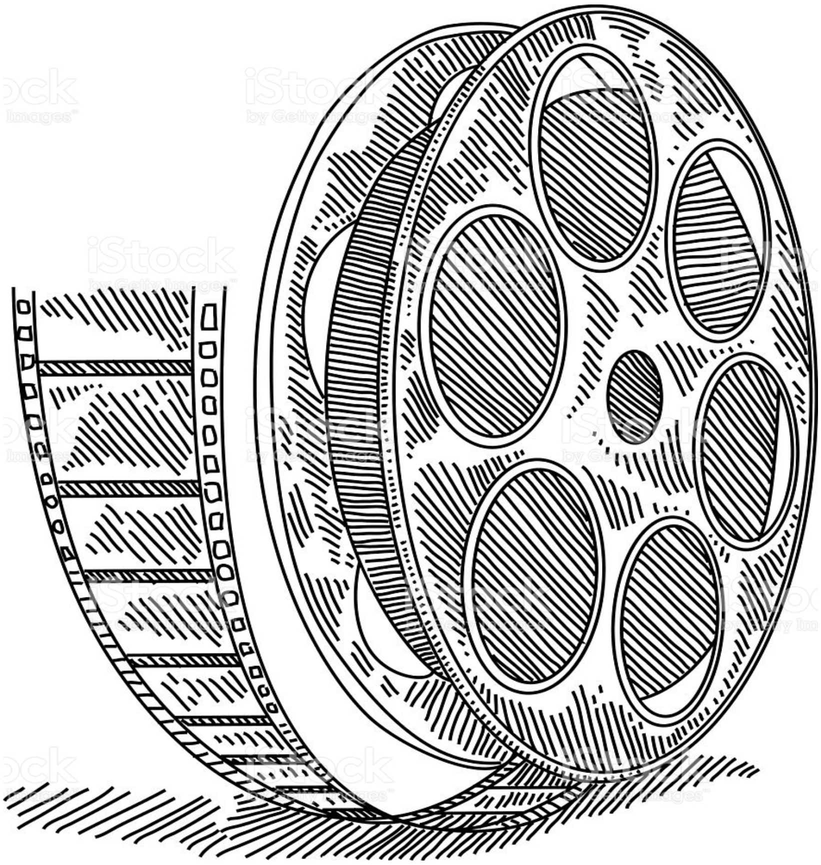
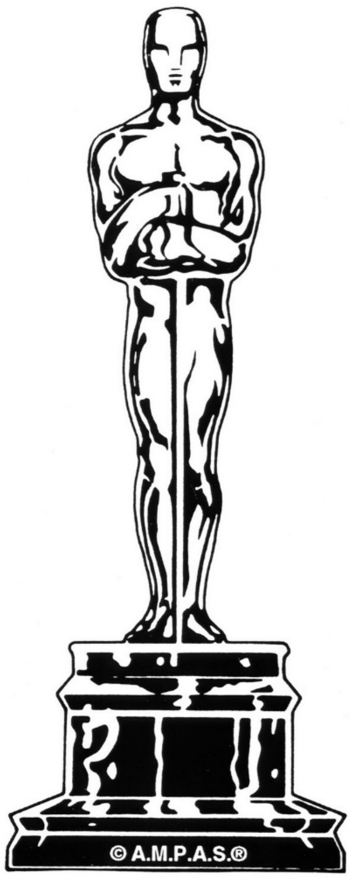
And the Oscar goes to:

A movie that we can totally predict?





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ABSTRACT

This research primarily aimed to combine and add to previous studies who delved into the individual aspects that are considered to influence a film's critical recognition (defined in this research as a film's success at the Oscars, both in terms of nominations and wins). For this study, three main influential factors were established, who operate as agents in the persuasion knowledge model (Friestad & Wright, 1994), as they try to influence the persuasion target, which is the Academy. The three factors in this study consisted of the box office performance, public reception and critical reception. For the critical reception, it was argued that the job of critics (namely, rewarding films of the highest quality) lines up with the main goal of the Academy, thus resulting in the facile assumption that there is a relation between the two. For the public, it was argued that films who appeal to the public regarding a certain contemporary social discussion, or controversy, have to a higher chance of being critically recognized (e.g. as evidenced by Moonlight (Jenkins et al., 2016) and the #OscarsSoWhite (Cox, 2017) controversy), which means that the public reception of a film has an influence on the Oscars. Finally, the box office indicates the films that were seen in theaters by the majority of the public. Given that the Academy frequently nominates (although never actually rewards) a few of these films in order to lure in viewers for their ceremony, it can also be argued that the box office has a persuasive effect on the Academy. Each of the four components of this research were operationalized. First, the public reception was operationalized by combining the online IMDb and Cinema scores. Second, the critical reception was operationalized by combining two statistics (Tomatometer and average rating) on the Rotten Tomatoes website. Third, the box office was operationalized as the domestic box office numbers, adjusted for inflation. And finally, critical recognition was operationalized in terms of a film's number of Oscars nominations, Oscar wins, and Oscar wins in the big five (the most prestigious Oscars) category. A sample of 290 films (*N* = 290*)* was drawn, ranging between the years 1995 and 2017, and consisting of all kinds of films that were eligible for Oscar recognition (blockbusters, flops, poorly reviewed films, big five winners, etcetera.). OLS regression models, negative binomial regression models and Baron-Kenny mediation models were calculated in order to analyze the relationships between the four components of this research. In the end, it was found that critical reception is a strong and consistent predictor for a film's critical recognition. The public reception was found to be a moderate predictor, and it was found that its predictive value decreases as the degree of critical recognition increases. Finally, the box office was the weakest (although still a significant) predictor. Moreover, the box office variable was found to be a weak and mostly insignificant mediator when mediating between public or critical reception (IV) and critical recognition (DV). This was explained by the Academy simply caring more about the critical or public reception, rather than the box office numbers.

KEYWORDS: *Box Office, Critics, Public Reception, Oscar Recognition, Film, Academy Awards*

Table of contents

1. Introduction

Billy Christal during the Academy Awards 2012: "Nothing can take the sting out of the world's economic problems like watching millionaires present each other golden statues" (Lachno, 2012, para. 1)

Every filmmaker has a dream. They dream of moving, entertaining or scaring the audience. They want their motion picture to making money, please the suits, and help with creating a legacy for themselves. Those are some high ideals, and succeeding in one of those would already be considered quite an achievement. Nevertheless, there is one dream that trumps them all, an honor so great that it passes everything else, and that is to win an Academy Award.

1.1 The relevance of the Oscars

The Academy Awards, or Oscars (these terms can be used interchangeably, as they mean the same) have a rather fascinating history. The first awards were bequeathed in 1929, in a small hotel room in front of 270 people ("History," n.d.). The ceremony itself was very brief, as the winners had been already announced in a newspaper one month earlier ("History," n.d.). The procedure was changed in the thirties, when newspapers were given a list of the winners on the day of the ceremony ("History," n.d.). By accident, the results leaked in 1940 ("History," n.d.).

Since then, the ceremony became more secretive in order to heighten its entertainment quality, but also in order to grow in scope, publicity, popularity, and impact. The event has nowadays become a popular global event (e.g. more than 65 million people watched the ceremony show in 2015 (Szalai, 2016)), and, as such, the attention the Oscars received has made it, and filmmaking at large, a voice in society highlighting the narratives that speak to the human condition throughout U.S. and global history of the past century (Gunter, 2018). According to Littlejohn (2017), there are two reasons for the Oscars gaining relevance in society. First of all, the Academy consists of voters who hail from all the corners of the film industry, whereas another well-known awards event, the Golden Globes, represent only the journalistic side of the film industry (Littlejohn, 2017). Moreover, the Academy simply has a larger amount of voters when compared to the organizations behind other awards (Littlejohn, 2017). Finally, as hinted at with the first paragraph, an Academy Award also represent a sense of prestige, or a sense of recognition from peers, which is logically something anyone in the film industry likes to strive for.

1.2 The Academy as a social institution

As the Academy rose to become a relevant societal institution, it also drew controversies reflecting societal issues and values at the time of such controversies. For example, the 2016 ceremony dealt with the #OscarsSoWhite (i.e. the public accusing the Academy of nominating too much Caucasian talent (Cox, 2017)) controversy, to which the Academy responded by applying changes in their voting system (Cox, 2017). The year after this controversy, Moonlight (Gardner, Kleiner, Romanski and Jenkins, 2016), a film with a completely non-Caucasian cast, won the award for best picture. This could very well be a coincidence, but at the same time, it can be argued that Moonlight's (Gardner et al., 2016) chances of winning were greater as a result of the public reception being higher, which could partially be attributed to the film's acclaim being related to a social discussion, and by extension, a widely reported controversy (the aforementioned #OscarsSoWhite) (Cox, 2017).

Broadshaw (2018) attributed some of the controversies to the fact that the Oscars only represent the audience of the time, and often reward art that is more relevant to the contemporary context rather than being forwarding thinking. In other words, it is not uncommon for rewarded films or people to have been forgotten about in the public consciousness of film fans (Broadshaw, 2018), while at the cost of people in film who have come to be referred to as cinematic geniuses by many film fans. For example, Alfred Hitchcock was never rewarded with an Academy Award (Broadshaw, 2018). In a more popular context, this would be referred to as a 'snub', which refers to the absence of rewarding (or nominating) a talent who in the public's eye deserves to be recognized (Pulver, 2017).

1.3 The influence of a film's reception on the Academy

These concepts of snubs and concepts tie into the idea of the public having a shared conscious, a conscious that proposes a consensus on what, in their opinion, deserves to be rewarded, and what does not. There has been much research about the public's cinematic consensus (it can also be referred to as public reception), and the way it connects with the Oscars. For example, Krauss, Nann, Simon, Fischbach and Gloor (2008) researched the relation between characteristics of IMDb (an online platform for film related content) discussion boards and best picture nominees, and found a relationship between the public's sentiment and the Oscar winners. Furthermore, other research found that all of the cinematic award shows form a consensus (in other words: they often reward the same thing), and that the Oscars are the closest to that consensus (Simonton, 2004). From both of these findings, it can be deduced that the Oscars have a need to appeal to certain social forces, one of which being the public.

Besides the public, critics can also be considered to be an influential force on the Academy. In short, the concept of a critic refers to the opinions of film journalists and cinephiles (Dellavigna & Hermle, 2016). Their response to a film is impactful, as there has been some research indicating that their response is a predictor of its public reception (Eliashberg & Shugan, 1997). Furthermore, critics tend to have a high ethical standard (Dellavigna & Hermle, 2016), and are tasked with rewarding films of the highest quality (Eliashberg & Shugan, 1997). Since this latter point aligns with the reason why the Academy Awards primarily exist, it can be assumed that there is a relation between the two.

Public and critics may play a clear role in influencing the Academy; however, there is another receptive factor that can be looked at, and how it relates to the critical recognition (i.e. Oscar nominations and wins) of a film, namely the box office performance. The box office performance is a representation of the quality that the audience assigns to a film, as it indicates the amount of money that a film earns when it is playing in theatres. In turn, the public already been argued to be a relevant factor, which is why it can be assumed that the economic success of a film also has an influence on the Academy.

Together, the public reception, critical reception and box office factors interact with each other in the persuasion knowledge model; a model that was originally introduced in marketing studies (Friestad & Wright, 1994). Nevertheless, some academic articles have argued that persuasion can also be used for explaining phenomena in entertainment media (Slater & Rouner, 2002). In the case of this specific research, it means that the three receptive factors act as persuasion agents (Friestad & Wright, 1994), or in other words, they persuade the Academy of rewarding one film over another.

Furthermore, there are multiple persuasion models that can be established; models that reverse the role of persuader and target, but this will be expanded on during the theoretical framework. From the primary PKM model that has been established above, the persuasion agents (i.e. public reception, critical reception, box office performance) and persuasion target (i.e. the Academy) will be the focus of this project, and analyzed through the following research question:

RQ: To what extent can the critical reception, public reception and box office performance of a film predict its critical recognition at the Oscars?

1.4 Academic and social relevance

Scientifically, this study adds to previous research that has already been conducted about this topic. Individually, some of these concepts relating to reception have been researched in terms of their relation with critical recognition. For example, the aforementioned Krauss et al. (2008) found that IMDb boards (public reception) were able to predict the Oscar winners for several categories. Moreover, the relation between being nominated for an Academy Award and box office boosts was researched by another study, and its results indicated that a nomination can result in a substantial box office boost (Ginsburgh, Gutierrez-Navratil & Pietro-Rodriguez, 2016). However, there is no research that combines all of these findings into one coherent model. Additionally, this research opens the door to updating the prior body of research in this area. For example, the aforementioned IMDb discussion forums no longer exist on the site, so audience reception requires a different source and operationalization. Moreover, this research can also debunk previous research that was found to be problematic, such as the aforementioned work by Ginsburgh et al. (2016). This latter point will be expanded upon during the theoretical framework.

Practically, the findings from this thesis would inform the movie business which films they should and should not emphasize in their campaigns for awards consideration. For example, if one of the findings is that the box office does not predict critical recognition, studio executives know that they do not have to push their biggest blockbusters for awards. A point of concern that remains, however, is the question as to why studios care about Oscars, especially when considering that professional literature argues movie studios are just interested in making as much money as they can (Arnold, 2017). However, that logic also happens to be the answer to the question. If movie studios can highlight their prestige and profitability by winning Oscars, they can then attract more well-known and skilled filmmaking talent. Better filmmaking talent means that the artistic quality of studios' films will improve, and in the long run, they will yield higher revenues (Kalb, 2013). Therefore, it is not surprising to observe that movie studios invest heavily in campaigns to enhance the chances of their films winning Oscars (Cunningham, 2017).

1.5 Chapter outline

The remaining parts of this research have been divided into several chapters. The second chapter explores the concepts and theories (e.g. WoM) that can be associated with this study, which was done through the lens of the persuasion knowledge model. The third chapter details the quantitative approach that was taken in order to analyze the data, and justifies its method. The fourth chapter consists of a detailed report regarding the OLS, negative binominal, and mediation analyses of statistical data. Finally, the fifth chapter forms a discussion that connects the findings of the results section back to the theories and concepts of the theoretical framework.

2. Theoretical framework

The previous chapter already explained why the Oscars are considered to be relevant, and why they can be justified as critical recognition. Therefore, this chapter will focus on the three concepts that have been suggested to influence critical recognition: which are the box office performance, the critical reception and the public reception. Each of these three topics will be discussed in their own subsections, but first, a larger theoretical foundation needs to be explored in order to understand how these concepts operate in a larger context.

2.1 Persuasion knowledge model

In the business and marketing domain, how people become persuaded by a message is of paramount concern, as ultimately the mechanisms of persuasion lead to their engagement with products (e.g., purchasing or informally promoting them). To better frame this dynamic, Friestad and Wright (1994) introduced one of the most well-known models in marketing studies that explains how these messages are communicated. This model is also referred to as the persuasion knowledge model (Friestad & Wright, 1994). In short, the persuasion knowledge model contains a theory that presents how persuasive communication works, and does so by highlighting the importance of both the sender and receiver of the message. Despite making a clear differentiation between these two, Friestad and Wright (1994) argued that both sides engage with the same resources in order to interpret a message: which are topic knowledge (how much one knows about the subject), persuasion knowledge (how well one knows how to persuade) and target/agent

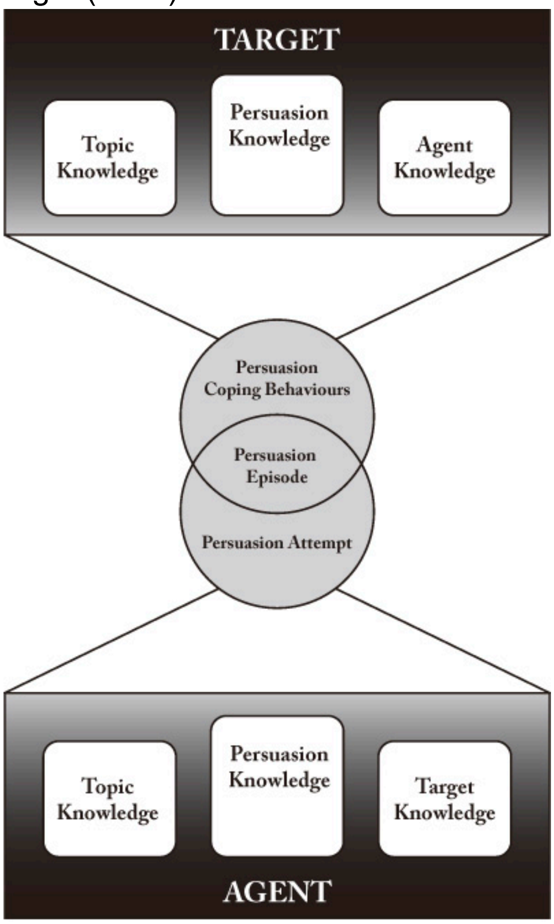


Figure 2.1.1.1: The persuasion knowledge model (Friestadt & Wright, 1994, p. 2)

knowledge (how well one know the persuader/persuaded. So, agent knowledge in regards to the target, and target knowledge in regards to the agent). According to their theory, the three resources from the target's side form 'persuasion coping behavior', and the three resources from the agent's side lead to a 'persuasion attempt'. Finally, the overlap between those two is referred to as the actual persuasion, or 'persuasion episode' (Friestad & Wright, 1994). This model has been widely applied to a variety of socio-cultural situations that include persuasion (e.g. politics), but it can also be applied to aspects that one might not immediately think of, like entertainment.

2.1.1 Persuasion in entertainment

Friestad and Wright's (1994) model can be applied to the three reception factors of this research in order to understand how the concepts connect with each other. Essentially, there are several persuasion models at play, the relations of which have been drawn in figure 2. In the first persuasion model, Hollywood is primarily using their topic knowledge (filmmaking and marketing skills) and target knowledge (knowledge about the critics, public and Academy) in order to convince the public, critics and the Academy of the high quality of their films (Waldfogel, 2016). Delving into this persuasion could lead to a richer study, but considering that a lot of hidden financial information (e.g. marketing strategy plans) from inside the industry would be needed in order to analyze this persuasion model, this will be left for future research.

Instead, this research focusses on the persuasion knowledge models that can be established between critics, the public and the Academy. In this study, the critics always operate as persuasion agents, as they are trying to convince the Academy that some films are of higher quality than others, and thus deserve to be rewarded. Moreover, the critics influence the public, given that the public assumes that critics have a high topic knowledge over the quality of films, in order to watch a film (Reinstein & Snyder, 2005). If a film connects with the public, and they also happens to praise the quality of the film as well, this leads to public discussion. This is an effective kind of marketing for Hollywood, as nobody has more target knowledge about the public than the public itself (Rosario, Sotgiu, Valck & Bijmolt, 2016). This makes the public both a target (from critics and itself) and agent (towards the Academy) of persuasion (Tuk, Verlegh, Smidts, & Wigboldus, 2009). Moreover, it can be argued that praise from the public about a film can lead to a higher box office performance for a film (Simonoff & Sparrow, 2000), which will be expanded on in a later section. The box office sales is an interesting concept in general, especially when it comes to the persuasion model, as it is just a number (or set of numbers), meaning that it is, factually speaking, impartial and has no agency in the scope of the PKM. However, it can be argued that the public posting, advertising or reporting of the box office performance adds to the resource of topic knowledge from the persuasion target in the overarching model of this study, which is the Academy. Together, the critics and public entail those who use their resources in order to influence the Academy, which they can do through the effective use of target and topic knowledge in particular. How this process works exactly will be expanded on in sections 2.3 and 2.4.

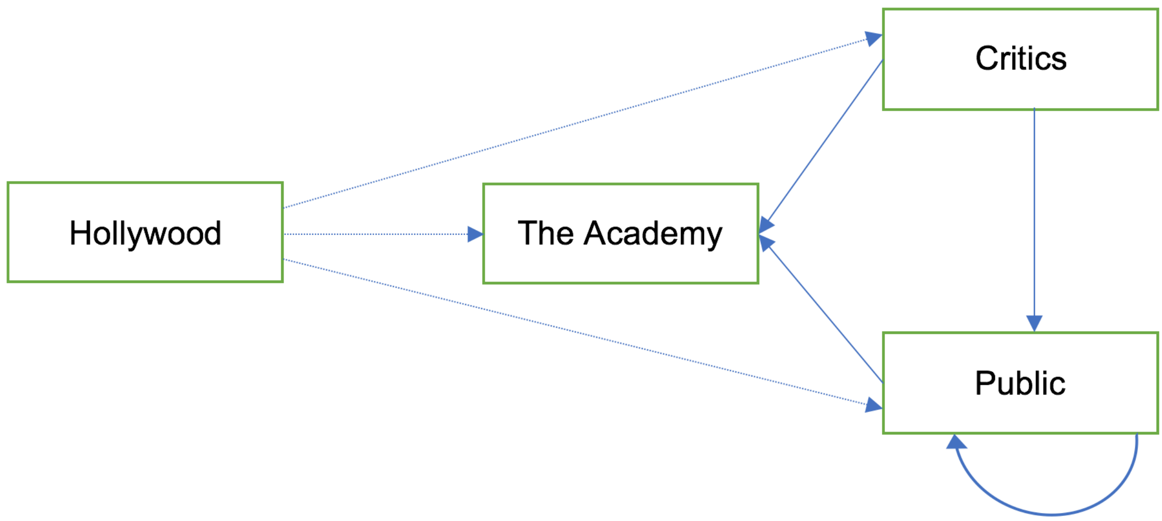


Figure 1.1.1.2: Proposed persuasion relations between the main players of this study.

Nevertheless, this does not reveal yet *why* each element of this research fits into the model the way it does. Therefore, persuasion has to also be used in order to understand how media texts are able to form the public reception and influence the Oscar procedure. Slater and Rouner (2002) wrote that persuasion in entertainment has a primary relation with the educative aspect of a product (the message/subtext). This educative aspect is tied to the narrative of the product, so in short, that means that if the individual is able to comprehend and assent the narrative, he/she will be more likely be persuaded by the high quality of the product (Slater & Rouner, 2002).

On the other hand, Artz and Tybout (1999) wrote that audiences already have a certain credibility bias when it comes to persuasion knowledge. This means that when a target is being persuaded by someone, or something, that they perceive as more credible, they tend have a more lenient attitude towards the fact that they are being persuaded (Knobloch-Westerwick, Mothes, Johnson, Westerwick & Donsbach, 2015). When applied to this study, this would mean that someone watching a film with, for example, a director or actor that he/she already admired before watching the film, can lead to being persuaded that the film is good more easily.

However, each individual has agency, meaning that a unanimous opinion is unattainable. Instead, one group obtains hegemony, which, according to Gramsci, is an invisible power exercised by those who are able to construct the dominant voice in a society (Bates, 1975). Interestingly, this does not automatically mean that the dominant voice is also the voice that is heard the most in terms of frequency, but instead, it is argued that hegemony constitutes of the voice with the strongest foundation (Bates, 1975). In short, this indicates that strong arguments with initially a low degree of exposure can triumph over weaker arguments that initially have a lot of exposure. This leads to the point of hegemony being obtained through interaction in traditional and social media. Media platforms serve as discussion forums, given that they assemble arguments from multiple voices in society. Through the distribution of these arguments in the media, one voice eventually becomes dominant, as most people simply agree with that particular stance on a certain matter (Bates, 1975).

When it comes to this particular research, hegemony is the concept that ultimately explains how the overall, dominant public reception of a film is formed. Once hegemony forms the dominant public reception, it can be assumed that its strength may persuade the critical recognition and other performance indicators of a film, such as box office sales; these elements will be expanded on during the next sections.

2.2 Box office performance

Box office sales (or ‘box office’ for short) are one of the most interesting aspects for measuring the performance of a film’s theatrical run. In short, it refers to the amount of money that a film receives from ticket sales when it is released in the cinemas (Hennig-Thurau, Houston & Walsh, 2007). Many analysts attempt to predict how much a film will earn in order to analyze the financial state of the industry (Hennig-Thurau, Houston & Walsh, 2007). In order to do so, they always differentiate between the domestic and worldwide box office (Lee & Bae, 2004). The domestic box office is the amount of money that a film makes in the United States and Canada, whereas the worldwide box office is the total amount of earned money from all countries that are not the US and Canada (Lee & Bae, 2004). Together, the domestic and worldwide box office form what is referred to as the total box office (Lee & Bae, 2004).

At first, it might seem illogical to look at the domestic box office, as this number is included in the total box office as well. Nevertheless, despite the rapid growth of the Asian (particularly Chinese) market, the combined US and Canadian market still form the largest movie going audience in the world (Tartaglione, 2017). Furthermore, studios earn more money from each movie ticket they sell in the domestic area, compared to overseas, as a result of lower tax rates and higher ticket prices (Lee & Bae, 2004). Therefore, it is highly important for a film to succeed in the domestic area, perhaps even more so than overseas (Lee & Bae, 2004; “Top 10 film countries by box office,” 2013), which is the reason why this research will predominantly focus on the domestic box office. Furthermore, there is also a practical reason for this, but this will be expanded upon during the method section. As mentioned before, these numbers can help with analyzing the financial state of the industry, but in order to do so, the box office has to be compared with the total cost of the film.

2.2.1 Box office potential

According to Prag and Casavant (1994), a higher budget allows filmmakers to make a film more appealing to a broader audience. For example, a higher budget allows for hiring A-list movie stars, spending more money on movie sets, and broadcasting more promotional material (Prag & Casavant, 1994). Hunter, Smith and Singh (2016) researched whether it is possible to predict the box office based on the pre-production aspects of a film (i.e., the production process before the shooting of the film, such as screenwriting), and they found that the size and inner-networks of a script are two indicators giving an appropriate idea of what should financially be expected. In that case, it can be assumed that the amount of money that a studio spends on a film tells analysts what they are financially expecting from a film. This was also been suggested by Basuroy, Chatterjee and Ravid (2003), as they found that the budget of a film indeed gives a good indication of how a studio expects a film to perform at the box office. This is important, because it stresses the fact that one cannot blatantly compare every movie with one another. They are not created as equal, thus they should not be compared as such. Therefore, this research has to control for the potential that each film has, which will be expanded on during the methodology section.

What makes this slightly more complicated, however, is the fact that the taste of the audience is somewhat unpredictable, as well as always changing. Therefore, many analysts are often surprised with films that overperform or underperform their expectations at the box office (Hennig-Thurau et al., 2007). For instance, last year's Get Out (Blum & Peele, 2017) ended up earning more at the domestic box office than Kong: Skull Island (Garcia, Jashni, Parent & Vogt-Roberts, 2017), despite the former film costing $4.5 million to make, and the latter film $185 million (Movie Budgets, n.d.). This was, however, considered to be an exception to the rule (Lang, 2017), as the budget usually tends to be a fairly good indicator of what is expected economically expected from a film (Barusoy et al, 2003; Wasserman et al., 2015). Furthermore, the financial results of these films stress the point of a relationship that can be assumed between critical reception, critical recognition and a high box office performance, as Get Out (Blum & Peele, 2017) was one of the best reviewed films, and most nominated films during the Academy Awards of 2018 (Dove, 2018).

2.2.2 The effect of critical recognition on box office performance

There is already some research about the effect of critical recognition (i.e. winning or being nominated for an Oscar) on the box office performance. For instance, Ginsburgh, Gutierrez-Navratil and Pietro-Rodriguez (2016) looked at the number of Oscar nominations that a film received, and how that can give a film a financial boost a week after the announcement. This is, financially speaking, very relevant to research; however, it is also slightly problematic in the sense that not every film is playing in the theaters when the nominations are announced. Granted, there is a period called 'Oscar season', in which many of the films that are nominated for Academy Awards are in the theaters, but this is not always the case, so some films do not benefit from the announcement. For example, the 2018 Oscar nominations were announced in February, and Dunkirk (Thomas & Nolan, 2017) was one of the films that received the most nominations, despite not being released during Oscar season. In fact, it was released during the summer, so how accurately can the causality be measured if only a few of the films can be included in the sample?

Despite this problem, research operating from this paradigm has found some interesting findings. Deuchert, Adjamah and Pauly (2005) found that Oscar nominations and wins contribute to the box office success of this film. This is already a far more relevant finding when compared to Ginsburgh et al. (2016), as the Oscar ceremony has far more media exposure than the nomination announcement event, thus resulting in a more substantial influence on the audience.

Moreover, previous research found that a higher recognition in terms of the importance of the Academy Award (for example: best picture is more valuable than best original song) is important for the degree of box office boost that a film receives for being recognized (Nelson, Waldman & Wheaton, 2007). Although this finding is not necessarily relevant for the relation that has been proposed above, it will be used during the methodology chapter for establishing the parameters of which films will be included for the analysis.

2.2.3 The effect of box office performance on critical recognition

While prior research has examined the effect of the box office on critical recognition, there is still a lack of research questioning why the box office performance should be looked at as a predictor of critical recognition. The Oscars are distributed through an award show on television, for which the largest portion of making revenue comes through its viewership, i.e. attracting viewers to watch their show. From that perspective, one might expect that the Oscars benefit from rewarding films that most of its viewers saw; or in other words, the ones with the highest box office performance. This also, once again, stresses the importance of including the domestic box office in the analysis, as the show is produced in the United States and primarily watched in that country as well (that is, through traditional television watching, which generates the most revenue for ABC (the network that broadcasts the Oscars)).

That assumption, however, might have become slightly more questionable over recent years, as Littleton (2018) reported that the 2018 Oscars hit a viewership low, which she attributed to the Oscars only nominating niche films for the important categories, and not the films with which public was familiar. On the other hand, it can also be argued that the Academy has been doing this for years, as it has been found that the Academy almost never nominates, and less so reward ‘blockbusters’ for any of the important categories, and tends to stick nominate one particular kind of movie in a general sense (these films being smaller/middle sized productions in terms of budget and box office potential, often falling under the ‘drama’ genre) (Simonoff & Sparrow, 2000), which confirms a previous finding of there being a disconnect between what the public and the Academy find to be the of the absolute highest quality (Ginsburgh & Weyers, 1999). However, considering that critically recognized films hardly flop at the box office (Looch, 2018), it can still be assumed that the public recognizes the quality in these films, just to a lower degree, considering that they find different qualities in their films more valuable (e.g. spectacle, compared to directing and acting) (Ginsburgh & Weyers, 1999). Therefore, this finding indicates that the box office performance can indicate a degree of quality leading to recognition. Moreover, it can still be proposed that the box office predicts which films are critically recognized, as Simonoff and Sparrow (2000) also found that this was the case in their own small-scaled study. As a result of this section, the following hypotheses can be proposed:

H1A: The box office revenue, pre-Oscar ceremony, positively predicts a film’s critical recognition (i.e. Oscar nominations and wins).

H1B: In turn, critical recognition positively predicts the total box office revenue of a film (inclusive of post-Oscar ceremony box office revenue).

2.3 Public reception

The public reception can be defined as the reaction of the audience towards the film (Liu, 2006). Again, there has already been much research about this topic. Davis and Khazanchi (2007) investigated the role of word of mouth (WoM) in public reception; WoM is considered to be “all informal communications directed at other consumers about the ownership, usage, characteristics of particular goods and services of their sales” (Davis & Khazanchi, 2007, p. 2). In short, it was found that consumers have an important impact on product sales through the use of word of mouth (Davis & Khazanchi, 2007). During the section about persuasion knowledge, it was argued that public discussion was an important influencer on the public itself. The public discussion, or WoM, as it can be referred to now, very quickly spreads through the use of traditional and social media, thus making it easier for one social group to obtain hegemony and dominate the social conversation. Therefore, it can be argued that in this study, WoM and hegemony add to the topic knowledge of both the agent and the target, as it informs the agent (or in this case: the entire public) about their dominant stance on a product, and the target about whether the product should be considered as Awards worthy, which will be expanded on during the next few paragraphs.

2.3.1 The effect of public reception on critical recognition

A previous study attempted to predict the outcome of the Oscars through the use of opinions and shared data on Twitter (Haughton, McLaughlin, Mentzer and Zhang. 2015). This method failed, as the researchers predicted the wrong winner Haughton et al., 2015). One of the possible reasons for this, as Haughton et al. (2015) also acknowledged in their work, is that they only looked at the public reception through a sentiment analysis. This once again emphasizes the notion that a broader framework for prediction is needed.

Nevertheless, other research was more successful in this regard. Krauss et al. (2008) operated from the perspective of the wisdom of the crowds: which means that a group of individuals knows more (and is therefore better at predicting things) than one individual expert. Their research had more success than Haughton et al. (2015), as they found through a sentiment analysis that positive sentiment surrounding a film was significant for predicting the box office performance, and through that factor even the Academy Award nominations. The first part of that notion is explained by Liu (2006), who found that word of mouth is the most important influencer on the box office performance of a film, which in turn can influence the critical recognition of a film, as discussed in an earlier subsection.

The difference between Haughton et al. (2015) and Kraus et al. (2008) is that the latter one used IMDb forums as a base for their analysis, which already points to their research's being a little outdated, as IMDb forums (besides no longer existing) do not constitute of the wide user base of social platforms that are nowadays often used for sentiment analyses (e.g. Twitter). On the other hand, it could be argued that film-related internet platforms are a little more representative of public opinion in this regard than social media. This is further backed up by Wong, Sen, and Chiang (2012), who found that IMDb reviews are in general more emotionally nuanced in comparison to Tweets. They explained this phenomenon with the fact that Tweets have a limited amount of characters, thus forcing the user to emote their feelings in a restrained manner, whereas typing a fleshed out review allows for more specificity (Wong, Sen & Chiang, 2012).

Additionally, it has been argued that the Oscars often have socio-political agendas attached to them, as there is a primarily a need to appeal to what is on the public agenda. As a cultural icon, the Oscars have come to represent elements of society, as well as call attention to societal shifts such as inequities. For example, there was a controversy surrounding the ceremony of two years ago, 2016. Many people outed their frustrations on Twitter using the hashtag #OscarsSoWhite, as they felt that the Oscars nominated too much Caucasian talent in all categories (Cox, 2017). The people demanded more diversity in their nominations, and the Academy responded by applying changes in the voting system (Cox, 2017). The year after the controversy, Moonlight (Gardner, Kleiner, Romanski and Jenkins, 2016), a film with a completely non-Caucasian cast, won the award for Best Picture. This could very well be a coincidence, but at the same time, it can be argued that Moonlight's (Gardner et al., 2016) chances of winning were greater as a result of the public reception being higher, which could partially be attributed to the film's acclaim being related to the public's agenda and a previous controversy (the aforementioned #OscarsSoWhite). Connecting this point back to the PKM model, it can be argued that the dominant discussion (obtained through hegemony) regarding this controversy added to the agent knowledge of the Academy (as they know what is on the public's agenda), and added to the persuasion of rewarding Moonlight (Gardner et al., 2016) with an Academy Award.

Furthermore, it has been argued that the quality (as assessed by the public) of a film influences is indicated by its box office performance, which in turn has been argued to influence the Academy. Therefore, it can be assumed that the public reception of a film predicts its critical recognition, which leads to the following hypothesis:

<u>H2A: Public reception positively predicts the critical recognition of a film (i.e. Oscar nominations and wins).</u>

Given that recent research also shows that the positive sentiment surrounding the public reception also can be predictive of box office revenue (Haughton et al., 2015), one can hypothesize:

<u>H2B: Public reception positively predicts box-office performance (pre-Oscar ceremony).</u>

Thus, the linkages between box-office performance and critical recognition and public reception and critical recognition (i.e. Oscar nominations and wins) can form the following hypothesis:

<u>H2C: A higher public reception positively predicts the critical recognition of a film, mediated by the box office revenue (pre-Oscar ceremony).</u>

2.3.2 The effect of critical recognition on the public

Interestingly, it should be noted that the hypothesized relationship of the public influencing critical recognition, as proposed above, does not go much further beyond that point. In return, critical recognition supposedly has a limited influence on the public (Jozefowicz, Kelley & Brewer, 2008). As mentioned before, many, if not most, of the films that are considered for Academy Awards are in the theaters during Oscar season. Typically, those movies leave the theaters and are released for home media entertainment, at some point soon after the Academy Awards have been rewarded. If it can be assumed that the public is able to influence the Academy, it would be logical to assume that the Academy is able to boost the home media release of a film as well. This is, however, not the case. As Jozefowicz et al. (2008) found that neither Academy Awards, nor Academy Award nominations, have an influence on the rental gross revenue of a film, including home media sales. Instead, they found that the MPAA rating and genre have the greatest influence on these sales from a statistical perspective. This is rather contradictory, and the question as to why this is the case presents an opportunity for follow-up research, given that the proposed hypotheses (H2A, B & C) are not rejected.

2.4 Critical reception

The critical reception is almost the same as the public reception, but the concept refers to a different audience. As mentioned before, whereas the public reception refers to the response of the general audience, the critical reception is the response of journalists (film critics) and cinephiles towards a film (Dellavigna & Hermle, 2016). They often have the opportunity to watch a movie before it is released to the public (Barusoy, Chatterjee and Ravid, 2003). Given this early access, their influence equals that of an opinion leader, opinion leaders are defined as groups of people who identify the different opinions on a subject, and then try to push the debate in a certain direction and have the influence to do so (Valente & Pumpuang, 2006). In other words, it can be argued that they are persuading the public and the Academy with their own opinions, which is why they fit into Friestad and Wrigcht's (1994) PKM as agents, considering they use their topic knowledge about the quality of films in order to persuade the Academy.

Critics are genuinely referred to as the agents who also maintain high artistic and ethical standards, and are not necessarily influenced by other interest groups. For example, one might assume that journalists who work for a big media conglomerate might have a bias for films that are made by that same conglomerate (so, do they reward those films more positively). However, it was found that this was not the case, and critics tend to give just as many negative reviews towards those films as films from any conglomerate (Dellavigna & Hermle, 2016),

Critics are, however, problematic given the complexities of evaluating art. Filmmaking is an art form, and because of that, there is no correct way of assessing it. Having a high artistic knowledge (like critics are supposed to have) should help with forming a judgement, but sometimes even critics change their opinion in hindsight. For example, Fight Club (Bell, Chaffin, Linson & Fincher, 1999) was a movie that originally received negative reviews during its release in theaters (Clark, 2001). Nowadays, it is commonly referred to as a masterpiece that was ahead of its time when it was released (Morgan, 2010). This emphasizes the importance of placing reviews in their original context, as the assessment on a film can be dynamic. This will be further explored during the methodology section.

