{\partial z_i} / \frac{\partial s_i}{\partial z_i}$, where s_i is the market share of product i. Table 5 presents the median diversion ratios, with diagonal entries representing diversion to the outside good and off-diagonal elements indicating substitution rates from the row product to the column product as the quality of the row product decreases. The diagonal diversion ratios are predominantly negative, indicating that animated films are substituted for non-animated movies. Notably, Disney shows a higher diversion to Pixar (0.376) compared to other studios, implying that as Disney's quality decreases, there is a higher level of substitution to Pixar's films. In contrast, Pixar has a lower diversion ratio to Disney (0.166), suggesting that consumers of Pixar movies are less likely to switch to watching Disney films. While various factors can influence changes in consumer choices, these results imply that Pixar has established a strong appeal as an animated studio in the estimation period, leading to a lower likelihood of consumers switching to other animated films.

Table 4: Own and cross elasticity of demand with respect to quality

Studio	Disney	Shin-Ei	Asatsu	Toei	Ghibli	20th Century	DreamWorks	Paramount	TMS	OLM	Universal	Sony	Pixar
Disney	2.715	-0.169	-0.448	-0.325	-1.38	-0.314	-0.824	-0.891	-0.268	-0.752	-0.001	-0.078	-3.328
Shin-Ei	-2.71	13.202	-0.774	-0.435	-2.536	-0.322	-1.408	-1.545	-0.429	-1.58	-0.001	-0.354	-6.056
Asatsu	-2.799	-0.303	15.115	-0.569	-4.583	-0.269	-1.339	-1.694	-0.314	-2.931	-0.002	-0.418	-7.119
Toei	-2.142	-0.286	-0.832	7.339	-4.068	-0.391	-1.385	-1.125	-0.245	-1.412	-0.001	-0.262	-5.009
Ghibli	-2.721	-0.266	-0.952	-0.459	11.772	-0.376	-1.424	-1.6	-0.522	-2.064	-0.001	-0.268	-5.591
20th Century	-0.512	-0.035	-0.096	-0.088	-0.497	1.5	-0.169	-0.207	-0.092	-0.095	-0.001	-0.013	-2.047
DreamWorks	-1.482	-0.098	-0.312	-0.212	-1.406	-0.167	8.821	-0.531	-0.183	-0.463	-0.001	-0.097	-2.715
Paramount	-2.386	-0.207	-0.696	-0.254	-0.629	-0.396	-1.021	13.69	-0.427	-1.059	-0.001	-0.164	-4.219
TMS	-2.355	-0.191	-0.561	-0.238	-0.753	-0.367	-0.954	-0.94	9.845	-0.837	-0.001	-0.202	-3.644
OLM	-2.362	-0.305	-1.315	-0.583	-3.013	-0.348	-0.927	-1.673	-0.512	7.502	-0.001	-0.304	-5.647
Universal	-2.867	-0.23	-0.829	-0.349	-1.161	-0.315	-1.058	-1.751	-0.595	-1.716	4.031	-0.339	-5.685
Sony	-2.692	-0.298	-1.198	-0.592	-2.845	-0.291	-1.089	-1.502	-0.281	-1.764	-0.001	0.435	-5.366
Pixar	-1.319	-0.149	-0.574	-0.399	-1.868	-0.289	-1.132	-0.714	-0.25	-1.293	-0.001	-0.321	5.136

Table 5: Median diversion ratios of products

Studio	Disney	Shin-Ei	Asatsu	Toei	Ghibli	20th Century	DreamWorks	Paramount	TMS	OLM	Universal	Sony	Pixar
Disney	-0.001	0.013	0.038	0.035	0.143	0.027	0.084	0.07	0.028	0.044	0.001	0.015	0.376
Shin-Ei	0.136	-0.001	0.038	0.027	0.14	0.023	0.079	0.066	0.025	0.054	0.001	0.02	0.254
Asatsu	0.106	0.01	-0.001	0.028	0.195	0.013	0.07	0.06	0.017	0.095	0.001	0.018	0.248
Toei	0.126	0.01	0.04	0.001	0.186	0.023	0.093	0.067	0.023	0.087	0.001	0.016	0.289
Ghibli	0.142	0.013	0.053	0.031	0.001	0.027	0.101	0.075	0.022	0.088	0.001	0.018	0.333
20th Century	0.141	0.015	0.032	0.038	0.115	-0.011	0.068	0.054	0.029	0.045	0.001	0.006	0.413
DreamWorks	0.229	0.012	0.034	0.033	0.163	0.044	0.005	0.091	0.023	0.039	0.001	0.019	0.275
Paramount	0.189	0.012	0.037	0.026	0.127	0.036	0.06	0.005	0.023	0.046	0.001	0.022	0.24
TMS	0.169	0.012	0.032	0.014	0.038	0.023	0.061	0.093	0.001	0.042	0.001	0.014	0.24
OLM	0.103	0.012	0.056	0.03	0.201	0.019	0.087	0.058	0.02	0.001	0.001	0.021	0.33
Universal	0.113	0.013	0.04	0.023	0.121	0.019	0.072	0.063	0.031	0.053	-0.001	0.022	0.261
Sony	0.119	0.016	0.049	0.038	0.156	0.015	0.086	0.064	0.019	0.067	0.001	-0.001	0.26
Pixar	0.166	0.017	0.05	0.041	0.188	0.042	0.131	0.086	0.031	0.082	0.001	0.034	-0.001