The Cost of Coming Out[*]

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Abstract

The fear of social stigma and discrimination leads many individuals worldwide to hesitate in openly disclosing their sexual orientation. Due to the large costs of concealing identity, it is crucial to understand the extent of anti-LGB sentiments and reactions to coming out. However, disclosing one's sexual orientation is a personal choice, complicating data access and introducing endogeneity issues. This paper tackles these challenges by using an innovative data source from a popular online video game together with a natural experiment. We exploit exogenous variation in the identity of a playable character to credibly identify the effects of disclosure on players' revealed preferences for that character. Leveraging detailed daily data, we monitor players' preferences for the character across diverse regions globally and employ synthetic control methods to isolate the effect of the disclosure on players' preferences. Our findings reveal a substantial and persistent negative impact of coming out. To strengthen the plausibility of social stigma as the primary explanation for the estimated effects, we systematically address and eliminate several alternative game-related channels.

Keywords: LGB economics, social stigma, concealable stigma.
JEL Codes: J15, J71, K38

1 Introduction

The fear of social stigma significantly shapes human behavior, steering individuals to conceal actions, behaviors, or identity (Goffman, 1956; Bharadwaj et al., 2017). One important part of identity that has increasingly captured public and academic attention over the last two decades is an individual's sexual orientation (see, e.g., Badgett et al., 2023). Despite significant progress in advancing lesbian, gay, and bisexual (LGB) rights, pervasive anti-LGB sentiments persist in many countries, leading many individuals worldwide to hesitate in openly disclosing their sexual orientation due to lingering fears (Badgett, 2020) and anticipated discrimination (Aksoy et al., 2023).

Existing research indicates that concealing one's identity comes with a cost (Akerlof & Kranton, 2000). For instance, the stress of hiding one's sexual orientation is one of the potential *minority stressors* (Meyer, 1995, 2003) that explain the higher prevalence of mental disorders among LGB individuals compared to their heterosexual counterparts (see, e.g., Pachankis et al., 2020). Therefore, understanding the extent of stigma and the challenges faced by individuals upon coming out is crucial to fostering the groundwork for supportive work and living environments (Badgett et al., 2021).

In this paper, we use an innovative source of data from an online video game together with a natural experiment to assess the stigma attached to sexual minority status by observing individuals' responses to sexual minority disclosure. Existing studies examining anti-LGB sentiments, which we review below, usually face two limitations. First, they rely on a selection-on-observables identification strategy that is likely to suffer from omitted variable bias. Second, they depend on survey data where individuals have the discretion to choose whether to disclose their sexual orientation, thereby introducing additional endogeneity issues (Coffman et al., 2017; Ham et al., 2024). Our use of video game data effectively avoids these selection concerns, and the natural experiment we leverage allows for a credible identification of the responses to revealing sexual minority status.

We use a rich data set from one of the most popular online video games, *League of Legends*. In this game, before a match starts, players are required to choose one playable character. Each character is characterized by game-relevant attributes and a background story that provides details about their history, origin, and relationships with other in-game characters. We leverage an unexpected change in the background story of a playable character, which discloses his sexual

orientation minority status, to examine individuals' responses to sexual minority disclosure.

Specifically, at the beginning of the 2022 LGBT Pride Month, the game developers announced that one of their playable characters is gay. This event introduces exogenous variation in the character's identity, providing a unique opportunity to examine reactions to sexual minority disclosure. We demonstrate that the announcement was not anticipated, thereby strengthening the credibility of our identification strategy. We then utilize detailed daily data to track players' revealed preferences for the character over a meaningful period. To isolate the effects of the disclosure on players' preferences from potential confounding influences, we employ synthetic control methods to construct a synthetic character closely resembling the pre-announcement preference history of our treated character (see, e.g., Abadie, 2021; Abadie & Vives-i-Bastida, 2022).

Our findings reveal a substantial and persistent negative impact of coming out on players' preferences for the treated character, with a decline of more than 30% of the pre-treatment average preferences for that character. This result consistently holds across various robustness checks. Additionally, we exploit another unique feature of our setting. The online video game is played by individuals around the world under very comparable circumstances but on different regional servers. We make use of information on the regional servers to compare how preferences for the treated character evolve across diverse regions worldwide. The results consistently demonstrate a negative response across regions.

To strengthen the credibility of social stigma as the primary explanation for the estimated effects, it is crucial to ensure that players' decisions to switch from the character are not influenced by other factors. We address and eliminate several alternative channels, thereby enhancing the plausibility of social stigma as the primary explanation for the observed behavior. First, we rule out the possibility that shifts in characters' relative strengths could explain our estimated effect. Second, we show that players' skills have no correlation with the choice to drop the character, thus dismissing the possibility that gameplay factors are the driving force behind the players' observed behavior. Additionally, we demonstrate that players are not leaving the game after the disclosure but are shifting their focus to other characters. Third, we provide evidence that switching to other characters does not affect the performance of the players involved, highlighting that the decision to abandon the character is not driven by performance considerations.

Finally, we exploit the presence of other playable characters with sexual minority status to

show that LGBT Pride Month, which started on the day of the announcement, is unlikely to explain our findings. To do so, we introduce a theoretical framework that formalizes the existence of two "simultaneous treatments" — the disclosure of the character's sexual orientation and the start of LGBT Pride Month. We outline sufficient assumptions that enable us to separate the impacts of these treatments on players' preferences for the character.[1] The empirical results support the interpretation that the estimated effects are driven by the character's disclosure.

While our setting is unconventional, it presents unique advantages for the identification of sentiments towards the LGB identity. First, video games offer a controlled research environment, enabling the observation of behaviors that might be challenging to capture through traditional methods (Palacios-Huerta, 2023).[2] Second, they allow us to leverage objective measures of behavior and identity, circumventing the limitations associated with self-reported identity in surveys (Coffman et al., 2017; Ham et al., 2024). Conventional survey questions have been shown to result in an underrepresentation of the LGB community, thus introducing additional selection concerns. Third, online gaming platforms offer the benefit of anonymity, minimizing social desirability bias and increasing the likelihood of individuals disclosing sensitive information such as their true attitudes toward sexual minority groups.

1.1 Relation to literature

Our paper contributes to three distinct strands of the literature. First, it relates to a growing literature studying the economics of LGBTQ individuals (see, e.g., Badgett et al., 2021; Badgett et al., 2023). The current body of research primarily focuses on measuring discrimination against LGB individuals by comparing their labor market outcomes with those of non-minority individuals with similar observable characteristics, mostly documenting wage penalties for gay and bisexual men and wage premiums for lesbian women (see, e.g., Badgett, 1995; Carpenter & Eppink, 2017; Martell, 2021; Carpenter et al., 2023).[3] However, despite their valuable contributions, these studies suffer from the endogeneity and selection issues discussed

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[1] See, e.g., Roller and Steinberg (2023) for a discussion on "simultaneous treatments" and methodologies for disentangling their effects under a difference-in-differences identification strategy.

[2] The recognition of video game data's potential for research is growing among economists, although at a gradual pace. Parshakov et al. (2018), Parshakov et al. (2023), and Dell'Acqua et al. (2023) are instances of this emerging trend. Parshakov et al. (2023) investigate consumer behavior in the video game industry. They examine the impact of marking products with a gay label on consumers' demand, finding a significant, albeit short-lived, decrease in demand following the introduction of the gay label.

[3] The only study finding a wage premium for gay men is that of Carpenter and Eppink (2017). Tampellini (2024) does not find a wage penalty but finds a lower probability of being full-time employed and a higher probability of being a victim of work-related violence for gay men. There is also evidence that transgender workers face earning and employment penalties (Geijtenbeek & Plug, 2018; Carpenter et al., 2022).

above that hinder the ability to draw causal inferences from their findings.[4] To tilt towards a more causal interpretation, other studies use correspondence designs to probe into hiring discrimination against LGB individuals, consistently revealing that LGB job candidates are less likely to be invited for interviews or offered job opportunities (Weichselbaumer, 2003; Drydakis, 2009; Tilcsik, 2011; Ahmed et al., 2013; Drydakis, 2014). Nevertheless, a significant challenge lies in communicating that an individual belongs to a sexual orientation minority group, since such information is not typically included in job applications. This raises the question of whether the observed results are affected by the choice and nature of the used signal (Bertrand & Duflo, 2017).