2.4.1 The effect of critical reception on the box office performance

Eliashberg and Shugan (1997) suggested that critics can be looked at through two lenses for predicting the box office, namely as predictor (i.e. proxy for audience) and influencer. In short, this means that the researchers were questioning whether critics represent the general audience, or whether they influence them. As influencers, it was found that their influence is extremely limited, but as predictors (or proxies) of the box office performance, they were found to be relevant (Eliashberg & Shugan, 1997).

Furthermore, Barusoy et al. (2003) stressed the second finding by Eliashberg and Shugan (1997). Both the positive and negative reviews have an influence on the box office of a film (Barusoy et al., 2003). Therefore, Barusoy et al. (2003) proposed a marketing strategy for movie studios: if a movie is considered to be good by critics, reviews should be disseminated as soon as possible, whereas if it is not, it is more strategic from an economic perspective to embargo reviews for as long as possible, as it slows down negative word of mouth from spreading. This is a bit precarious, considering that the industry has to make an estimation of the quality from their own film. From the embargo strategy, it can be deduced that it was found that critics do have a significant influence on the audience, which is why the strategy is widely applied by movie studios nowadays (Barusoy et al., 2003; Brew, 2017). It is, however, not a rule of thumb. For instance, Star Wars: The Force Awakens (Kennedy & Abrams, 2015) had a review embargo until the day before its worldwide release, which normally indicates that the studio does not have faith in their product (Sneider, 2015). The reason for this embargo date is that Disney did not want plot details to leak before the movie started screening (Foutch, 2015). Star Wars is a widely popular and recognized brand, so it has to be stated that a strategy like this can only be afforded for films that are already guaranteed to have a high box office performance.

It can be argued that the contemporary situation presents a changed landscape in regards to the critical reception. Back in 1997 and 2003, there was no Web 2.0, and online platforms, like Rotten Tomatoes (a review aggregator website), were not as well-known as they are today. Therefore, the studies from the previous paragraph by Barusoy et al. (2003) and Eliashberg and Shugan (1997) have become outdated. As a result of the proliferation and popularity of these platforms, critics reviews have become more accessible. Thus, it has also become possible for the public to assess film quality quickly by looking at quantitative measurements (e.g. ratings) of critical and audience reception, across many critics and audience members, in addition to the qualitative review prose or single critic’s ratings that used to be the only way of consuming critics reviews in traditional news media. These critic ratings are valuable, as Boor (1990) found that critics tend to be more nuanced in rating films than the general public, meaning that the range of outliers in ratings is much lower. This leads to a variability in critics' ratings, which stresses the fact that the consensus among critics can be reliable.

2.4.2 The effect of critical reception on critical recognition

Surprisingly, research does not delve into the relation between critical reception and critical recognition. This lack could be explained by scholars and journalists' assumption that this is naturally the case, but it should be noted that the Academy does not just consist of professional critics; that would be the Golden Globes award show, which occurs before the Oscars. However, as mentioned before, the Academy Awards usually represent the consensus of other award shows in regards to what they reward. Many of those other award shows are organized by critics (e.g. the Golden Globes). Therefore, journalists like Mumford (2018) used previous award shows of the same year to predict the Oscars, meaning that a relationship between critical reception and critical recognition can be assumed.

Besides representing the audience and rewarding what the audience is paying for, one of the primary goals of the Oscars is to reward the movies with the highest quality. Critics have the same goal for writing reviews; therefore, the facile assumption is that there will be a relation between critical reception and critical recognition. Furthermore, when taking the aforementioned findings and suggestions by Barusoy et al. (2003), most importantly about critics having an influence on the public, as evidenced by review embargoes, it can be assumed that the critical reception also influences the box office performance of a film. In turn, it has been argued above that the box office predicts a film's critical recognition. Therefore, the following hypotheses can be proposed:

<u>H3A: A higher critical reception positively predicts the critical recognition of a film (i.e. Oscar nominations and wins).</u>

<u>H3B: Critical reception positively predicts box office performance (pre-Oscar ceremony).</u>

Given these predictive linkages along with the earlier hypothesis that box-office performance predicts critical reception, one can hypothesize that:

H3C: A higher critical reception positively predicts the critical recognition of a film, mediated by the box office revenue (pre-Oscar ceremony).

3. Methodology

3.1 Research design

The research question (to what extent can the critical reception, public reception and box office performance of a film predict its critical recognition at the Oscars?) consists of variables that can be operationalized and measured in the empirical world, as will be illustrated with data that has been chosen to operationalize the three factors from the theoretical framework. Therefore, this thesis will use a quantitative approach, based on a data set manually assembled by the researcher, in order to answer the research question. The strengths of this approach are that it allows for a study that uses data from multiple years (yet the collection is cross-sectional) study, as well as data that is relatively accessible, and limits any bias that may result from data drawn from direct human interaction (e.g., social desirability bias) (Rose, Spinks & Canhoto, 2015). These essentially quantitative data lends itself for statistical analyses that can directly confirm or deny the hypotheses. On the other hand, data that is unavailable or missing can create a bias, as well as the decision of the researcher to include certain aspects over others (Rose, Spinks & Canhoto, 2015), which form methodological limitations for this research. The sampling frame will attempt to address this bias by including a random sampling strategy.

3.2 Sampling

3.2.1 Sampling units and sampling frame

This research is in the fortunate position where a sampling frame of the units - the units being films that are eligible for an Oscar nomination - can be obtained. Collection of the data was commenced through obtaining a list of the research units on the Box Office Mojo website (Box Office Mojo, n.d.), as their data (besides the box office numbers) contains yearly lists of all the wide and limited releases in the US cinema; or in other words, lists of all the movies that are eligible for the Oscars of their following Oscar season. In general, this means that films that were only released on streaming platforms were not included in the sample. However, this does not form a limitation, as movies that are only released through streaming platforms are currently not eligible for Oscar awards (Lee, 2018). Instead, if a streaming platform feels confident about the chances of a streaming movie gaining critical recognition, they organize a limited release for that film (Lee, 2018), which would put that movie on the Box Office Mojo list of yearly releases.

When it comes to the entire sampling frame (so, the yearly lists of the Box Office Mojo website), the material on the list was found to be varied, and consisted of blockbusters, moderately performing films and films that performed poorly (which can also be referred to as 'flops') at the box office. Moreover, both the critically recognized and non-recognized films were on this list, and as a result, the entire sampling frame was found to be large enough for this research.

3.2.2 Constructing the sample

Initially, it was decided that is would be logical to distinguish between Oscar, and non-Oscar winning films for the analyses. However, this differentiation changed once the parameters for this research started were set. As mentioned during the theoretical framework, not every Oscar category is considered to be as valuable as the next one; for example, Best Original Song is not as valuable as Best Editing. In other words, winning in a 'lower' category should definitely be considered as praiseworthy for filmmakers; however, when compared to the 'higher', or more important categories, they are the not the films that have truly achieved a proper critical distinction from the Academy. For that reason, the sample consisted of two groups, namely films with at least one 'big five' Oscar win on the one hand (which are considered to be the most important Oscar categories (Lokker, 2018)), and every other film that was eligible for the Oscars on the other hand. The big five technically consists of six categories (as screenplay is split up into two categories), which are:

- ✓ Best picture.
- ✓ Best director.
- ✓ Best actor in a leading role.
- ✓ Best actress in a leading role.
- ✓ Best original screenplay.
- ✓ Best adapted screenplay.

In order to ensure that enough films would belong to big five winning Oscar films, all of the winners from these categories were automatically included (that is, if the year was included) in the sample. Importantly, the sample still included plenty of films that were only nominated and/or only won in a non-big five category, but if this was the case, it happened as a result of random sampling for the ‘other films that are eligible for Oscars’ part of the sample.

3.2.3 Sample

According to the guidelines (Janssen & Verboord, 2017), between 150-250 units are needed for a Master’s thesis. However, since this research primarily rests on the use of secondary data, a slightly larger sample of 290 units (N = 290) was drawn. As mentioned during the previous section, films with at least one big five win, as well as other films that were eligible for Oscars, were included in the sample.

2017 was chosen as the latest year for the data collection (given that at the point of research, this year had the most recently announced winners), and from there on, every other year was included in the sample, all the way back to 1995 (thus 2017, 2015 … 1997, 1995). Every other year was chosen so that the manual collection of measures would be feasible within the timeframe of this thesis. Between 21-26 movies were drawn for each year. Each year consisted of twenty movies that served as the non-big five winners on the one hand, and the winners from the big five category on the other hand. Sometimes, winners in the ‘big five’ categories overlapped (which means a film won in more than one of the big five categories), which is why not every year ended up with an equal amount of entries. Also, if one of the twenty non-big five winners accidentally ended up being a big five winner as a result of random sampling, another film was randomly selected in its place.

Given that this research did not use a traditional questionnaire, which is common for most quantitative research, there are only few relevant ancillary characteristics of the research units (such as socio-demographics) that can be reported. For one, the *Genre* of a movie characterizes the broad entertainment area of the film, and this data was practically obtainable as IMDb listed the primary three genres per film (hence, the percentages in each column do not add up to 100%). The genres that were found in this sample included:

Table 3.2.3.1: Distribution of genres for the entire sample, films with at least one Oscar nomination, films with at least one Oscar win, and films with at least one Oscar win in the big five category (e.g. 6.0% of the films that have won at least one 'big five' Oscar belong to the fantasy genre).

Genre	**Entire sample (*N* = 290)**	**Oscar nominated films only (*N* = 86)**	**Oscar winning films only (*N* = 56)**	**Big 5 Oscar winning films only (*N* = 50)**
Action	28.3%	10.5%	3.6%	-
Adventure	20.7%	19.8%	10.7%	6.0%
Animation	4.8%	7.0%	1.8%	-
Biography	8.3%	22.1%	25.0%	26.0%
Comedy	36.6%	20.9%	14.3%	14.0%
Crime	19.7%	17.4%	21.4%	24.0%
Drama	49.0%	75.6%	89.3%	94.0%
Documentary	.7%	1.2%	1.8%	-
Family	5.2%	2.3%	-	-
Fantasy	11.4%	15.1%	8.9%	6.0%
History	3.4%	9.3%	12.5%	12.0%
Horror	9.3%	1.2%	1.8%	2.0%
Music	3.1%	4.7%	5.4%	6.0%
Musical	.3%	1.2%	-	-
Mystery	8.3%	5.8%	8.9%	10.0%
Romance	19.3%	19.8%	21.4%	24.0%
Science Fiction	7.6%	4.7%	3.6%	4.0%
Sports	1.7%	1.2%	1.8%	2.0%
Thriller	17.6%	11.6%	12.5%	14.0%
War	.7%	1.2%	-	-
Western	1.0%	-	-	-

Furthermore, it was also found that the amount of money that studios spend on their movies varies a lot between films. This is surprising, considering that the films that were included in the sample all had a wide release in the United States at some point during their theatrical run, so one could assume that these films would have at least a somewhat similar production budget. Instead, the *Budget* of all the films in the sample ranged between $15,000 and $250,000,000. More specifically, these values were found in regards to *Budget:*

Table 3.2.3.2: Means and standard deviations of the variable Budget for the entire sample, films with at least one Oscar nomination, films with at least one Oscar win, and films with at least one Oscar win in the big five category.

Descriptor	**Full sample (*N* = 290)**	**Oscar nominated films only (*N* = 86)**	**Oscar winning films only (*N* = 56)**	**Big 5 Oscar winning films only (*N* = 50)**
M	$43,736,948.3	$50,080,232.6	$35,766,071.4	$28,218,000.0
SD	$45,020,951.0	$57,798,442.5	$50,210,246,2	$36,182,607,7

3.3 Operationalization

3.3.1 Critical recognition

Each of the concepts discussed in the theoretical framework can be measured in different ways. In regards to critical recognition, there are three main statistics that can be considered to be relevant to look at, which have technically already been introduced during the previous section. Together, these three variables encapsulate the concept of critical recognition:

- ✓ Total number of nominations (numerical)
  - Variable name in dataset: *Oscar_Nominations*
- ✓ Total number of wins (numerical)
  - Variable name in dataset: *Oscar_Wins*
- ✓ Total number of wins in the big five category (numerical) (best picture; best actor; best actress; best director; best adapted/original screenplay (Lokker, 2018))
  - Variable name in dataset: *Oscar_Wins_Big5*

3.3.2 Box office performance

In regards to box office performance, all of the data needed for this research can be retrieved from the aforementioned Box Office Mojo website, which was already done by some previous studies (e.g. Hennig-Thurau et al. (2007)). Logically, it would make sense to look at the total worldwide gross of the films, and these numbers should adjusted for inflation, considering that ticket prices change from year to year. However, that approach is problematic. There is no data regarding the fluctuating ticket prices of the worldwide cinema. In addition, for movies prior to the burst of the digital age, not all of the worldwide data is available (especially for movies released in fewer US theaters). As argued during the theoretical framework, however, the domestic box office (US and Canada) is incredibly important to a film's overall success, given the fact that it is the largest market and has the lowest tax rates for the studios. Furthermore, this data is more accessible and allows for accurate data collection for older movies. Therefore, this research only collected the domestic box office numbers that were adjusted for inflation (the inflation was also calculated on the Box Office Mojo website, using 2018 ticket prices as indicator).

Moreover, as can be seen in the hypotheses, the box office was measured at two points in time: pre- and post- the awards ceremony, with pre awards' being defined as the domestic box office at the day prior to the Oscar ceremony (adjusted for inflation), and post ceremony being the total domestic box office at the end of a film's theatrical run (adjusted for inflation). This was done as the prediction has to be time dependent, as was argued during the theoretical framework. For each year, the domestic box office total (adjusted for inflation) for the day prior to the Oscar ceremony was also collected, which served as operationalization for the domestic box office at the first point in time. In total, there were three variables relating to the box office in the dataset:

- ✓ Domestic box office prior to the Oscar Ceremony (adjusted for inflation) (ratio level)
    - Variable name in dataset: *Pre_Domestic_Adjusted*
- ✓ Total domestic box office (adjusted for inflation) (ratio level)
    - Variable name in dataset: *Post_Domestic_Adjusted*
- ✓ Movie in theaters during the Oscar season? (nominal, dummy/binary indicator)
    - Variable name in dataset: *Oscar_Season*

3.3.3 Public reception

The public reception can be measured using two ways, neither of which are entirely flawless. Fortunately, they do complement each other. IMDb scores are available for every film; hence, they were used by Kraus et al. (2008), but not reliable as users have the possibility to vote multiple times by creating multiple accounts for the website. This could result in the fluctuation of the IMDb score, and there is some empirical evidence that points towards their score being influenced by, what in internet slang, is referred to as 'trolls'. According to Doyle (2016, para. 2), a troll is "a person who posts provocative, controversial, libelous, or irreverent comments online." For example, with the release of Black Panther (Feige, 2018), some internet trolls that were bothered with the constant high box office performance of Disney movies assembled online to lower the IMDb score of the film in order to have moviegoers refrain from seeing the film, thus resulting in a lower box office performance (Fernandez, 2018). It could be argued that the lowering of the score was successful, as the IMDb score of the film is considerably lower when compared to the other scores that can be used to measure public reception (Han, 2018).

One of those other scores, for example, is the Cinemascore, which is a website that has its staff poll the opinion of movie-goers towards a film at the theaters. Therefore, their score is considered to be superior to the IMDb score. However, they do not have data for every film that is available (in particular for the films that have a smaller theatrical release before they get to a wider release), and often skip movies that only have a smaller release. Therefore, it was decided that it would make the most sense to measure both of the aforementioned statistics:

- ✓ IMDb score (numerical 0-10)
  - Variable name in dataset: *IMDB_Score*
- ✓ Cinemascore (numerical 0-12; translated from A+ to F)
  - Variable name in dataset: *Cinema_Score*

3.3.4 Critical reception

Also, the critical reception can be operationalized and collected directly, with some manual transcription effort. Rotten Tomatoes is a very reliable website that allows for statistics on aggregated scores of critics, and has been used by many previous researchers, such as Barusoy et al. (2003). Fortunately, Rotten Tomatoes includes reviews that were written before the launch of its website, so it is possible to trace the critical reception of older movies. Moreover, their websites also includes retrospective reviews. However, as explained in the previous chapter, this is problematic given the whole critical perception change of films like Fight Club (Bell et al., 1999) over time. Since this research intends to delve into the critical reception at the time of a film's release, these retrospective reviews were manually removed (by recalculating the percentage) from the data collection and omitted from this study.

Two of Rotten Tomatoes' numbers are interesting for this particular research. In fact, they both have to be used for this research, as the popular Tomatometer (percentage of the critics giving a positive review) is not fully representative of the critics' opinion. For example, if all critics gave a film a 6/10, the Tomatometer would be at 100%. At the same time, if almost every critic gave a film a 10/10, but one a 5/10, the Tomatometer would be at 99%. In this example, critics are, on average, much more positive about the second film, but this would not be represented by the Tomatometer alone.

This raises the question as to why the Tomatometer should even be considered as relevant. Therefore, it should be stated that the Tomatometer is the primary statistic reported by journalists and online streaming platforms (Wilkinson, 2018), such as iTunes. Given this wide application of the Tomatometer, and the accuracy of the average score, both measurements were taken into account for this research:

- ✓ RT Tomatometer [% critics giving positive review] (numerical 0-100)
  - o Variable name in dataset: *RT_Tomatometer*
- ✓ RT average score (numerical 0-10)
  - o Variable name in dataset: *RT_Average*

3.3.5 Budget

During the theoretical framework, it was argued that the budget has a relationship with the box office performance of a film, and starts to influence at the point of critical and public reception. This research is not particularly interested in the effects of the budget; however, good statistical practice calls for controlling this variable during this study. Therefore, some of the models used the budget, unadjusted for inflation (the number was retrieved from the Box Office Mojo website) as a control variable:

- ✓ Budget of the film (numerical)
  - o Variable name in dataset: *Budget*

Importantly, it has to be stated that the direction of this variable in this research depends on the hypothesis. First of all, it was argued that the box office benefits from a higher budget (as a result of being able to afford movie stars and a better marketing campaign), so for the models predicting the box office, budget is expected to have a positive effect. On the other hand, it was also stated that the

Academy likes to only recognize films with a lower/middle sized budget; therefore, it is expected to have a negative effect in the models that predict critical recognition.

3.4 Data analysis

SPSS was used in order to analyze the data of this research after all of the data had been inserted manually. Different tests were used in order to test the hypotheses. First of all, the hypotheses relating to prediction were tested using regression models (H1A; H1B; H2A; H2B; H3A and H3B). Standard OLS regression models were calculated for every model; however, considering that a substantial amount of the hypotheses had integer data as a dependent variable, negative binomial models/Poisson regression models are appropriate for data that constitutes counts (such as the count of the number of awards). The latter model (Poisson) was not used, considering that the *M* and *variance* (SD^2) for the critical recognition variables were too far removed from each other. Moreover, the regression coefficients of the negative binomial models were compared to the OLS models.

Secondly, the mediation hypotheses (H2C and H3C) were tested by using the Baron/Kenny approach with the unstandardized regression coefficients of two aforementioned regression models. Furthermore, *Sobel's Z* was calculated in order to statistically prove partial or complete mediation.

3.5 Reliability and validity

According to Janssen and Verboord (2017, p. 12), validity refers to "(a) the complexity, (b) the multidimensionality of the concept, and (c) whether or not other researchers have already come up with valid indicators (e.g. valorized psychological scales, or standard questions to measure educational attainment or cultural participation)". The validity for this thesis' measures are slightly complex. For example, there are different ways of measuring the box office, and if all of them were included, one can truly explore the multidimensionality of the concept, and also isolate the most important and predictive dimensions. This is, however, not very practical, and as pointed out before, impossible to achieve. The public and critical ratings, in particular, have many latent features, and to measure all of them separately, or through survey research, would be impossible to achieve within the scope of this research. Therefore, it was decided to merely focus on the aspects that were considered to be the most relevant for this research, which was based on previous research, and has been outlined in the sections above. In order to do so, the complexity in regards to the validity was assured by operationalizing the concepts into multiple variables instead of just one (e.g. through the use of both the reliable Cinemascore and availability of the IMDb score for public reception, the accurate average of the RT score and widely applied Tomatometer for critical reception, the three different variables for critical recognition). In particular, the use of multiple variables was important for the public reception, as self-selection presented a challenge for this research. People who rate movies on the internet tend to have an agenda, or motive, for doing so (e.g. someone really hated a film, and felt the need to express their hatred). This might result in a bias, and not accurately represent the public's opinion about a film. By adding the Cinemascore, however, this issue was partly resolved (only partly, as availability is a challenge for the Cinemascore).

Reliability, on the other hand, is defined by Janssen and Verboord (2017, p. 12) as the "consistency is your measurement if you or someone else would conduct it again". In regards to a quantitative analysis, another coder has to be able to understand how the coding process was performed. This was not an issue, as most of the statistics were collected directly from public sources on the internet. Moreover, measures that required alteration, e.g. Cinemascores that range from A-F had to be mapped to a quantitative range: 0-12, for practical analytical purposes, which is a logical and reliable translation from its original statistic.

4. Results

4.1 Transformations

Some of the data had to be transformed in order to improve the feasibility of this research.

4.1.1 Public reception

The public reception previously consisted of two scores, which were the *IMDB_Score* and the *Cinema_Score.* As argued during the methodology chapter, these scores complement each other (i.e. the *IMDB_Score* is available for everything, *Cinema_score* is more reliable), which is why these variables were combined into one average score. Given the fact that these two variables did not have the same range when they were initially coded into the dataset (IMDb scores ranged between 0-10, whereas Cinemascores ranged between 0-12), the *Cinema_Score* variable was recalculated in order to fit with the same range as the IMDb score (new variable: *Cinema_Score_10*). After that, a reliability analysis was conducted, which revealed that the two variables were decently reliable as a scale (Cronbach's α = .617). Therefore, a new variable was computed, called *Public_Reception,* will be referred to from now on. When the *Cinema_Score_10* was unavailable (in 68 cases), the IMDb score was directly used.

4.1.2 Critical reception

The critical reception also consisted of two scores, namely the *RT_Tomatometer* and the *RT_Average.* Just like with the public reception, these two scores complement each other (i.e. *RT_Average* is more widely applied by journalists, cinephiles and streaming platforms, whereas the *RT_Tomatometer* is a more accurate representation) were combined after a reliability analysis revealed that these two scores work together very well as a scale, after dividing the percentage of positive reviews (*RT_Tomatometer*) by ten (new variable: *RT_Tomatometer_10)*, which gave the percentage the same range as the average score (Cronbach's α = .910). Therefore, this new variable, called *Critical_Reception,* will be used as the primary variable when referring to this concept from now on.

4.1.3 Critical recognition

The three critical recognition variables (*Oscar_Nominations, Oscar_Wins* and *Oscar_Wins_Big5)* were also tested for reliability, which resulted in a decently reliable scale (Cronbach's α = .780). However, considering that removing items from the scale would improve the reliability, it was decided to keep each item as separate, and instead conduct three separate analyses with each critical recognition variable in order to make the results as precise as possible.

4.1.4 Other transformations

All of the financial numbers (i.e. the budget and domestic box office numbers (adjusted for inflation)) were divided by 100 Million in order to render the range of regression coefficients (i.e. number of digital digits) be similar to the other variables that entered the regression analysis (new variables: *Budget_100; Pre_Domestic_Adjusted_100; Post_Domestic_Adjusted_100)*.

Moreover, some of the models used the domestic box office data (adjusted for inflation) as a dependent variable. On the box office mojo data, these numbers are precisely reported. For the OLS models, this does not present a problem; however, regarding the negative binomial models, these variables were transformed to integer variables (new variables: *Pre_Domestic_Adjusted_100_Int* and *Post_Domestic_Adjusted_100_Int*) in order to make them applicable for analysis.

Finally, for the OLS models, all of the dependent variables were transformed into logarithms, given that at least one of the assumptions of normality was violated for each model. This will be discussed in-depth during the following sections.

4.1.5 Reporting

During the theoretical framework, it was argued that all of the hypotheses are directional (e.g. earning more money at the domestic box office (adjusted for inflation) is predicted to lead to more critical recognition). Therefore, all of the *p* values from the regression coefficients were divided by two in order to account for the one-tailed statistics.

Continuing on the topic of regression of regression coefficients, for all of the OLS models, the <u>standardized regression coefficients</u> were reported in the tables. However, these coefficients do not exist for the negative binomial models, which is why the tables relating to those analyses report the <u>unstandardized regression</u>

coefficients. Finally, for the mediation models, only the unstandardized regression coefficients were reported (also for the mediation models based on OLS regression), as the Sobel statistic, which can be calculated using the Baron-Kenny approach, requires the unstandardized coefficients and their standard deviations.

Traditionally, *b* and *b** are used for reporting the coefficients of regression models. However, considering that this study also used mediation models, which also requires a *b* value for reporting (namely, the path that of the mediator predicting the dependent variable), it was decided that *B* would be used as a replacement for the unstandardized regression coefficients. In short, these are the symbols that will be used for reporting from now on:

- ✓ *b** = standardized regression coefficient.
- ✓ *B* = unstandardized regression coefficient.
- ✓ *b* = mediation path of the mediator predicting the dependent variable.

4.2 Box office hypotheses

4.2.1 Domestic box office predicting critical recognition

For predicting the critical recognition of a film, three OLS regression models and three negative binomial regression models were calculated that used *Pre_Domestic_Adjusted_100* as predictor. The OLS models were tested for normality, and it was found that none of the models' residuals had a normal distribution using the Shapiro-Wilk test (Model 1A: $p < .001$; Model 2A: $p < .001$; Model 3A: $p < .001$), which can also be seen in the appendix. Therefore, the dependent variables for the OLS models were transformed into logarithmic variables with a +1 offset to account for zero values, *LN_Oscar_Nominations, LN_Oscar_Wins* and *LN_Oscar_Wins_Big 5.* Nevertheless, the Shapiro-Wilk test was still insignificant when testing with the logarithmic residuals (Model 1A: $p < .001$; Model 2A: $p < .001$; Model 3A: $p < .001$), so there might be a bias in the model results (see Appendix). Moreover, all of the OLS models were tested for the constant error variance. When looking at the three graphs that were calculated, it can be stated that the data is relatively equally spread across the graph, thus this assumption was not violated.

All of the regression coefficients and R^2 values for these analyses were calculated, and can be found in table 4.2.1.1 for the OLS models, and table 4.2.1.2 for the negative binomial models. For the first OLS model (1A), *LN_Oscar_Nominations* were used as dependent variable. A significant equation was found (F(1,288) = 31.532, p < .001), R^2_{adj} = .096, meaning that 9.6% of the variance was explained by this model, which indicates a moderate prediction. The relationship is positive (b^* = .314, p < .001, one-tailed), meaning that the domestic box office prior to the Oscar ceremony (adjusted for inflation) indeed has a moderate, positive influence on the Oscar nominations. This finding was stressed by model 1B, as the negative binomial regression revealed a significant equation (*Likelihood Ratio* χ^2 (1) = 37.823, p < .001), $R^2_{Nagelkerke}$ = .304, meaning that 30.4% of the variance was explained by this model, which again, indicates a moderate prediction. Moreover, this model consisted of a positive B value (.302, p < .001, one-tailed). This can be translated to an increase of $100 million of domestic box office contributes to increasing the logarithm of the number of nominations by .302, which equates to 1.35 more nominations per $100 million domestic box office take (adjusted for inflation).

In the second OLS model (2A), the *LN_Oscar_Wins* were tested as dependent variable. Once again, a significant equation was found (F(1,288) = 25.160, p < .001), R^2_{adj} = .077, meaning that 7.7% of the variance was explained by this model, which indicates a weak prediction. The relationship between the variables was also positive and significant (b^* = .283, p < .001, one-tailed), which means that a higher domestic box office prior to the Oscar ceremony (adjusted for inflation) indeed has a weak effect (close to moderate) on winning Oscars. In addition, the negative binomial regression model (2B) was also found to be significant (*Likelihood Ratio* χ^2 (1) = 43.471, p < .001), $R^2_{Nagelkerke}$ = .165, meaning that 16.5% of the variance was explained by this model, which indicates moderate prediction. Moreover, this model found positive B value (.363, p < .001, one-tailed), as each Oscar win translates to $e^{.363}$ = 1.43 more wins per $100 million domestic box office take (adjusted for inflation). Given these two models, it can be assumed that the effect of the box office (prior to the nominations) on the critical recognition is larger for the nominations than the actual wins. Moreover, the variance between the negative binomial models (1B and 2B) descreased steeply.

For the final OLS model (3A), *LN_Oscar_Wins_Big5* were tested as dependent variable. A significant equation was found (F(1,288) = 4.947, p < .05), R^2_{adj} = .013 (1.3% of the variance explained, which indicates weak prediction) with a weak positive effect (b^* = .130, p < .05, one-tailed). This was confirmed by the 3B model, in which a significant equation was also found (*Likelihood Ratio* χ^2 (1)= 5.514, p < .05) with weak predictive power, $R^2_{Nagelkerke}$ = .027 (2.7% of the variance explained), yet a positive *B* value (.189, $p < .01$, one-tailed), which can be translated to an increase of $100 million of domestic box office contributes to increasing the logarithm of the number of nominations by .189, meaning 1.21 more Oscar Wins in the big five categories for each $100 million domestic box office take (adjusted for inflation). This result indicates that the domestic box office (adjusted for inflation) has a positive effect on winning Oscars in the important categories; however, when compared to the previous two variables, its effects are lower. Still, the results are not completely unbiased as the more appropriate model (a right censored or truncated negative binomial model) was unavailable. Nevertheless, given the significance of all 6 models, H1A can be fully accepted.

Table 4.2.1.1: Standardized regression coefficients and R^2 of the OLS regression analyses with LN_Oscar_Nominations, LN_Oscar_Wins, and LN_Oscar_Wins_Big5 as dependent variable.

	Model 1A (nominations)	**Model 2A (wins)**	**Model 3A (wins big 5)**
Predictor			
Pre_Domestic_ Adjusted_100	**.314*** **	**.283*** **	**.130***
	$R^2_{adj} = .096$ $p < .001$	$R^2_{adj} = .077$ $p < .001$	$R^2_{adj} = .013$ $p < .05$

Note: *$p < .05$ (one-tailed), **$p < .01$ (one-tailed),, ***$p < .001$ (one-tailed)

Table 4.2.1.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Oscar_Nominations, Oscar_Wins, and Oscar_Wins_Big5 as dependent variable.

	Model 1B (nominations)	**Model 2B (wins)**	**Model 3B (wins big 5)**
Predictor			
Pre_Domestic_ Adjusted_100	**.302*** **	**.363*** **	**.189** **
	$R^2_{Nagelkerke} = .304$ $p < .001$	$R^2_{Nagelkerke} = .165$ $p < .001$	$R^2_{Nagelkerke} = .027$ $p < .05$

Note: *$p < .05$ (one-tailed), **$p < .01$ (one-tailed), ***$p < .001$ (one-tailed)

4.2.2 Critical recognition predicting the domestic box office (Post Oscar ceremony)

For these models, only the films that were playing during Oscar season (*Oscar_Season* = 1) were selected. In order to predict the domestic office after the Oscar ceremony, three separate OLS regression models (that used *LN_Post_Domestic_Adjusted_100* as dependent variable), and three negative binomial regression models (that used *Post_Domestic_Adjusted_100_Int* as dependent variable) were calculated. The predictors were put in separate models, after it was found that that using *Oscar_nominations, Oscar_Wins,* and *Oscar_Wins_big5* in one model resulted into a high degree of collinearity (*Oscar_Nominations*: VIF = 2.839; *Oscar_Wins*: VIF = 3.020; *Oscar_Wins_Big5*: VIF = 2.430).

All three OLS models were tested for normality, and it was found that none of the models' residuals had a normal distribution using the Shapiro-Wilk test (Model 1A: $p < .001$; Model 2A: $p < .001$; Model 3A: $p < .001$), which can also be seen in the appendix. Therefore, the post domestic box office numbers were transformed into a logarithmic equation, with a +1 offset in order to account for the zero values, resulting in the new variable *LN_Post_Domestic_Adjusted_100* (thus, the actual domestic numbers were transformed twice, first they were divided by 100 Million in order to render predictive coefficients more presentable, and after that they were changed to their logarithms). Nevertheless, the Shapiro-Wilk test was still significant when testing with the residuals of the logarithmic dependent variable (Model 1A: $p < .001$; Model 2A: $p < .001$; Model 3A: $p < .001$), which again hints at a possible bias in the data (see Appendix), so the accuracy of the following models harbor a slight bit of uncertainty. Moreover, all three OLS models were tested for the constant error variance. As can be seen in the appendix, this assumption was not violated thanks to the relative equal spread of residual data over the x and y-axis.

All of the standardized beta weights and R^2 values of the OLS analysis were calculated and can also be found in table 4.2.2.1, and the unstandardized regression coefficients for the negative binomial models in table 4.2.2.2. For the first OLS model (1A), *Oscar_Nominations* were used as predictor. A significant equation was found ($F(1,69) = 6.911$, $p < .05$), $R^2_{adj} = .078$, meaning that 7.8% of the variance was explained by this model, which indicates weak (close to moderate) prediction. The relationship was found to be positive ($b^* = .302$, $p < .001$, one-tailed), meaning that more Oscar nominations have a moderate effect on the domestic box office after the Oscar ceremony (adjusted for inflation). The explained variance was slightly improved in the negative binomial model (1B) (*Likelihood Ratio* χ^2 (1) = 34.938, $p <$ .001), $R^2_{Nagelkerke}$ = .123 (12.3% of the variance explained, indicating moderate prediction), and had a positive *B* value (.150, $p <$ .001, one-tailed), which, after transforming from its logarithmic value ($e^{.150}$), equals to \$116 million dollars more of total domestic box office (adjusted for inflation) for every Oscar nomination. Nevertheless, both models had a low adjusted R^2, which indicates that only a small portion of the variance in the dependent variable is explained by purely the Oscar nominations. Still, low R2 are not atypical for social behavior and especially for small models.

In the second OLS model (2A), the *Oscar_Wins* were tested as predictor. Once again, a significant equation was found (F(1,69) = 17.283, $p <$ .001), R^2_{adj} = .189. This means that the model explained 18.9% of the variance, which indicates moderate prediction. The relationship was also positive (b^* = .448, $p <$ .001, one-tailed), meaning that winning more Oscars leads indeed has a moderate effect on the domestic box office after the Oscar ceremony (adjusted for inflation). Despite both variables having a moderate effect, it was found that winning Oscars has a stronger effect on the domestic box office (adjusted for inflation) than just being nominated. However, this finding was contradicted by the negative binomial model (2B), which had its explained variance decreased when compared to the 1B model (*Likelihood Ratio* χ^2 (1) = 26.526, $p <$ .001), $R^2_{Nagelkerke}$ = .094 (9.4% of the variance explained, indicating moderate prediction). The *B* value in this model was found to be positive (.226, $p <$ .001, one-tailed), which translates to every Oscar win increasing the logarithm of post domestic box office (adjusted for inflation) with $e^{.226}$ (\$125 million dollars).

For the final models, *Oscar_Wins_Big5* were tested as predictor. An insignificant equation was found for the OLS model (1C) (F(1,69) = 1.152, $p >$ .05), R^2_{adj} = .002 (.2% of the variance, indicating very weak prediction). This steep drop in explained variance was also found in the negative binomial model (2C), although this model was still found to be significant (*Likelihood Ratio* χ^2 (1) = 11.174, $p <$ .01), $R^2_{Nagelkerke}$ = .041, explaining 4.1% of the variance. Nevertheless, it included a positive *B* value (.385, $p <$ .001, one-tailed) that translates to every Oscar win in the big five category leading to \$147 million dollars ($e^{.385}$ = 1.47) more of domestic box office take (adjusted for inflation). The difference in significance between both models results between seems to be contradictory, although this can be explained when looking at the low degree of explained variance for both models (as lower variance relatively increases the chances of insignificance). Given that five out of six models were found to be significant, H1B can be mostly accepted.

Table 4.2.2.1: Standardized regression coefficients and R^2 of the OLS regression analyses with LN_Post_Domestic_100 as dependent variable.

	Model 1A	**Model 2A**	**Model 3A**
Predictor			
Oscar_Nominations	**.302***		
Oscar_Wins		**.448*****	
Oscar_Wins_Big5			.128
	$\boldsymbol{R^2_{adj} = .078}$	$\boldsymbol{R^2_{adj} = .189}$	$R^2_{adj} = .002$
	$\boldsymbol{p < .05}$	$\boldsymbol{p < .001}$	$p > .05$

Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Table 4.2.2.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Post_Domestic_Adjusted_100_Int as dependent variable.

	Model 1B	**Model 2B**	**Model 3B**
Predictor			
Oscar_Nominations	**.150*****		
Oscar_Wins		**.226*****	
Oscar_Wins_Big5			**.385*****
	$\boldsymbol{R^2_{Nagelkerke} = .123}$	$\boldsymbol{R^2_{Nagelkerke} = .094}$	$\boldsymbol{R^2_{Nagelkerke} = .041}$
	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .01}$

Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

4.3 Public reception hypotheses

4.3.1 Public reception predicting critical recognition

In order to predict critical recognition using the public reception of a film, six OLS models and six negative binomial models were calculated. In all twelve models, either one or two of the predictors of *Public_Reception* and/or *Budget_100* (the latter variable was expected to have a negative effect) were tested, which had a low degree of collinearity (VIF = 1.047; see appendix), meaning that this assumption of normality was not violated. Moreover, regarding the OLS models, the Shapiro-Wilk test found that none of the residuals from the six models had a normal distribution, when using the original data variables (model 1A-6A: $p < .001$; see appendix). Therefore, *LN_Oscar_Nominations, LN_Oscar_Wins* and *LN_Oscar_Wins_Big5* were used in the final OLS models, which still resulted in a violation of the assumption of normality (model 1A-6A: $p < .001$; see appendix). Therefore, the data might possibly be biased. Moreover, all models were tested for constant error variance. This assumption was not violated, as the distribution of residuals within each column had a similar variance for every OLS model. The results for both analyses can be found in tables 4.3.1.1 (OLS) and 4.3.1.2 (negative binomial)

In the first OLS model (1A), *Public_Reception* was used at the only predictor for *LN_Oscar_Nominations*. A significant equation was found ($F(1,288) = 96.002$, $p < .001$), $R^2_{adj} = .247$. The relationship was found to be positive ($b^* = .500$, $p < .001$, one-tailed), meaning that the public reception is a strong predictor for the amount of Oscar nominations that a film can receive. Moreover, this model explained nearly 25% of the variance that was found, a statistic which was even doubled for the negative binomial regression model (1B). For that model, a significant equation was also found (*Likelihood Ratio* $\chi^2(1) = 220.049$, $p < .001$), $R^2_{Nagelkerke} = .555$ (55.5% of the variance explained, indicating strong prediction), with a positive *B* value for *Public_Reception* (1.499, $p < .001$, one-tailed), meaning that every full point of increase on the *Public_Reception* scale results in 4.47 ($e^{1.499} = 4.47$) more Oscar nominations. Regarding both models, it can be concluded that the public reception is a strong predictor for the Oscar nominations.

For the second step of the OLS model (2A), the control variable of *Budget_100* was added. This model was also found to be significant ($F(2,287) = 48.064$, $p < .001$), although none of the other variance was explained, $\Delta R^2 = .001$, $p > .05$. Therefore, *Budget_100* was unsurprisingly found to be insignificant as predictor. On the other hand, *Public_Reception* remained a significant, positive predictor ($b^* = .506$, $p < .001$, one-tailed), with a slightly higher effect than in the previous model. In the negative binomial model (2B), a significant equation (*Likelihood Ratio* $\chi^2(2) = 221.767$, $p < .001$), $R^2_{Nagelkerke} = .558$ (55.8% of the variance explained, still indicating strong prediction), was found. The results of the predictors in this model same remained the same as in the OLS model, meaning that the budget was insignificant, and *Public_Reception* ($B = 1.535$, $p < .001$, one-tailed), remained a strong predictor, as the regression coefficient equals 4.64 ($e^{1.535}$ = 4.64) more Oscar nominations for every full point of increase on the public reception scale (when controlling through the budget).

For the third and fourth models, the same procedure was repeated, albeit with a different set of dependent variables, namely *LN_Oscar_Wins* (3A and 4A) and *Oscar_Wins* (3B and 4B). For model 3A, a significant equation was found for using *Public_Reception* as the only predictor (F(1,288) = 66.970, p < .001), R^2_{adj} = .186, meaning that 18.6% of the variance was explained, indicating moderate prediction. This was lower than the explained variance of the first model that used the nominations as variable, which was also the case for the negative binomial model (3B) (*Likelihood Ratio* χ^2 (1) = 157.314, p < .001), $R^2_{Nagelkerke}$ = .498 (49.8% of the variance explained, indicating strong prediction). Nevertheless, it was still found that the public reception was a moderate (3A) to strong (3B), positive predictor (b^* = .434, p < .001, one-tailed, in model 3A; B = 1.804, p < .001, one-tailed, in model 3B), the latter B value being equal to 6.07 ($e^{1.804}$ = 6.07) more Oscar wins for every full point of increase on the *Public_Reception* scale.

When adding *Budget_100* as control variable in the fourth models, a significant equation was found for the OLS model (4A) (F(2,287) = 34.505, p < .001), ΔR^2 = .005, p > .05. As was the case with the ΔR^2 between models 1A and 2A, the difference in explained variance between models 3A and 4A was low and insignificant. Therefore, the standardized beta value for the control variable *Budget_100* was also low and insignificant, whereas the *Public_Reception* had a slightly stronger, positive effect (b^* = .450, p < .001, one-tailed) compared to the previous model. This was, however, not the case with the negative binomial model, as model 4B revealed (*Likelihood Ratio* χ^2 (2) = 161.466, p < .001), $R^2_{Nagelkerke}$ = .508, which means that 50.8% of the variance was explained, indicating strong prediction, that both predictors were found to be significant. *Budget_100* operated as a negative, significant predictor (B = $^-$.480, p < .05, one-tailed), while *Public_Reception* still operated as a positive predictor (B = 1.959, p < .001, one-tailed), which means 7.09 ($e^{1.959}$ = 7.09) more Oscar wins for every full point of increase on the *Public_Reception* scale (when controlling for the budget). Compared to the nomination models, it can be concluded that a higher budget decreases the chance of winning an Oscar (when using the negative binomial model).

In the final two models, *LN_Oscar_Wins_Big5* (model 5A and 6A) and *Oscar_Wins_Big5* (model 5B and 6B) were used as the dependent variable. For the 5A model, the predictor *Public_Reception* resulted in a significant equation ($F(1,288) = 55.888$, $p < .001$), $R^2_{adj} = .160$ (16.0% of the variance explained, indicating moderate prediction). In the negative binomial model (5B), which found a significant equation (*Likelihood Ratio* $\chi^2(1) = 78.766$, $p < .001$) with less predictive power than models 1B and 3B, $R^2_{Nagelkerke} = .334$ (33.4% of the variance explained, indicating strong prediction). Nevertheless, the public reception was still found to be significant, and a moderate, positive predictor ($b^* = .403$, $p < .001$, one-tailed, in model 5A; $B = 1.531$, $p < .001$, one-tailed, in model 5B), the latter value being equal to 4.62 ($e^{1.531} = 4.62$) more Oscar wins in the big five category for every full point of increase on the *Public_Reception* scale for the Oscars in the big five categories.

When adding the control variable of *Budget_100* in the final OLS model (6A), a significant equation was found ($F(2,287) = 36.961$, $p < .001$), $\Delta R^2 = .042$, $p < .01$. This difference in ΔR^2 was higher and significant compared to ΔR^2 of models 2A and 4A, which is also why it was found that the control variable *Budget_100* was a significant, yet weak, negative predictor effect-wise ($b^* = -.210$, $p < .001$, one-tailed) in this model. Furthermore, *Public_Reception* remained a significant, as well as positive, moderate predictor ($b^* = .448$, $p < .001$, one-tailed) in this model. In the negative binomial model (6B), a significant equation was also found (*Likelihood Ratio* $\chi^2(2) = 96{,}688$ $p < .001$), $R^2_{Nagelkerke} = .399$ (39.9% of the variance explained, indicating strong prediction), which included the same direction for the predictors as in the OLS model (*Budget_100*: $B = -1.533$, $p < .001$, one-tailed; *Public_Reception*: $B = 1.859$, $p < .001$, one-tailed, which means 6.42 ($e^{1.859} = 6.42$) more Oscar wins in the big five category for every point of increase on the *Public_Reception* scale (when controlling for the budget)). Looking at both regression coefficients, it can be concluded that the effect of the budget was found to be more significant than in the OLS model.

In short, it can be concluded that public reception of a film becomes less and less predictive as the importance of critical recognition increases. On the other hand, the budget of a film only starts to influence the Oscars when it comes to the winning in the important categories. Given that all twelve models were found to be significant, H2A can be fully accepted.

Table 4.3.1.1: Standardized regression coefficients and R^2 of the OLS regression analyses with LN_Oscar_Nominations, LN_Oscar_Wins and LN_Oscar_Wins_Big5 as dependent variable.

	Model 1A (nominations)	**Model 2A (nominations)**	**Model 3A (wins)**	**Model 4A (wins)**	**Model 5A (wins big 5)**	**Model 6A (wins big 5)**
Predictor						
Public_Reception	**.500***	**.506***	**.434***	**.450***	**.403***	**.448***
Budget_100		-.031		-.074		**-.210***
	R^2_{adj} **= .247**	ΔR^2 = .001	R^2_{adj} **= .186**	ΔR^2 = .005	R^2_{adj} **= .160**	ΔR^2 **= .042**
	p **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**

Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Table 4.3.1.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Oscar_Nominations, Oscar_Wins, and Oscar_Wins_Big5 as dependent variable.

	Model 1B (nominations)	**Model 2B (nominations)**	**Model 3B (wins)**	**Model 4B (wins)**	**Model 5B (wins big 5)**	**Model 6B (wins big 5)**
Predictor						
Public_Reception	**1.499***	**1.535***	**1.804***	**1.959***	**1.531***	**1.859***
Budget_100		-.236		**-.480***		**-1.533***
	$R^2_{Nagelkerke}$ **= .555**	$R^2_{Nagelkerke}$ **= .558**	$R^2_{Nagelkerke}$ **= .498**	$R^2_{Nagelkerke}$ **= .508**	$R^2_{Nagelkerke}$ **= .334**	$R^2_{Nagelkerke}$ **= .399**
	p **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**	***p*** **< .001**

Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

4.3.2 Public reception predicting the domestic box office (prior to the Oscar ceremony)

For predicting the domestic box office (prior to the Oscar ceremony), two OLS and two negative binomial regression models were calculated. The same predictors from the previous section (*Public_Reception* and *Budget*_100 (the latter variable was expected to have a positive effect)) were used, meaning that the collinearity assumption was not violated (VIF = 1.047 (same for both); see appendix). Furthermore, both OLS models were tested for normality. It was found that none of the models' residuals had a normal distribution using the Shapiro-Wilk test (Model 1A: $p < .001$; Model 2A: $p < .001$; see appendix). Therefore, the Pre domestic box office numbers (adjusted for inflation) were transformed into a logarithmic equation with a +1 offset in order to account for the zero values, resulting in the new variable *LN_Pre_Domestic_Adjusted_100* (thus, the actual domestic numbers were transformed twice, first they were divided by 100 Million in order to render predictive coefficients more presentable, and after that they were changed to their logarithms). Nevertheless, the Shapiro-Wilk test was still significant when testing with the logarithmic residuals (Model 1A: $p < .001$; Model 2A: $p < .001$), which stresses the point of the data's being slightly biased, possibly. Moreover, all three models were tested for the constant error variance. As can be seen in the appendix, this assumption was not violated, as a result of a relatively equal spread of data over all the graphs. All of the data from the analyses in this section can be found in tables 4.3.2.1 (OLS) and 4.3.2.2 (negative binomial).

In the first OLS model (1A), *Public_Reception* was used at the only predictor. A significant equation was found ($F(1,288) = 95.470$, $p < .001$), $R^2_{adj} = .0.246$, meaning that 24.6% of the variance was explained, indicating moderate prediction. The relationship was found to be positive ($b^* = .499$, $p < .001$, one-tailed), meaning that the public reception of a film indeed has a moderate (one could also argue strong) effect on the domestic box office performance prior to the Oscar ceremony (adjusted for inflation). The explained variance slightly increased for the negative binomial model (1B) when compared to the OLS model (*Likelihood Ratio* $\chi^2(1) = 79.585$, $p < .001$), $R^2_{Nagelkerke} = .260$ (26.0% of the variance explained, indicating moderate prediction), and found a positive *B* value (.762, $p < .001$, one-tailed), which equals \$214 million ($e^{.762} = 2.14$) more domestic box office take (adjusted for inflation) for every full point of increase on the *Public_Reception* scale.

For the second models, the control variable of *Budget_100* was added on top of the *Public_Reception*. Again, a significant equation was found for the OLS model (2A) ($F(2,287) = 169.193$, $p < .001$), with more predictive power than the previous model, $\Delta R^2 = .292$, $p < .001$ (29.2% more of the variance explained compared to model 1A). Both relationships were found to be positive ($b^* = .382$, $p < .001$, one-tailed (*Public_Reception)*; $b^* = .533$, $p < .001$, one-tailed (*Budget_100*), meaning that in this model, the public reception had a moderate effect, and the budget a strong effect, on the domestic box office performance prior to the Oscars (adjusted for inflation). In the negative binomial model (2B), the amount of explained variance also increased (*Likelihood Ratio* $\chi^2(1) = 116.801$, $p < .001$), $R^2_{Nagelkerke} = .360$ (36.0% of the variance explained, indicating strong prediction), though the change in R^2 was not as drastic as for the OLS models. Furthermore, positive *B* values were found for both predictors (*Budget_100:* 1.062, $p < .001$, one-tailed; *Public_Reception*: .585, $p < .001$, one-tailed, which equals $179 million ($e^{.585} = 1.79$) domestic box office take more for every full point of increase on the *Public_Reception* scale (when controlling for the budget)). Given the significance of all four models, H2B can be fully accepted.

Table 4.3.2.1: Standardized regression coefficients and R^2 of the OLS regression analyses with LN_Pre_Domestic_100 as dependent variable.

	Model 1A	**Model 2A**
Predictor		
Public_Reception	**.499*** **	**.382*** **
Budget_100 (control variable)		**.533*** **
	$\boldsymbol{R^2_{adj} = .246}$	$\boldsymbol{\Delta R^2 = .292}$
	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$

Note: *$p < .05$ (one-tailed), **$p < .01$ (one-tailed), ***$p < .001$ (one-tailed)

Table 4.3.2.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Pre_Domestic_Adjusted_100_Int as dependent variable.

	Model 1B	**Model 2B**
Predictor		
Public_Reception	**.762*** **	**.585*** **
Budget_100 (control variable)		**1.062*** **
	$\boldsymbol{R^2_{Nagelkerke} = .260}$	$\boldsymbol{R^2_{Nagelkerke} = .360}$
	p **< .001**	***p*** **< .001**

Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

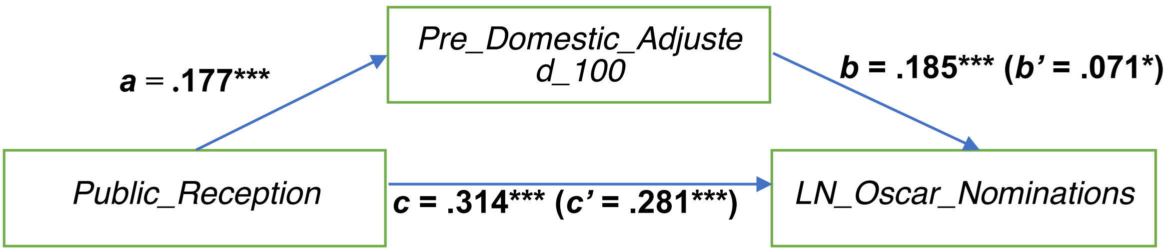
4.3.3 Public reception predicting critical recognition, mediated by the domestic box office (prior to the Oscar Ceremony)

Previously, it was already found that each of the variables have a significant effect on each other separately. The results from previous sections were used for the *a, b* and c paths, but in order to test for mediation, a new equation had to be calculated for each new model, which determined the *b'* and *c'* values. This equation contained the mediator and independent variable (as well as the control variable for some models) predicting the dependent variable. Whenever a new regression model will be introduced, this specific equation is referred to as the 'added equation'. Moreover, some of the models used *Budget_100* as a control variable, which was expected to have a negative effect for these models.

For the first mediation analysis (figure 4.3.3.1), the effect of *Public_Reception* on *LN_Oscar_Nominations* was tested, when mediated by *Pre_Domestic_Adjusted_100.* The added equation of *Public_Reception* and *Pre_Domestic_Adjusted_100* predicting *LN_Oscar_Nominations* was found to be significant ($F(2,287) = 50.891$, $p < .001$), $R^2_{adj} = .257$ (25.7% of the variance explained, indicating moderate prediction). Furthermore, partial mediation was found to hold (*Sobel's Z* = 2.102; $p < .05$), as the unstandardized regression coefficient of *c* (.314, $p < .001$, one-tailed) decreased in *c'* (.281, $p < .001$, one-tailed), yet still remained significant. This was, however, not the case when using the coefficients from the negative binomial model (figure 4.3.3.2). For that model, the added equation was found to be significant (*Likelihood Ratio* $\chi^2(2) = 221.745$, $p < .001$), $R^2_{Nagelkerke} = .557$ (55.7% of the variance explained, indicating strong prediction). However, the regression coefficient of *c* (1.499, $p < .001$, one-tailed) increased when being analyzed through mediation in *c'* (1.585, $p < .001$, one-tailed), which is why mediation did not hold (*Sobel's Z* = -1.309; $p > .05$).

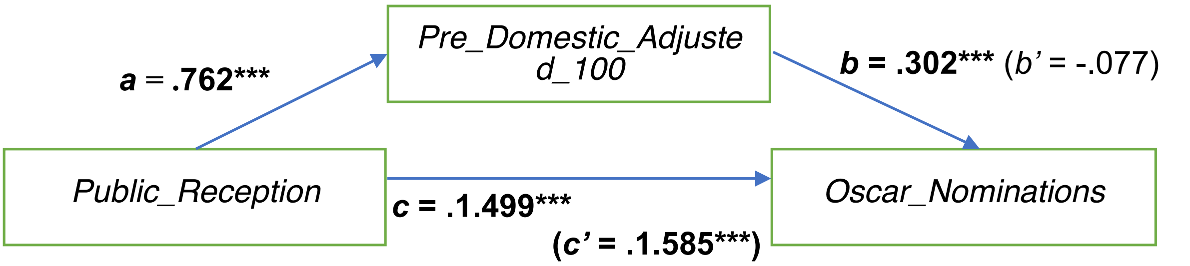
For the next two models, the procedure of the previous paragraph was repeated, although the control variable of *Budget_100* was added. In the OLS model (figure 4.3.3.3), the added equation was found to be significant ($F(3,286) = 36{,}729$, $p < .001$), $R^2_{adj} = .271$ (27.1% of the variance explained, indicating moderate prediction). Specifically, it was found that the regression coefficient for *Budget_100* was significant (-.291, $p < .01$, one-tailed), and partial mediation was still found to hold for the previous variables (*Sobel's Z* = 3.064; $p < .001$); and interestingly, the regression coefficient for *Public_Reception* dropped further in this model (*c* = .318 , $p < .001$, one-tailed; *c'* = .272, $p < .001$, one-tailed) when compared to the non-budget OLS model (*c* = .314, $p < .001$, one-tailed; *c'* = .281, $p < .001$, one-tailed). In regards to the negative binomial model (figure 4.3.3.4), different results were found. The added equation (*Likelihood Ratio* $\chi^2(3) = 221.977$, $p < .001$), had a very small increase in its explained variance compared to the non-budget model, $R^2_{Nagelkerke}$ = .558 (55.8% of the variance explained, indicating strong prediction). Therefore, *Budget_100* was found to be insignificant, and mediation did unsurprisingly not hold for this negative binominal model either (*Sobel's Z* = -.464, $p > .05$), although the difference between *c* (1.499, $p < .001$, one-tailed, in the non-budget model; 1.535, $p < .001$, one-tailed, in the budget model) and *c'* (1.585, $p < .001$, one-tailed, in the non-budget model; 1.567, $p < .001$, one-tailed, in the budget model) still decreased when *Budget_100* was added to the equation. In conclusion, considering mediation only held for the OLS models, mediation here is dubious.

Figure 4.3.3.1: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.



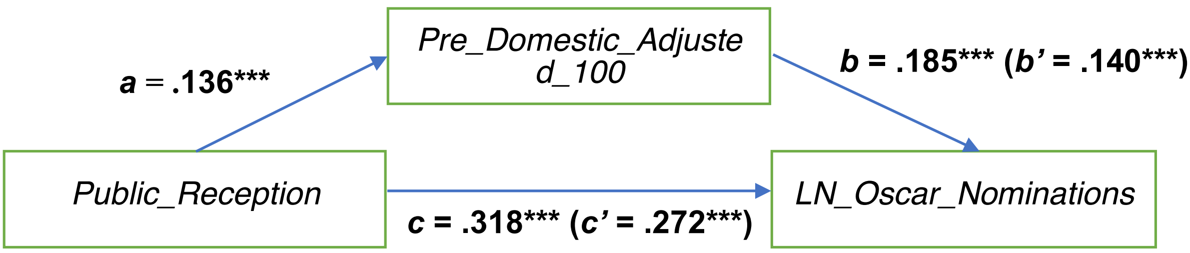
Note: *$p < .05$ (one-tailed), **$p < .01$ (one-tailed), ***$p < .001$ (one-tailed)

Figure 4.3.3.2: *Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.*



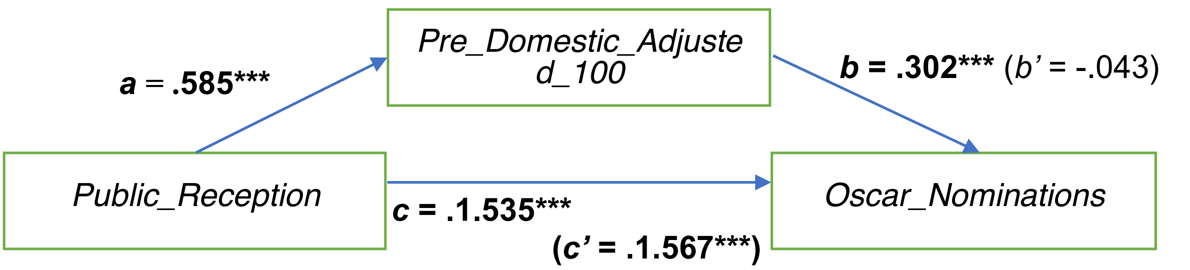
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.3: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.4: Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100t, analyzed through negative binomial regression.

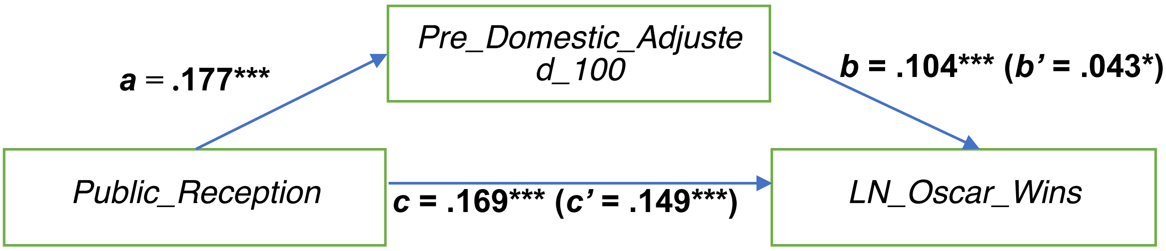


Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

In the second set of mediation analyses using OLS, the dependent variable was changed to *LN_Oscar_Wins*, with the independent variable and mediator staying the same as the previous model (see figure 4.3.3.5). As a result of sections 4.2.1, 4.3.1 and 4.3.2, it was already found that each of the variables have a significant effect on each other. The added equation was significant (F(2,287) = 35.855, p < .001), R^2_{adj} = .194 (19.4% of the variance explained, indicating moderate prediction). Partial mediation was found to hold (*Sobel's Z* = 2.004, p < .05), as the regression coefficient of *c* (.169, p < .001, one-tailed) decreased in *c'* (.149, p < .001, one-tailed), yet still remained significant. Moreover, just like with the nomination models, mediation did not hold through the negative binomial regression model (figure 4.3.3.6). The added equation was found to be significant (*Likelihood Ratio* χ^2 (2) = 158.854, p < .001), $R^2_{Nagelkerke}$ = .502. However, the unstandardized regression coefficient of *c* (1.804, p < .001, one-tailed) increased when being analyzed through mediation in *c'* (1.970, p < .001, one-tailed), while *b'* became insignificant (-.089, p > .05, one-tailed). Therefore, mediation did not hold (*Sobel's Z* = -1.255, p > .05).

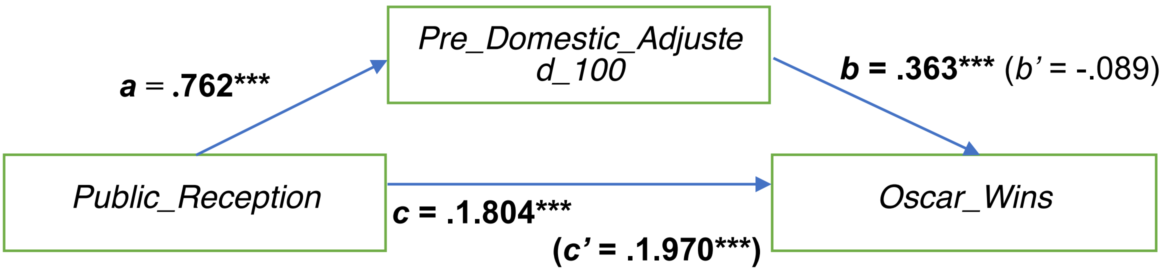
For the next two models, the procedure of the previous paragraph was repeated, although the control variable of *Budget_100* was added. In the OLS model (figure 4.3.3.7), the added equation was found to be significant (F(3,286) = 28.845, p < .001), R^2_{adj} = .224 (22.4% of the variance explained, moderate prediction). All predictors were found to be significant (*Public_Reception (c')* = .141, p < .001, one-tailed; Pre*_Domestic_Adjusted_100 (b')* = .103, p < .001, one-tailed; *Budget_100* = -.255, p < .001, one-tailed). The *c* path in particular had a bigger decrease in its regression coefficient when compared to the non-budget OLS model (*c* = .169, p < .001, one-tailed, in the non-budget model; .175, p < .001, one-tailed in the budget model; *c'* = .149, p < .001, one-tailed in the non-budget model; .141, p < .001, one-tailed in the budget model), which is why it was unsurprising to see that partial mediation was holding stronger (*Sobel's Z* = 3.516, p < .001) compared to the non-budget OLS model. In regards to the negative binomial model (figure 4.3.3.8), the added equation (*Likelihood Ratio* χ^2 (3) = 161.810, p < .001), $R^2_{Nagelkerke}$ = .509, explained around 5% less of the variance (yet, its predictive power was still strong) compared to the budget mediation model of the *Oscar_Nominations* (4.3.3.4). Mediation did not hold in this model either (*Sobel's Z* = .602, p > .05), which can be attributed to the insignificance of *b',* as the regression coefficient for *c'* (1.866, p <. 001, one-tailed) was lower than *c* (1.959, p <. 001, one-tailed). Nevertheless, *Budget_100* was found to be a significant variable (-.676, p <. 05, one-tailed). Considering partial mediation only held for the OLS models, mediation here is, once again, questionable.

Figure 4.3.3.5: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.



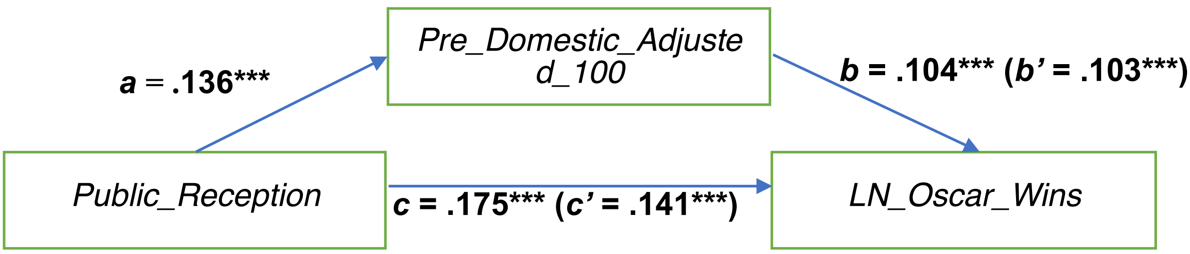
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.6: Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.



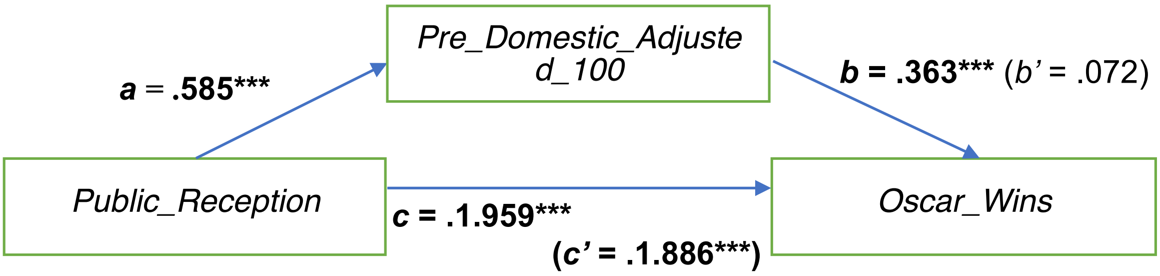
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.7: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.8: Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through negative binomial regression.



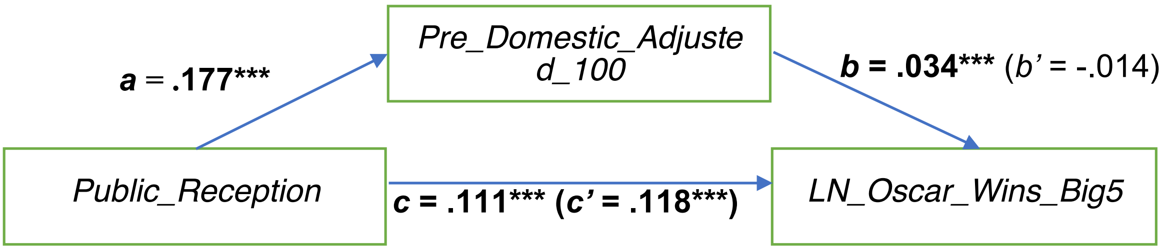
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Finally, the *LN_Oscar_Wins_Big5* were tested for the final OLS models (figure 4.3.3.9), with the independent variable and mediator staying the same as the previous models*.* As a result of sections 4.2.1, 4.3.1 and 4.3.2, it was already found that each of the variables have a significant effect on each other. The added equation was significant (F(2,287) = 28.344, p < .001), R^2_{adj} = .159 (15.9% of the variance explained, moderate predictive power). However, mediation did not hold (*Sobel's Z* = -.929, p > .05), as the regression coefficient of *c* (.111, p < .001, one-tailed) increased for *c'* (.118, p < .001, one-tailed), and remained significant. On the other hand, the added equation explained 20.8% of the variance (R^2_{adj} = .208, moderate predictive power) when *Budget_100* was added to the OLS model as control variable (figure 4.3.3.11). Moreover, partial mediation was now found to hold (*Sobel's Z* = 2.002, p < .05; *c* = .123*,* p < .001, one-tailed; *c'* = .110*,* p < .001), as the control variable found to also be a significant predictor (B = -.226, p < .001, one-tailed).

Regarding the negative binomial, non-budget model (figure 4.3.3.10), the added equation was found to be significant (*Likelihood Ratio* χ^2 (2) = 87.992, p < .001), $R^2_{Nagelkerke}$ = .365) and explained 36.5% of the variance, indicating moderate prediction. *Sobel's Z* (-2.576, p > .05), however, was found to be insignificant, because the unstandardized regression coefficient of *c* (1.948, p < .001, one-tailed) increased when being analyzed through mediation in *c'* (1.531, p < .001, one-tailed). In this case, adding *Budget_100* to the negative binomial modelas control variable (figure 4.3.3.12), did not make a difference for the mediation (*Sobel's Z* = -2.576, p < .001), as the new equation (*Likelihood Ratio* χ^2 (3) = 96,907, p < .001), $R^2_{Nagelkerke}$ = .399 (39.9% of the variance explained, indicating moderate prediction), found that *b'* was still an insignificant regression coefficient. Despite that, in this model, the unstandardized regression coefficient of *c'* (1.859, *p* < .001, one-tailed) was found to be lower than *c* (1.801, *p* < .001, one-tailed), and *Budget_100* as a control variable was found to be a significant predictor (*B* = -1.744, *p* < .05, one-tailed).

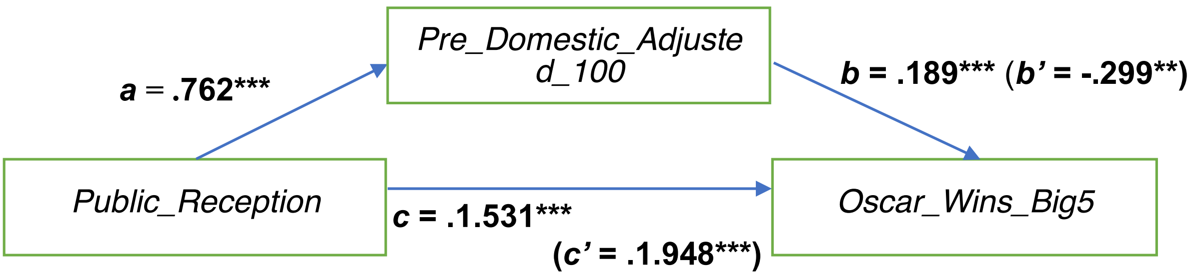
In conclusion, the OLS mediation models got weaker as the degree of critical recognition increased, although the addition of the budget as control variable helped with making some mediation hold as the critical recognition increased. Moreover, none of the negative binomial models were found to account for mediation due to the insignificance of *b'* (except 4.3.3.10) in every model. In total, five out of twelve models were found to be significant, which means that H2C can only be partly accepted.

Figure 4.3.3.9: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.



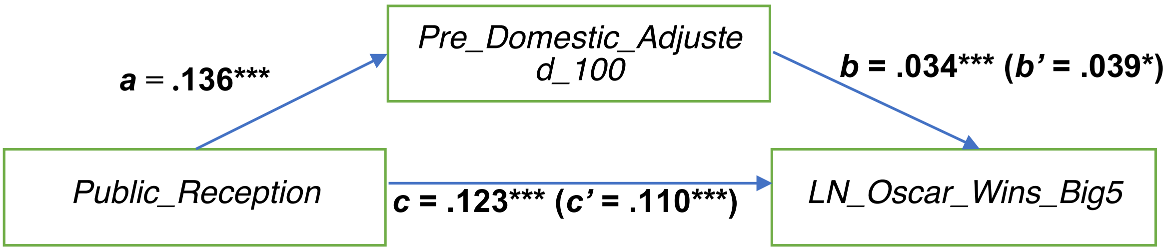
Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

Figure 4.3.3.10: Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.



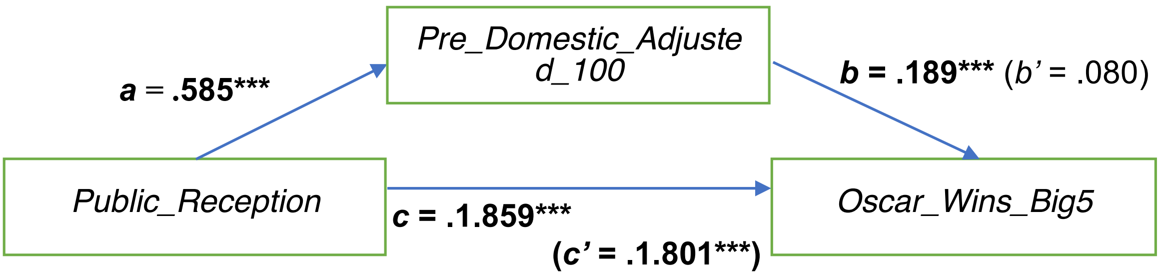
Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

Figure 4.3.3.11: Unstandardized regression coefficients for the relationship between Public_Reception and LN_Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.3.3.12: Unstandardized regression coefficients for the relationship between Public_Reception and Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through negative binomial regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

4.4 Critical reception hypotheses

4.4.1 Critical reception predicting critical recognition

In order to predict critical recognition using the critical reception of a film, six OLS models and six negative binomial regression models were calculated. In all models, either one or two of the predictors of *Critical_Reception* and/or *Budget_100* (the latter variable was expected to have a negative effect) were used, which had had a low degree of collinearity (VIF = 1.007; see appendix), meaning that this normality assumption was not violated. Moreover, the Shapiro-Wilk test found that none of the six models had a normal distribution (model 1A-6A: p < .001; see appendix). Therefore, *LN_Oscar_Nominations, LN_Oscar_Wins* and *LN_Oscar_Wins_Big5* were used in the final OLS models, which still resulted in a violation of the assumption of normality (model 1A-6A: p < .001; see appendix). Therefore, the data might possibly be biased. Moreover, all models were tested for constant error variance, which was not violated as a result of a relatively equal spread of data over the graphs.

In the first model (1A), *Critical_Reception* was used at the only predictor for *LN_Oscar_Nominations*. A significant equation was found (F(1,288) = 193.320, p < .001), $R^2{}_{adj}$ = .400, meaning that 40.0% of the variance was explained, indicating strong prediction. Moreover, the relationship between the variables was found to be positive (b* = .634, p < .001, one-tailed), meaning that the critical reception is a strong predictor for the number of Oscar nominations that a film can receive. This model is very strong in general, given that it is capable of explaining 40% of the variance that was found. On top of that, this even improved for the negative binomial model (1B), in which a significant equation was also found (*Likelihood Ratio* χ^2 (1) = 308,738, p < .001) $R^2{}_{Nagelkerke}$ = .683 (68.3% of the variance explained, indicating very strong prediction), with a positive B value (.952, p < .001, one-tailed), which equates to 2.59 ($e^{.952}$ = 2.59) more Oscar nominations for every full point of increase on the *Critical_Reception* scale. Therefore, it can be concluded that the critical reception is a very strong predictor for the Oscar nominations.

For the OLS model (2A), the control variable of *Budget_100* was added. This model was also found to be significant (F(2,287) = 96.251, p < .001), with slightly less predictive power than the previous model, ΔR^2 = .000, p > .05. Therefore, *Budget_100* was unsurprisingly found variable to be insignificant when controlling for *LN_Oscar_Nominations*, whereas *Critical_Reception* remained a significant, positive predictor (b* = .632). This was contradicted by the significant negative binomial model (2B) (*Likelihood Ratio* χ^2 (2) = 312.461, p < .001), $R^2{}_{Nagelkerke}$ = .688 (68,8% of the variance explained, indicating very strong prediction). In this model, *Budget_100* was surprisingly found to be a positive predictor (B = .958, p < .05, one-tailed), and given that it was argued to be a negative predictor during the theoretical framework (and has been found to be a negative predictor for every siginificant coefficient until this model), this value was treated as insignificant. On the other hand, *Critical_Reception* (B = .958, p < .001, one-tailed) was found to be significant which means that in this model, every full point of increase on the *Critical_Reception* scale leads to 2.60 ($e^{.958}$ = 2.60) more Oscar nominations (when controlling for the budget).