We make several contributions to this literature. First, our use of data from an online video game allows us to overcome the endogeneity issues of previous studies and to identify preferences toward LGB status. Second, to the best of our knowledge, our study is the first to investigate the immediate reactions to coming out. Due to the substantial anecdotal and scientific evidence that individuals often hide their sexual orientation status (see, e.g., Badgett, 2020) and the prevalent evidence of the associated costs (Meyer, 2003; Pachankis et al., 2020), several studies have explicitly focused on investigating the determinants and incentives of coming-out decisions. Seror and Ticku (2021) investigate the impact of same-sex marriage legalization on coming-out decisions using a revealed preference mechanism inferred from data on Catholic priests' vow of celibacy, finding reduced demand for priestly studies after the adoption of same-sex legalization. Gromadzki and Siemaszko (2022) explore spillover effects of coming-out decisions using Twitter data, discovering positive externalities, as exposure to peers coming out is associated with a higher probability of individuals coming out themselves. Aksoy et al. (2023) conduct a lab experiment demonstrating that individuals strategically hide their sexual orientation in anticipation of discrimination in prosocial behavior, a result consistent with that of Kudashvili and Lergetporer (2022). Our study complements these studies by focusing on responses to revealing sexual minority status, potentially providing a rationale for the observed underrepresentation of individuals with sexual minority status in many areas.

Second, our contribution extends to the literature exploring the intersection of identity and decision-making, as discussed by Akerlof and Kranton (2000). Empirical investigations

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[4] A related literature studies whether changes in laws and norms affect labor market outcomes and attitudes towards LGB individuals (see, e.g., Burn, 2018; Ofosu et al., 2019; Sansone, 2019; Burn, 2020; Delhommer, 2020; Deal, 2022, 2023). Broockman and Kalla (2016) show that a randomized intervention that encourages actively taking the perspective of others can reduce transphobia.

encounter a challenge where causality is likely bidirectional - meaning it can operate both from identity to economics and from economics to identity. Furthermore, identity is a multifaceted concept, thus isolating a particular component of identity is empirically challenging (Shayo, 2020). Previous research overcomes these challenges and documents in-group and out-group behavior using either individuals' inherent identities (see, e.g., Giuliano et al., 2009; Price & Wolfers, 2010; Oh, 2023) or by experimentally introducing identities (see, e.g., Chen & Li, 2009; Chen & Chen, 2011).[5] Results highlight the importance of an individual's identity in shaping their behaviors, revealing a tendency for preferential treatment or bias towards those who share similar characteristics (in-group bias). To the best of our knowledge, our study is among the first studies to causally show the influence of sexual orientation status on preferences. Because sexual orientation is a key but non-salient facet of social identity, our paper makes an important contribution to this literature.

Third, our findings also contribute to the broader literature on discrimination. Early work by Becker (1957) paved the way for an extensive literature investigating discrimination instances, mostly based on gender and ethnicity, across diverse economic domains (see, e.g., Kuhn & Shen, 2013; Arnold et al., 2022). A substantial portion of the empirical evidence stems from field experiments, in which researchers use audit and correspondence studies to isolate the causal impact of identity on behavior (see, e.g., Ayres & Siegelman, 1995; Oreopoulos, 2011).[6] Our study contributes by exploring sentiments against sexual orientation minorities. The concealable nature of sexual orientation allows individuals to anticipate discrimination and strategically choose to hide their identity (Aksoy et al., 2023). This complicates the use of traditional methods to investigate discrimination against individuals based on their sexual orientation and necessitates innovative strategies for understanding sentiments against groups with stigmatized identities, particularly in environments prone to discrimination.

The rest of the paper unfolds as follows. Section 2 describes the key elements of League of Legends that are relevant to our study and outlines the natural experiment we leverage to identify the effects of coming out. Section 3 introduces the data and explains the methodology we use to isolate the effects of coming out. Section 4 presents our main results. Section 5 examines the underlying mechanisms driving the estimated effects. Section 6 concludes.

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[5] For recent reviews of the literature, see Kalin and Sambanis (2018), Charness and Chen (2020), and Shayo (2020).

[6] For recent surveys, see Bertrand and Duflo (2017) and Neumark (2018). Onuchic (2022) provides a detailed review of traditional statistical and taste-based discrimination models, along with a discussion of recent theories that expand on these models.

2 Context

In this section, we explore the contextual framework that enables us to measure social reactions to the disclosure of sexual orientation. Specifically, we turn our attention to the online video game *League of Legends* as our source of data and the natural experiment we leverage to credibly identify the causal effects of coming out.

The next subsection describes the key elements of League of Legends that are relevant to our study. Our analysis does not rely on in-game information, but instead focuses on the pre-match phase. Therefore, we do not provide an exhaustive account of how matches unfold, but rather emphasize the details that inform our research. Then, we discuss the coming-out event we exploit and its implications for identification purposes.

2.1 League of Legends

League of Legends is a prominent multiplayer online game developed and published by Riot Games. Originally launched on October 27th, 2009, the game attracted an impressive player base, with an average of over 32 million daily players and a total of 180 million players in 2022. League of Legends has also achieved significant financial success, with its microtransaction system generating an average daily revenue of $2.64 million.

In League of Legends, players are divided into two teams of five players each to compete in matches with the aim of destroying the opposing team's base. Players in each team sort themselves into one of five roles: *top lane*, *jungle*, *mid lane*, *bottom lane*, and *support*. These roles are not mere labels but represent crucial strategic positions, each requiring specific playstyles and contributing differently to the team's final objective.

Before a match begins, players must select a playable character to control during the match from a pool of 165 available characters. In our analysis, we measure players' revealed preferences for a specific character by quantifying how frequently they select that character for their matches. Our objective is to investigate whether these preferences undergo any shifts following the disclosure of the character's sexual orientation. Thus, we devote the rest of this section to exploring the design of characters in League of Legends and the process through which players select their characters for matches.

Each character has a unique set of skills and abilities and is specifically designed to excel in one or two of the distinct roles that players can assume within the team. Additionally,

characters are crafted with a rich background that adds a narrative dimension to the game but does not have any impact on the game's mechanics. This is achieved through the creation of detailed biographies and short stories that provide players with a deeper understanding of the character's history and motivations, thus offering players the opportunity to connect with their chosen characters on a more personal level.[7]

The character selection process occurs in a virtual lobby where players can communicate with their teammates through a chat function. In a random order that alternates between teams, players take turns selecting their characters for the match. Once a player chooses a character, their selection becomes visible to all players participating in the match, including the opposing team. Once all players have selected their characters, the match begins.

When making their character selection, players consider various factors. First, they consider the role they are assigned to fulfill in the game. Each role has its own set of responsibilities and playstyle requirements, and players aim to choose a character that aligns with their designated role. Second, players take into account their personal mastery of specific characters, opting for those they are most skilled and comfortable with. Third, players may also consider their personal preferences, such as the playstyle and background story of the character, adding a subjective element to the selection process.

2.2 Identification

Every year in June, *LGBT Pride Month*, a dedicated time to honor and celebrate the LGBT community, takes place. Since 2018, Riot Games has actively participated in this month-long celebration by integrating new content into League of Legends during the month of June. This includes the introduction of in-game cosmetics, such as character skins, as well as emotes that allow players to express themselves in the game. It is important to note that while these additions enhance the visual and expressive elements of the game, they do not alter the game's mechanics or the characteristics and abilities of the League of Legends characters.[8]

Riot has also supported the representation of the LGBT community in the game by unveiling the sexual minority status of specific characters.[9] In our paper, we primarily focus on the

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[7] The list of all characters along with details about their abilities and histories is available at https://www.leagueoflegends.com/it-it/champions/.

[8] We check this in Section 5.1, where we demonstrate that characters' strength was unaffected by LGBT Pride Month.

[9] For instance, in 2018, the character *Neeko* was confirmed as lesbian, marking her as the first openly LGBT character in the game. Furthermore, in 2021, the characters *Diana* and *Leona* were revealed to be lesbians, while the character *Nami* was declared to be lesbian and polyamorous.

character *Graves*, chosen due to the existence of a well-defined announcement regarding his sexual orientation.

At the beginning of the 2022 LGBT Pride Month, Riot Games released a short story featuring Graves and *Twisted Fate*. This story officially unveils Graves' sexual orientation, establishing him as a gay character.[10] The following quotes provide two pivotal passages of the narrative:[11]

> *I do not have terrible taste in men. I have good taste in terrible men.* (Graves)

> *[. . .] asked Fate with a tinge of poorly concealed jealousy, despite Graves having been gay for the better part of four decades.* (Storyteller)

This *coming-out event* closely approximates an ideal experiment where individuals randomly disclose their sexual minority status, thus providing a unique setting to investigate the effects of coming out on players' preferences for Graves.[12]

To ensure the credibility of our identification, it is crucial that the disclosure was not anticipated by players. The top panel of Figure 2.1 displays the Google search interest for the query *"Graves gay."* We observe minimal interest in this search term throughout the year 2022, with a remarkable spike occurring during the week of the coming-out event. This pattern supports our assumption of no anticipation and strengthens the credibility of our identification strategy.

Furthermore, the lower panel of Figure 2.1 displays the Google search interest for the query *"LoL Graves."*[13] Similarly to the previous search term, we observe a remarkable spike in interest during the week of the treatment. What is particularly interesting is that this surge in interest surpasses the level observed during the 2022 League of Legends World Championship (held from September 29th to November 5th), despite Graves being among the top-eight most played characters during the tournament. This finding emphasizes the substantial impact and attention that the coming-out event received from players.