For the third and fourth model, the same procedure was repeated, albeit with a different dependent variable, namely *LN_Oscar_Wins.* For the third model, a significant equation was found for using *Critical_Reception* as the only predictor

($F(1,288) = 96.251$, $p < .001$), $R^2_{adj} = .263$, meaning that 26.3% of the variance was explained, indicating moderate to strong prediction. The critical reception was found to have a strong effect on the amount of Oscar wins ($b^* = .515$, $p < .001$, one-tailed), although the effect was not as strong as it was for the nominations. This was the same case for the negative binomial model (3B), in which a significant equation was found (*Likelihood Ratio* $\chi^2(1) = 183.220$, $p < .001$), $R^2_{Nagelkerke} = .556$ (55.6% of the variance explained, indicating strong prediction) with a positive B value (1.100, $p < .001$, one-tailed), which indicates that every full point of increase on the *Critical_Reception* scale leads to 3.00 ($e^{1.100} = 3.00$) more Oscar wins.

When adding *Budget_100* as a control variable in the fourth model, a significant equation was still found in the OLS model (4A) ($F(2,287) = 51.932$, $p < .001$), albeit with less predictive power than the previous OLS model (3A), $\Delta R^2 = .001$, $p > .05$. As was the case with the ΔR^2 between models 1A and 2A, the difference in explained variance between the two models is low. Therefore, the standardized beta value for *Budget_100* was low and insignificant, whereas the *Critical_Reception* still had a strong effect ($b^* = .517$, $p < .001$, one-tailed). The negative binomial model (4B) was also found to be significant (*Likelihood Ratio* $\chi^2(2) = 186.294$, $p < .001$). Its predictive power increased slightly ($R^2_{Nagelkerke} = .563$), and *Budget_100,* once again, was a positive predictor ($B = .371$, $p < .05$, one-tailed), which makes it insignificant for this research. This is slightly surprising, given that the budget was found to be significant when predicting with the *Public_Reception* together in the 4B model of paragraph 4.3.2. On the other hand, *Critical_Reception* ($B = 1.109$, $p < .001$, one-tailed, which translates to 3.03 ($e^{1.109} = 3.03$) more Oscar win for every full point of increase on the *Critical_Reception* scale (when controlling for budget)) remained a significant, positive predictor.

In the final two models, *LN_Oscar_Wins_Big5* was used as the dependent variable. For the 5A model, the predictor *Critical_Reception* resulted in a significant equation ($F(1,288) = 101.878$, $p < .001$), $R^2_{adj} = .259$, meaning that 25.9% of the variance was explained, indicating moderate (close to strong) prediction. This was a lower R^2_{adj} than models 1A and 3A, meaning that it can be concluded that the critical reception of a film becomes less and less predictive as the importance of critical recognition increases, as was also the case with the public reception models. Nevertheless, the critical reception was still found to be significant, and a strong, positive predictor ($b^* = .511$, $p < .001$, one-tailed) for the Oscars in the important categories. In the negative binomial model (5B), a significant equation was also found (*Likelihood Ratio* $\chi^2(1) = 110.890$, $p < .001$), $R^2_{Nagelkerke} = .447$ (44.7% of the variance explained, indicating strong prediction), that included the same direction for the predictor as in the OLS model (*Critical_Reception*: $B = 1.067$, $p < .001$, one-tailed, which means 2.91 ($e^{1.067} = 2.91$) more Oscar wins in the big five category for every full point of increase on the *Critical_Reception* scale).

When adding the control variable of *Budget_100* in model 6A, a significant equation was found ($F(2,287) = 57.755$, $p < .001$), with more predictive power than the previous model, $\Delta R^2 = .026$, $p < .001$. In this model, it was found that *Budget_100* was a significant, although weak effect-wise, negative predictor ($b^* = -.161$, $p < .001$, one-tailed), when controlling for *Critical_Reception*. *Critical_Reception*, on the other hand, remained a significant, positive predictor ($b^* = .525$, $p < .001$, one-tailed). In regards to the negative binomial model (6B) (*Likelihood Ratio* $\chi^2(2) = 112.556$, $p < .001$, $R^2_{Nagelkerke} = .399$) explained 39.9% of the variance, indicating strong prediction; however, it was found that *Budget_100* an insignificant, negative predictor. Nevertheless, *Critical_Reception* was still a significant, positive predictor ($B = 1.045$, $p < .001$, one-tailed), which means 2.84 ($e^{1.045} = 2.84$) more Oscar wins in the big five category for every full point of increase on the *Critical_Reception* scale (when controlling for the budget).

In conclusion, the results in this section were similar to the models that used *Public_Reception* as independent variable. The regression coefficients decreased as the degree of critical recognition increased; however, the decrease was much less steep for the *Critical_Reception* models. Furthermore, the effect of the budget was found to be much less significant when compared to the *Public_Reception* models. In fact, it was only found to have a significant effect in one of the models. Given that all twelve models were found to be significant, H3A can be fully accepted.

Table 4.4.1.1: Standardized beta weights and R^2 of the OLS regression analyses with LN_Oscar_Nominations, LN_Oscar_Wins and LN_Oscar_Wins_Big5 as dependent variable.

	Model 1A (nominations)	**Model 2A (nominations)**	**Model 3A (wins)**	**Model 4A (wins)**	**Model 5A (wins big)**	**Model 6A (wins big 5)**
Predictor						
Critical_Reception	**.634*** **	**.632*** **	**.515*** **	**.517*** **	**.511*** **	**.525*** **
Budget_100		-.022		-.023		**-.161*** **
	$\boldsymbol{R^2_{adj}}$ **= .400**	$\Delta R^2 = .000$	$\boldsymbol{R^2_{adj}}$ **= .263**	$\Delta R^2 = .001$	$\boldsymbol{R^2_{adj}}$ **= .259**	$\boldsymbol{\Delta R^2 = .026}$
	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$

Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

Table 4.4.1.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Oscar_Nominations, Oscar_Wins, and Oscar_Wins_Big5 as dependent variable.

	Model 1B (nominations)	**Model 2B (nominations)**	**Model 3B (wins)**	**Model 4B (wins)**	**Model 5B (wins big 5)**	**Model 6B (wins big 5)**
Predictor						
Critical_Reception	**.952*** **	**.958*** **	**1.100*** **	**1.109*** **	**1.067*** **	**1.045*** **
Budget_100		.349*		.371*		-.419
	$\boldsymbol{R^2_{Nagelkerke}}$ **= .683**	$\boldsymbol{R^2_{Nagelkerke}}$ **= .688**	$\boldsymbol{R^2_{Nagelkerke}}$ **= .556**	$\boldsymbol{R^2_{Nagelkerke}}$ **= .563**	$\boldsymbol{R^2_{Nagelkerke}}$ **= .447**	$\boldsymbol{R^2_{Nagelkerke}}$ **= .452**
	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$	$\boldsymbol{p < .001}$

Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

4.4.2 Critical reception predicting the domestic box office (prior to the Oscar ceremony)

For predicting the domestic box office prior to the Oscar ceremony (adjusted for inflation), two OLS regression models and two negative binominal regression models were calculated. As mentioned before, the two predictors that were used (*Critical_reception* and *Budget_100* (the latter variable was expected to have a positive effect)) had a low degree of collinearity (VIF = 1.007; see appendix), meaning that this regression assumption was not violated. Furthermore, both models were tested for normality. For both models, their residuals did not have a normal distribution using the Shapiro-Wilk test (Model 1: $p < .001$; Model 2: $p < .001$), which can also be found in the appendix. Therefore, *LN_Pre_Domestic_Adjusted_100* was used during the regression. Despite this, the Shapiro-Wilk test was still significant when testing with the logarithmic residuals (Model 1: $p < .001$; Model 2: $p < .001$), which as stated before, stresses the point of the data being slightly biased, possibly. Both models were tested for the constant error variance. As can be seen in the appendix, this assumption was not as a relatively equal spread of data over the graphs.

In the first OLS model (1A), *Critical_Reception* was used at the only predictor. A significant equation was found ($F(1,288) = 47.922$, $p < .001$), $R^2_{adj} = .246$, meaning that 24.6% of the variance was explained, indicating moderate prediction. The relationship was found to be positive ($b^* = .378$, p < .001, one-tailed), meaning that the critical reception of a film indeed had a moderate (almost strong) effect on the domestic box office performance prior to the Oscar ceremony (adjusted for inflation). Also, this is a relatively strong regression model, given that it explains nearly 25% of the variance that was found. The explained variance decreased slightly for the negative binomial model (1B) (*Likelihood Ratio* $\chi^2(1) = 46.430$, $p < .001$), $R^2_{Nagelkerke} = .161$ (16.1% of the variance explained, still indicating moderate prediction), but still found a positive *B* value (.762, p < .001, one-tailed), which equals \$133 ($e^{.762} = 1.33$) more domestic box office take (adjusted for inflation) for every full point of increase on the *Critical_Reception* scale.

In the second model, the control variable of *Budget_100* was added on top of the *Critical_Reception*. Again, a significant equation was found ($F(2,287) = 147.537$, $p < .001$), with more predictive power than the previous model, $\Delta R^2 = .292$, $p < .001$. Both relationships were positive ($b^* = .326$, p < .001, one-tailed, for

Critical_Reception; b^* = .606, p < .001, one-tailed for *Budget_100*), meaning that in this model, the critical reception still had a moderate effect (albeit less than in the previous model), and the budget was found to have a strong effect on the domestic box office performance prior to the Oscars (adjusted for inflation). In the negative binomial model (2B), the amount of explained variance also increased (*Likelihood Ratio* $\chi^2(1) = 101.954$, $p < .001$), $R^2_{Nagelkerke} = .321$, meaning that 32.1% of the variance was explained, indicating strong prediction. Furthermore, positive *B* values were found for both predictors: *Budget_100* = 1.235, p < .001, one-tailed; *Public_Reception* = .228, p < .001, one-tailed, which equals $126 ($e^{.228} = 1.26$) million domestic box office take more for every full point of increase on the *Critical_Reception* scale.

All of the models were found to be significant, and despite the fact that the models using *Public_Reception* as independent variable explained more of the variance (although this is logical, given the fact that the public directly determines what the domestic box office take is going to be), H2B can be fully supported.

Table 4.4.2.1: Standardized beta weights and R^2 of the OLS regression analyses with LN_Pre_Domestic_Adjusted_100 as dependent variable.

	Model 1A	**Model 2A**
Predictor		
Critical_Reception	**.378*** **	**.326*** **
Budget_100 (control variable)		**.606*** **
	R^2_{adj} = .246	**ΔR^2 = .292**
	***p* < .001**	***p* < .001**

Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

Table 4.4.2.2: Unstandardized regression coefficients and pseudo R^2 of the negative binomial regression analyses with Pre_Domestic_Adjusted_100_Int as dependent variable.

	Model 1B	**Model 2B**
Predictor		
Critical_Reception	**.287*** **	**.228*** **
Budget_100 (control variable)		**1.235*** **
	$\boldsymbol{R^2_{Nagelkerke} = .161}$ $\boldsymbol{p < .001}$	$\boldsymbol{R^2_{Nagelkerke} = .321}$ $\boldsymbol{p < .001}$

Note: **p* < .05 (one-tailed), ***p* < .01 (one-tailed), ****p* < .001 (one-tailed)

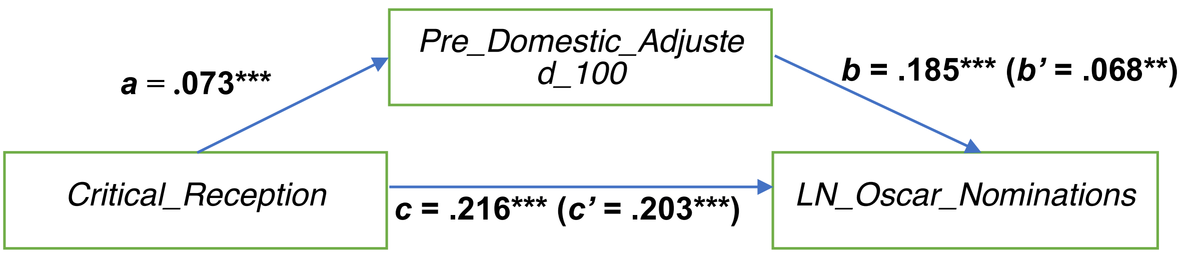
4.4.3 Critical reception predicting critical recognition, mediated by the domestic box office (prior to the Oscar Ceremony)

As a result of sections 4.2.1, 4.4.1 and 4.4.2, it was already found that each of the variables have a significant effect on each other separately. The results from previous sections were used for the *a, b* and c paths, but in order to test for mediation, one new equation had to be calculated for each new model, which determined the *B* values of the *b'* and *c'* paths. This equation contained the mediator and independent variable (as well as the control variable for some models) predicting the dependent variable. Whenever a new mediation model will be introduced, this specific equation is referred to as the 'added equation'. Furthermore, some of the models used *Budget_100* as a control variable, which was expected to have a negative effect for these models.

For the first OLS mediation analyses, the effect of *Critical_Reception* on *LN_Oscar_Nominations* was tested, when mediated by *Pre_Domestic_Adjusted_100* (figure 4.4.3.1). The added equation of *Critical_Reception* and *Pre_Domestic_Adjusted_100* predicting *LN_Oscar_Nominations* was found to be significant ($F(2,287) = 101.692$, $p < .001$), $R^2_{adj} = .0.409$, meaning that 40.9% of the variance was explained, indicating strong prediction. Furthermore, partial mediation was found to hold (*Sobel's Z* = 2.358, $p < .05$), as the unstandardized regression coefficient of *c* (.216, $p < .001$, one-tailed) decreased for *c'* (.203, $p < .001$, one-tailed), yet still remained significant. This was, however, not the case when using the coefficients from the negative binomial model (figure 4.4.3.2). For that model, the added equation was found to be significant (*Likelihood Ratio* χ^2 (2) = 312.675, p < .001), R^2 *Nagelkerke* = .688, explaining 68.8% of the variance, indicating very strong prediction. The regression coefficient of *c* (.952, p < .001, one-tailed) decreased when being analyzed through mediation in *c'* (.928, p < .001, one-tailed), however *b'* (.105, p > .05, one-tailed) was found to be insignificant, which is why mediation did not hold for this model *(Sobel's Z* = 1.773, p > .05).

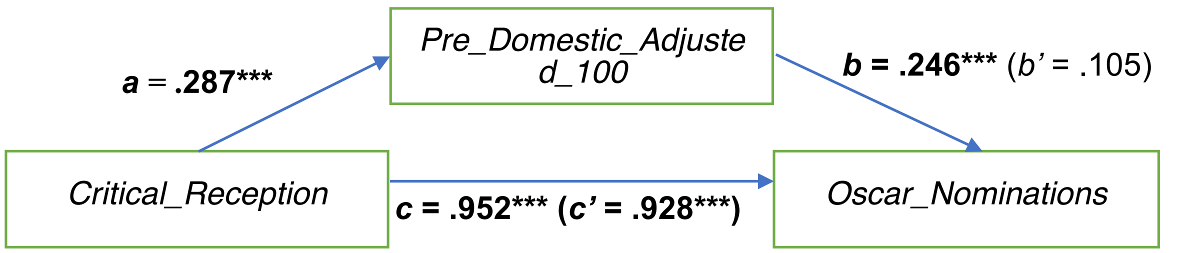
For the next two models, this procedure was repeated, although the control variable of *Budget_100* was added. In the OLS model (figure 4.4.3.3), the added equation was found to be significant ($F(3,286) = 68.446$, p < .001) R^2_{adj} = .412, meaning that 41.2% of the variance was explained, indicating strong prediction. Specifically, it was found that the regression coefficient for *Budget_100* was insignificant, but despite that, partial mediation was still found to hold for the previous variables (*Sobel's Z* = 2.607; p < .001); and interestingly, the regression coefficient for *Critical_Reception* dropped further in this model (*c* = .215 , p < .001, one-tailed; *c'* = .198, p < .001, one-tailed) when compared to the non-budget OLS model (*c* = .216, p < .001, one-tailed; *c'* = .203, p < .001, one-tailed). In regards to the negative binomial model (figure 4.4.3.4), the added equation (*Likelihood Ratio* χ^2 (3) = 312.977, p < .001), R^2 *Nagelkerke* = .688, made for a very strong prediction model that explained 68.8% of the variance. This model resulted into similar results as the previous negative binomial model (*c* = .958, p < .001, one-tailed; *c'* = .940, p < .001, one-tailed). Mediation still did not hold, as the insignificance of *b'* resulted in an insignificant *Sobel Z* (= .715, p > .05) Considering that mediation only held for the OLS models, mediation here is questionable.

Figure 4.4.3.1: Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.



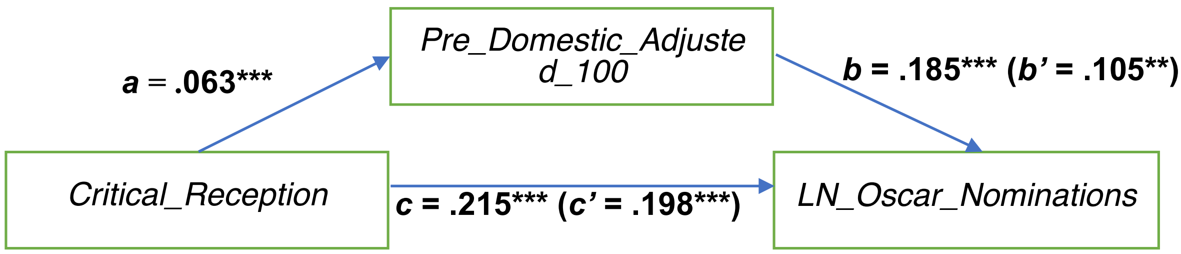
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.2: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.



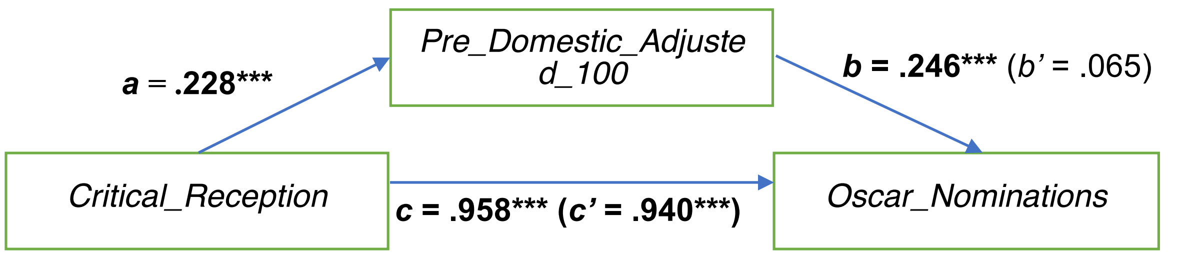
Note: $*p < .05$ (one-tailed), $**p < .01$ (one-tailed), $***p < .001$ (one-tailed)

Figure 4.4.3.3: Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.



Note: $*p < .05$ (one-tailed), $**p < .01$ (one-tailed), $***p < .001$ (one-tailed)

Figure 4.4.3.4: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Nominations as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through negative binomial regression.

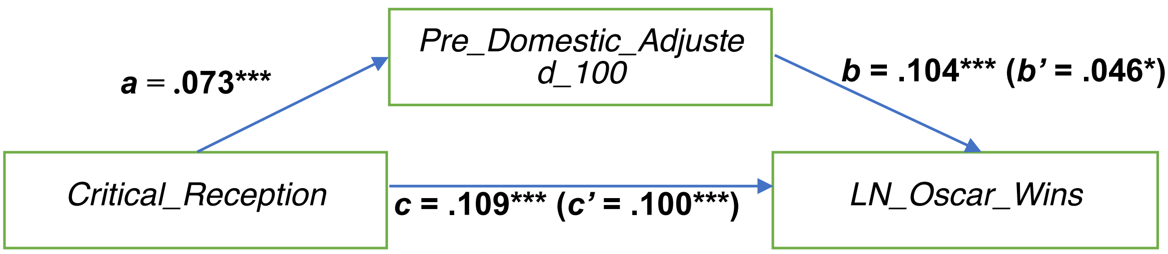


Note: $*p < .05$ (one-tailed), $**p < .01$ (one-tailed), $***p < .001$ (one-tailed)

For the third OLS mediation analysis, the dependent variable was changed to *LN_Oscar_Wins* (figure 4.4.3.5), with the independent variable and predictor staying the same as the previous models. The added equation of *Critical_Reception* and *Pre_Domestic_Adjusted_100* predicting *LN_Oscar_Wins* was significant ($F(2,287) = 51.253$, $p < .001$), $R^2_{adj} = .274$, explaining 27.4% of the variance, indicating moderate prediction. Partial mediation was found to hold (*Sobel's Z* = 2.251, $p < .05$), as the regression coefficient of *c* (.109, $p < .001$, one-tailed) decreased for *c'* (.100, $p < .001$, one-tailed), yet remained significant. Moreover, the negative binomial model was also found to be significant (figure 4.4.3.6) (*Likelihood Ratio* $\chi^2(2) = 191.815$, $p < .001$) $R^2_{Nagelkerke} = .575$, explaining 57.5% of the variance (strong prediction model), and hold for partial mediation (*Sobel's Z* = 2.543, $p < .05$), as the regression coefficient of *c* (1.100, $p < .001$, one-tailed) decreased in *c'* (1.060, $p < .001$, one-tailed), yet remained significant. This was the only time partial mediation was found to hold for both the OLS and negative binomial models.

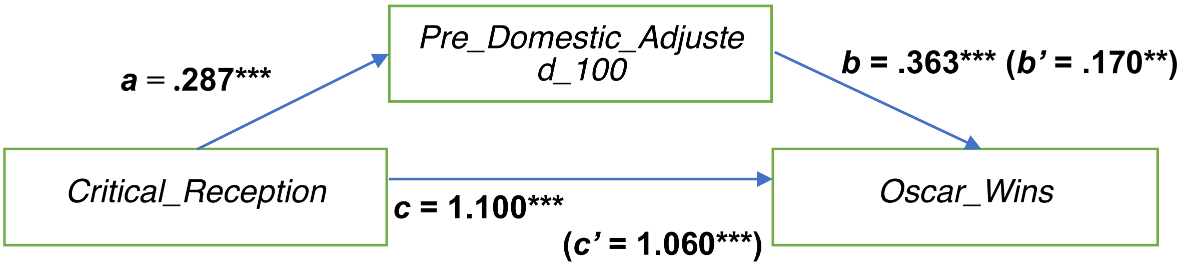
In the next two models, the procedure of the previous two paragraphs was repeated, although the control variable of *Budget_100* was added. In the OLS model (figure 4.4.3.7), the added equation was found to be significant ($F(3,286) = 40.348$, $p < .001$), $R^2_{adj} = .290$, explaining 29.0% of the variance, indicating moderate prediction. The two variables from the previous model remained significant (*Critical_Reception* = .094, $p < .001$, one-tailed; Pre_*Domestic_Adjusted_100* = .092, $p < .001$, one-tailed), whereas the budget was not found to be significant, which is slightly surprising, considering that during the *Public_Reception* mediation analyses, this was the model for which *Budget_100* became a significant predictor. In regards to the negative binomial model (figure 4.3.3.8), the added equation (*Likelihood Ratio* $\chi^2(3) = 193.409$, $p < .001$), $R^2_{Nagelkerke} = .579$, explained nearly 60% of the variance (strong prediction model). Partial mediation also held through this model (*Sobel's Z* = .602, $p < .05$; $c = 1.109$, $p < .001$, one-tailed; $c' = 1.024$, $p < .001$, one-tailed), which made this the only set of models for which all four mediation models were found to partially hold statistically.

Figure 4.4.3.5: Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.



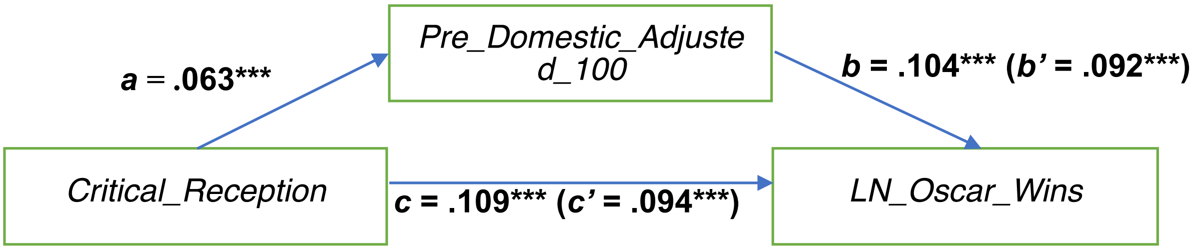
Note: *$p < .05$ (one-tailed), **$p < .01$ (one-tailed), ***$p < .001$ (one-tailed)

Figure 4.4.3.6: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.



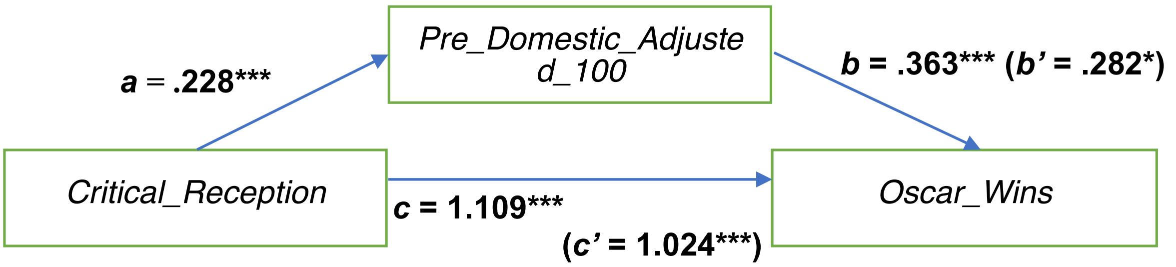
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.7: Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.8: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through negative binomial regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

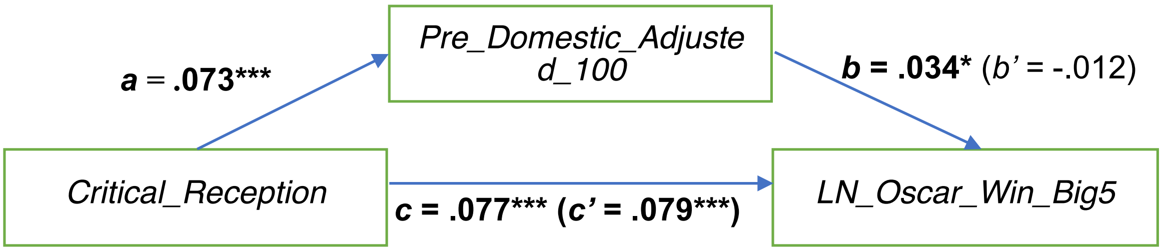
Finally, the *LN_Oscar_Wins_Big5* were tested for the final OLS models (figure 4.4.3.10), with the independent variable and predictor staying the same as the previous model. The added equation of *Public_Reception* and *Pre_Domestic_Adjusted_100* predicting *LN_Oscar_Wins_Big5* was significant

($F(2,287) = 51.253$, $p < .001$), $R^2_{adj} = .258$, explaining 25.8% of the variance, indicating moderate prediction. However, no mediation was found (*Sobel's Z* = -.854; $p > .05$), as the regression coefficient of *c* (.077, $p < .001$, one-tailed) increased for *c'* (.079, $p < .001$, one-tailed), and remained significant. Adding *Budget_100* to the OLS model as a control variable (figure 4.4.3.11) did not contribute to making mediation hold (*Sobel's Z* = .369, $p > .05$), despite the fact that the variable was found to be a significant, negative predictor ($B = -.178$, $p < .001$, one-tailed), and resulted in a slight decease of *c'* (.074, $p < .001$, one-tailed) compared to *c* (.079, $p < .001$, one-tailed),

A similar result was found for the non-budget, negative binomial regression (figure 4.4.3.10), as the added equation was found to be significant (*Likelihood Ratio* $\chi^2(2) = 110.895$, $p < .001$), $R^2_{Nagelkerke} = .447$, explaining 44.7 of the variance, indicating a strong prediction model. The unstandardized regression coefficient of *c* (1.067, $p < .001$, one-tailed) stayed relatively the same for *c'* (1.066, $p < .001$, one-tailed), while *b'* was not found to be insignificant. Therefore, it can be concluded that mediation did not hold through this model (*Sobel's Z* = .071, $p > .05$). Again, adding *Budget_100* to the negative binomial model did not improve the model (*Likelihood Ratio* $\chi^2(3) = 116.232$, $p < .001$), $R^2_{Nagelkerke} = .463$ (explaining 46.3% of the variance, indicating strong prediction), as *b'* remained insignificant, which is why mediation did not hold (*Sobel's Z* = 1.747, $p > .05$; $c = 1.045$, $p < .001$, one-tailed; $c' = .983$, $p < .001$, one-tailed), despite the fact that the control variable was found to be significant ($B = -1.347$, $p < .05$, one-tailed).

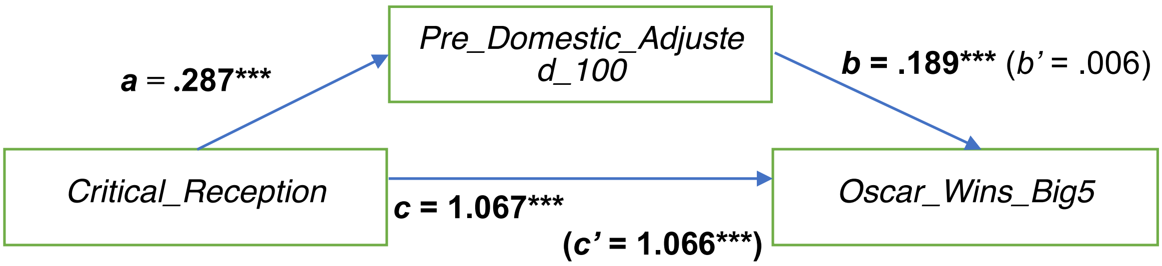
In conclusion, the pattern that can be found in the mediation models for the critical reception is a bit unconventional; they are the strongest for the middle (wins) category of critical recognition, and weaker for the first (nominations) and third categories (big five wins). Moreover, budget did not play a substantial role in any of these mediation models (contrary to the *Public_Reception* models), as none of the coefficients drastically changed as a result of the addition from *Budget_100.* Given that six out of twelve models were found to be significant, H3C can be partly accepted.

Figure 4.4.3.9: *Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when analyzed through OLS regression.*



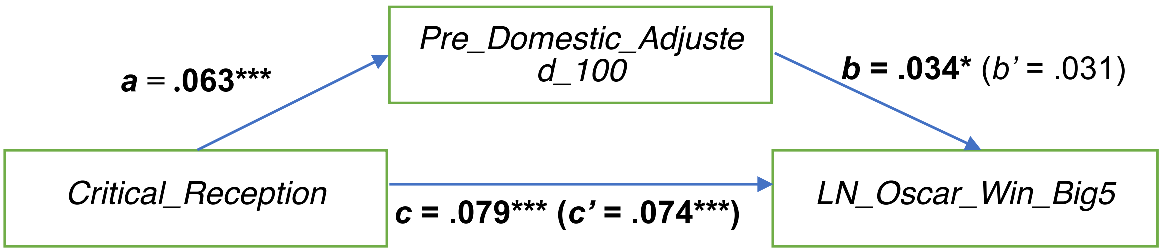
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.10: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Wins_Big5 as mediated by Pre_Domestic_Adjusted_100, when analyzed through negative binomial regression.



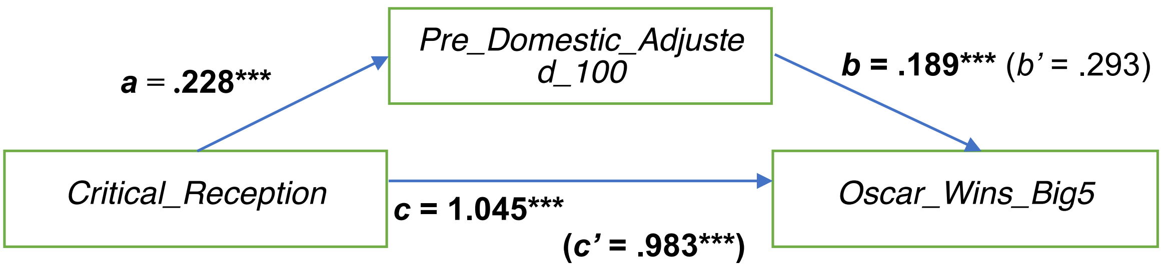
Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.11: *Unstandardized regression coefficients for the relationship between Critical_Reception and LN_Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through OLS regression.*



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

Figure 4.4.3.12: Unstandardized regression coefficients for the relationship between Critical_Reception and Oscar_Wins as mediated by Pre_Domestic_Adjusted_100, when controlling for Budget_100, analyzed through negative binomial regression.



Note: *p < .05 (one-tailed), **p < .01 (one-tailed), ***p < .001 (one-tailed)

5. Discussion

5.1 Summary of findings and theoretical implications

This subsection will revisit the three receptive factors and their hypotheses that were introduced during the theoretical framework chapter of this study. Together, their conclusions enable this research to answer its research question (to what extent can the critical reception, public reception and box office performance of a film predict its critical recognition at the Oscars?)

5.1.1 Box office

In short, this study found that critical recognition is a decent predictor for the total box office (post Oscars) (H1B), although insignificant for the box office regarding the winners in the 'big five' category. This latter finding contradicts the aforementioned Nelson et al. (2007) article, who found that a higher degree of critical recognition gives a significant boost to a film's box office performance. The difference in findings can be explained when looking at a list of films that had a front-loaded box office run (i.e. the films that most of their box office was made in the first week of their release in theaters). On that list, it can be seen that a considerable number of the movies came out after the Nelson et al. (2007) article ("Movies with Most Front-Loaded Opening Weekend," n.d.). In fact, the top 50 currently consists of 9 movies that were released before 2007 ("Movies with Most Front-Loaded Opening Weekend," n.d.). This could explain why films do not receive as much as a boost in general as they used to, as the contemporary public feels the need to see a movie immediately when they are released in theaters. Assuming that this pattern is accurate, this should mean that the effect of being nominated and/or winning (that is, winning in any category) should decrease even further over time.

Moreover, Jozefowicz et al. (2008) stated that critical recognition does not lead to a boost of home media and streaming sales. That statement contrasts with this studies' aforementioned findings for H1B, as both studies used economic measurements that determine the success of a film after the Oscar Awards ceremony. Again, this can be explained by the fact that the ancillary market (i.e. the non-theatrical film market) has changed over the past ten years. For instance, it was recently reported that disc sales (DVD, Blu-ray) have declined substantially over the past ten years (e.g. more than 14% in 2017, compared to 2016), whereas the streaming market gained new ground (Lopez, 2018). Streaming makes films instantly available to the consumer, and this has been found to lead to a higher degree of impulse buying (Turkyilmaz, Erdem, & Uslu, 2015). Therefore, it can be argued that when consumers see films being critically recognized, they are more likely to spend money on critically recognized films now then ten years ago, as they can buy and watch them instantly.

In turn, this research also found that the box office (prior to the Oscars) is a decent predictor for critical recognition (H1A); however, its predictive power decreases once the degree of critical recognition increases. This lines up with what was proposed in the theoretical framework, as it was stated that the Academy tends to nominate some popular audience films/blockbusters, yet ultimately not reward them, in order to lure in viewers for their awards show (Simonoff & Sparrow, 2000). Given that Littleton (2018) reported a declining trend for the Oscar viewership, it would make economical sense for the Academy to increase the amount of popular films they nominate (they should maybe even consider rewarding some of them with an award) in order to attract more viewers again. If this were the case, the predictive power of the statistical models should increase over time. Furthermore, the findings of this hypothesis also support the article from Simonoff and Sparrow (2000), who found that the Academy likes to reward one kind of movie in particular, these being mostly drama movies (as evidenced by the consistently high percentage of drama movies regarding critically recognized movies in the sample) with a low to middle-sized budget (as evidenced by the declining *Budget* mean for the increase of critical recognition, as well as its increase of importance once the degree of critical recognition becomes higher).

5.1.2 Public reception

In the theoretical framework, it was argued that public controversies surrounding the Oscars help with improving the chances of being critically recognized, based on the empirical evidence of the publically well-received Moonlight (Gardner et al., 2017) winning the best picture Oscar the year after the #OscarsSoWhite controversy. Based on the results, this assumption was found to be true (H2A), which, first of all, stresses the fact that using numeric scores as operationalized indicator for the public reception is a more nuanced representation of the audience's stance on a film (Wong et al., 2012) when compared to a sentiment analysis (Haughton et al., 2015), despite the validity issue of self-selection. Secondly, regarding the PKM model in which the public is the agent, and the Academy the target, this entails that it can now be argued that the public reception of a film adds to the agent knowledge of the Academy (as the Academy finds it important to know what is on the public's agenda).

Kraus et al. (2008) found that positive public sentiment surrounding a film helps with boosting its box office performance. Based on this research, it was found that the largest influencer on the box office performance is the budget of the film (a far larger influencer when compared to operating as control variable between public reception and critical recognition). This makes sense, given that it was argued that movies with a higher budget allow to create a more substantial box office potential. Nevertheless, it was also argued that a PKM model can be established in which the public is both the agent and the target of itself, as the spreading of the public reception through word of mouth influences the box office (Liu, 2006). Given the support of all models in H2B, this was also found to be true.

Regarding the support of hypotheses H1A, H2A and H2B, it would seem like no stretch that all of the mediation models would be found to be significant. However, this was not the case. The domestic box office performance (prior to the Oscar ceremony) only mediated between the public reception and critical recognition for a few models, most of which used a low degree of critical recognition as dependent variable (H2C). The two preceding paragraphs already illustrated that the public reception and box office had the strongest influence for the lowest degree of critical recognition in their individual models; hence, it is not entirely surprising that some mediation models were found to insignificant. A possible reason for this is that the Academy simply cares more about the public reception of a film than its box office performance, which is stressed by the fact that the individual public reception models predicting critical recognition were found to be more predictive than the individual box office models predicting critical recognition.

Instead, given the decrease of significance for most of the *b'* coefficients during mediation, it almost seemed to be the case that mediation works in a different way, namely with the public reception acting as mediator, and box office as independent variable. However, given that it seems illogical to assume that the box office influences how much people enjoyed a film, this line of thought does not hold much weight.

5.1.3 Critical reception

In the theoretical framework, it was argued that the Academy is tasked with rewarding films of the highest quality, which lines up directly with the job of movie critics, resulting in the assumption that they should, by default, be the best predictors of critical recognition. In the PKM model, they fit in as agents that persuade the Academy, as they use their topic knowledge about the quality of films in order to inform and persuade the Academy. These assumptions were found to be true, as the predictive power of critics remained relatively stable for every degree of critical recognition (H3A), especially when compared to the public reception. This makes sense, given that a higher degree of critical recognition should mean that a film is of higher quality.

Furthermore, it was found that the critical reception has a moderate influence on the box office of a film (H3B), which confirms the research by Eliahberg and Shugan (1997), who found that critics can be seen as predictors of the box office. Furthermore, this finding confirms that is indeed logical, from a business perspective, to implement review embargos for movies that do not meet the quality standards of critics, in order to limit negative word of mouth from spreading (Barusoy et al., 2003).

Finally, just like with the public reception models, it was found that only a few of the mediation models for the critical reception hold (H3C). This could, one again, be explained by the assumption that the Academy simply cares more about the critical reception than the box office, which was also evidenced by the individual models. Nevertheless, some mediation models were found to hold; most notably, the Oscar winner models were found to be the strongest, which is somewhat logical considering that these films are of higher quality than the nominated-only films, whose models were best predicted by the public reception. The big five models formed the outlier, as they constitute of the highest degree of critical recognition, yet mediation was found to be weak.

Again, given the decrease of significance for most of the *b'* coefficients during mediation, it almost seemed to be the case that mediation works the other way around, with the critical reception acting as mediator, and box office as independent variable. Again, this line of thought is nonsensical, given that it is illogical to assume that a good box office performance stimulates more positive reviews, especially considering the high ethical standard of critics (Dellavigna & Hermle, 2016). Besides, review embargoes are always lifted before the official release, which means that a vast majority of the reviews are always posted online before a film is playing in theaters (Fine, 2016).

5.2 Conclusion

The research question for this study was:

RQ: To what extent can the critical reception, public reception and box office performance of a film predict its critical recognition at the Oscars?

During the previous results and discussion sections, it was found that most of the hypotheses were found to be true. Some of the hypotheses that went a little deeper by combining previous assumptions were found to be only partly true, but no hypothesis was outright rejected. The answer to the research question could be summarized like:

Overall, it was found that the reception of a film can predict its critical recognition. The box office was found to be a moderate predictor of critical recognition (when proposed in reverse, this was also true, yet to a lesser extent), and its effect decreased as the amount of critical recognition increased. The public reception was found to be a moderate (although strong for nominations/lower degree of critical recognition) predictor for critical recognition and a strong predictor for the box office performance. When used together in a mediation model, however, it was found that the relation between public reception and critical recognition is only partly explained through the box office performance, and mostly the case for a lower degree of critical recognition. Finally, the critical reception was found to be the strongest predictor of critical recognition (also the most stable across every degree of critical recognition), and moderate for the box office performance. Again, when used in a mediation model with the box office, it was found that the relation between critical reception and critical *recognition is only partly explained through the box office performance, the strongest being through the Oscar winners (second degree of critical recognition).*

For the movie producers, this result first and foremost stresses that making quality entertainment helps with gathering more critical recognition, which in the long run leads to a higher box office for the entire studio, as they can hire better filmmaking talent (Kalb, 2013). Furthermore, it was also found that pushing movies that traditionally do well at the Oscars are still the movies that obtain the highest rewards. Pushing big audience movies, or blockbusters, for consideration for a higher, degree of critical recognition does not seem to be a very logical business move, although it was hinted that from an economical standpoint, this could change in the future, as it is one way for the Academy to lure in more viewers for the ceremony.

In scientific regard, this research clarified some of the conflicting findings between previous research (e.g. the question as to whether critics are influencers or predictors), supported some previous research, and contrasted some earlier research, all of which has been outlined during the discussion. Furthermore, this research opened new research gaps, which could be topics for future research, and will be outlined in the next paragraph.

5.3 Limitations and future research

As is the case with any study, this research had its limitations, some of which have already been stated during the previous chapters. For example, this research only focused on a part (although the most relevant part) of the box office. Using the worldwide box office would result into more accurate result, although it could be argued that there is also a trade-off in the sense that the researchers would be forced to only focus on more recent movies, considering older movies with a smaller theatrical release do not have their worldwide box office reported, which would result in another validity issue. Moreover, other operational extensions may include data from the years not collected in this study.

Secondly, the measures of the critical reception and public reception could be improved by broadening the way in which they were measured. During the paper, it was argued that average scores are the best method of measuring the public and critical reception of a film, and although this argument should be supported, there are ways of improving the measurement, in particular for the public reception. The Cinemascore is an average that is calculated based on a poll of random American moviegoers at the theaters, but they are not available for every film. This is a limitation that can be omitted from future research by distributing a random survey on the internet, and asking people to rate the films included in the sample. By doing so, future research could also omit the issue of self-selection that was included here through the usage of IMDb scores. Furthermore, using content analysis or automated methods such as sentiment analysis can provide alternate insights into the subject.

Thirdly, there are opportunities for future research to build on some of the questions that this research left. These questions are:

- ✓ Why do Oscar wins boost the box office performance, but not the box office for winners in the 'big five' category? (this was also suggested for future research by Deuchert et al., 2005).
- ✓ Why does critical recognition (in a general sense) boost the box office performance, but not the home media/streaming sales, as suggested by Jozefowicz et al. (2008)? Or, has the article become outdated due to the assumed change of consumption on the ancillary market (Lopez, 2018; (Turkyilmaz et al., 2015)?
- ✓ Why is mediation weak, and only partial, for the critical and public reception models, especially when considering that all of the individual relationships are significant?
- ✓ Why does the predictive value of critical reception predicting the critical recognition (when mediated through the box office prior to the Oscar ceremony) decrease when predicting the Oscar wins in the 'big five' category (when mediated through the box office prior to the Oscar ceremony), compared to all Oscar winners?
- ✓ When predicting critical recognition, why is the budget almost completely insignificant when predicting with critical reception together (in fact, it was found to be significant in the opposite direction for nominations and wins with the negative binominal models), but less so when it comes to predicting with the public reception together?

Finally, this research was quite broad in its execution. Measurements were collected from ‘big data’ sources that represented many individuals’ opinions, and they were predicting a critical recognition number. It could be interesting, however, to focus more on some of the smaller aspects that were only briefly mentioned during this research, such as the ‘genre’ categories, for example. A few concrete ideas regarding this line of thought in particular:

- ✓ The list of ‘best visual effects’ nominees mostly consists of big audience movies/Blockbusters (as these films have a larger budget, and require a lot of visual effects work in general). How much stronger is the effect of the public reception on critical recognition in this category when compared to the other categories?
- ✓ ‘Best cinematography’ is a category that a film can be rewarded for based purely on artistic and visual merits. Given that critics should be more appreciative of this (given their higher artistic standard), how much stronger is the effect of critical reception on critical recognition in this category when compared to the other categories?
- ✓ How much of an effect does genre have? How much do the chances of being critically recognized decrease when not being a film that traditionally appeals to the Oscars? (this would also build on previous research that delved into the relation of genre and box office from Gemser, Leenders and Wijnberg (2007)).
- ✓ To what extent has time effected critical recognition? Have the effects of the three receptive factors grown stronger with the rise of Web 2.0? (this would form an extension for the research by Amatriain, Lathia, Pujol, Kwak and Oliver (2009), who argued that the influence of Rotten Tomatoes on the public has been growing with the rise of Web 2.0).

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Appendix A: Socio-demographics

Genre - full sample

Action genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	208	71,7	71,7	71,7
	Yes	82	28,3	28,3	100,0
	Total	290	100,0	100,0	

Adventure genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	230	79,3	79,3	79,3
	Yes	60	20,7	20,7	100,0
	Total	290	100,0	100,0	

Animation genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	276	95,2	95,2	95,2
	Yes	14	4,8	4,8	100,0
	Total	290	100,0	100,0	

Biography genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	266	91,7	91,7	91,7
	Yes	24	8,3	8,3	100,0
	Total	290	100,0	100,0	

Comedy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	184	63,4	63,4	63,4
	Yes	106	36,6	36,6	100,0
	Total	290	100,0	100,0	

Crime genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	233	80,3	80,3	80,3
	Yes	57	19,7	19,7	100,0
	Total	290	100,0	100,0	

Documentary genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	288	99,3	99,3	99,3
	Yes	2	,7	,7	100,0
	Total	290	100,0	100,0	

Drama genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	148	51,0	51,0	51,0
	Yes	142	49,0	49,0	100,0
	Total	290	100,0	100,0	

Family genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	275	94,8	94,8	94,8
	Yes	15	5,2	5,2	100,0
	Total	290	100,0	100,0	

Fantasy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	257	88,6	88,6	88,6
	Yes	33	11,4	11,4	100,0
	Total	290	100,0	100,0	

History genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	280	96,6	96,6	96,6
	Yes	10	3,4	3,4	100,0

	Total	290	100,0	100,0	

Horror genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	263	90,7	90,7	90,7
	Yes	27	9,3	9,3	100,0
	Total	290	100,0	100,0	

Music genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	281	96,9	96,9	96,9
	Yes	9	3,1	3,1	100,0
	Total	290	100,0	100,0	

Musical genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	289	99,7	99,7	99,7
	Yes	1	,3	,3	100,0
	Total	290	100,0	100,0	

Mystery genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	266	91,7	91,7	91,7
	Yes	24	8,3	8,3	100,0
	Total	290	100,0	100,0	

Romance genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	234	80,7	80,7	80,7
	Yes	56	19,3	19,3	100,0
	Total	290	100,0	100,0	

Scifi genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	268	92,4	92,4	92,4
	Yes	22	7,6	7,6	100,0
	Total	290	100,0	100,0	

Sports genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	285	98,3	98,3	98,3
	Yes	5	1,7	1,7	100,0
	Total	290	100,0	100,0	

Thriller genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	239	82,4	82,4	82,4
	Yes	51	17,6	17,6	100,0
	Total	290	100,0	100,0	

War genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	288	99,3	99,3	99,3
	Yes	2	,7	,7	100,0
	Total	290	100,0	100,0	

Western genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	287	99,0	99,0	99,0
	Yes	3	1,0	1,0	100,0
	Total	290	100,0	100,0	

Genre – Oscar nominated films

Action genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	77	89,5	89,5	89,5
	Yes	9	10,5	10,5	100,0
	Total	86	100,0	100,0	

Adventure genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	69	80,2	80,2	80,2
	Yes	17	19,8	19,8	100,0
	Total	86	100,0	100,0	

Animation genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	80	93,0	93,0	93,0
	Yes	6	7,0	7,0	100,0
	Total	86	100,0	100,0	

Biography genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	67	77,9	77,9	77,9
	Yes	19	22,1	22,1	100,0
	Total	86	100,0	100,0	

Comedy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	68	79,1	79,1	79,1
	Yes	18	20,9	20,9	100,0
	Total	86	100,0	100,0	

Crime genre?

		Frequency	Percent	Valid Percent	Cumulative Percent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	71	82,6	82,6	82,6
	Yes	15	17,4	17,4	100,0
	Total	86	100,0	100,0	

Documentary genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	85	98,8	98,8	98,8
	Yes	1	1,2	1,2	100,0
	Total	86	100,0	100,0	

Drama genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	21	24,4	24,4	24,4
	Yes	65	75,6	75,6	100,0
	Total	86	100,0	100,0	

Family genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	84	97,7	97,7	97,7
	Yes	2	2,3	2,3	100,0
	Total	86	100,0	100,0	

Fantasy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	73	84,9	84,9	84,9
	Yes	13	15,1	15,1	100,0
	Total	86	100,0	100,0	

History genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	78	90,7	90,7	90,7
	Yes	8	9,3	9,3	100,0
	Total	86	100,0	100,0	

Horror genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	85	98,8	98,8	98,8
	Yes	1	1,2	1,2	100,0
	Total	86	100,0	100,0	

Music genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	82	95,3	95,3	95,3
	Yes	4	4,7	4,7	100,0
	Total	86	100,0	100,0	

Musical genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	85	98,8	98,8	98,8
	Yes	1	1,2	1,2	100,0
	Total	86	100,0	100,0	

Mystery genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	81	94,2	94,2	94,2
	Yes	5	5,8	5,8	100,0
	Total	86	100,0	100,0	

Romance genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	69	80,2	80,2	80,2
	Yes	17	19,8	19,8	100,0
	Total	86	100,0	100,0	

Scifi genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	82	95,3	95,3	95,3
	Yes	4	4,7	4,7	100,0

	Total	86	100,0	100,0	

Sports genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	85	98,8	98,8	98,8
	Yes	1	1,2	1,2	100,0
	Total	86	100,0	100,0	

Thriller genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	76	88,4	88,4	88,4
	Yes	10	11,6	11,6	100,0
	Total	86	100,0	100,0	

War genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	85	98,8	98,8	98,8
	Yes	1	1,2	1,2	100,0
	Total	86	100,0	100,0	

Western genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	86	100,0	100,0	100,0

Genre – Oscar winning films

Action genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	54	96,4	96,4	96,4
	Yes	2	3,6	3,6	100,0
	Total	56	100,0	100,0	

Adventure genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	89,3	89,3	89,3
	Yes	6	10,7	10,7	100,0
	Total	56	100,0	100,0	

Animation genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	55	98,2	98,2	98,2
	Yes	1	1,8	1,8	100,0
	Total	56	100,0	100,0	

Biography genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	42	75,0	75,0	75,0
	Yes	14	25,0	25,0	100,0
	Total	56	100,0	100,0	

Comedy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	48	85,7	85,7	85,7
	Yes	8	14,3	14,3	100,0
	Total	56	100,0	100,0	

Crime genre?

		Frequency	Percent	Valid Percent	Cumulative Percent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	44	78,6	78,6	78,6
	Yes	12	21,4	21,4	100,0
	Total	56	100,0	100,0	

Documentary genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	55	98,2	98,2	98,2
	Yes	1	1,8	1,8	100,0
	Total	56	100,0	100,0	

Drama genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	6	10,7	10,7	10,7
	Yes	50	89,3	89,3	100,0
	Total	56	100,0	100,0	

Family genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	56	100,0	100,0	100,0

Fantasy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	51	91,1	91,1	91,1
	Yes	5	8,9	8,9	100,0
	Total	56	100,0	100,0	

History genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	49	87,5	87,5	87,5
	Yes	7	12,5	12,5	100,0
	Total	56	100,0	100,0	

Horror genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	55	98,2	98,2	98,2
	Yes	1	1,8	1,8	100,0
	Total	56	100,0	100,0	

Music genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	53	94,6	94,6	94,6
	Yes	3	5,4	5,4	100,0
	Total	56	100,0	100,0	

Musical genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	56	100,0	100,0	100,0

Mystery genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	51	91,1	91,1	91,1
	Yes	5	8,9	8,9	100,0
	Total	56	100,0	100,0	

Romance genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	44	78,6	78,6	78,6
	Yes	12	21,4	21,4	100,0
	Total	56	100,0	100,0	

Scifi genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	54	96,4	96,4	96,4
	Yes	2	3,6	3,6	100,0
	Total	56	100,0	100,0	

Sports genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	55	98,2	98,2	98,2
	Yes	1	1,8	1,8	100,0
	Total	56	100,0	100,0	

Thriller genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	49	87,5	87,5	87,5
	Yes	7	12,5	12,5	100,0
	Total	56	100,0	100,0	

War genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	56	100,0	100,0	100,0

Western genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	56	100,0	100,0	100,0

Genre – Big five Oscar winning films

Action genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Adventure genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	47	94,0	94,0	94,0
	Yes	3	6,0	6,0	100,0
	Total	50	100,0	100,0	

Animation genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Biography genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	37	74,0	74,0	74,0
	Yes	13	26,0	26,0	100,0
	Total	50	100,0	100,0	

Comedy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	43	86,0	86,0	86,0
	Yes	7	14,0	14,0	100,0
	Total	50	100,0	100,0	

Crime genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	38	76,0	76,0	76,0
	Yes	12	24,0	24,0	100,0
	Total	50	100,0	100,0	

Documentary genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Drama genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	3	6,0	6,0	6,0
	Yes	47	94,0	94,0	100,0
	Total	50	100,0	100,0	

Family genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Fantasy genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	47	94,0	94,0	94,0
	Yes	3	6,0	6,0	100,0
	Total	50	100,0	100,0	

History genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	44	88,0	88,0	88,0
	Yes	6	12,0	12,0	100,0
	Total	50	100,0	100,0	

Horror genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	49	98,0	98,0	98,0
	Yes	1	2,0	2,0	100,0
	Total	50	100,0	100,0	

Music genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	47	94,0	94,0	94,0
	Yes	3	6,0	6,0	100,0
	Total	50	100,0	100,0	

Musical genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Mystery genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	45	90,0	90,0	90,0
	Yes	5	10,0	10,0	100,0
	Total	50	100,0	100,0	

Romance genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	38	76,0	76,0	76,0
	Yes	12	24,0	24,0	100,0
	Total	50	100,0	100,0	

Scifi genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	48	96,0	96,0	96,0
	Yes	2	4,0	4,0	100,0
	Total	50	100,0	100,0	

Sports genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	49	98,0	98,0	98,0
	Yes	1	2,0	2,0	100,0

	Total	50	100,0	100,0	

Thriller genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	43	86,0	86,0	86,0
	Yes	7	14,0	14,0	100,0
	Total	50	100,0	100,0	

War genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Western genre?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	50	100,0	100,0	100,0

Budget – entire sample

Descriptive Statistics	N	Minimum	Maximum	Mean	Std. Deviation
Budget of the film	290	$15,000	$250,000,000	$43,736,948.28	$45,020,951.040
Valid N (listwise)	290				

Budget – Oscar nominations

Descriptive Statistics	N	Minimum	Maximum	Mean	Std. Deviation
Budget of the film	86	$2,000,000	$250,000,000	$50,080,232.56	$57,798,442.520
Valid N (listwise)	86				

Budget – Oscar winners

Descriptive Statistics	N	Minimum	Maximum	Mean	Std. Deviation
Budget of the film	56	$2,000,000	$237,000,000	$35,766,071.43	$50,210,246.240
Valid N (listwise)	56				

Budget – Big 5 Oscar Winners

Descriptive Statistics	N	Minimum	Maximum	Mean	Std. Deviation
Budget of the film	50	$2,000,000	$200,000,000	$28,218,000.00	$36,182,607.670
Valid N (listwise)	50				

Appendix B: Statistical analyses

Reliability

Critical recognition

Reliability Statistics

Cronbach's Alpha	N of Items
,780	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Total number of oscar nominations	,72	3,636	,866	,774
Total number of oscar wins	1,59	10,554	,855	,535
Total number of oscar wins in the big 5 category	1,81	15,287	,861	,800

Public reception

Reliability Statistics

Cronbach's Alpha	N of Items
,617	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CInemascore_10	6,3820	1,223	,501	.
Current IMDB Score	7,0045	3,260	,501	.

Critical reception

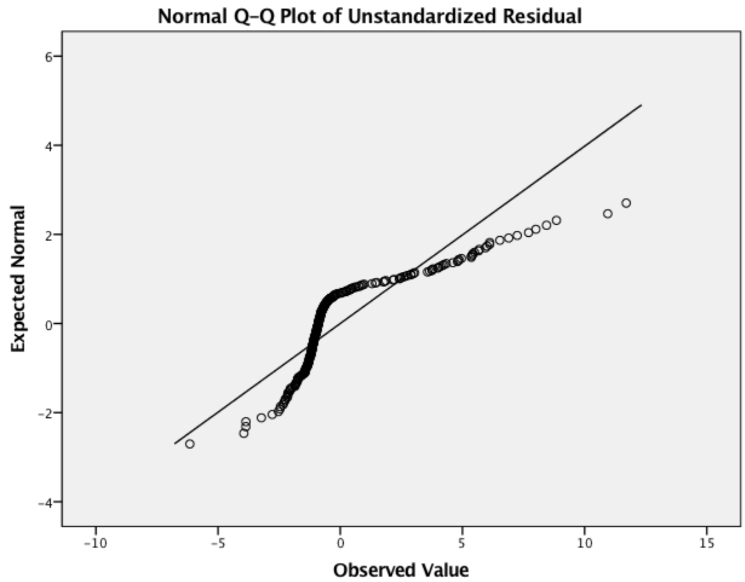
Reliability Statistics	
Cronbach's Alpha	N of Items
,910	2

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RT_Tomatometer_10	5,8431	2,744	,974	.
Average score given by critics	5,5014	8,566	,974	.

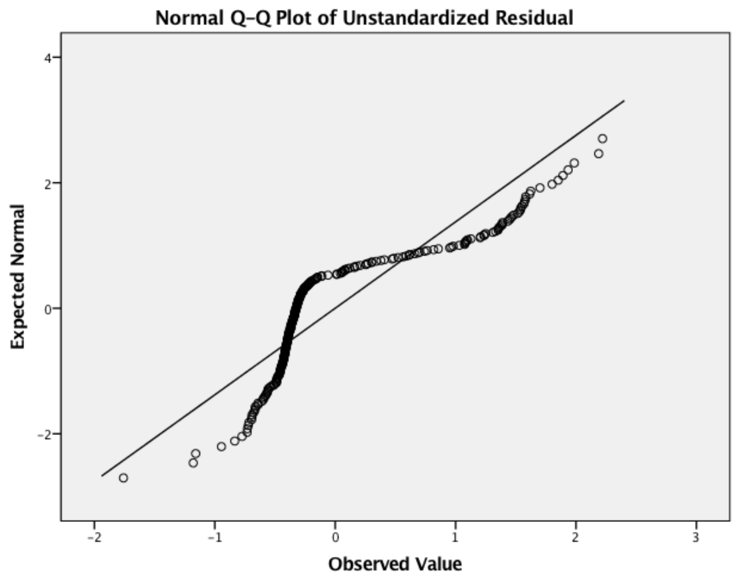
Normality (H1A-nominations)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,283	290	,000	,744	290	,000
Unstandardized Residual LN	,277	290	,000	,789	290	,000



Oscar_Nominations



LN_Oscar_Nominations

OLS Regression & constant error variance (H1A-nominations)

Model Summary[b]

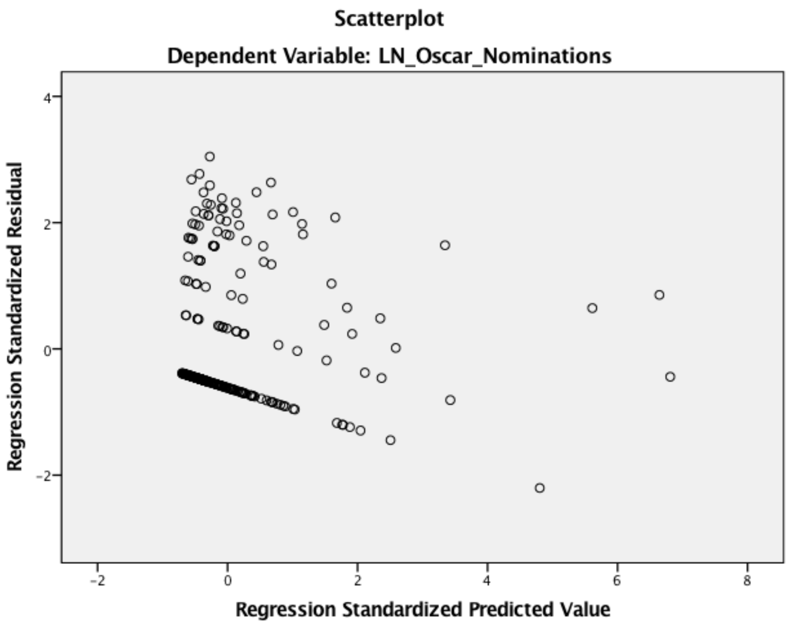
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,314[a]	,099	,096	,73855	,099	31,532	1	288

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,199	1	17,199	31,532	,000[b]
	Residual	157,090	288	,545		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance
1	(Constant)	,282	,053		5,304	,000	
	Pre_Domestic_Adjusted_100	,185	,033	,314	5,615	,000	1,000



Negative binomial regression (H1A-nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	478,902	288	1,663
Scaled Deviance	478,902	288	
Pearson Chi-Square	650,240	288	2,258
Scaled Pearson Chi-Square	650,240	288	
Log Likelihood[b]	-445,049		
Akaike's Information Criterion (AIC)	894,097		
Finite Sample Corrected AIC (AICC)	894,139		
Bayesian Information Criterion (BIC)	901,437		
Consistent AIC (CAIC)	903,437		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
37,823	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	,709	1	,400
Pre_Domestic_Adjusted_100	25,294	1	,000

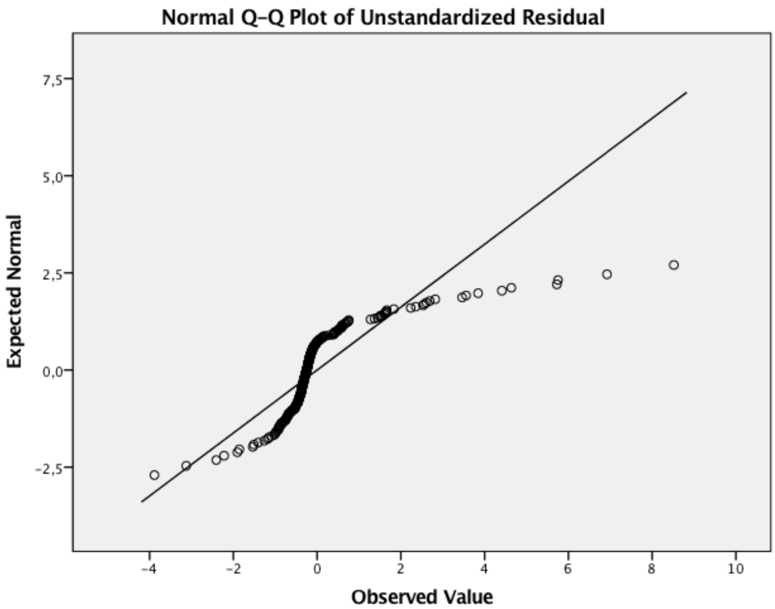
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-,086	,1025	-,287	,115	,709	1	,400
Pre_Domestic_Adjusted_100	,302	,0600	,184	,419	25,294	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

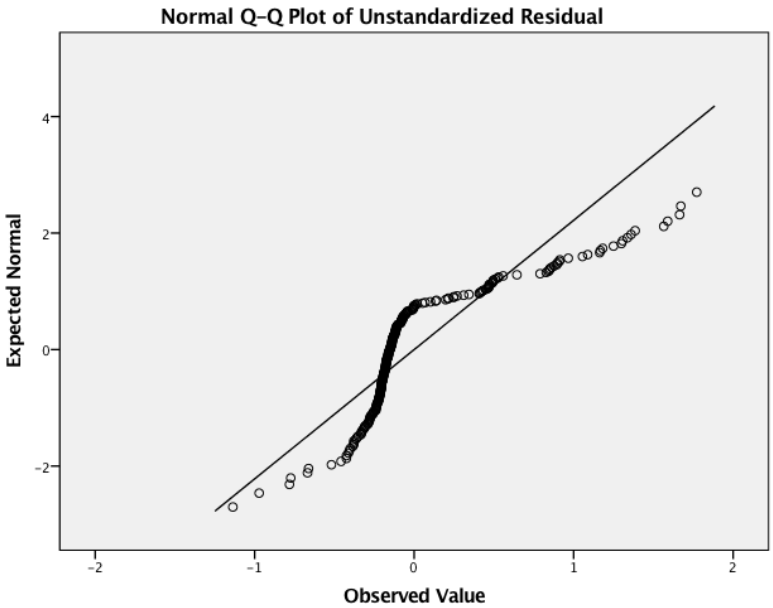
Normality (H1A-wins)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,271	290	,000	,658	290	,000
Unstandardized Residual LN	,284	290	,000	,746	290	,000



Oscar_Wins



LN_Oscar_Wins

OLS regression & constant error variance (H1A-wins)

Model Summary[b]

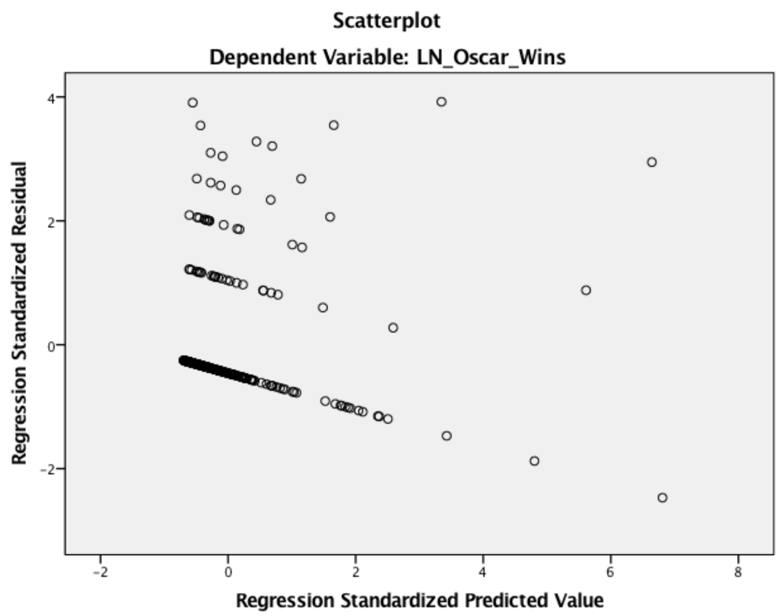
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,283[a]	,080	,077	,46301	,080	25,160	1	288

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,394	1	5,394	25,160	,000[b]
	Residual	61,740	288	,214		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
		B	Std. Error	Beta			Tolerance
1	(Constant)	,115	,033		3,451	,001	
	Pre_Domestic_Adjusted_100	,104	,021	,283	5,016	,000	1,000



Negative binomial regression (H1A-wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	279,095	288	,969
Scaled Deviance	279,095	288	
Pearson Chi-Square	518,182	288	1,799
Scaled Pearson Chi-Square	518,182	288	
Log Likelihood[b]	-245,069		
Akaike's Information Criterion (AIC)	494,138		
Finite Sample Corrected AIC (AICC)	494,180		
Bayesian Information Criterion (BIC)	501,478		
Consistent AIC (CAIC)	503,478		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
43,471	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	83,854	1	,000
Pre_Domestic_Adjusted_100	31,161	1	,000

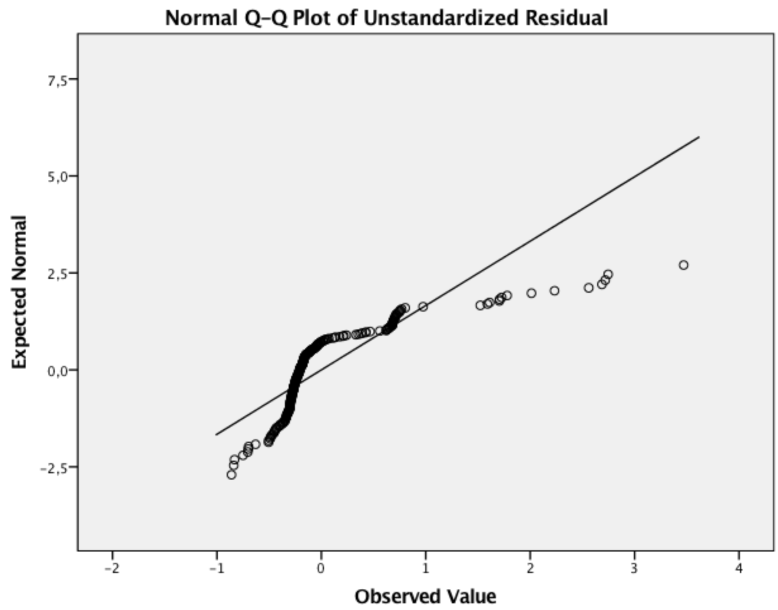
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-1,279	,1396	-1,552	-1,005	83,854	1	,000
Pre_Domestic_Adjusted_100	,363	,0650	,235	,490	31,161	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

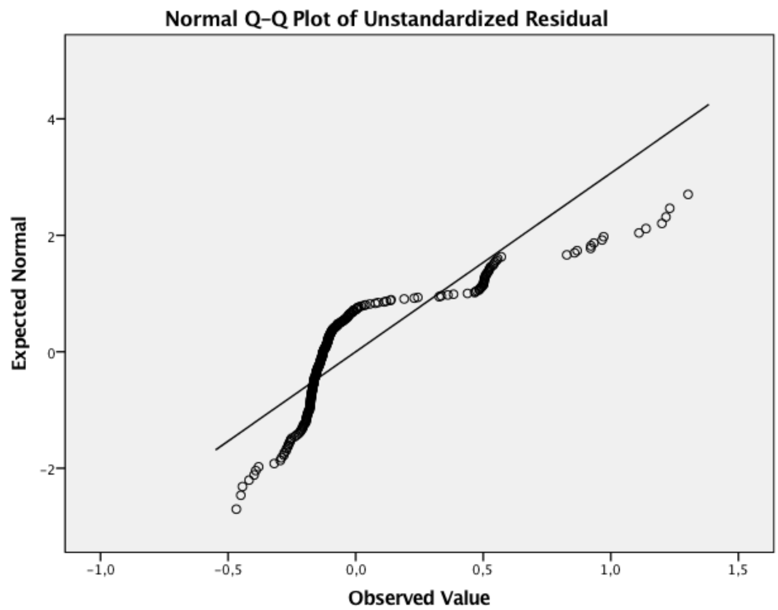
Normality (H1A-wins_big5)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,272	290	,000	,667	290	,000
Unstandardized Residual	,276	290	,000	,719	290	,000



Oscar_Wins_Big5



LN_Oscar_Wins_Big5

OLS regression & constant error variance (H1A-wins_Big5)

Model Summary[b]

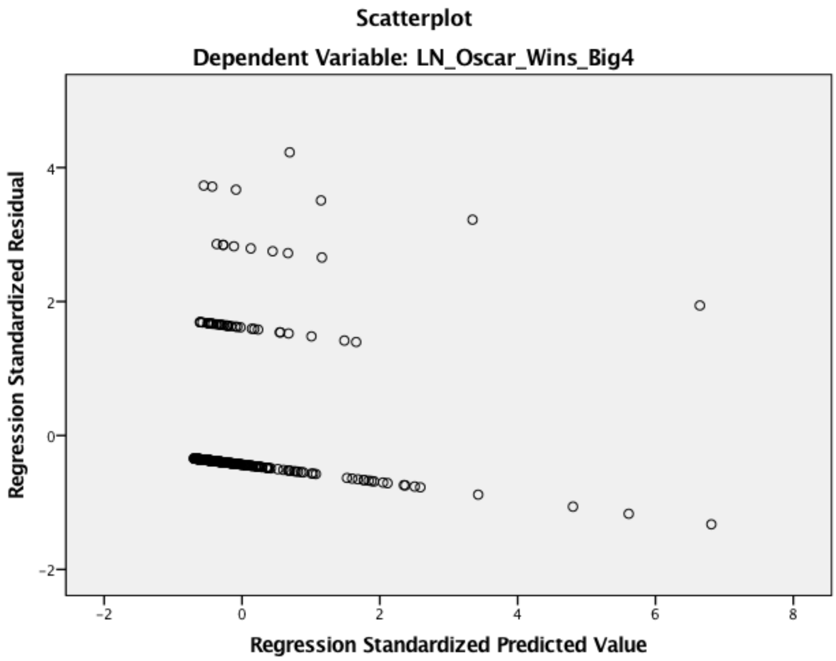
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,130[a]	,017	,013	,33864	,017	4,947	1	288

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,567	1	,567	4,947	,027[b]
	Residual	33,027	288	,115		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance
1	(Constant)	,116	,024		4,736	,000	
	Pre_Domestic_Adjusted_100	,034	,015	,130	2,224	,027	1,000



Negative binomial regression (H1A-wins_big5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	196,756	288	,683
Scaled Deviance	196,756	288	
Pearson Chi-Square	348,164	288	1,209
Scaled Pearson Chi-Square	348,164	288	
Log Likelihood[b]	-177,833		
Akaike's Information Criterion (AIC)	359,666		
Finite Sample Corrected AIC (AICC)	359,707		
Bayesian Information Criterion (BIC)	367,005		
Consistent AIC (CAIC)	369,005		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
5,514	1	,019

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	96,429	1	,000
Pre_Domestic_Adjusted_100	5,770	1	,016

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-1,608	,1637	-1,929	-1,287	96,429	1	,000
Pre_Domestic_Adjusted_100	,189	,0785	,035	,343	5,770	1	,016
(Scale)	1[a]						
(Negative binomial)	1[a]						

Collinearity H1B

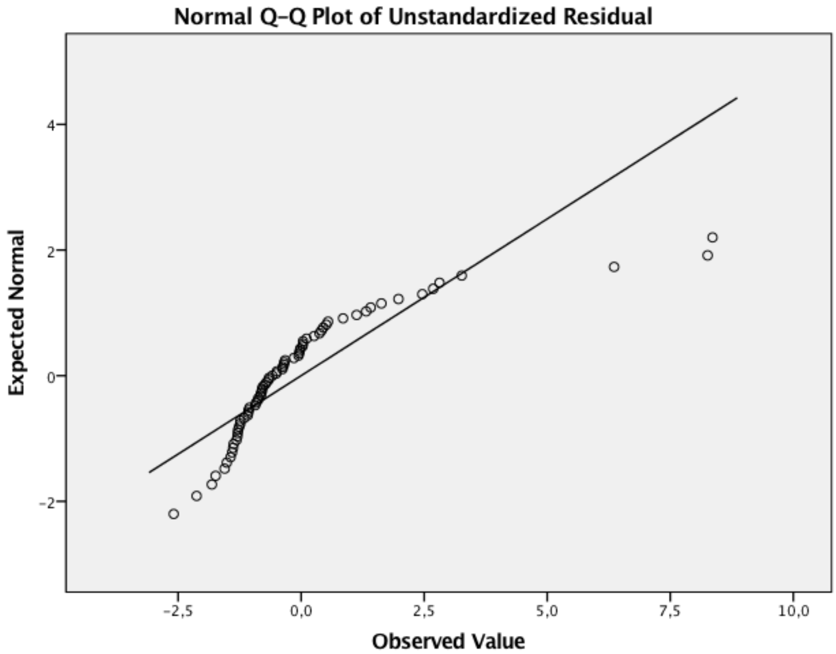
Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Total number of oscar nominations	,352	2,839
	Total number of oscar wins	,331	3,020
	Total number of oscar wins in the big 5 category	,412	2,430