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[10] The story unveiling Graves' sexual orientation also subtly hints at Twisted Fate's pansexuality, although this is not explicitly stated. We investigate whether this implied revelation has captured the players' attention in Appendix C. We highlight the relatively low attention directed towards Twisted Fate from players, who were primarily focused on Graves and the explicit establishment of his sexual orientation. As a result, we concentrate our analysis on Graves and his disclosure for a more credible identification of the effects of coming out.

[11] The whole story is available at https://universe.leagueoflegends.com/en_SG/story/the-boys-and-bombolini/.

[12] It is crucial to distinguish between the *coming-out event* and the disclosure of Graves' sexual orientation. The coming-out event encompasses both Graves' disclosure and the start of LGBT Pride Month. While this is not a concern for identification, it requires careful interpretation of the findings. To maintain clarity, we generally refer to the effects of the coming-out event in our analysis. Further discussion on this topic is deferred to Section 5.4 and Appendix D.

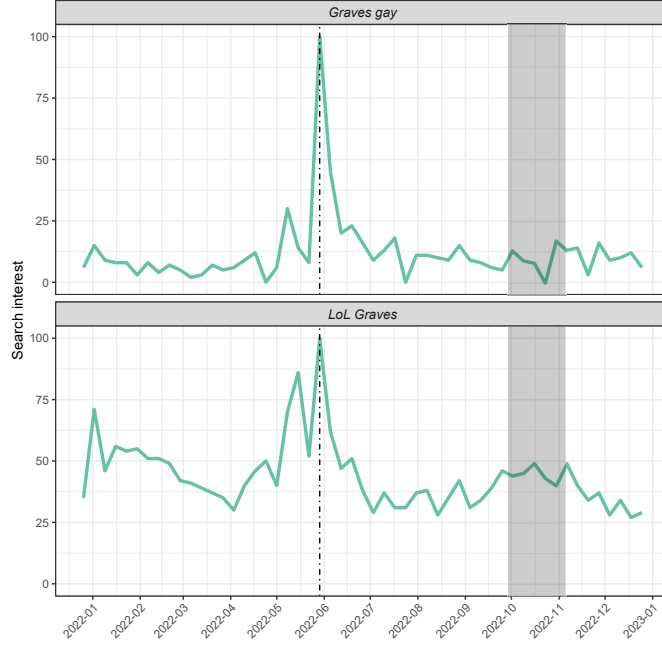[13] *LoL* is the common short-hand for League of Legends.

Figure 2.1: Google search interest over time for the queries *"Graves gay"* (top panel) and *"LoL Graves"* (bottom panel). The dashed vertical line denotes the week of disclosure, and the shaded area highlights the League of Legends World Championship.

3   Data and Methodology

In this section, we introduce the data and explain the methodology employed in our analysis. The next subsection outlines the construction of our data set and details how we gauge players' revealed preferences for characters. We then provide a formal review of the synthetic control estimator employed to isolate the effects of the coming-out event on players' preferences for Graves.

3.1   Data

We obtain our data by accessing the Riot Games API, which provides us with valuable information about League of Legends matches.

The game operates on multiple servers located worldwide, and we focus on specific servers for our analysis. These servers include Brazil, North and East Europe, West Europe, Korea, North Latin America, South Latin America, and North America.

Within these servers, we target the top tier of the League of Legends ranked system, which comprises the top 200 or 300 players (approximately the top 0.01% of players) on each server. By targeting this specific group of players, we aim to minimize the noise that may arise from players who are not fully engaged in the game, thus reducing the risk of attenuation bias. Furthermore,

this focus increases the chances that players in our data set are aware of the coming-out event, thereby strengthening the credibility of our identification strategy.

Specifically, we identified the players within the top tier of each server as of July 2022. For each of these players, we gathered data on all the matches they engaged in the ranked mode during the period January-July 2022.[14] This approach inherently includes players who were not in the top tier as of July 2022 but have been matched with our focal players during the time span we consider.

From these data, we construct a balanced daily panel data set that tracks the usage of each character over time. This results in a final data set composed of $161,756$ players, engaging in a total of $142,856$ matches played over 193 days, encompassing a total of 159 characters.

To gauge players' revealed preferences for characters, we construct a metric called *pick rate*, which measures the frequency with which players choose a specific character in their games each day. Our primary objective is to investigate whether the disclosure of Graves' sexual orientation influences the pick rate of this character.

3.2 Methodology

A simple comparison of Graves' pick rates before and after the disclosure may not accurately reflect the impact of the coming-out event on players' preferences for that character, as other unobserved factors could have changed during that period. To address this issue, we construct a synthetic control unit (see, e.g., Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021; Abadie & Vives-i-Bastida, 2022) by weighting other characters to approximate the pick rates of Graves before the disclosure. This method allows us to isolate the effects of the coming-out event on players' revealed preferences for Graves and gain insight into how these preferences would have behaved in the absence of the disclosure.

Formally, our data set comprises $n = 159$ characters ($i = 1, \ldots, n$) observed over $T = 191$ days ($t = 1, \ldots, T$). T^{pre} is the length of the period (150 days) before the coming-out event, which occurs at time $T^{pre} + 1$ (i.e., June 1st, 2022). For each unit i and time t, we denote the observed pick rate as $Y_{i,t}$. We represent the coming out as a binary variable $C_i \in \{0, 1\}$ equal to one if character i discloses his sexual orientation at time $T^{pre} + 1$. We then posit the existence of two

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[14] Players can choose between *draft* or *ranked* matches. Both game modes share the same mechanics and objectives. However, while draft matches are more casual and do not have consequences for players' rankings or ratings, in ranked matches players earn or lose points based on the outcome of the match to determine their position within the ranked system. By focusing on ranked matches we aim to further reduce the risk of attenuation bias.

potential pick rates $Y_{i,t}^c$, where one denotes the pick rate in the absence of disclosure ($Y_{i,t}^0$) and the other denotes the pick rate in the presence of disclosure ($Y_{i,t}^1$).[15]

Without loss of generality, we let the first unit $i = 1$ be Graves. This implies that $C_1 = 1$ and $C_i = 0$ for all $i \neq 1$. Then, for each period $t > T^{pre}$, we define the effect of the coming-out event on players' preferences for Graves as the difference in Graves's potential pick rates at time t:

$$\tau_t := Y_{1,t}^1 - Y_{1,t}^0 \tag{3.1}$$

Note that we allow the effects to change over time.

Since Graves' sexual orientation has been disclosed after period T^{pre}, under a standard SUTVA assumption (see, e.g., Imbens & Rubin, 2015) we observe $Y_{1,t} = Y_{1,t}^1$ for all $t > T^{pre}$. Thus, as shown in equation (3.1), the challenge in estimating our causal effects of interest is to estimate $Y_{1,t}^0$ for $t > T^{pre}$, i.e., how Graves' pick rates would have evolved in the absence of the disclosure. To this end, we can construct a synthetic control unit that approximates the pick rates of Graves before the coming out. The idea is that if the synthetic control and Graves behave similarly before the disclosure, then the synthetic control can serve as a valid counterfactual.

The synthetic control unit is characterized by a set of weights, denoted as $\omega := (\omega_2, \ldots, \omega_n)$, chosen to align the pre-treatment pick rates of the synthetic unit with those of Graves. This is achieved by solving the following optimization problem (Arkhangelsky et al., 2021):

$$\hat{\omega} = \underset{\omega \in \Omega}{\arg\min}\, \ell(\omega)$$

$$\ell(\omega) = \sum_{t=1}^{T^{pre}} \left(\sum_{i=2}^{n} \omega_i Y_{i,t} - Y_{1,t} \right)^2 + \zeta^2 T^{pre} \|\omega\|_2^2, \quad \Omega = \left\{ \omega \in \mathbb{R}_+^{n-1} : \sum_{i=2}^{n} \omega_i = 1 \right\} \tag{3.2}$$

where the weights are restricted to be non-negative and to sum up to one and a ridge penalty is employed to ensure the uniqueness of the weights. In our main specification, we set the regularization parameter to zero, thus employing a standard synthetic control estimator. As a robustness check, we follow Arkhangelsky et al. (2021) and set $\zeta = (T - T^{pre})^{1/4} \hat{\sigma}$, with $\hat{\sigma}$ denoting the standard deviation of first differences of $Y_{i,t}$ for control units over the pre-treatment period.

We estimate the counterfactual outcome of Graves as a weighted average of the outcome of the control units:

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[15] These potential outcomes are based on Rubin's model for causal inference (Rubin, 1974).

$$\widehat{Y}_{1,t}^0 = \sum_{i=2}^{n} \hat{\omega}_i Y_{i,t} \tag{3.3}$$

Finally, to estimate the causal effects of interest, we compute the differences between Graves' observed pick rates and the synthetic counterfactual for all $t > T^{pre}$:

$$\hat{\tau}_t = Y_{1,t}^1 - \widehat{Y}_{1,t}^0 \tag{3.4}$$

We summarize the estimated effects by reporting the average treatment effect on players' preferences for Graves, with the averaging carried out over the post-treatment periods:

$$\hat{\tau} = \frac{1}{T - T^{pre}} \sum_{t=T^{pre}+1}^{T} \hat{\tau}_t \tag{3.5}$$

We employ the "placebo approach" of Arkhangelsky et al. (2021) to estimate the variance of $\hat{\tau}$. We then use the estimated variance to construct asymptotically valid conventional confidence intervals.[16]

4   Results

In this section, we present our main results. First, we present our main findings and a series of robustness checks that validate the reliability of our estimates. We then explore the possibility of regional variations in attitudes toward the LGB community by replicating our analysis across different servers.