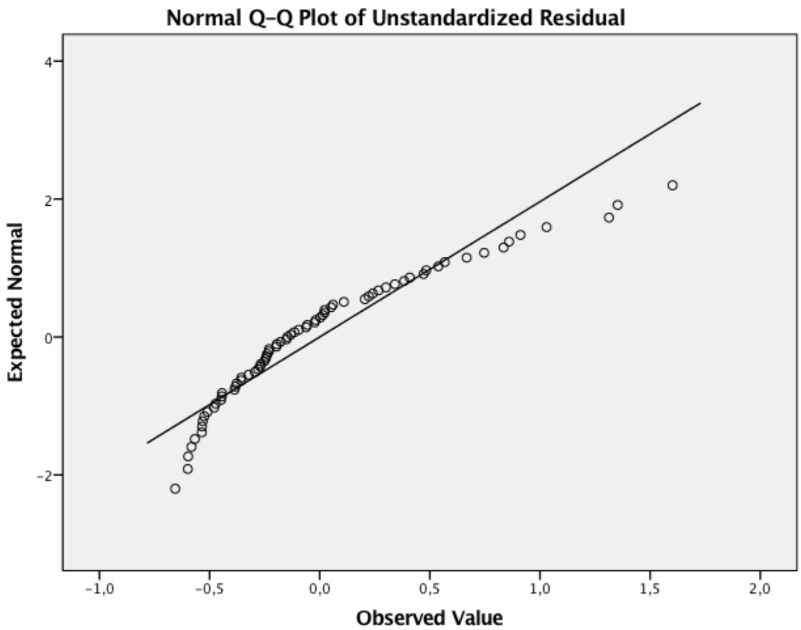
Normality (H1B-nominations)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,211	71	,000	,722	71	,000
Unstandardized Residual LN	,144	71	,001	,897	71	,000



Post_Domestic_Adjusted_100



LN_ Post_Domestic_Adjusted_100

OLS regression & constant error variance (H1B-nominations)

Model Summary[b]

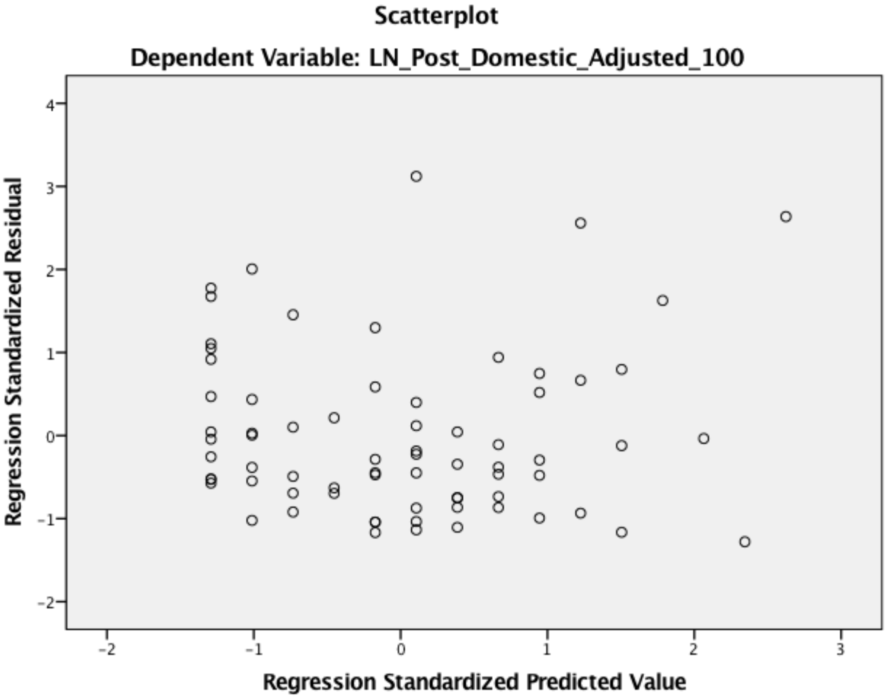
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,302[a]	,091	,078	,51321	,091	6,911	1	69

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,820	1	1,820	6,911	,011[b]
	Residual	18,174	69	,263		
	Total	19,994	70			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,564	,100		5,640	,000
	Total number of oscar nominations	,045	,017	,302	2,629	,011



Negative binomial regression (H1B – nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	228,721	288	,794
Scaled Deviance	228,721	288	
Pearson Chi-Square	257,912	288	,896
Scaled Pearson Chi-Square	257,912	288	
Log Likelihood[b]	-359,172		
Akaike's Information Criterion (AIC)	722,343		
Finite Sample Corrected AIC (AICC)	722,385		
Bayesian Information Criterion (BIC)	729,683		
Consistent AIC (CAIC)	731,683		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
34,938	1	,000

Tests of Model Effects

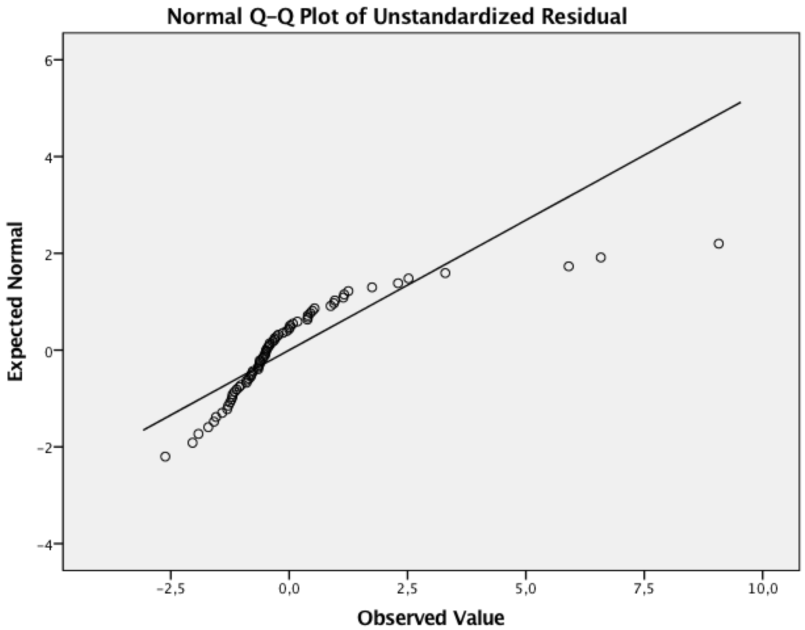
	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	18,712	1	,000
Total number of oscar nominations	30,360	1	,000

Parameter Estimates

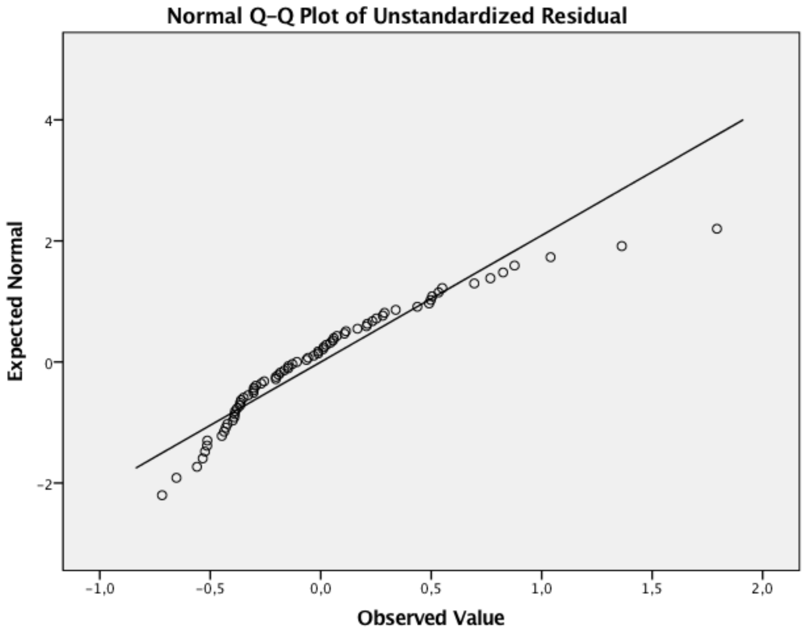
			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-,446	,1031	-,648	-,244	18,712	1	,000
Total number of oscar nominations	,150	,0273	,097	,204	30,360	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Normality (H1B-wins)

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,204	71	,000	,716	71	,000
Unstandardized Residual LN	,115	71	,021	,905	71	,000



Post_Domestic_Adjusted_100



LN_ Post_Domestic_Adjusted_100

OLS regression & constant error variance (H1B-wins)

Model Summary[b]

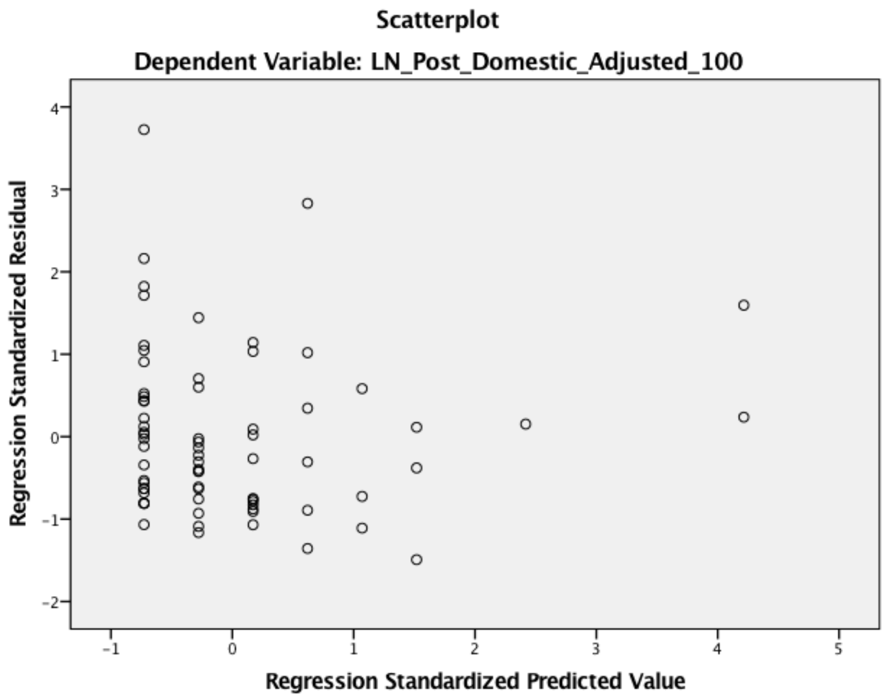
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,448[a]	,200	,189	,48138	,200	17,283	1	69

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,005	1	4,005	17,283	,000[b]
	Residual	15,989	69	,232		
	Total	19,994	70			

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,598	,071		8,444	,000
	Total number of oscar wins	,107	,026	,448	4,157	,000



Negative binomial regression (H1B –wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	237,133	288	,823
Scaled Deviance	237,133	288	
Pearson Chi-Square	297,553	288	1,033
Scaled Pearson Chi-Square	297,553	288	
Log Likelihood[b]	-363,378		
Akaike's Information Criterion (AIC)	730,755		
Finite Sample Corrected AIC (AICC)	730,797		
Bayesian Information Criterion (BIC)	738,095		
Consistent AIC (CAIC)	740,095		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
26,526	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	11,181	1	,001
Total number of oscar wins	18,880	1	,000

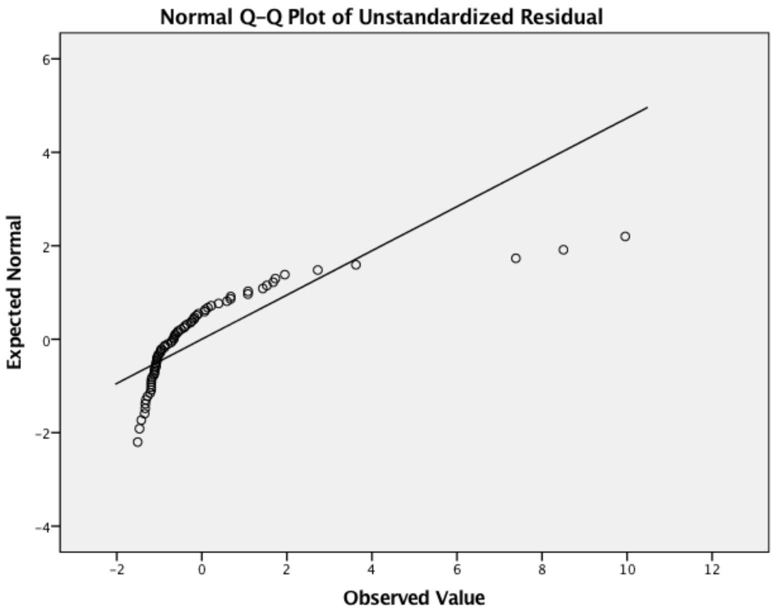
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-,316	,0944	-,500	-,131	11,181	1	,001
Total number of oscar wins	,226	,0519	,124	,327	18,880	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

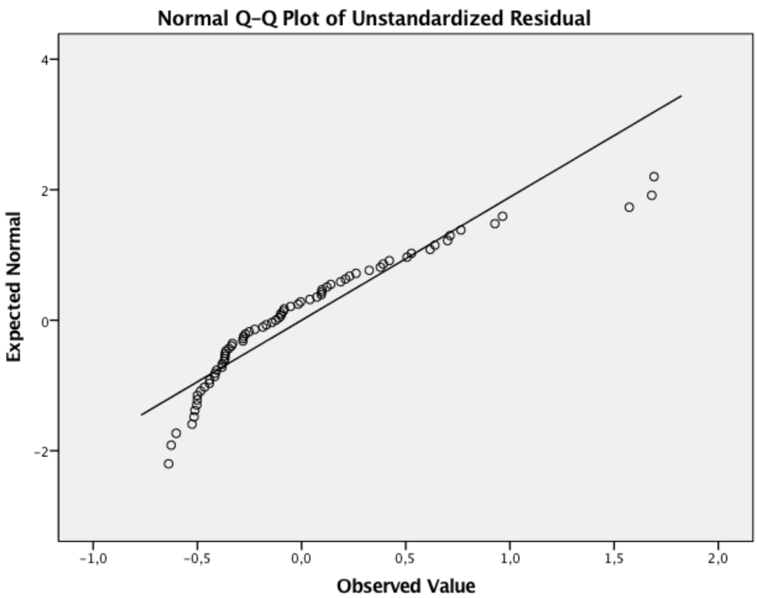
Normality (H1B-Wins_big5)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,238	71	,000	,605	71	,000
Unstandardized Residual LN	,140	71	,001	,864	71	,000



Post_Domestic_Adjusted_100



LN_Post_Domestic_Adjusted_100

OLS regression & constant error variance (H1B-wins_big5)

Model Summary[b]

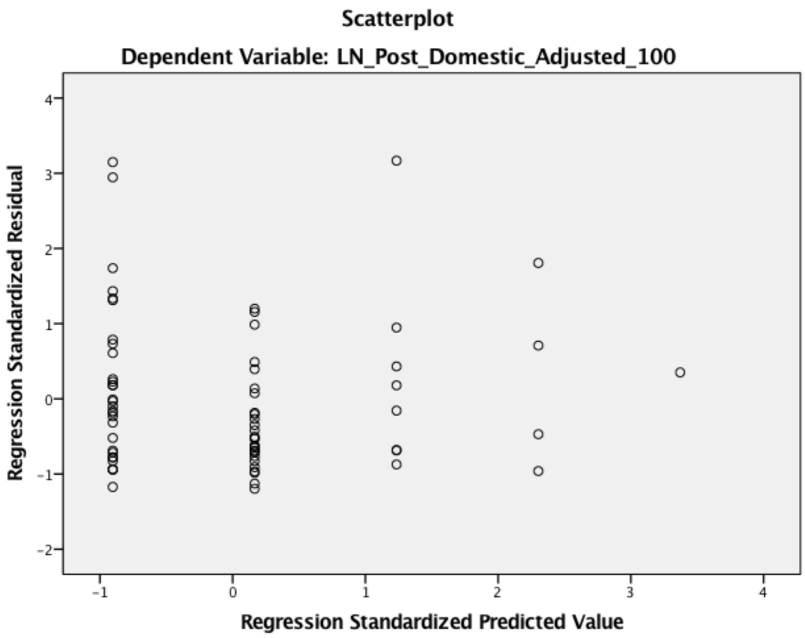
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,128[a]	,016	,002	,53386	,016	1,152	1	69

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,328	1	,328	1,152	,287[b]
	Residual	19,666	69	,285		
	Total	19,994	70			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,710	,086		8,294	,000
	Total number of oscar wins in the big 5 category	,073	,068	,128	1,073	,287



Negative binomial regression (H1B –wins big 5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	252,484	288	,877
Scaled Deviance	252,484	288	
Pearson Chi-Square	342,118	288	1,188
Scaled Pearson Chi-Square	342,118	288	
Log Likelihood[b]	-371,054		
Akaike's Information Criterion (AIC)	746,107		
Finite Sample Corrected AIC (AICC)	746,149		
Bayesian Information Criterion (BIC)	753,447		
Consistent AIC (CAIC)	755,447		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
11,174	1	,001

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	7,553	1	,006
Total number of oscar wins in the big 5 category	10,423	1	,001

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-,262	,0952	-,448	-,075	7,553	1	,006
Total number of oscar wins in the big 5 category	,385	,1193	,151	,619	10,423	1	,001
(Scale)	1[a]						
(Negative binomial)	1[a]						

Collinearity (H2A and H2B)

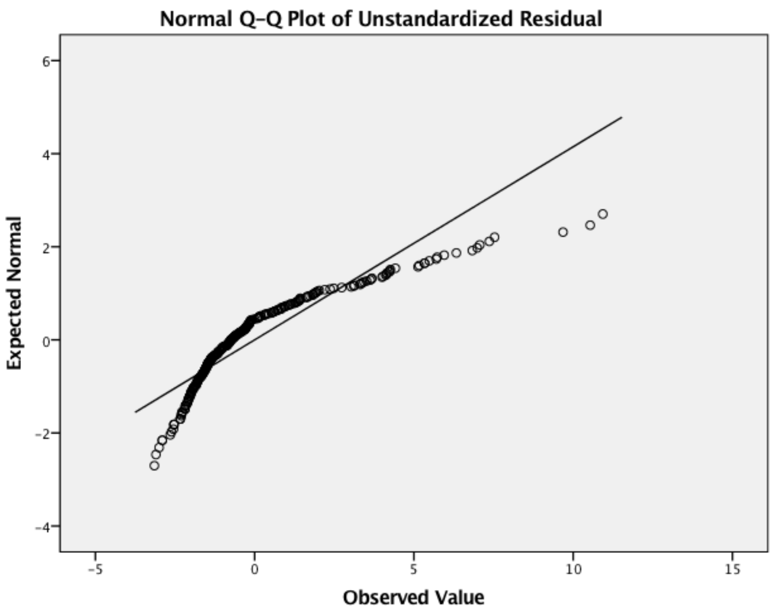
Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Public_reception	,955	1,047
	Budget_100	,955	1,047

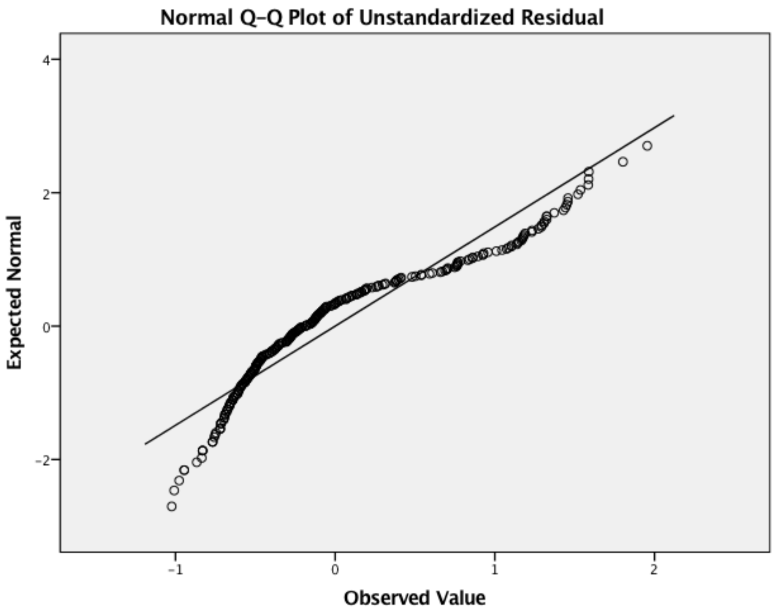
Normality (H2A-nominations)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,188	290	,000	,826	290	,000
Unstandardized Residual LN	,149	290	,000	,902	290	,000



Oscar_nominations

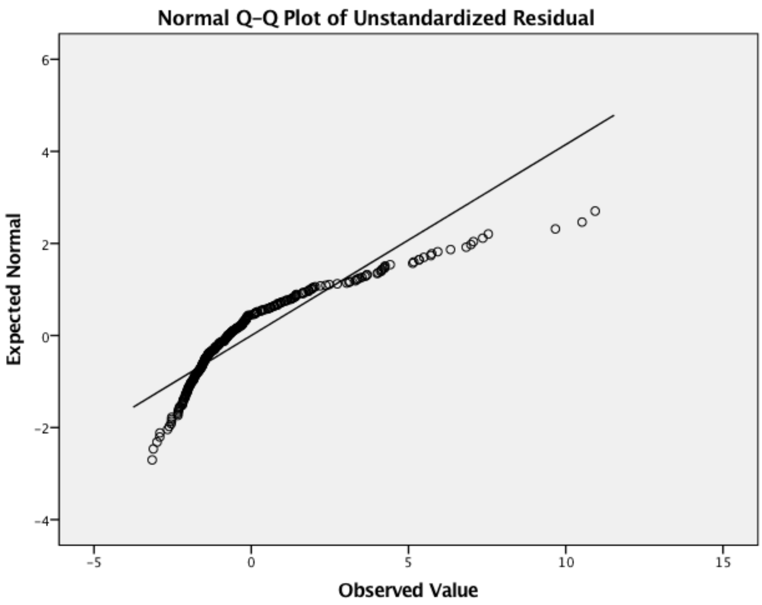


LN_Oscar_nominations

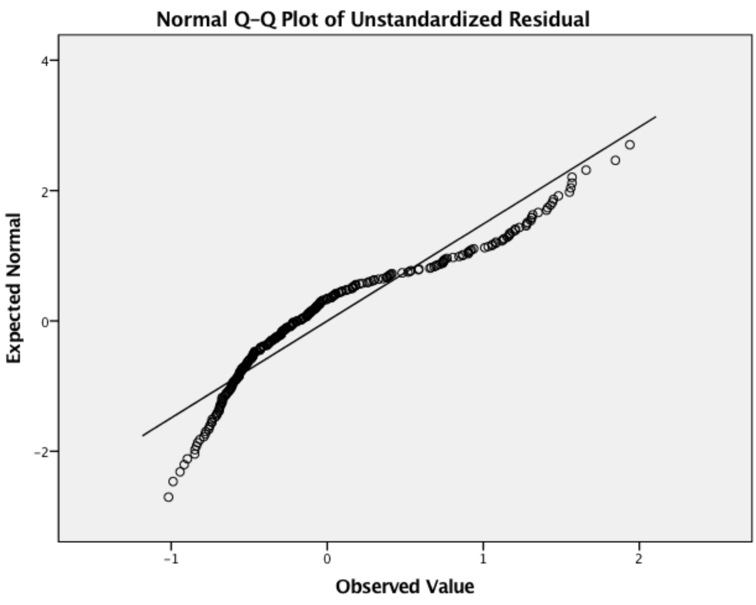
Normality (H2A-nominations & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,188	290	,000	,826	290	,000
Unstandardized Residual LN	,143	290	,000	,903	290	,000



Oscar_nominations



LN_Oscar_nominations

OLS regression & constant error variance (H2A-nominations & budget)

Model Summary[c]

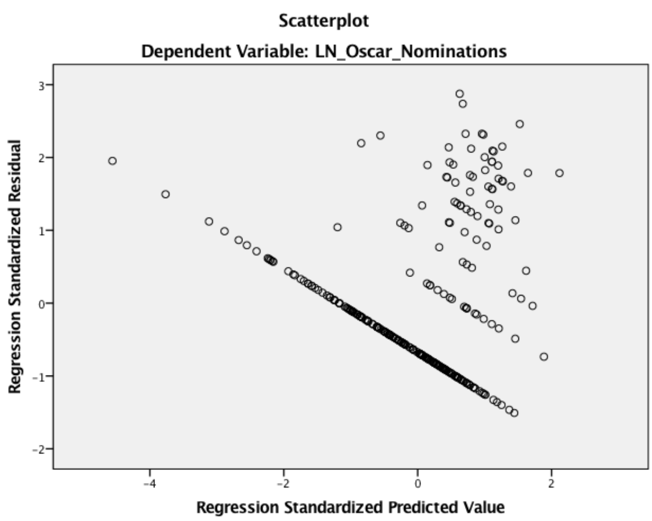
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,500[a]	,250	,247	,67370	,250	96,002	1	288
2	,501[b]	,251	,246	,67447	,001	,344	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	43,573	1	43,573	96,002	,000[b]
	Residual	130,717	288	,454		
	Total	174,290	289			
2	Regression	43,730	2	21,865	48,064	,000[c]
	Residual	130,560	287	,455		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1,668	,220		-7,569	,000
	Public_reception	,314	,032	,500	9,798	,000
2	(Constant)	-1,672	,221		-7,576	,000
	Public_reception	,318	,033	,506	9,690	,000
	Budget_100	-,053	,090	-,031	-,587	,558



Negative binomial regression (H2A- nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	296,676	288	1,030
Scaled Deviance	296,676	288	
Pearson Chi-Square	513,102	288	1,782
Scaled Pearson Chi-Square	513,102	288	
Log Likelihood[b]	-353,936		
Akaike's Information Criterion (AIC)	711,871		
Finite Sample Corrected AIC (AICC)	711,913		
Bayesian Information Criterion (BIC)	719,211		
Consistent AIC (CAIC)	721,211		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
220,049	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	115,789	1	,000
Public_reception	125,253	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-10,881	1,0112	-12,862	-8,899	115,789	1	,000
Public_reception	1,499	,1339	1,237	1,762	125,253	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H2A-nominations & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	294,959	287	1,028
Scaled Deviance	294,959	287	
Pearson Chi-Square	555,357	287	1,935
Scaled Pearson Chi-Square	555,357	287	
Log Likelihood[b]	-353,077		
Akaike's Information Criterion (AIC)	712,154		
Finite Sample Corrected AIC (AICC)	712,238		
Bayesian Information Criterion (BIC)	723,163		
Consistent AIC (CAIC)	726,163		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
221,767	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	115,441	1	,000
Public_reception	123,558	1	,000
Budget_100	,766	1	,184

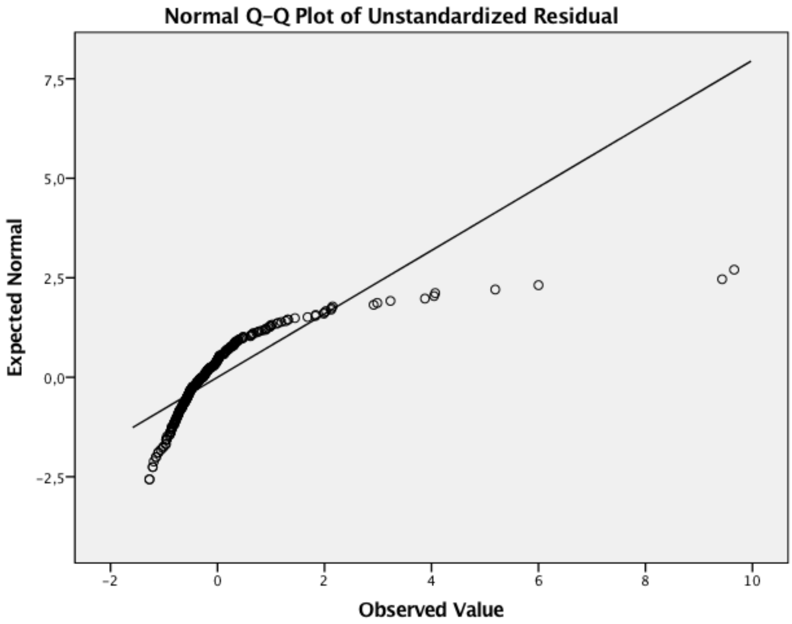
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-11,046	1,0281	-13,061	-9,031	115,441	1	,000
Public_reception	1,535	,1381	1,264	1,806	123,558	1	,000
Budget_100	-,236	,1773	-,583	,112	1,766	1	,184
(Scale)	1[a]						
(Negative binomial)	1[a]						

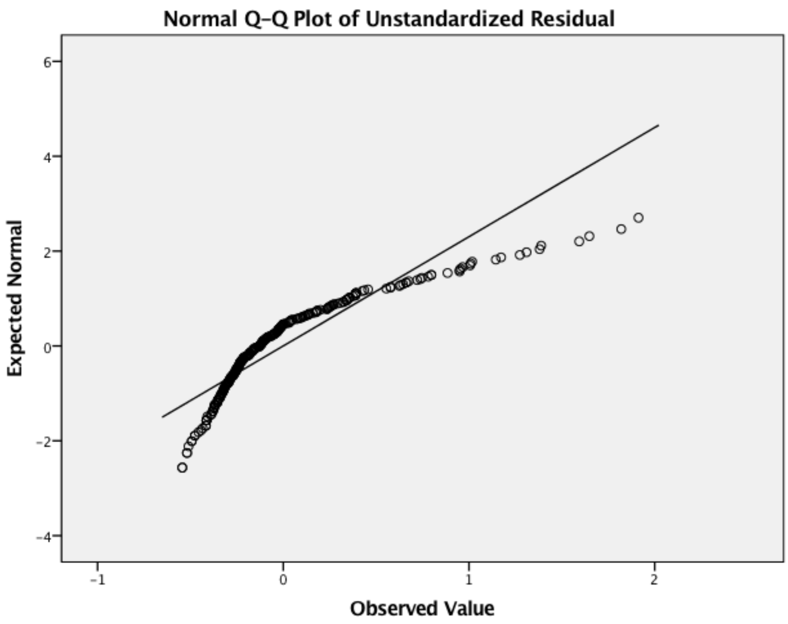
Normality (H2A- wins)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,211	290	,000	,618	290	,000
Unstandardized Residual LN	,183	290	,000	,820	290	,000



Oscar_Wins

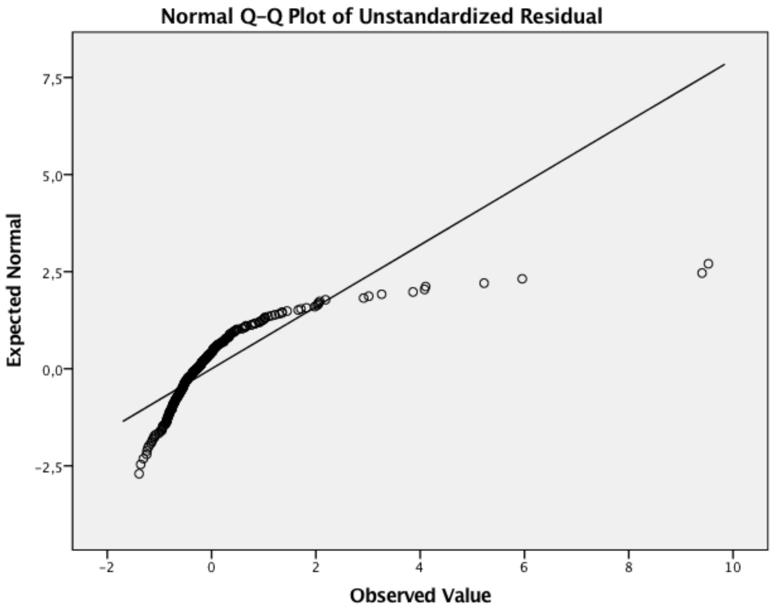


LN_Oscar_Wins

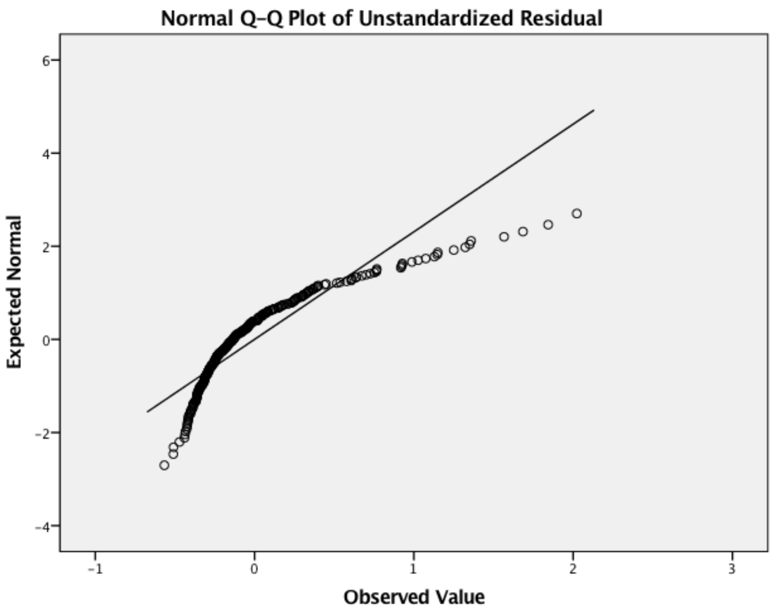
Normality (H2A-wins & budget))

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,207	290	,000	,627	290	,000
Unstandardized Residual LN	,162	290	,000	,810	290	,000



Oscar_Wins



LN_Oscar_Wins

OLS regression & constant error variance (H2A-wins & budget)

Model Summary[c]

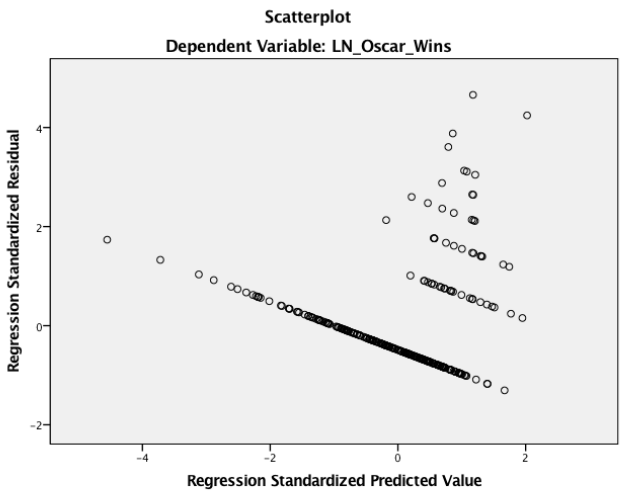
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,434[a]	,189	,186	,43489	,189	66,970	1	288
2	,440[b]	,194	,188	,43425	,005	1,843	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,666	1	12,666	66,970	,000[b]
	Residual	54,468	288	,189		
	Total	67,134	289			
2	Regression	13,013	2	6,507	34,505	,000[c]
	Residual	54,120	287	,189		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,933	,142		-6,557	,000
	Public_reception	,169	,021	,434	8,184	,000
2	(Constant)	-,939	,142		-6,609	,000
	Public_reception	,175	,021	,450	8,297	,000
	Budget_100	-,079	,058	-,074	-1,358	,176



Negative binomial regression (H2A- wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	165,253	288	,574
Scaled Deviance	165,253	288	
Pearson Chi-Square	269,958	288	,937
Scaled Pearson Chi-Square	269,958	288	
Log Likelihood[b]	-188,148		
Akaike's Information Criterion (AIC)	380,296		
Finite Sample Corrected AIC (AICC)	380,337		
Bayesian Information Criterion (BIC)	387,635		
Consistent AIC (CAIC)	389,635		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
157,314	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	81,953	1	,000
Public_reception	77,697	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-14,410	1,5918	-17,530	-11,291	81,953	1	,000
Public_reception	1,804	,2047	1,403	2,205	77,697	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H2A-wins & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	161,121	287	,561
Scaled Deviance	161,121	287	
Pearson Chi-Square	270,054	287	,941
Scaled Pearson Chi-Square	270,054	287	
Log Likelihood[b]	-186,082		
Akaike's Information Criterion (AIC)	378,164		
Finite Sample Corrected AIC (AICC)	378,248		
Bayesian Information Criterion (BIC)	389,173		
Consistent AIC (CAIC)	392,173		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
161,446	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	79,294	1	,000
Public_reception	74,435	1	,000
Budget_100	4,065	1	,044

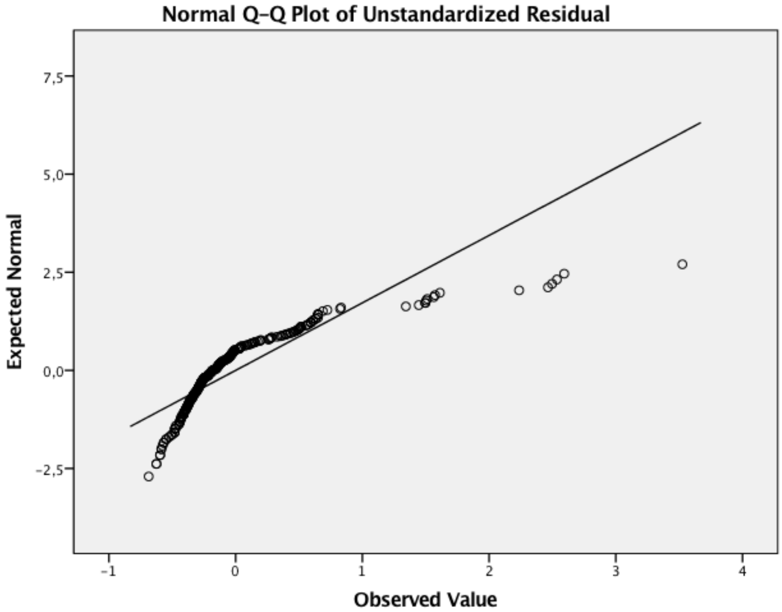
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-15,371	1,7262	-18,754	-11,988	79,294	1	,000
Public_reception	1,959	,2271	1,514	2,404	74,435	1	,000
Budget_100	-,480	,2382	-,947	-,013	4,065	1	,044
(Scale)	1[a]						
(Negative binomial)	1[a]						