4.1   Main Results

We apply the synthetic control estimator of Section 3.2 to estimate the effects of the coming-out event on players' revealed preferences for Graves. To mitigate the potential for spillover effects, we exclude Twisted Fate and other four characters (*Diana*, *Leona*, *Nami*, and *Neeko*) that were already members of the LGB community prior to the coming-out event from the donor pool.[17]

Figure 4.1 displays Graves' actual and synthetic pick rate series, while the first column of Table 4.1 displays the point estimate and 95% confidence interval for the average treatment

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[16] The validity of this placebo approach hinges on a homoskedasticity assumption which requires that treated and control units have the same noise distribution. In general, with only one treated unit, nonparametric variance estimation for treatment effect estimators is typically impossible without a homoskedasticity assumption (Arkhangelsky et al., 2021).

[17] Nevertheless, even if included in the donor pool, the estimator assigns these characters zero weight.

effect.[18] Overall, our analysis suggests a substantial negative impact of the coming-out event on players' preferences for Graves. Before the disclosure, the synthetic control estimator closely approximates the trajectory of Graves' pick rates, providing support for the estimator's ability to predict the counterfactual series. However, starting from June 1st, 2022, the two series diverge substantially, with Graves' pick rates consistently dropping below those of the synthetic control. This gap persists over time, extending even beyond the conclusion of LGBT Pride Month. The average effect is estimated to be around −7 percentage points and is statistically different from zero at the 5% significance level.[19] This implies a decline of −38.69% of the pre-treatment average preferences for Graves.

We examine the robustness of our results to the choice of the estimator and the composition of units in the donor pool. In particular, we repeat our analysis employing a regularized synthetic control estimator (see Section 3.2) and we explore different donor pool configurations focusing on characters from distinct roles. Notably, Graves is predominantly designed for and played in the top lane, jungle, and mid lane positions. Consequently, there is a possibility of spillover effects on other characters mainly played in these positions, as players transitioning away from
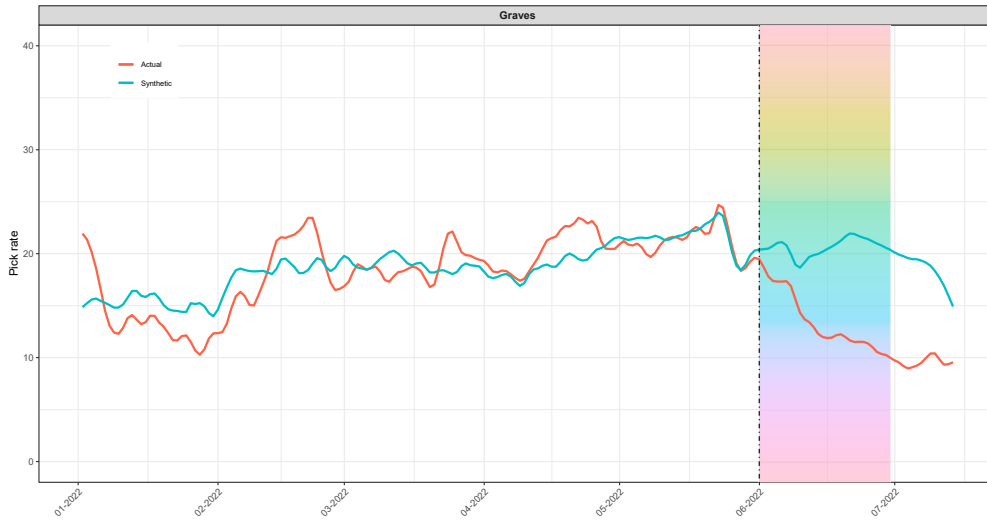

Figure 4.1: Graves' daily pick rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

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[18] Figure A.1 in Appendix A displays the identities and the contributions of the characters in the donor pool with non-zero estimated weights.

[19] To provide further evidence that our main estimate is not driven by chance, we reassigned the treatment to all control characters in our data set. This allowed us to generate a distribution of "placebo" effects, which serves as a basis for comparing the impact on Graves (see, e.g., Abadie et al., 2010, 2015). We report the ratios of post- to pre-treatment root mean squared error (RMSE) in Figure B.1 in Appendix B, where Graves ranks second in terms of RMSE ratio. This implies that the impact on Graves is unusually large compared to the distribution of placebo effects, reinforcing the interpretation that our analysis provides significant evidence of a negative effect of the coming-out event.

Graves are likely to switch to these alternatives.[20] To mitigate this potential for spillover effects, we restrict our donor pool to characters that are "non-substitutes" of Graves, that is, those primarily designed for the bottom lane and support roles.

The first panel of Table 4.1 displays the results. For any donor pool composition, the results are not sensitive to the choice of the regularization parameter. Point estimates are consistently negative across the considered specifications and are statistically different from zero at the 5% significance level. An exception arises in the second column, where employing a standard synthetic control estimator while restricting the donor pool to bottom lane and support roles leads to a confidence interval that encompasses zero. The results are consistent also quantitatively across all specifications, with a decline ranging between -38.69% and -37.49% of the pre-treatment average preferences for Graves. Overall, these results support our main finding of a substantial negative impact of the coming-out event on players' preferences for

	Synthetic Controls		Regularized Synthetic Controls	
	(1) All characters	(2) Only non-substitutes	(3) All characters	(4) Only non-substitutes
Panel 1: All				
$\hat{\tau}$	-7.156	-6.954	-7.059	-6.933
95% CI	[-13.826, -0.486]	[-14.070, 0.162]	[-11.900, -2.219]	[-14.154, 0.286]
N. Donors	4	4	4	5
RMSE	2.250	2.354	2.267	2.272
Panel 2: Europe				
$\hat{\tau}$	-8.961	-11.443	-8.368	-10.298
95% CI	[-15.013, -2.910]	[-19.246, -3.639]	[-14.357, -2.380]	[-17.566, -3.030]
N. Donors	6	5	7	8
RMSE	2.151	2.524	2.189	2.477
Panel 3: Korea				
$\hat{\tau}$	-10.158	-8.983	-10.377	-8.798
95% CI	[-18.022, -2.293]	[-19.356, 1.391]	[-18.973, -1.780]	[-17.820, 0.225]
N. Donors	3	3	3	3
RMSE	6.145	6.487	6.178	6.500
Panel 4: Latin America				
$\hat{\tau}$	-6.826	-6.803	-5.769	-5.456
95% CI	[-11.595, -2.057]	[-12.704, -0.902]	[-10.509, -1.028]	[-11.885, 0.973]
N. Donors	4	4	7	7
RMSE	2.400	2.520	2.401	2.480
Panel 5: North America				
$\hat{\tau}$	0.945	0.945	0.984	0.983
95% CI	[-4.855, 6.746]	[-6.215, 8.106]	[-4.207, 6.175]	[-6.470, 8.437]
N. Donors	3	3	4	4
RMSE	4.521	4.521	4.523	4.526

Table 4.1: Point estimates and 95% confidence intervals for $\hat{\tau}$. Additionally, the number of donors receiving a non-zero weight and the pre-treatment root mean squared error are displayed. The first panel reports the results obtained using all the observed matches. The remaining four panels report the results obtained using only matches from a particular region. Each column corresponds to a different specification, with the specifications differing solely in the employed estimator and donor pool composition.

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[20] The findings of Section 5.2 support this intuition.

Graves.

We also assess the credibility of the synthetic control estimator by conducting a robustness check that artificially shifts the coming-out event ten days earlier. This backdating exercise allows us to evaluate the estimator's predictive accuracy during a ten-day hold-out period (see e.g., Abadie & Vives-i-Bastida, 2022). The upper panel of Figure B.2 in Appendix B presents the results of this analysis. We observe three key findings. First, the estimated effects remain qualitatively and quantitatively consistent, confirming a negative and persistent impact of the coming-out event on players' revealed preferences for Graves. Second, the synthetic control estimator demonstrates a good fit during the hold-out period, indicating its ability to accurately capture Graves' behavior prior to the disclosure. Third, the actual and the synthetic series begin to diverge on the true day of disclosure, even when the estimator has no knowledge of the actual disclosure date. The absence of estimated effects before the coming-out event also lends support to the plausibility of a no-anticipation assumption (see e.g., Abadie, 2021).

Finally, we conduct an additional robustness test by performing a leave-one-out exercise, where we repeatedly estimate the synthetic control series by excluding one character with non-zero estimated weights at a time from the donor pool (see e.g., Abadie, 2021). The lower panel of Figure B.2 in Appendix B presents the results of this analysis. Overall, our finding of a negative and persistent impact of the coming-out event on players' preferences for Graves is robust to the exclusion of any particular character. Most of the leave-one-out synthetic series closely align with the main estimate, thus reinforcing the robustness of the main conclusion of our study. One leave-one-out series falls beneath the other synthetic series, suggesting a somewhat reduced, although still negative, impact. However, this series diverges from the actual series in the weeks prior to the treatment, which undermines the reliability of its results.[21]

4.2 Regional Heterogeneity

Previous research has demonstrated that attitudes toward LGB people can substantially vary between countries, causing also a large variation in the number of individuals openly identifying with the LGB community (see, e.g., Badgett, 2020; Badgett et al., 2021).[22] To explore regional differences in players' attitudes towards this community, we exploit the regional information of

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[21] This series is obtained by excluding the character *Ezreal* from the donor pool. Figure A.1 shows that this character receives the largest weight in our main specification. Therefore, the divergence of this leave-one-out series from the actual series is unsurprising.

[22] An OECD report shows that even within a set of relatively comparable OECD countries, the size of the LBG communities differs by a factor of four (OECD, 2019).

the matches. We divide our sample based on the server on which the matches were hosted. For comparability and data availability reasons, the matches are classified into four regional categories: European matches (North and East Europe and West Europe servers), Korean matches, Latin American matches (Brasil, North Latin America, and South Latin America servers), and North American matches. We then apply the synthetic control estimator of Section 3.2 to each of these categories separately.

Figure 4.2 and Table 4.1 display the results. The synthetic control estimator closely approximates the trajectory of Graves' pick rates for matches in Europe and Latin America before the disclosure, exhibiting pre-treatment root mean squared errors comparable to those of the pooled specifications. However, discrepancies arise in Korean and North American matches, where the pre-treatment root mean squared error is two to three times higher than that achieved with European and Latin American matches. In Europe and Latin America, we estimate a negative and persistent effect of the coming-out event on players' preferences for Graves. Point estimates are consistently negative across the considered specifications.

Although the magnitudes of the estimated effects vary across regions, it is important to consider that this does not necessarily reflect differential attitudes towards the LBG community, as various other factors may differ across servers. One such factor could be the differential levels of competitiveness on different servers, which may affect the character selection process
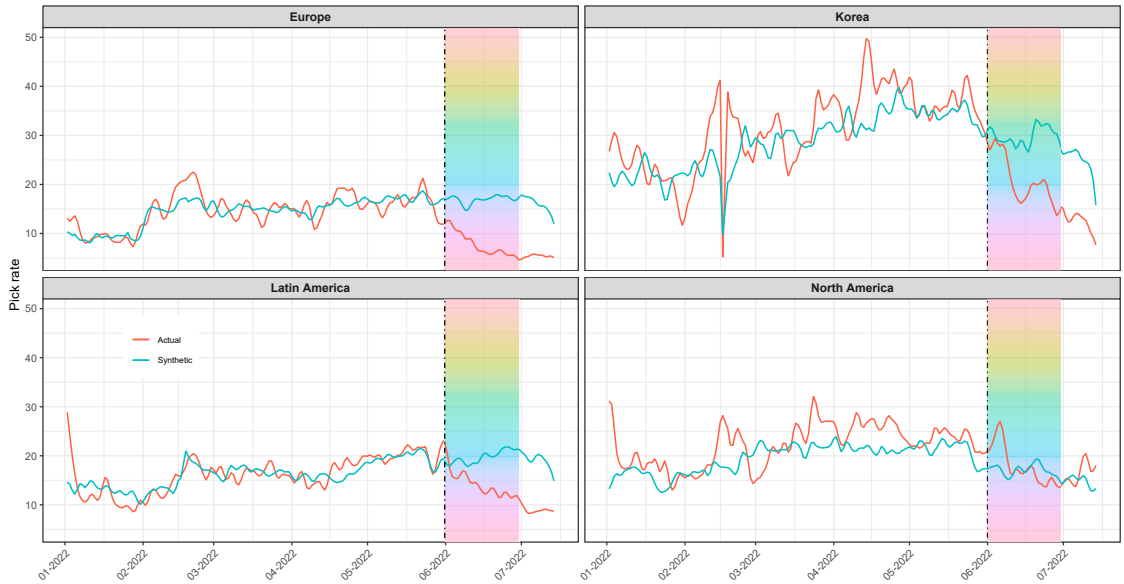

Figure 4.2: Graves' daily pick rates and synthetic control estimation results by region. The actual series are smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

by introducing different levels of subjectivity. We therefore carefully interpret our results in this section as evidence for anti-LGB sentiments in various regions, rather than interpreting the differences in the effect sizes.

5   Mechanisms

In Section 4, we established evidence of a substantial negative impact of the coming-out event on players' revealed preferences for Graves. However, the players' decision to switch from this character might be influenced by factors beyond the social stigma attached to playing an LGB character. The objective of this section is to eliminate these alternative channels, thereby enhancing the plausibility of social stigma as the primary explanation for the observed behavior.

First, we examine the idea that shifts in character relative strengths could explain our estimated effect. We rule out this possibility in Section 5.1 by demonstrating that Graves' strength remained unaffected by the coming-out event. Second, we explore the potential influence of players' skills on their decision to abandon Graves. In Section 5.2, we show that players' skills have no correlation with the choice to drop the character, thus dismissing the possibility that gameplay factors are the driving force behind the players' observed behavior. Third, we investigate whether players transitioning away from Graves experience any performance-related consequences. This is the topic of Section 5.3, where we present evidence that switching to other characters does not affect the performance of the players involved. This emphasizes our ability to measure players' true social attitudes and stigma, avoiding any potential biases stemming from strategic performance considerations.

Finally, we acknowledge that questions may arise about whether the findings of Section 4.1 are solely a consequence of Graves' disclosure or if they are influenced by the broader context of LGBT Pride Month. We exploit the presence of other playable characters with sexual minority status to show that LGBT Pride Month is unlikely to explain our findings. Specifically, Appendix D introduces a theoretical framework that formalizes the existence of two "simultaneous treatments" and outlines sufficient assumptions that enable us to separate the impacts of coming out and LGBT Pride Month on players' preferences for Graves. The results, detailed in Section 5.4, support the interpretation that the estimated effects are driven by Graves' disclosure.

5.1 Graves' Performance

Crucial to the plausibility of social stigma attached to playing an LGB character as the primary explanation for the players' observed behavior is the fact that Graves' strength remained unaffected by the coming-out event, as any change in character relative strengths could explain why players' preferences shift away from Graves.

To address this concern, we employ the synthetic control estimator described in Section 3.2 to examine the potential impact of the coming-out event on Graves' performance. We measure characters' performance using daily win rates, which indicate the percentage of matches won by a character out of the total matches they participated in each day.

Figure 5.1 displays the results. Overall, our analysis reveals that the coming-out event had no impact on Graves' strength. Despite the actual series exhibiting daily fluctuations around the 50% mark, the synthetic control estimator effectively captures its pre-treatment trend, showcasing its ability to predict the counterfactual trend. After the treatment date, the synthetic control estimator continues to align with Graves' win rate trend, confirming that the character's strength was unaffected by the disclosure. The average effect is estimated to be -1.446 percentage points (standard error: 3.506), and the conventional 95% confidence interval encompasses zero, indicating a failure to reject the null hypothesis of no effect. These findings demonstrate that Graves' strength remained unchanged during the coming-out event, dismissing the possibility of a shift in his strength as an explanation for the results of Section 4.1.
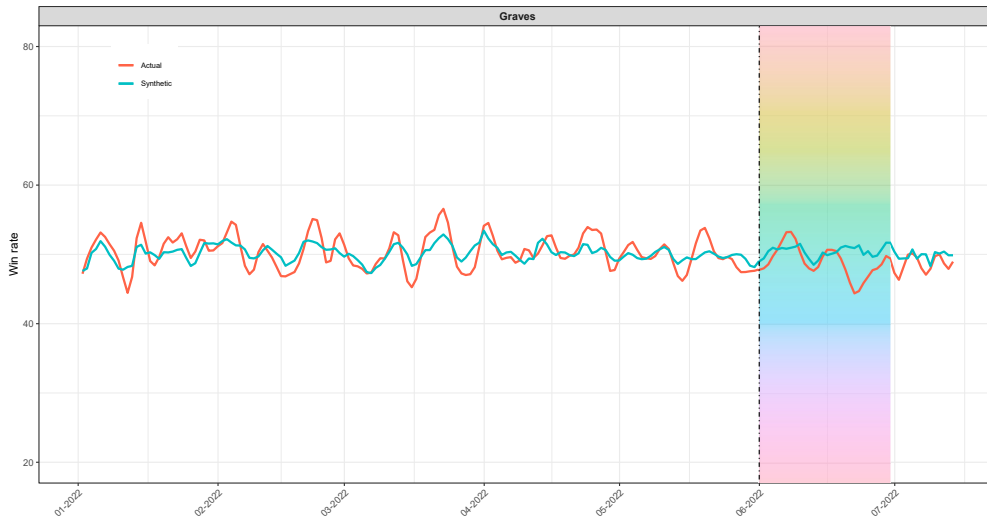

Figure 5.1: Graves' daily win rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

Moreover, we note that players have real-time access to detailed information regarding characters' strengths, weaknesses, and overall performance, as numerous websites continuously provide updated data on characters' in-game statistics.[23] Therefore, players were well-informed that no game-relevant skills or attributes were altered during the treatment period, and they could observe that Graves's strength remained consistent. These factors suggest that the negative impact of the coming-out event estimated in Section 4.1 is unlikely to be driven by actual or presumed changes in character relative strengths.