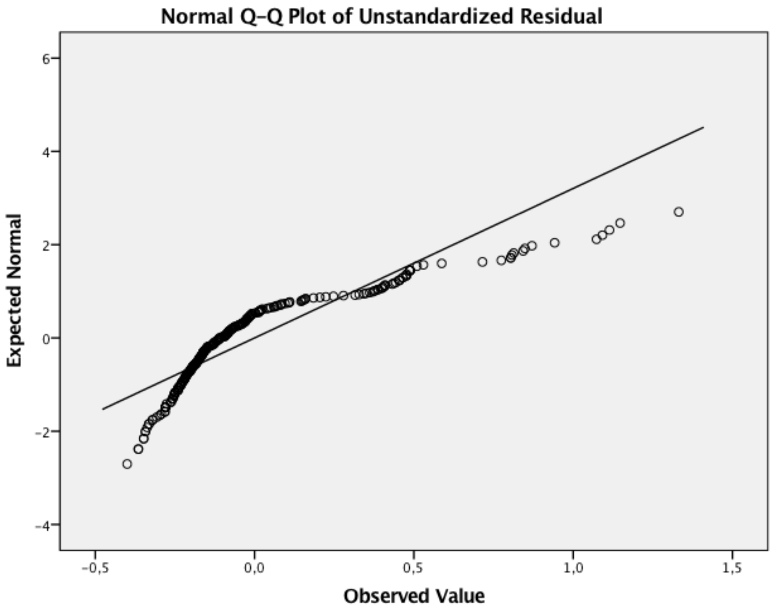
Normality (H2A-wins_big5)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,208	290	,000	,734	290	,000
Unstandardized Residual LN	,213	290	,000	,807	290	,000



Oscar_Wins_Big5

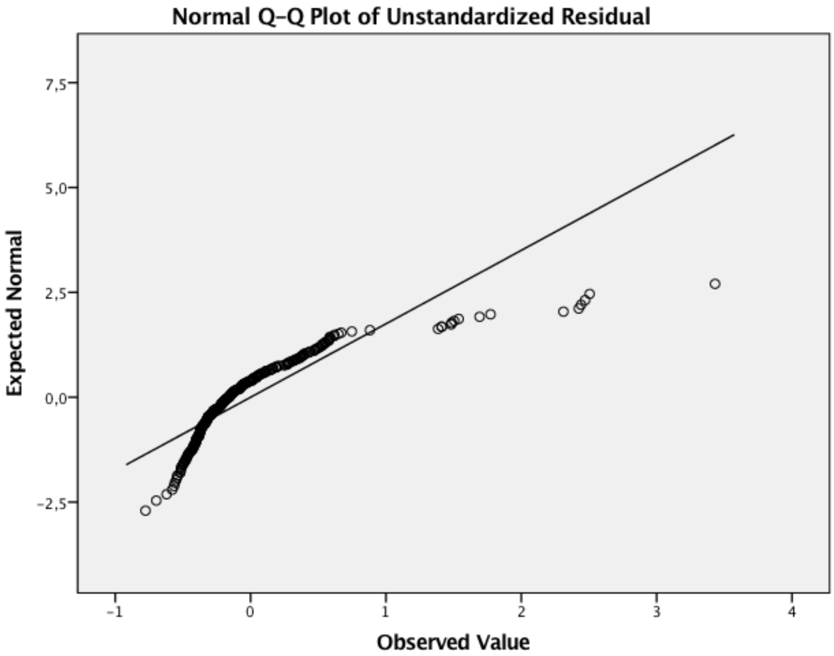


LN_Oscar_Wins_Big5

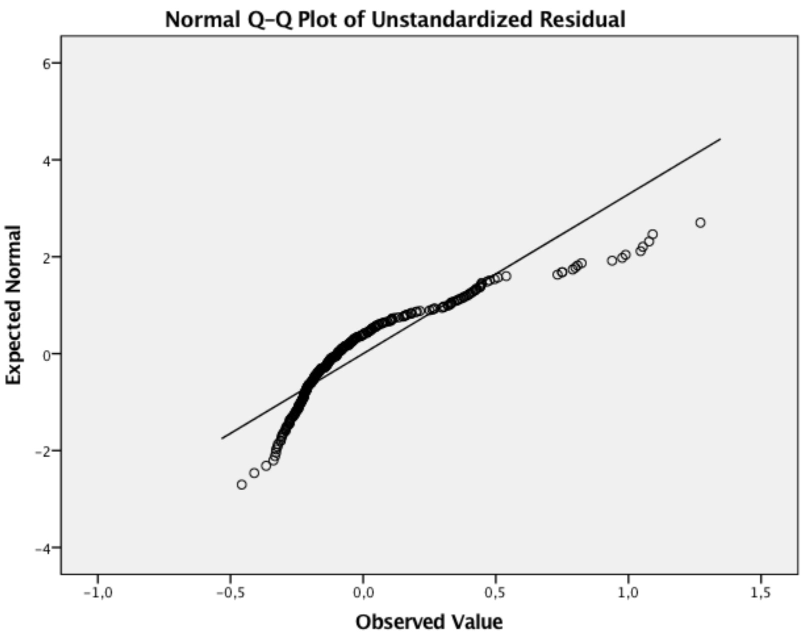
Normality (wins_big5 & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,163	290	,000	,740	290	,000
Unstandardized Residual	,168	290	,000	,830	290	,000



Oscar_Wins_Big5



LN_Oscar_Wins_Big5

OLS regression & constant error variance (H2A-wins_big5)

Model Summary[c]

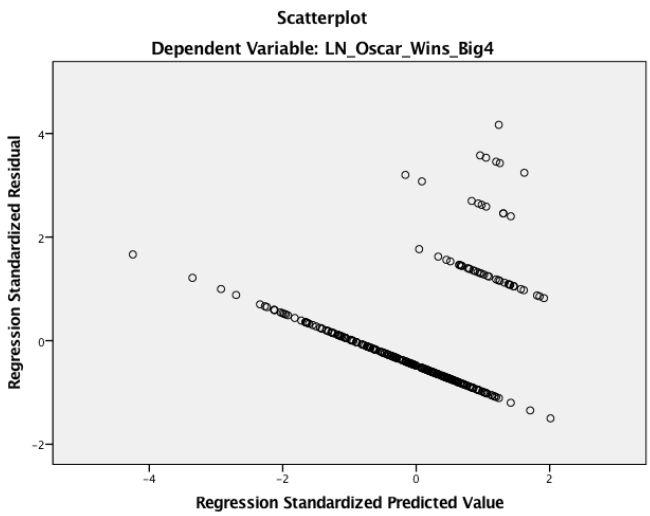
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,403[a]	,163	,160	,31255	,163	55,888	1	288
2	,453[b]	,205	,199	,30509	,042	15,265	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,460	1	5,460	55,888	,000[b]
	Residual	28,134	288	,098		
	Total	33,594	289			
2	Regression	6,881	2	3,440	36,961	,000[c]
	Residual	26,713	287	,093		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,605	,102		-5,914	,000
	Public_reception	,111	,015	,403	7,476	,000
2	(Constant)	-,618	,100		-6,187	,000
	Public_reception	,123	,015	,448	8,311	,000
	Budget_100	-,159	,041	-,210	-3,907	,000



Negative binomial regression (H2A- wins_big5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	123,504	288	,429
Scaled Deviance	123,504	288	
Pearson Chi-Square	174,373	288	,605
Scaled Pearson Chi-Square	174,373	288	
Log Likelihood[b]	-141,207		
Akaike's Information Criterion (AIC)	286,414		
Finite Sample Corrected AIC (AICC)	286,456		
Bayesian Information Criterion (BIC)	293,753		
Consistent AIC (CAIC)	295,753		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
78,766	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	53,006	1	,000
Public_reception	45,506	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-12,842	1,7639	-16,300	-9,385	53,006	1	,000
Public_reception	1,531	,2270	1,086	1,976	45,506	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H2A-wins_big5 & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	105,581	287	,368
Scaled Deviance	105,581	287	
Pearson Chi-Square	165,019	287	,575
Scaled Pearson Chi-Square	165,019	287	
Log Likelihood[b]	-132,246		
Akaike's Information Criterion (AIC)	270,491		
Finite Sample Corrected AIC (AICC)	270,575		
Bayesian Information Criterion (BIC)	281,501		
Consistent AIC (CAIC)	284,501		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
96,688	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	52,822	1	,000
Public_reception	48,528	1	,000
Budget_100	13,355	1	,000

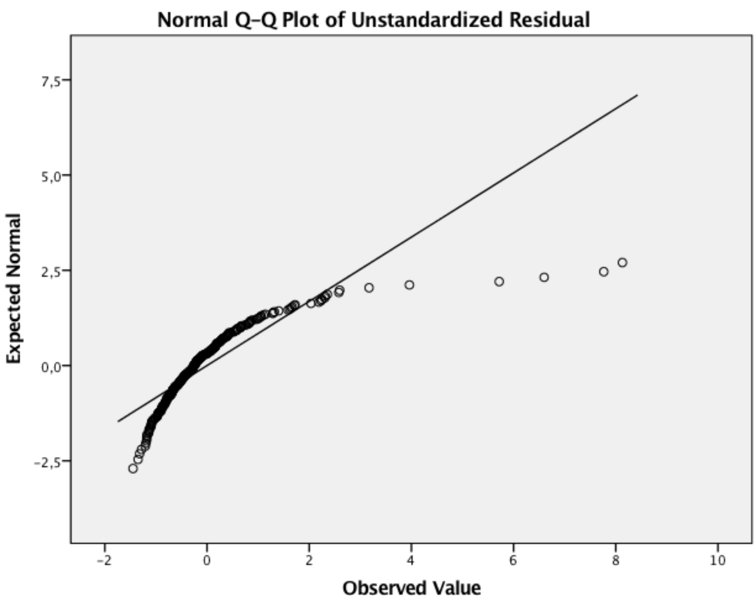
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-14,768	2,0319	-18,750	-10,785	52,822	1	,000
Public_reception	1,859	,2669	1,336	2,383	48,528	1	,000
Budget_100	-1,533	,4196	-2,356	-,711	13,355	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

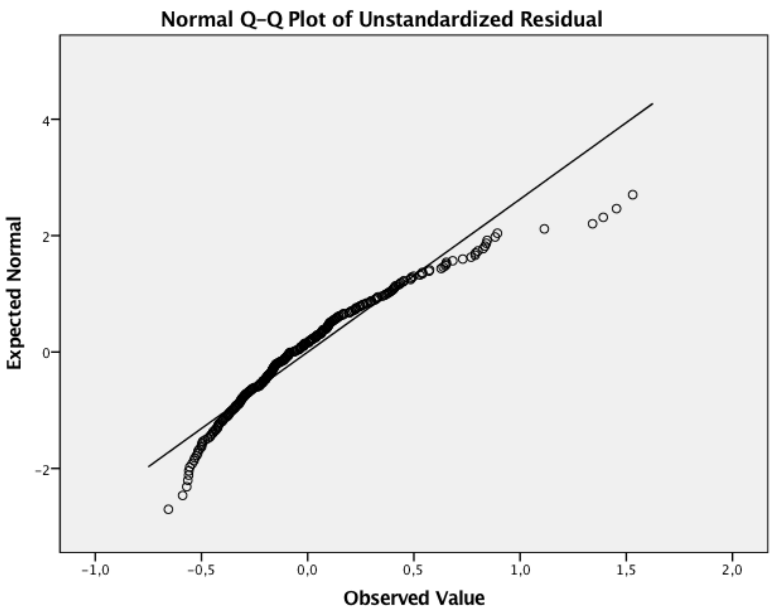
Normality (H2B-public reception)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,166	290	,000	,704	290	,000
Unstandardized Residual LN	,087	290	,000	,933	290	,000



Pre_Domestic_Adjusted_100

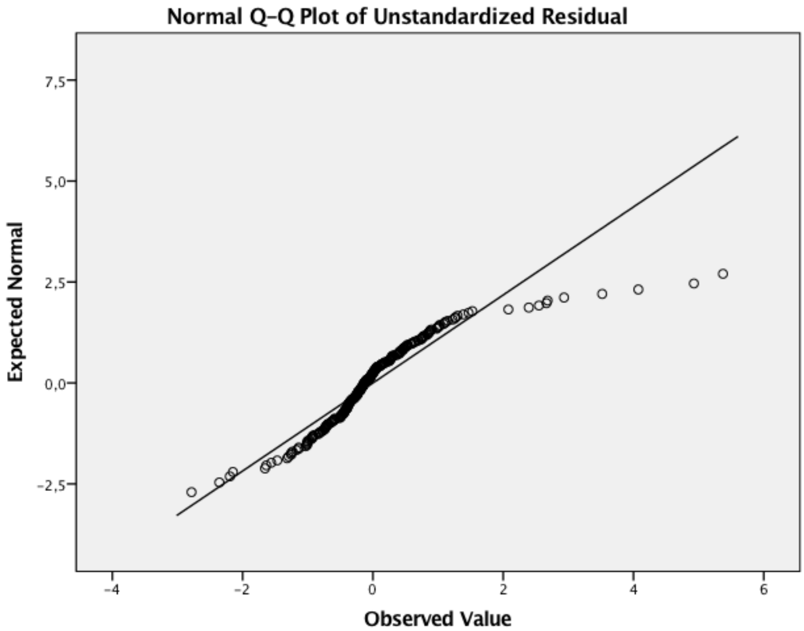


LN_Pre_Domestic_Adjusted_100

Normality (H2B-public reception & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,129	290	,000	,849	290	,000
Unstandardized Residual LN	,079	290	,000	,977	290	,000



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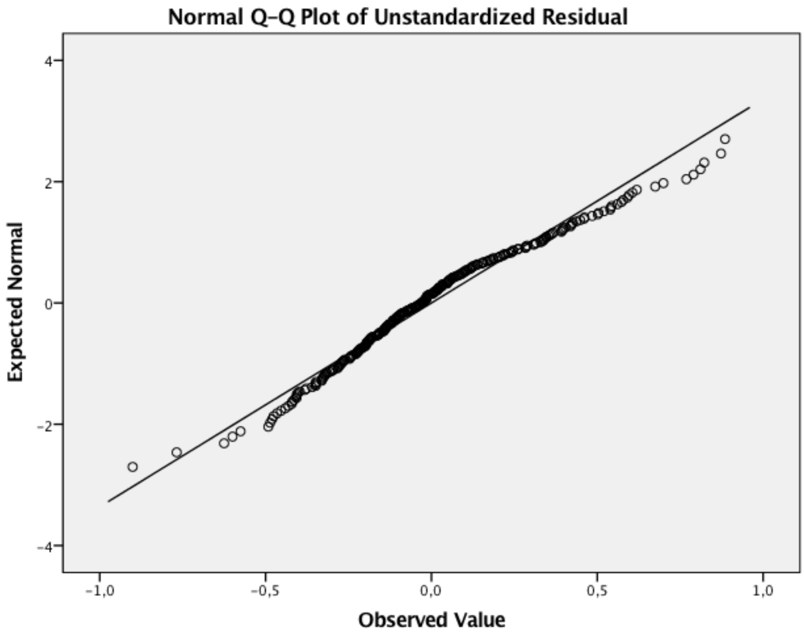


LN_Pre_Domestic_Adjusted_100

OLS rgression & constant error variance (H2B-public reception & budget)

Model Summary[c]

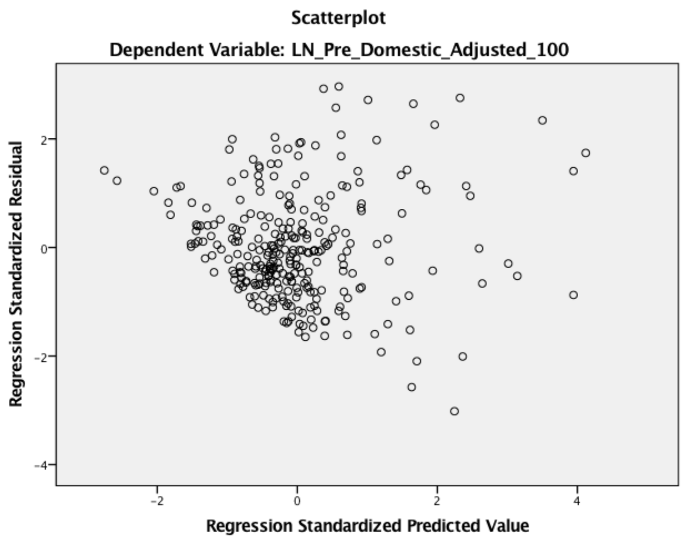
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,499[a]	,249	,246	,38123	,249	95,470	1	288
2	,736[b]	,541	,538	,29852	,292	182,688	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,875	1	13,875	95,470	,000[b]
	Residual	41,856	288	,145		
	Total	55,731	289			
2	Regression	30,155	2	15,077	169,193	,000[c]
	Residual	25,576	287	,089		
	Total	55,731	289			

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.
1	(Constant)	-,661	,125		-5,298	,000
	Public_reception	,177	,018	,499	9,771	,000
2	(Constant)	-,616	,098		-6,306	,000
	Public_reception	,136	,015	,382	9,343	,000
	Budget_100	,539	,040	,553	13,516	,000



Negative binomial regression (H2B – public reception)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	179,933	288	,625
Scaled Deviance	179,933	288	
Pearson Chi-Square	175,542	288	,610
Scaled Pearson Chi-Square	175,542	288	
Log Likelihood[b]	-329,146		
Akaike's Information Criterion (AIC)	662,293		
Finite Sample Corrected AIC (AICC)	662,334		
Bayesian Information Criterion (BIC)	669,632		
Consistent AIC (CAIC)	671,632		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
79,585	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	62,666	1	,000
Public_reception	61,477	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-5,702	,7203	-7,114	-4,290	62,666	1	,000
Public_reception	,762	,0972	,572	,953	61,477	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H2B – public reception & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	142,718	287	,497
Scaled Deviance	142,718	287	
Pearson Chi-Square	121,758	287	,424
Scaled Pearson Chi-Square	121,758	287	
Log Likelihood[b]	-310,539		
Akaike's Information Criterion (AIC)	627,077		
Finite Sample Corrected AIC (AICC)	627,161		
Bayesian Information Criterion (BIC)	638,087		
Consistent AIC (CAIC)	641,087		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
116,801	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	49,421	1	,000
Public_reception	34,325	1	,000
Budget_100	31,382	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-5,061	,7199	-6,472	-3,650	49,421	1	,000
Public_reception	,585	,0999	,389	,781	34,325	1	,000
Budget_100	1,062	,1895	,690	1,433	31,382	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & mediation (H2C-nominations)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,512[a]	,262	,257	,66955	,262	50,891	2	287

ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45,629	2	22,814	50,891	,000[b]
	Residual	128,661	287	,448		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1,513	,231		-6,562	,000
	Public_reception	,281	,035	,448	7,963	,000
	Pre_Domestic_Adjusted_100	,071	,033	,120	2,141	,033

Negative binomial regression & mediation (H2C-nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	294,981	287	1,028
Scaled Deviance	294,981	287	
Pearson Chi-Square	533,815	287	1,860
Scaled Pearson Chi-Square	533,815	287	
Log Likelihood[b]	-353,088		
Akaike's Information Criterion (AIC)	712,175		
Finite Sample Corrected AIC (AICC)	712,259		
Bayesian Information Criterion (BIC)	723,185		
Consistent AIC (CAIC)	726,185		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
221,745	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	104,926	1	,000
Public_reception	108,796	1	,000
Pre_Domestic_Adjusted_100	1,813	1	,178

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-11,431	1,1159	-13,618	-9,244	104,926	1	,000
Public_reception	1,585	,1520	1,287	1,883	108,796	1	,000
Pre_Domestic_Adjusted_100	-,077	,0575	-,190	,035	1,813	1	,178
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & Mediation (H2C – nominations & budget)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,512[a]	,262	,257	,66955	,262	50,891	2	287
2	,527[b]	,278	,271	,66326	,016	6,466	1	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45,629	2	22,814	50,891	,000[b]
	Residual	128,661	287	,448		
	Total	174,290	289			
2	Regression	48,473	3	16,158	36,729	,000[c]
	Residual	125,817	286	,440		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B
		B	Std. Error	Beta			Lower Bound
1	(Constant)	-1,513	,231		-6,562	,000	-1,967
	Public_reception	,281	,035	,448	7,963	,000	,211
	Pre_Domestic_Adjusted_100	,071	,033	,120	2,141	,033	,006
2	(Constant)	-1,388	,234		-5,941	,000	-1,848
	Public_reception	,272	,035	,433	7,738	,000	,203
	Pre_Domestic_Adjusted_100	,140	,043	,237	3,284	,001	,056
	Budget_100	-,291	,115	-,169	-2,543	,012	-,517

Negative binomial regression & mediation (H2C – nominations & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	294,749	286	1,031
Scaled Deviance	294,749	286	
Pearson Chi-Square	548,969	286	1,919
Scaled Pearson Chi-Square	548,969	286	
Log Likelihood[b]	-352,972		
Akaike's Information Criterion (AIC)	713,944		
Finite Sample Corrected AIC (AICC)	714,085		
Bayesian Information Criterion (BIC)	728,624		
Consistent AIC (CAIC)	732,624		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
221,977	3	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-11,281	1,1558	-13,546	-9,015	95,261	1	,000
Public_reception	1,567	,1559	1,262	1,873	101,063	1	,000
Pre_Domestic_Adjusted_100	-,043	,0926	-,224	,139	,211	1	,646
Budget_100	-,136	,2815	-,687	,416	,232	1	,630
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS Regression & Mediation (H2C-wins)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,447[a]	,200	,194	,43261	,200	35,855	2	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,421	2	6,710	35,855	,000[b]
	Residual	53,713	287	,187		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,839	,149		-5,630	,000
	Public_reception	,149	,023	,383	6,549	,000
	Pre_Domestic_Adjusted_100	,043	,021	,118	2,009	,046

Negative binomial regression & Mediation (H2C-wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	163,712	287	,570
Scaled Deviance	163,712	287	
Pearson Chi-Square	271,581	287	,946
Scaled Pearson Chi-Square	271,581	287	
Log Likelihood[b]	-187,378		
Akaike's Information Criterion (AIC)	380,755		
Finite Sample Corrected AIC (AICC)	380,839		
Bayesian Information Criterion (BIC)	391,765		
Consistent AIC (CAIC)	394,765		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
158,854	2	,000

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	67,239	1	,000
Public_reception	61,338	1	,000
Pre_Domestic_Adjusted_100	1,593	1	,207

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-15,555	1,8969	-19,273	-11,837	67,239	1	,000
Public_reception	1,970	,2515	1,477	2,463	61,338	1	,000
Pre_Domestic_Adjusted_100	-,089	,0703	-,227	,049	1,593	1	,207
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & mediation (H2C – wins & budget)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,447[a]	,200	,194	,43261	,200	35,855	2	287
2	,482[b]	,232	,224	,42451	,032	12,060	1	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,421	2	6,710	35,855	,000[b]
	Residual	53,713	287	,187		
	Total	67,134	289			
2	Regression	15,594	3	5,198	28,845	,000[c]
	Residual	51,540	286	,180		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B
		B	Std. Error	Beta			Lower Bound
1	(Constant)	-,839	,149		-5,630	,000	-1,132
	Pre_Domestic_Adjusted_100	,043	,021	,118	2,009	,046	,001
	Public_reception	,149	,023	,383	6,549	,000	,104
2	(Constant)	-,730	,150		-4,879	,000	-1,024
	Pre_Domestic_Adjusted_100	,103	,027	,281	3,784	,000	,049
	Public_reception	,141	,022	,363	6,285	,000	,097
	Budget_100	-,255	,073	-,238	-3,473	,001	-,399

Negative binomial regression & mediation (H2C – wins & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	160,747	286	,562
Scaled Deviance	160,747	286	
Pearson Chi-Square	271,250	286	,948
Scaled Pearson Chi-Square	271,250	286	
Log Likelihood[b]	-185,895		
Akaike's Information Criterion (AIC)	379,790		
Finite Sample Corrected AIC (AICC)	379,931		
Bayesian Information Criterion (BIC)	394,470		
Consistent AIC (CAIC)	398,470		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
161,819	3	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-14,823	1,9221	-18,590	-11,056	59,477	1	,000
Public_reception	1,886	,2537	1,389	2,383	55,249	1	,000
Budget_100	-,676	,4054	-1,471	,118	2,785	1	,095
Pre_Domestic_Adjusted_100	,072	,1192	-,161	,306	,368	1	,544
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS Regression & Mediation (H2C-wins_big5)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,406[a]	,165	,159	,31264	,165	28,344	2	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,541	2	2,771	28,344	,000[b]
	Residual	28,053	287	,098		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,635	,108		-5,901	,000
	Public_reception	,118	,016	,427	7,133	,000
	Pre_Domestic_Adjusted_100	-,014	,015	-,055	-,912	,362

Negative binomial regression & Mediation (H2C-wins_big5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	114,978	287	,401
Scaled Deviance	114,978	287	
Pearson Chi-Square	166,761	287	,581
Scaled Pearson Chi-Square	166,761	287	
Log Likelihood[b]	-136,944		
Akaike's Information Criterion (AIC)	279,887		
Finite Sample Corrected AIC (AICC)	279,971		
Bayesian Information Criterion (BIC)	290,897		
Consistent AIC (CAIC)	293,897		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
87,292	2	,000

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	51,557	1	,000
Public_reception	45,313	1	,000
Pre_Domestic_Adjusted_100	7,149	1	,008

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-15,666	2,1817	-19,942	-11,389	51,557	1	,000
Public_reception	1,948	,2894	1,381	2,515	45,313	1	,000
Pre_Domestic_Adjusted_100	-,299	,1120	-,519	-,080	7,149	1	,008
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & Mediation (H2C – wins_big5 & budget)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,453[a]	,205	,199	,30509	,205	36,961	2	287
2	,465[b]	,216	,208	,30350	,011	4,012	1	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6,881	2	3,440	36,961	,000[b]
	Residual	26,713	287	,093		
	Total	33,594	289			
2	Regression	7,250	3	2,417	26,237	,000[c]
	Residual	26,344	286	,092		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B
		B	Std. Error	Beta			Lower Bound
1	(Constant)	-,618	,100		-6,187	,000	-,814
	Public_reception	,123	,015	,448	8,311	,000	,094
	Budget_100	-,159	,041	-,210	-3,907	,000	-,240
2	(Constant)	-,538	,107		-5,036	,000	-,749
	Public_reception	,110	,016	,401	6,871	,000	,079
	Budget_100	-,226	,052	-,298	-4,307	,000	-,329
	Pre_Domestic_Adjusted_100	,039	,019	,150	2,003	,046	,001

Negative binomial resresssion & mediation (H2C – Wins_big5 & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	105,363	286	,368
Scaled Deviance	105,363	286	
Pearson Chi-Square	168,503	286	,589
Scaled Pearson Chi-Square	168,503	286	
Log Likelihood[b]	-132,136		
Akaike's Information Criterion (AIC)	272,273		
Finite Sample Corrected AIC (AICC)	272,413		
Bayesian Information Criterion (BIC)	286,952		
Consistent AIC (CAIC)	290,952		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
96,907	3	,000

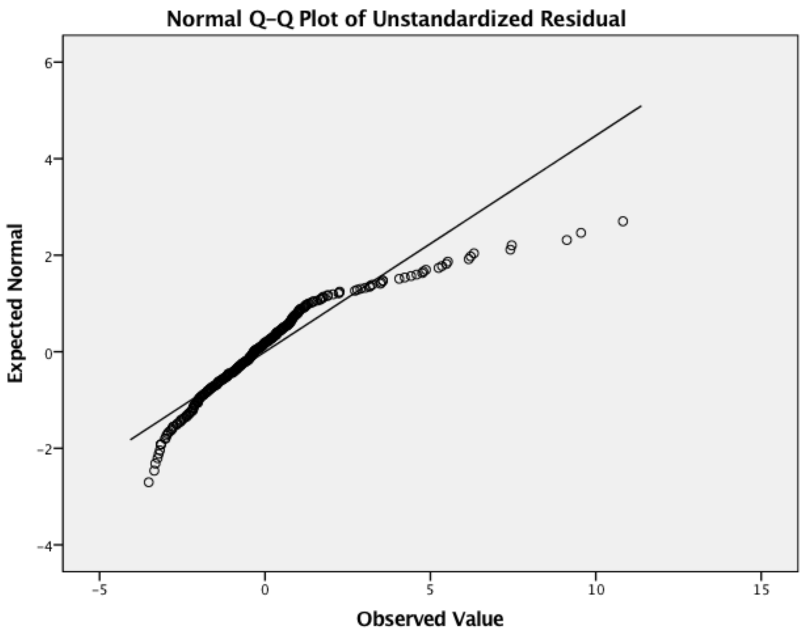
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-14,335	2,2165	-18,680	-9,991	41,829	1	,000
Public_reception	1,801	,2933	1,226	2,375	37,697	1	,000
Budget_100	-1,744	,6255	-2,970	-,518	7,778	1	,005
Pre_Domestic_Adjusted_100	,080	,1715	-,256	,416	,219	1	,640
(Scale)	1[a]						
(Negative binomial)	1[a]						

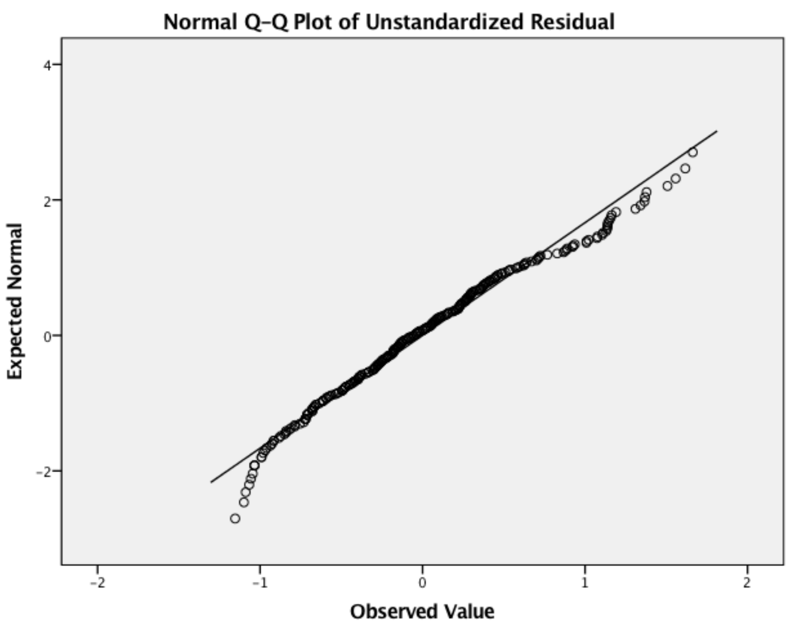
Normality (H3A- nominations)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,132	290	,000	,883	290	,000
Unstandardized Residual LN	,049	290	,085	,979	290	,000



Oscar_Nominations

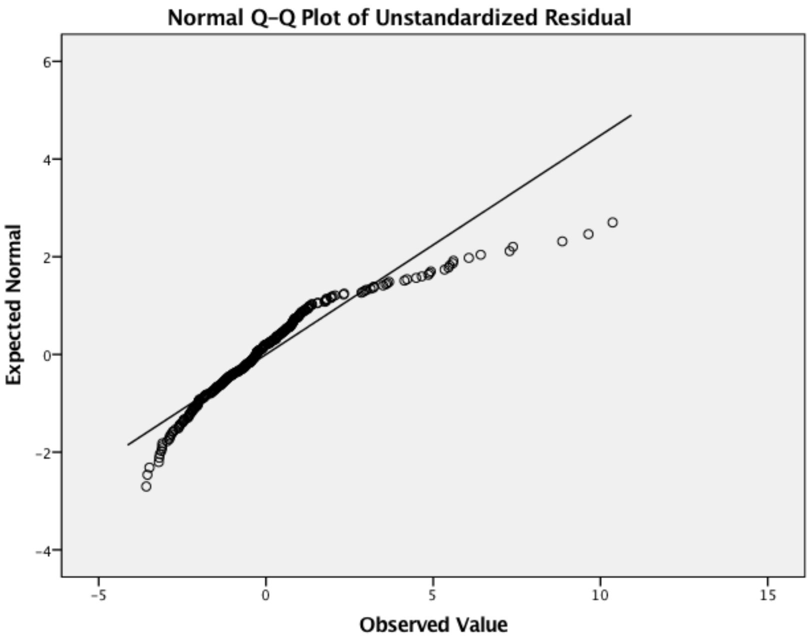


LN_Oscar_Nominations

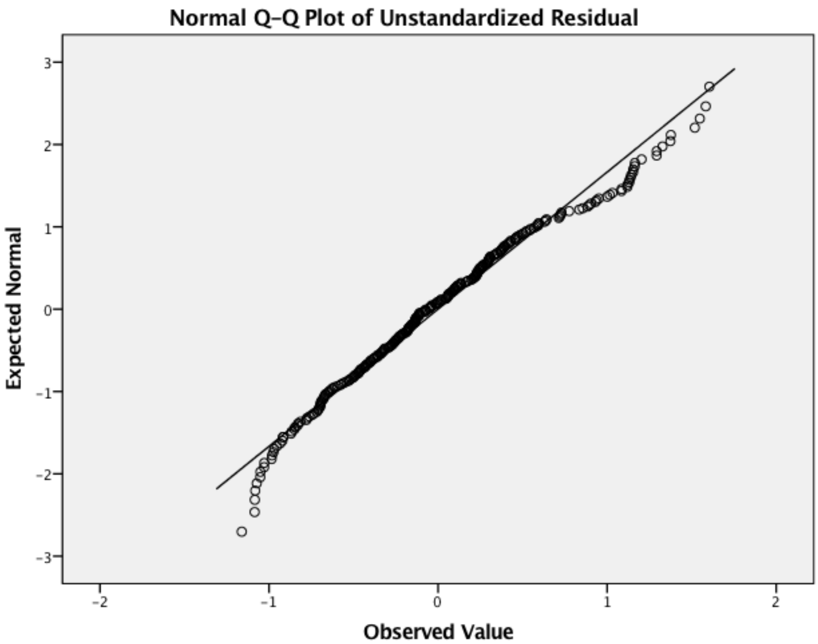
Normality (H3A-nominations & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,127	290	,000	,889	290	,000
Unstandardized Residual LN	,056	290	,031	,979	290	,000



Oscar_Nominations



LN_Oscar_Nominations

OLS regression & constant error variance (H3A-nominations)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,634[a]	,402	,400	,60175	,402	193,320	1	288
2	,634[b]	,402	,398	,60255	,000	,235	1	287

ANOVA[a]

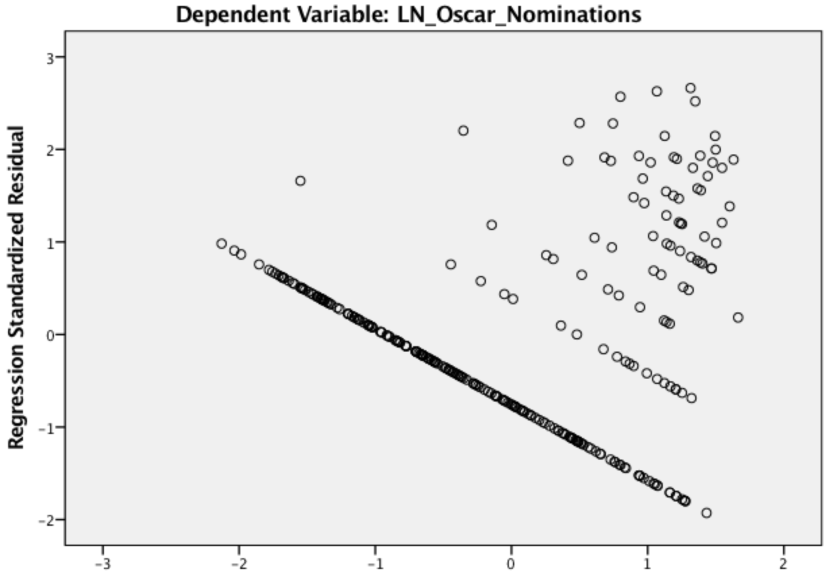
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	70,003	1	70,003	193,320	,000[b]
	Residual	104,287	288	,362		
	Total	174,290	289			
2	Regression	70,088	2	35,044	96,521	,000[c]
	Residual	104,202	287	,363		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,769	,095		-8,103	,000
	Critical_reception	,216	,016	,634	13,904	,000
2	(Constant)	-,783	,099		-7,917	,000
	Critical_reception	,215	,016	,632	13,793	,000
	Budget_100	,038	,079	,022	,485	,628

Scatterplot

Dependent Variable: LN_Oscar_Nominations



Negative binomial regression (H3A- nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	207,987	288	,722
Scaled Deviance	207,987	288	
Pearson Chi-Square	428,720	288	1,489
Scaled Pearson Chi-Square	428,720	288	
Log Likelihood[b]	-309,591		
Akaike's Information Criterion (AIC)	623,182		
Finite Sample Corrected AIC (AICC)	623,224		
Bayesian Information Criterion (BIC)	630,522		
Consistent AIC (CAIC)	632,522		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
308,738	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	121,404	1	,000
Critical_reception	147,492	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-6,690	,6072	-7,880	-5,500	121,404	1	,000
Critical_reception	,952	,0784	,799	1,106	147,492	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H3A-nominations & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	204,264	287	,712
Scaled Deviance	204,264	287	
Pearson Chi-Square	412,914	287	1,439
Scaled Pearson Chi-Square	412,914	287	
Log Likelihood[b]	-307,730		
Akaike's Information Criterion (AIC)	621,459		
Finite Sample Corrected AIC (AICC)	621,543		
Bayesian Information Criterion (BIC)	632,469		
Consistent AIC (CAIC)	635,469		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
312,461	2	,000