5.2 Players' Skills

If highly skilled players exhibit distinct preferences for Graves or are less influenced by the character's sexual orientation, the decision to switch from Graves might be driven by gameplay factors rather than social preferences for sexual orientation, thus challenging our social stigma narrative.

To address this concern, we examine the correlation between players' skills and their decision to abandon Graves. We classify players into two groups based on their preferences for Graves before his disclosure: the first group comprises those who never selected Graves before the coming-out event (henceforth labeled as *non-prior users*), while the second group comprises those who chose Graves at least once in their matches before the coming-out event (henceforth labeled as *prior users*). We then examine performance differences both within and between these groups before and after the treatment. To mitigate potential noise from players with limited match appearances, we restrict our analysis to players who engaged in a minimum of 100 matches before the disclosure. This yields a sample of 2872 players, with 1834 being non-prior users.

The top panel of Figure 5.2 displays the average pick rate for Graves among prior and non-prior users before and after the treatment. We observe a sharp decline in pick rates among prior users following the coming-out event, similar in size to the decrease shown in Figure 4.1. Conversely, non-prior users exhibit a marginal increase in average pick rates post-treatment, although this increase is practically negligible.

In the remaining panels of Figure 5.2, we investigate whether prior and non-prior users exhibit differences in their characteristics. First, the bottom left panel displays the average

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[23] Examples of such websites include https://lolalytics.com/lol/graves/build/ and https://www.leagueofgraphs.com/champions/stats/graves.

number of daily matches played by players. We observe similar numbers between groups both before and after the treatment, indicating that prior and non-prior users tend to engage in a comparable number of matches each day. We also note no differences in matches played post-treatment within both groups. This suggests that players are not leaving the game after the coming-out event. Instead, they are shifting their focus to other characters. Furthermore, Figure A.2 in Appendix A reveals that neither prior nor non-prior users change roles following Graves' disclosure. This observation aligns with the intuition that players have sufficient alternatives, allowing them to easily switch to other characters and express their preferences at a low cost.

Second, the bottom right panel displays the players' average win rates, a metric capturing players' skills by measuring the percentage of matches won out of their total engagements. We observe no substantial disparities within and between groups, indicating that the preference for Graves and the decision to abandon this character are unrelated to players' skill levels. Overall, these findings dismiss the possibility that game-play factors are the driving force behind the estimated effects of Section 4.1, lending additional support to the social stigma attached to playing an LGB character as the mechanism underlying the players' observed behavior.
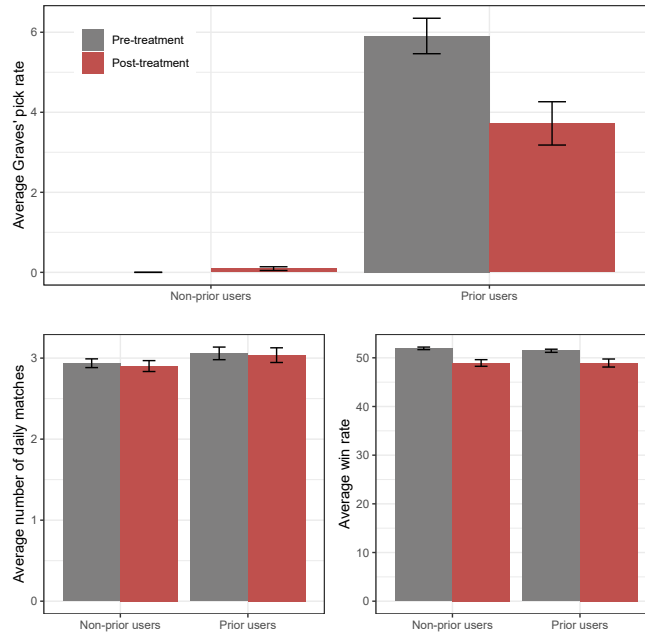

Figure 5.2: Players' average pick rates for Graves and performance measures. Players are divided into two groups based on their preferences for Graves before his disclosure. The panels display the average pick rates for Graves, number of daily matches, and win rate of each group before and after the coming-out event.

5.3 Players' Performance

To ensure the accuracy of our measurement of players' genuine attitudes toward the LGB community, it is crucial to assess whether shifting away from Graves to other characters impacts players' performance. If there are performance costs, our estimates could be biased toward zero, as players might continue using Graves for strategic considerations. Moreover, if players switch characters primarily for convenience, our analysis might unintentionally capture a different phenomenon instead of the intended social stigma.

We employ difference-in-differences identification and estimation strategies to assess the impact of players abandoning Graves on their performance. We gauge players' performance by their daily win rate, which measures the percentage of matches won out of their total engagements. Our analysis focuses on the 1038 prior-users of Section 5.2, who are classified into treated or control groups based on their responses to Graves' disclosure. We consider different definitions of the treatment, sorted by their intensity. In the first version, labeled *any reduction*, we classify as treated those players who decreased their average pick rate for Graves following his disclosure, regardless of the extent (the number of treated units is 857). In the second version, labeled *substantial reduction*, we classify as treated those players who reduced their average pick rate for Graves by at least 50% post-disclosure (the number of treated units is 738). In the third version, labeled *complete abandonment*, we classify as treated those players who exhibit a zero pick rate for Graves after the treatment (the number of treated units is 586).

Under the standard assumptions of parallel trends and no anticipation (see, e.g., Roth et al., 2023), we can identify the average treatment effect on the treated (ATT) using observable data. The parallel trend assumption posits that the performance of treated and untreated players would have evolved similarly if Graves' disclosure had not occurred. While we cannot formally test this assumption, the findings of Section 5.1 and Section 5.2 provide substantial support for its plausibility.[24] As for the no anticipation assumption, it stipulates that in the weeks preceding the disclosure, players' performance did not change due to the incoming Graves' disclosure. The plausibility of this assumption was thoroughly discussed in Section 2.2 and Section 4.1.

We implement the approach of Callaway and Sant'Anna (2021) to target the ATT at a particular day $t > T^{pre}$:[25]

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[24] Moreover, we demonstrate below the absence of pre-treatment differences in trends by reporting placebo estimates of the ATT that are not statistically different from zero. This is often viewed as a natural plausibility check, although even if pre-trends are perfectly parallel, this does not necessarily guarantee the satisfaction of the post-treatment parallel trends assumption (see, e.g., Roth et al., 2023).

[25] The framework outlined in Callaway and Sant'Anna (2021) is broader as it accommodates multiple groups

$$ATT(t) := \mathbb{E}\left[Y_{i,t}(1) - Y_{i,t}(0) \,|\, D_i = 1\right] \tag{5.1}$$

where potential outcomes are defined as in Section 3.2, and D_i is a binary variable indicating whether a player is treated or not. Under the assumptions of parallel trends and no anticipation, Callaway and Sant'Anna (2021) show that $ATT(t)$ can be identified by comparing the change in outcomes between the latest period before the coming-out event and day t experienced by treated players to the change in outcomes experienced by control players.[26]

The left panels of Figure 5.3 display the point estimates and simultaneous 95% confidence bands for the $ATT(t)$.[27] Overall, we find that shifting away from Graves to other characters has no impact on players' performance. None of the estimated $ATT(t)$ is statistically different from zero, suggesting that transitioning to other characters does not result in any performance-related consequences. This finding highlights that the decision to move away from Graves is not influenced by performance considerations.
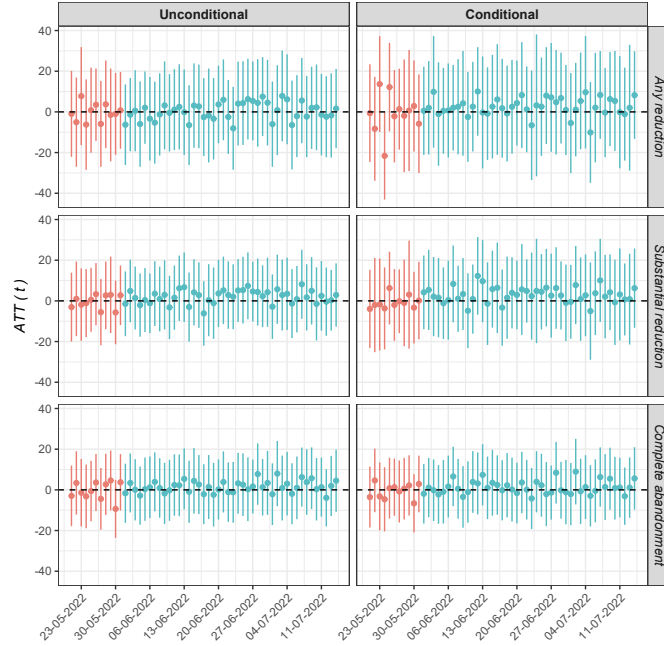