Tests of Model Effects

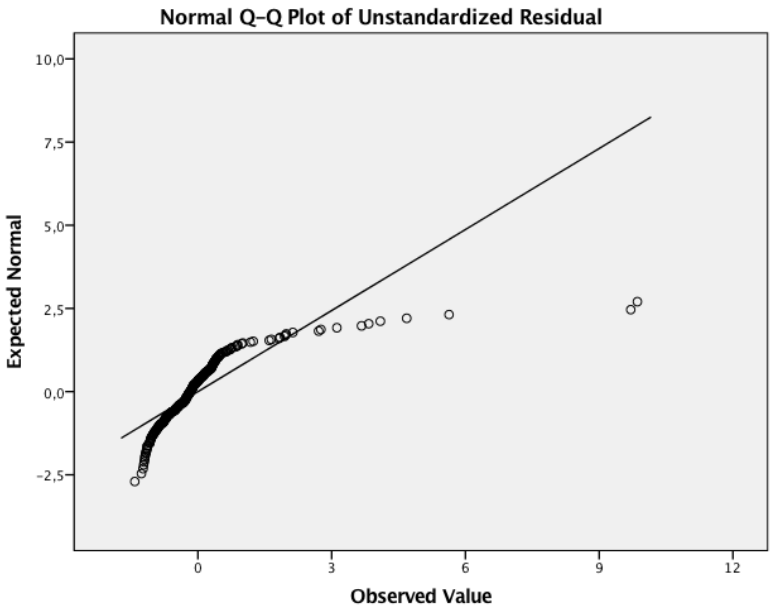
Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	121,344	1	,000
Critical_reception	146,562	1	,000
Budget_100	3,459	1	,063

Parameter Estimates

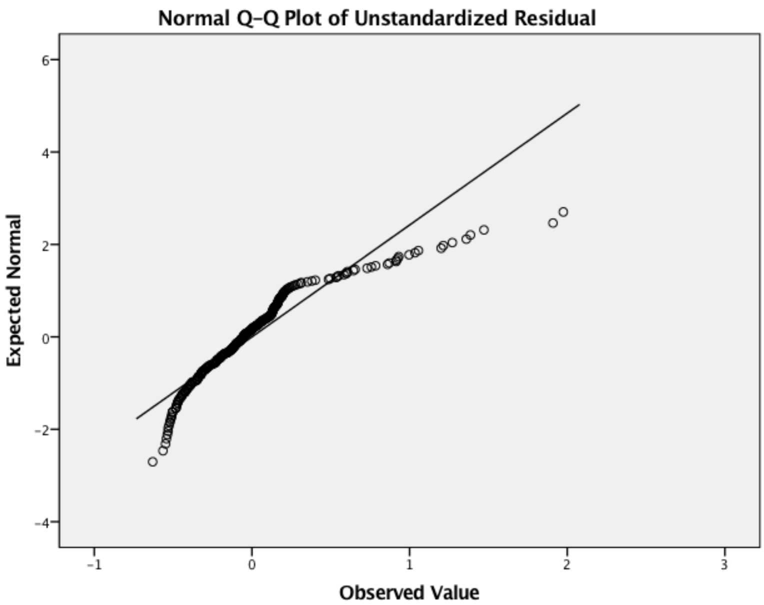
			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-6,911	,6274	-8,141	-5,681	121,344	1	,000
Critical_reception	,958	,0791	,803	1,113	146,562	1	,000
Budget_100	,349	,1874	-,019	,716	3,459	1	,063
(Scale)	1[a]						
(Negative binomial)	1[a]						

Normality (H3A– wins)

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,215	290	,000	,624	290	,000
Unstandardized Residual LN	,149	290	,000	,869	290	,000



Oscar_Wins

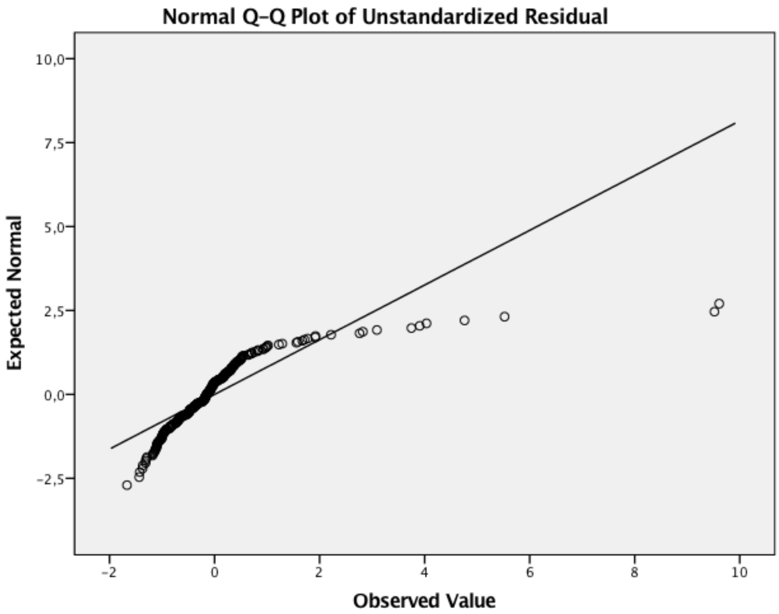


LN_Oscar_Wins

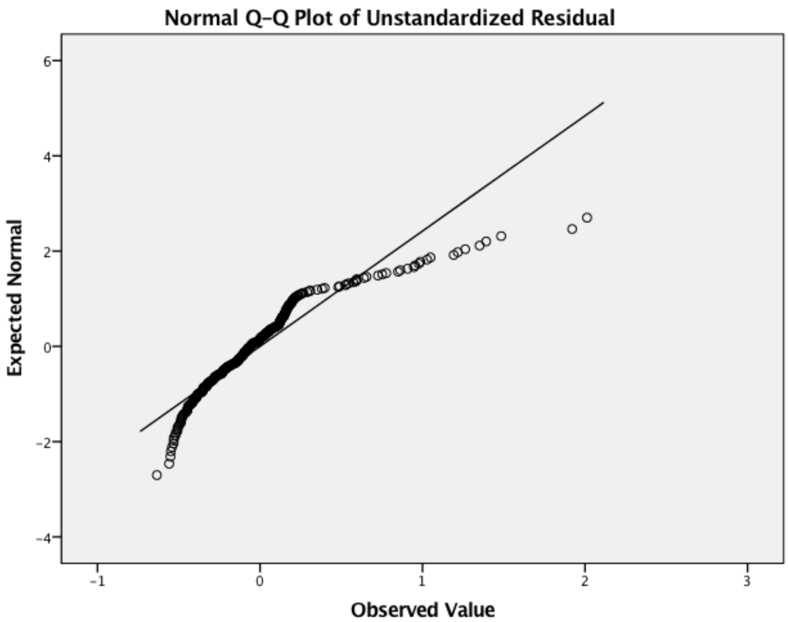
Normality (H3A-wins & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,208	290	,000	,647	290	,000
Unstandardized Residual LN	,152	290	,000	,866	290	,000



Oscar_Wins



LN_Oscar_Wins

OLS regression & constant error variance (H3A-wins)

Model Summary[c]

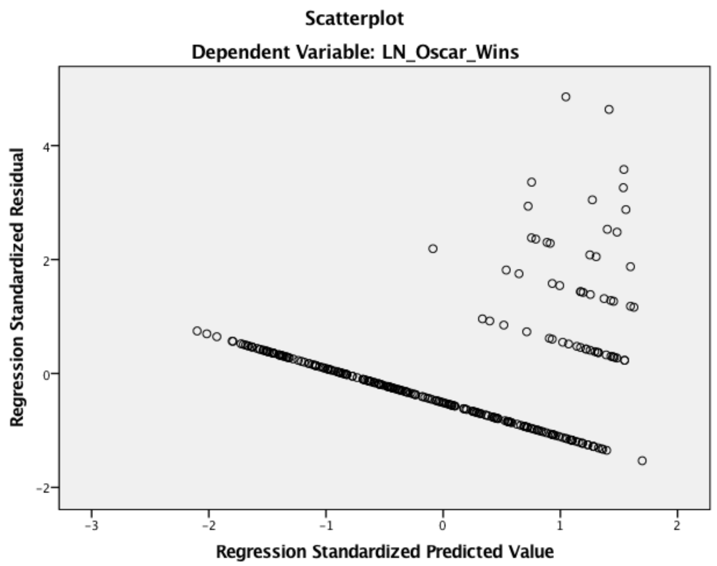
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,515[a]	,265	,263	,41386	,265	103,949	1	288
2	,515[b]	,266	,261	,41444	,001	,202	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,805	1	17,805	103,949	,000[b]
	Residual	49,329	288	,171		
	Total	67,134	289			
2	Regression	17,839	2	8,920	51,932	,000[c]
	Residual	49,294	287	,172		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,406	,065		-6,211	,000
	Critical_reception	,109	,011	,515	10,196	,000
2	(Constant)	-,397	,068		-5,844	,000
	Critical_reception	,109	,011	,517	10,183	,000
	Budget_100	-,024	,054	-,023	-,450	,653



Negative binomial regression (H3A- wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	139,346	288	,484
Scaled Deviance	139,346	288	
Pearson Chi-Square	267,425	288	,929
Scaled Pearson Chi-Square	267,425	288	
Log Likelihood[b]	-175,195		
Akaike's Information Criterion (AIC)	354,389		
Finite Sample Corrected AIC (AICC)	354,431		
Bayesian Information Criterion (BIC)	361,729		
Consistent AIC (CAIC)	363,729		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
183,220	1	,000

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	72,854	1	,000
Critical_reception	71,936	1	,000

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square	df	Sig.
(Intercept)	-8,987	1,0530	-11,051	-6,924	72,854	1	,000
Critical_reception	1,100	,1297	,846	1,354	71,936	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H3A- wins & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	136,272	287	,475
Scaled Deviance	136,272	287	
Pearson Chi-Square	263,330	287	,918
Scaled Pearson Chi-Square	263,330	287	
Log Likelihood[b]	-173,658		
Akaike's Information Criterion (AIC)	353,315		
Finite Sample Corrected AIC (AICC)	353,399		
Bayesian Information Criterion (BIC)	364,325		
Consistent AIC (CAIC)	367,325		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
186,294	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	72,471	1	,000
Critical_reception	70,478	1	,000
Budget_100	2,996	1	,083

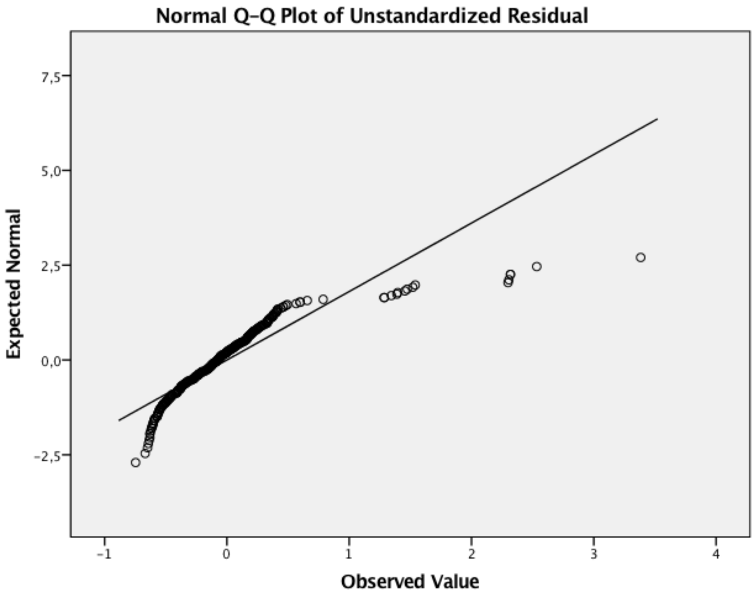
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-9,263	1,0881	-11,396	-7,130	72,471	1	,000
Critical_reception	1,109	,1321	,850	1,368	70,478	1	,000
Budget_100	,371	,2142	-,049	,791	2,996	1	,083
(Scale)	1[a]						
(Negative binomial)	1[a]						

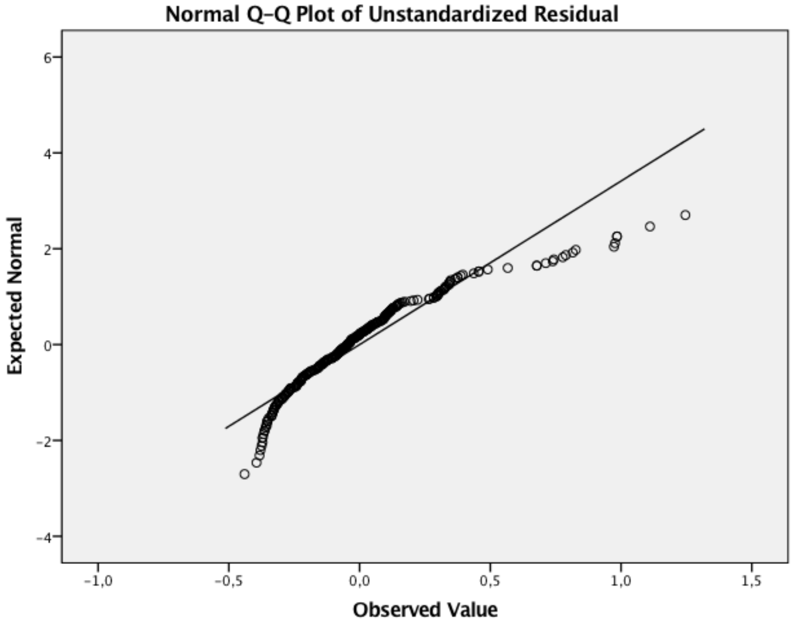
Normality (H3A-wins_big5)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,140	290	,000	,783	290	,000
Unstandardized Residual LN	,113	290	,000	,892	290	,000



Oscar_Wins_Big5

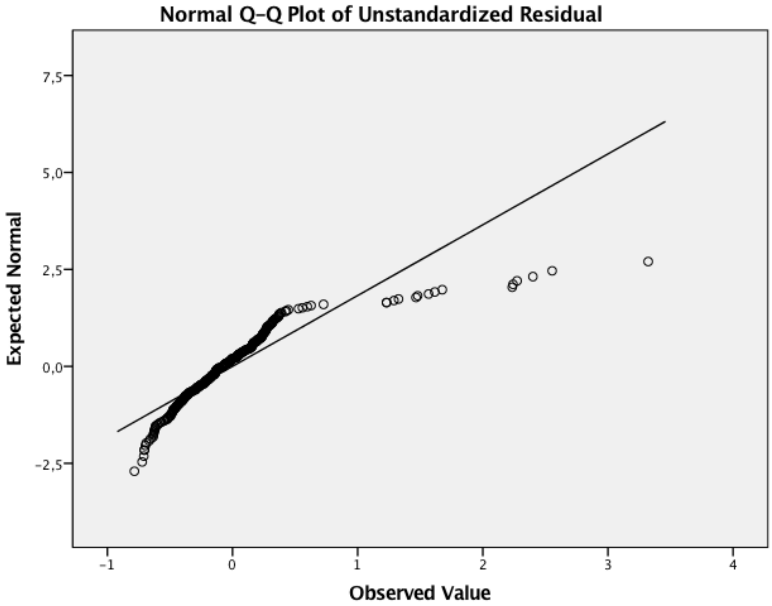


LN_Oscar_Wins_Big5

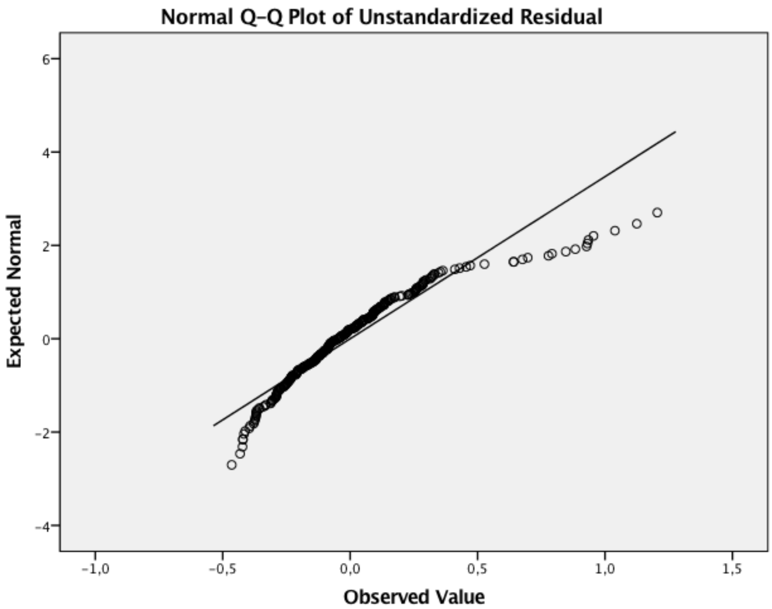
Normality (H3A- wins_big5 & budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,162	290	,000	,776	290	,000
Unstandardized Residual LN	,104	290	,000	,895	290	,000



Oscars_Win_Big5



LN_Oscars_Win_Big5

OLS Regression & constant error variance (H3A-wins_Big5)

Model Summary[c]

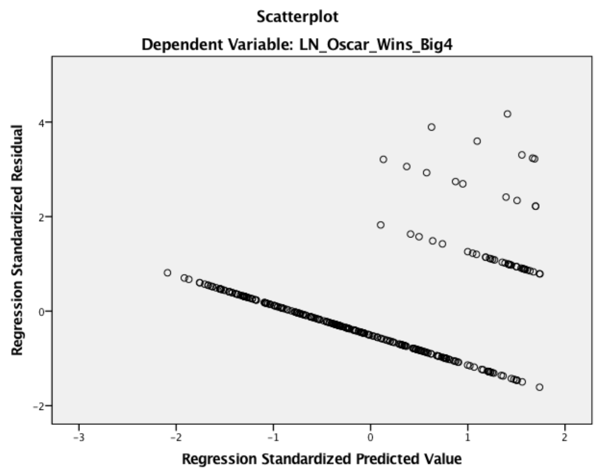
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,511[a]	,261	,259	,29354	,261	101,878	1	288
2	,536[b]	,287	,282	,28890	,026	10,332	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,778	1	8,778	101,878	,000[b]
	Residual	24,816	288	,086		
	Total	33,594	289			
2	Regression	9,641	2	4,820	57,755	,000[c]
	Residual	23,953	287	,083		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,287	,046		-6,191	,000
	Critical_reception	,077	,008	,511	10,093	,000
2	(Constant)	-,245	,047		-5,174	,000
	Critical_reception	,079	,007	,525	10,493	,000
	Budget_100	-,122	,038	-,161	-3,214	,001



Negative binomial regression (H3A– wins_big5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	91,380	288	,317
Scaled Deviance	91,380	288	
Pearson Chi-Square	160,104	288	,556
Scaled Pearson Chi-Square	160,104	288	
Log Likelihood[b]	-125,145		
Akaike's Information Criterion (AIC)	254,290		
Finite Sample Corrected AIC (AICC)	254,332		
Bayesian Information Criterion (BIC)	261,630		
Consistent AIC (CAIC)	263,630		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
110,890	1	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	50,680	1	,000
Critical_reception	44,470	1	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-9,351	1,3136	-11,926	-6,777	50,680	1	,000
Critical_reception	1,067	,1599	,753	1,380	44,470	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H3A- wins_big5 & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	89,714	287	,313
Scaled Deviance	89,714	287	
Pearson Chi-Square	158,787	287	,553
Scaled Pearson Chi-Square	158,787	287	
Log Likelihood[b]	-124,312		
Akaike's Information Criterion (AIC)	254,624		
Finite Sample Corrected AIC (AICC)	254,708		
Bayesian Information Criterion (BIC)	265,634		
Consistent AIC (CAIC)	268,634		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
112,556	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	47,069	1	,000
Critical_reception	43,819	1	,000
Budget_100	1,545	1	,214

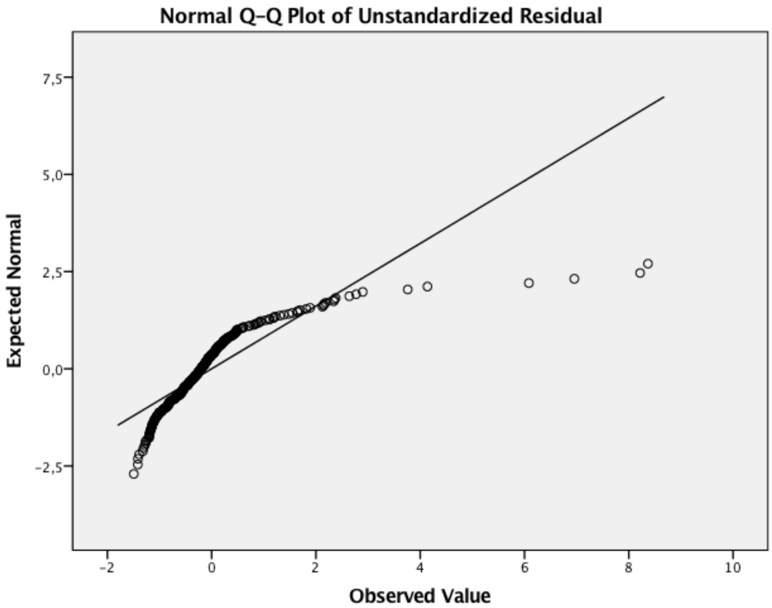
Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-9,005	1,3126	-11,578	-6,433	47,069	1	,000
Critical_reception	1,045	,1578	,735	1,354	43,819	1	,000
Budget_100	-,419	,3372	-1,080	,242	1,545	1	,214
(Scale)	1[a]						
(Negative binomial)	1[a]						

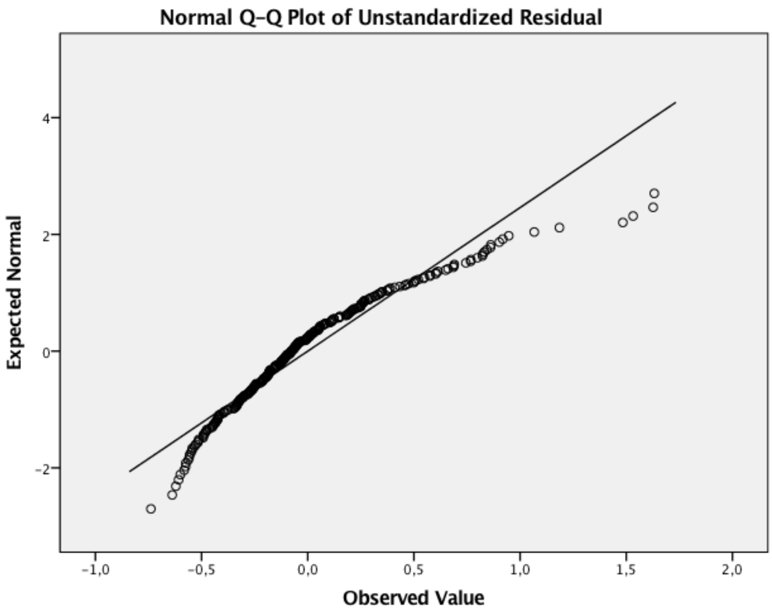
Normality (H3B-critical_reception)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,195	290	,000	,693	290	,000
Unstandardized Residual LN	,111	290	,000	,922	290	,000



Pre_Domestic_Adjusted_100

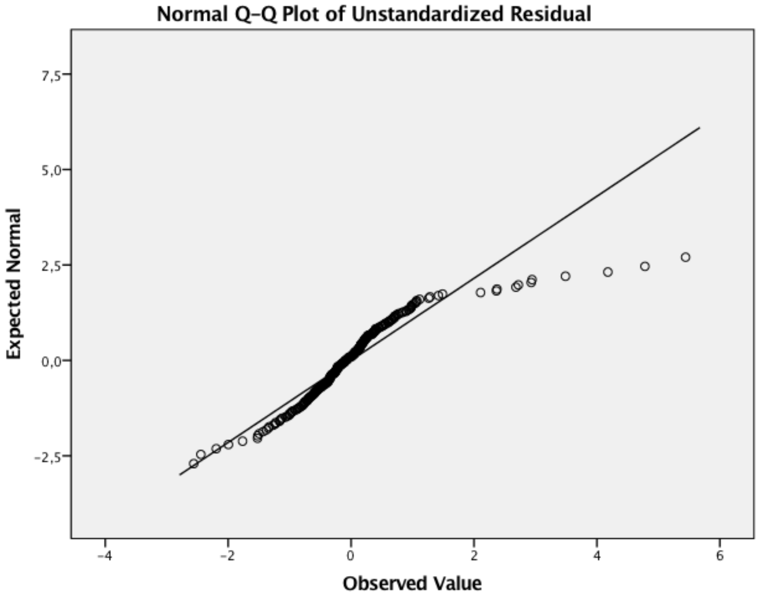


LN_Pre_Domestic_Adjusted_100

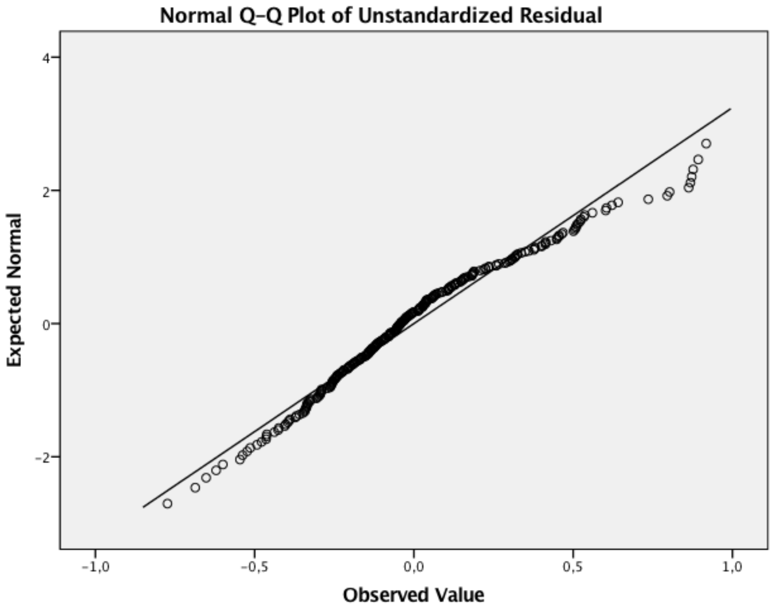
Normality (H3B-critical_reception & Budget)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,133	290	,000	,854	290	,000
Unstandardized Residual LN	,089	290	,000	,971	290	,000



Pre_Domestic_Adjusted_100



LN_Pre_Domestic_Adjusted_100

OLS Regression & constant error variance (H3B-critical_reception & budget)

Model Summary[c]

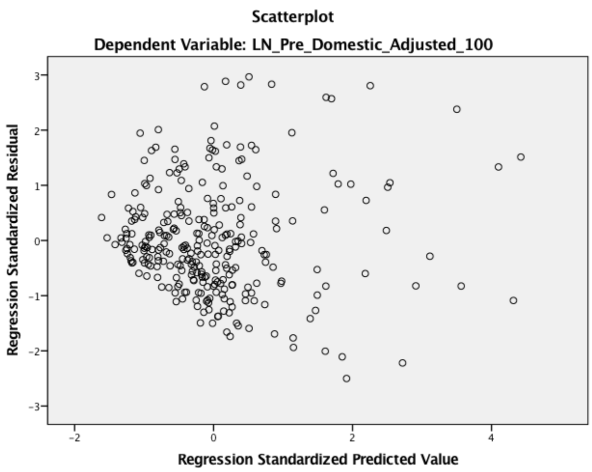
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,378[a]	,143	,140	,40731	,143	47,922	1	288
2	,712[b]	,507	,503	,30943	,364	212,037	1	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,950	1	7,950	47,922	,000[b]
	Residual	47,780	288	,166		
	Total	55,731	289			
2	Regression	28,252	2	14,126	147,537	,000[c]
	Residual	27,479	287	,096		
	Total	55,731	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,125	,064		1,942	,053
	Critical_reception	,073	,011	,378	6,923	,000
2	(Constant)	-,077	,051		-1,516	,131
	Critical_reception	,063	,008	,326	7,834	,000
	Budget_100	,591	,041	,606	14,562	,000



Negative binomial regression (H3B – critical_reception)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	213,088	288	,740
Scaled Deviance	213,088	288	
Pearson Chi-Square	207,405	288	,720
Scaled Pearson Chi-Square	207,405	288	
Log Likelihood[b]	-345,724		
Akaike's Information Criterion (AIC)	695,447		
Finite Sample Corrected AIC (AICC)	695,489		
Bayesian Information Criterion (BIC)	702,787		
Consistent AIC (CAIC)	704,787		

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	44,001	1	,000
Critical_Reception	41,978	1	,000

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square	df	Sig.
(Intercept)	-1,990	,3000	-2,578	-1,402	44,001	1	,000
Critical_Reception	,287	,0444	,200	,374	41,978	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression (H3B – critical_reception & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	157,565	287	,549
Scaled Deviance	157,565	287	
Pearson Chi-Square	133,761	287	,466
Scaled Pearson Chi-Square	133,761	287	
Log Likelihood[b]	-317,962		
Akaike's Information Criterion (AIC)	641,924		
Finite Sample Corrected AIC (AICC)	642,008		
Bayesian Information Criterion (BIC)	652,934		
Consistent AIC (CAIC)	655,934		

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	55,067	1	,000
Critical_Reception	24,173	1	,000
Budget_100	44,120	1	,000

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-2,373	,3198	-3,000	-1,746	55,067	1	,000
Critical_Reception	,228	,0463	,137	,319	24,173	1	,000
Budget_100	1,235	,1859	,870	1,599	44,120	1	,000
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & mediation (H3C-nominations)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,643[a]	,413	,409	,59680	,413	101,169	2	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	72,068	2	36,034	101,169	,000[b]
	Residual	102,222	287	,356		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,759	,094		-8,047	,000
	Critical_reception	,203	,016	,595	12,412	,000
	Pre_Domestic_Adjusted_100	,068	,028	,115	2,408	,017

OLS regression & mediation (H3C-nominations & budget)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,646[a]	,418	,412	,59559	,418	68,446	3	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	72,838	3	24,279	68,446	,000[b]
	Residual	101,451	286	,355		
	Total	174,290	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,701	,102		-6,865	,000
	Critical_Reception	,198	,017	,582	11,956	,000
	Budget_100	-,154	,104	-,089	-1,474	,142
	Pre_Domestic_Adjusted_100	,105	,038	,178	2,784	,006

Negative bininominal regression & mediation (H3C-nominations)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	204,051	287	,711
Scaled Deviance	204,051	287	
Pearson Chi-Square	420,504	287	1,465
Scaled Pearson Chi-Square	420,504	287	
Log Likelihood[b]	-307,623		
Akaike's Information Criterion (AIC)	621,246		
Finite Sample Corrected AIC (AICC)	621,330		
Bayesian Information Criterion (BIC)	632,256		
Consistent AIC (CAIC)	635,256		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
312,675	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	120,136	1	,000
Critical_reception	137,917	1	,000
Pre_Domestic_Adjusted_100	3,458	1	,063

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-6,666	,6081	-7,857	-5,474	120,136	1	,000
Critical_reception	,928	,0791	,773	1,083	137,917	1	,000
Pre_Domestic_Adjusted_100	,105	,0567	-,006	,217	3,458	1	,063
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression & mediation (H3C-nominations & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	203,729	286	,712
Scaled Deviance	203,729	286	
Pearson Chi-Square	414,966	286	1,451
Scaled Pearson Chi-Square	414,966	286	
Log Likelihood[b]	-307,462		
Akaike's Information Criterion (AIC)	622,924		
Finite Sample Corrected AIC (AICC)	623,064		
Bayesian Information Criterion (BIC)	637,603		
Consistent AIC (CAIC)	641,603		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
312,997	3	,000

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-6,783	,6468	-8,050	-5,515	109,986	1	,000
Critical_Reception	,940	,0822	,779	1,101	130,789	1	,000
Budget_100	,172	,3044	-,425	,769	,319	1	,572
Pre_Domestic_Adjusted_100	,065	,0902	-,111	,242	,527	1	,468
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS regression & mediation (H3C-wins)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,528[a]	,279	,274	,41061	,279	55,589	2	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,745	2	9,372	55,589	,000[b]
	Residual	48,389	287	,169		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,398	,065		-6,141	,000
	Critical_reception	,100	,011	,473	8,899	,000
	Pre_Domestic_Adjusted_100	,046	,019	,126	2,362	,019

OLS regression & mediation (H3C-wins & budget)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2
1	,545[a]	,297	,290	,40612	,297	40,348	3	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19,964	3	6,655	40,348	,000[b]
	Residual	47,170	286	,165		
	Total	67,134	289			

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,325	,070		-4,674	,000
	Critical_Reception	,094	,011	,446	8,346	,000
	Budget_100	-,193	,071	-,180	-2,719	,007
	Pre_Domestic_Adjusted_100	,092	,026	,252	3,589	,000

Negative binomial regression & mediation (H3C- wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	130,751	287	,456
Scaled Deviance	130,751	287	
Pearson Chi-Square	247,907	287	,864
Scaled Pearson Chi-Square	247,907	287	
Log Likelihood[b]	-170,897		
Akaike's Information Criterion (AIC)	347,794		
Finite Sample Corrected AIC (AICC)	347,878		
Bayesian Information Criterion (BIC)	358,804		
Consistent AIC (CAIC)	361,804		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
191,815	2	,000

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	69,915	1	,000
Critical_reception	64,279	1	,000
Pre_Domestic_Adjusted_100	7,469	1	,006

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-8,970	1,0728	-11,073	-6,868	69,915	1	,000
Critical_reception	1,060	,1322	,801	1,319	64,279	1	,000
Pre_Domestic_Adjusted_100	,170	,0624	,048	,293	7,469	1	,006
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression & mediation (H3C- wins)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	129,158	286	,452
Scaled Deviance	129,158	286	
Pearson Chi-Square	239,449	286	,837
Scaled Pearson Chi-Square	239,449	286	
Log Likelihood[b]	-170,100		
Akaike's Information Criterion (AIC)	348,201		
Finite Sample Corrected AIC (AICC)	348,341		
Bayesian Information Criterion (BIC)	362,880		
Consistent AIC (CAIC)	366,880		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
193,409	3	,000

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	-8,625	1,0880	-10,758	-6,493	62,848	1	,000
Critical_Reception	1,024	,1329	,764	1,285	59,373	1	,000
Budget_100	-,501	,4032	-1,292	,289	1,546	1	,214
Pre_Domestic_Adjusted_100	,282	,1102	,066	,498	6,554	1	,010
(Scale)	1[a]						
(Negative binomial)	1[a]						

OLS mediation & regression (H3C-wins_Big5)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,513[a]	,263	,258	,29368	,263	51,253	2	287

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,841	2	4,420	51,253	,000[b]
	Residual	24,753	287	,086		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,289	,046		-6,221	,000
	Critical_reception	,079	,008	,526	9,794	,000
	Pre_Domestic_Adjusted_100	-,012	,014	-,046	-,852	,395

OLS mediation & regression (H3C – wins_big5 & budget)

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			
					R Square Change	F Change	df1	df2
1	,536[a]	,287	,282	,28890	,287	57,755	2	287
2	,542[b]	,294	,287	,28797	,007	2,845	1	286

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,641	2	4,820	57,755	,000[b]
	Residual	23,953	287	,083		
	Total	33,594	289			
2	Regression	9,877	3	3,292	39,699	,000[c]
	Residual	23,717	286	,083		
	Total	33,594	289			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B
		B	Std. Error	Beta			Lower Bound
1	(Constant)	-,245	,047		-5,174	,000	-,338
	Critical_reception	,079	,007	,525	10,493	,000	,064
	Budget_100	-,122	,038	-,161	-3,214	,001	-,196
2	(Constant)	-,221	,049		-4,483	,000	-,318
	Critical_reception	,074	,008	,492	9,171	,000	,058
	Budget_100	-,178	,050	-,235	-3,534	,000	-,277
	Pre_Domestic_Adjusted_100	,031	,018	,119	1,687	,102	-,005

Negative binomial regression & mediation (H3C- wins_big5)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	91,375	287	,318
Scaled Deviance	91,375	287	
Pearson Chi-Square	159,799	287	,557
Scaled Pearson Chi-Square	159,799	287	
Log Likelihood[b]	-125,142		
Akaike's Information Criterion (AIC)	256,285		
Finite Sample Corrected AIC (AICC)	256,369		
Bayesian Information Criterion (BIC)	267,294		
Consistent AIC (CAIC)	270,294		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
110,895	2	,000

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	50,569	1	,000
Critical_reception	44,254	1	,000
Pre_Domestic_Adjusted_100	,005	1	,943

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	-9,355	1,3156	-11,934	-6,777	50,569	1	,000
Critical_reception	1,066	,1602	,752	1,380	44,254	1	,000
Pre_Domestic_Adjusted_100	,006	,0842	-,159	,171	,005	1	,943
(Scale)	1[a]						
(Negative binomial)	1[a]						

Negative binomial regression & mediation (H3C – wins_big5 & budget)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	86,038	286	,301
Scaled Deviance	86,038	286	
Pearson Chi-Square	150,531	286	,526
Scaled Pearson Chi-Square	150,531	286	
Log Likelihood[b]	-122,474		
Akaike's Information Criterion (AIC)	252,948		
Finite Sample Corrected AIC (AICC)	253,088		
Bayesian Information Criterion (BIC)	267,627		
Consistent AIC (CAIC)	271,627		

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
116,232	3	,000

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square	df	Sig.
(Intercept)	-8,554	1,3125	-11,127	-5,982	42,477	1	,000
Critical_reception	,983	,1589	,672	1,294	38,292	1	,000
Budget_100	-1,347	,6353	-2,592	-,102	4,494	1	,034
Pre_Domestic_Adjusted_100	,293	,1567	-,014	,600	3,487	1	,203
(Scale)	1[a]						
(Negative binomial)	1[a]						