Figure 5.3: Point estimates and simultaneous 95% confidence bands allowing for clustering at the player level for the $ATT(t)$ estimated under an unconditional parallel trend (left panels) and a conditional parallel trend assumption (right panels). Red lines refer to pre-treatment periods, while blue lines refer to post-treatment periods. Each row corresponds to a different version of the treatment.

defined by the timing of treatment reception. This enables the identification and estimation of the group-time ATTs, defined as $ATT(g,t) := \mathbb{E}\left[Y_{i,t}(g) - Y_{i,t}(0) \,|\, G_g = 1\right]$, where G_g is a binary variable indicating treatment reception in period g. However, our data set features a single group, given that all treated players receive the treatment simultaneously (i.e., at Graves' disclosure date). This allows us to simplify notation and focus on the time ATTs in equation (5.1) for the single group we observe.

[26] Formally, Callaway and Sant'Anna (2021) show that $ATT(t) = \mathbb{E}\left[Y_{i,t} - Y_{i,T^{pre}} \,|\, D_i = 1\right] - \mathbb{E}\left[Y_{i,t} - Y_{i,T^{pre}} \,|\, D_i = 0\right]$. Estimation is carried out by replacing expectations with their sample analogs.

[27] Table A.1 in Appendix A reports aggregated results by displaying the average time ATT.

As a robustness check, we explore an alternative scenario where the parallel trends assumption is required to hold only conditional on pre-treatment covariates. In this context, we identify and estimate $ATT(t)$ using the doubly-robust approach of Callaway and Sant'Anna (2021).[28] Our pre-treatment covariates encompass players' skills information, such as average kills, deaths, assists, and gold earned prior to the treatment, as well as the average number of daily matches they engaged in before the treatment. The right panels of Figure 5.3 display the results. The results are consistent with those obtained under the unconditional parallel trend assumption.

Finally, Figure 5.3 also displays placebo estimates of the time ATTs for the ten days before the treatment.[29] As explained above, these estimates are valuable for "pre-testing" the credibility of the parallel trend assumption (Callaway & Sant'Anna, 2021). Notably, all placebo time ATTs in the pre-treatment periods are statistically insignificant, supporting the validity of the parallel trends assumption.

5.4 Coming Out versus LGBT Pride Month

As described in Section 2.2, the disclosure of Graves' sexual orientation coincided with the start of LGBT Pride Month. This means that the coming-out event encompasses two "simultaneous treatments" (see, e.g., Roller & Steinberg, 2023), namely the announcement of Graves' homosexuality and the introduction of visual and expressive elements in League of Legends that support the LGBT community. It is therefore plausible that the findings presented in Section 4.1 may, to some extent, be influenced by the presence of LGBT Pride Month, which might elicit negative reactions from certain players, leading them to shift their preferences away from LGB characters. While this alternative perspective does not undermine the validity of our identification strategy, it does raise questions about our interpretation of the estimated effects as solely stemming from Graves' disclosure.

In Appendix D, we introduce a theoretical framework that formalizes the existence of two simultaneous treatments and discuss the implications for interpretation. Additionally, we outline sufficient assumptions that enable us to separate the impacts of coming out and LGBT Pride Month on players' preferences for Graves. Here, we provide the main intuitions behind our approach, directing the reader to the appendix for technical details.

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[28] In essence, this approach entails estimating the change in outcomes for control players conditional on the pre-treatment covariates X_i and averaging out X_i over the distribution of covariates for treated players. For a more detailed understanding of this approach, readers are referred to Callaway and Sant'Anna (2021).

[29] Figure A.3 in Appendix A displays the remaining estimated placebo $ATT(t)$.

To examine the potential impact of LGBT Pride Month on players' preferences for LGB characters, we leverage the existence in our data set of other four characters (*Diana*, *Leona*, *Nami*, and *Neeko*) already acknowledged as part of the LGB community before the coming-out event. These characters are subject only to a part of our treatment, specifically being part of the LGB community while LGBT Pride Month is ongoing, whereas Graves experiences both the disclosure of his sexual orientation and LGBT Pride Month.

We create a composite LGB unit by averaging the pick rates of Diana, Leona, Nami, and Neeko and employ the synthetic control estimator described in Section 3.2 to estimate the effect of LGBT Pride Month on players' preferences for LGB characters. Then, under the assumption that the influence of LGBT Pride Month is uniform across all LGB characters, we can compare the results with those obtained for Graves to separate the impacts of coming out and LGBT Pride Month on players' preferences for Graves. Intuitively, if the estimated impact of LGBT Pride Month on players' preferences for LGB characters is small relative to the estimated impact of the coming-out event on players' preferences for Graves, this suggests that the findings of Section 4.1 must be primarily attributed to Graves' disclosure.

Figure 5.4 displays the actual and the synthetic pick rate series for the composite LGB unit. Overall, our analysis suggests that LGBT Pride Month had no impact on players' preferences for LGB characters. Before the treatment, the synthetic control estimator closely aligns with the actual series, providing support for the estimator's ability to predict the counterfactual series. After the treatment date, the synthetic control estimator continues to align with the actual
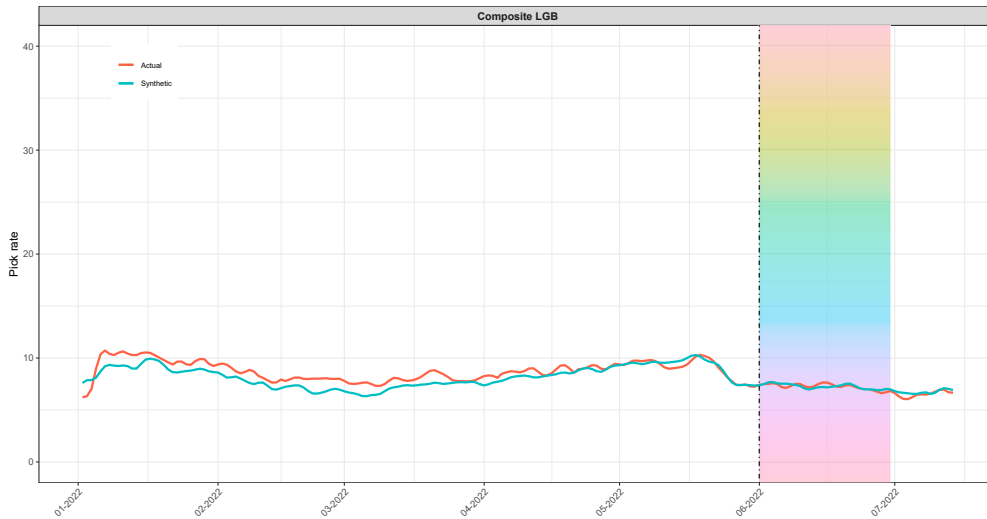

Figure 5.4: Composite LGB unit's daily pick rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

series, confirming that the players' preferences for LGB characters were unaffected by LGBT Pride Month. The average effect is estimated to be −0.149 percentage points (standard error: 2.832), and the conventional 95% confidence interval encompasses zero, indicating a failure to reject the null hypothesis of no effect. Under the homogeneity assumption discussed above, these findings support the interpretation that the estimated effects presented in Section 4.1 are primarily driven by Graves' disclosure rather than being influenced by the broader context of LGBT Pride Month.

6   Conclusion

Discrimination based on sexual orientation is first and foremost a human rights issue. However, when individuals with a stigmatized identity are unfairly targeted in education, health, social, and political settings, there is a loss of human capital that can have detrimental effects on the economy as a whole (Badgett, 2020). For example, bullying and discrimination act as barriers to students' acquisition of skills and knowledge. Furthermore, even short experiences of bullying can have severe long-term health consequences (Boden et al., 2016). Therefore, understanding the barriers that individuals from stigmatized groups face is of large societal importance.

In this study, we utilize a comprehensive data set sourced from the widely popular online video game *League of Legends* and exploit exogenous variation in the identity of a playable character to credibly identify sentiments towards LGB status. Players in the game select a playable character before each match. Each playable character is characterized by game-relevant attributes and a background story. Leveraging an unexpected revelation during the 2022 LGBT Pride Month, wherein game developers disclosed the sexual orientation minority status of a playable character, we investigate individuals' responses to this disclosure. By tracking players' revealed preferences for the character over a meaningful period, we provide insights into reactions following the disclosure. To isolate the effects on player preferences from potential confounding influences, we employ synthetic control methods. Our findings reveal a substantial and persistent negative impact, with preferences for this character decreasing by more than 30% over a meaningful period. This underscores the potential negative consequences of disclosing one's sexual minority status and provides a rationale for the underrepresentation of individuals with LGB status in many regions and professions.

To bolster the credibility of stigma as the primary explanation for the estimated effects, we address and eliminate several alternative channels. First, we rule out the possibility that shifts in characters' relative strengths could explain our estimated effect. Second, we show that players' skills have no correlation with the choice to drop the character. Third, we provide evidence that switching to other characters does not affect the performance of the players involved. Fourth, we introduce a theoretical framework that formalizes the existence of two "simultaneous treatments" and use information on other playable characters that belong to the LGB group to rule out that LGBT Pride Month serves as the main explanation for the observed result.

Our data and institutional setting offer great advantages, as they allow for a credible identification and reduced social desirability bias to identify attitudes towards LGB status (Palacios-Huerta, 2023). However, it is important to consider at least three aspects when thinking about the implications of our results. First, our population is likely not representative of the general population, as the former is possibly less diverse. We recognize that responses might be different in a more diverse audience. Second, we study the responses of a male character revealing his sexual minority status. In line with previous evidence suggesting differential labor market discrimination for gay men and lesbian women, (Badgett et al., 2023), we acknowledge the possibility for heterogeneous treatment effects when investigating responses of male and female characters revealing sexual orientation minority status. Third, we explore preference for a fictitious character rather than an actual human being. Factors influencing preferences for characters (e.g., prestige, popularity) might therefore play an important role. Our setting could be most analogous to the choice of supporting a prominent soccer player.

We have dismissed the possibility that any actual or presumed change in the character's performance is driving our results. This strongly suggests that the estimated cost of coming out is unlikely to be driven by factors other than stigmatization. This insight holds significant implications for policymakers aiming to develop interventions that effectively tackle stigmatization and improve the overall well-being of LGB individuals. Policies should be formulated to discourage discriminatory behavior, either by increasing its costs or by creating inclusive social environments that promote the acceptance of sexual minority individuals and reduce the stigma. Raising awareness about the reaction to sexual minority disclosure could be an important step to develop such a society. At the same time, policymakers may also consider providing resources and support to individuals who have recently come out, such as access to counseling and mental

health services. By doing so, they can mitigate some of the negative outcomes that may arise from coming out.

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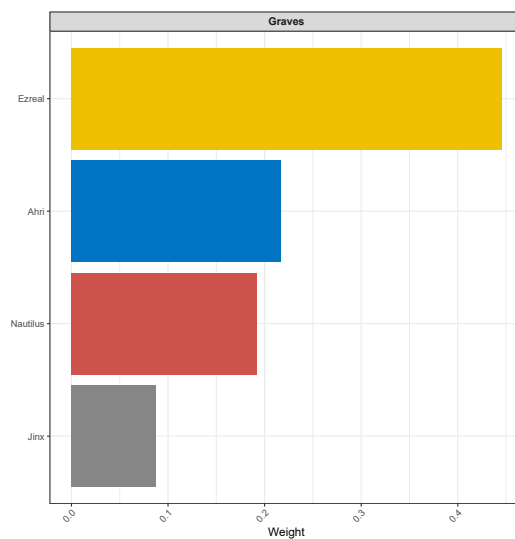
Appendix A   Additional Results

Figure A.1: Identities and contributions of characters in the donor pool for the Graves' synthetic control displayed in Figure 4.1.
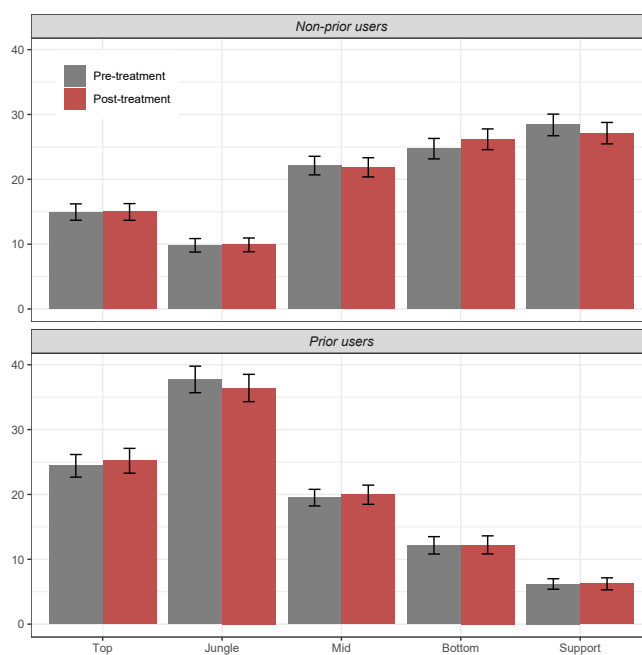

Figure A.2: Shares of matches played in each role before and after the coming-out event. Players are divided into two groups based on their preferences for Graves before his disclosure.
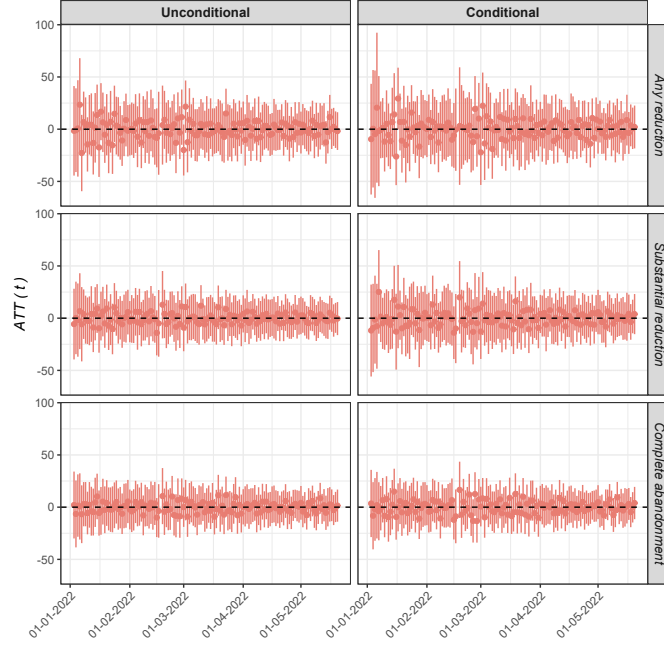
Figure A.3: Point estimates and simultaneous 95% confidence bands allowing for clustering at the player level for the placebo $ATT(t)$ estimated under an unconditional parallel trend (left panels) and a conditional parallel trend assumption (right panels). Each row corresponds to a different version of the treatment.

	Any Reduction		Substantial Reduction		Complete Abandonment	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{ATT(t)}$	0.373	2.603	2.095	3.064	1.526	1.234
	[-6.602, 7.347]	[-6.855, 12.061]	[-4.268, 8.457]	[-4.037, 10.164]	[-4.272, 7.324]	[-4.951, 7.420]
Conditional PT		✓		✓		✓
Players	1,038	1,038	1,038	1,038	1,038	1,038
Treated	857	857	738	738	586	586
Observations	89,650	89,650	89,650	89,650	89,650	89,650

Table A.1: Point estimates and 95% confidence intervals for the average time ATT $\left(\overline{ATT(t)}\right)$. Standard errors are clustered at the player level and computed using the multiplier bootstrap. Columns marked with checkmarks under "Conditional PT" display the results obtained with the doubly-robust approach. The remaining columns display the results obtained with the unconditional approach.

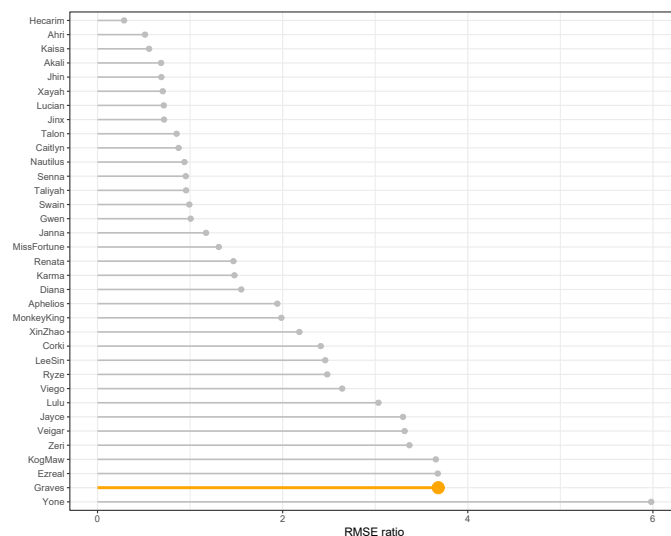# Appendix B Robustness Checks

Figure B.1: Ratio of post- to pre-treatment RMSE for Graves and control characters. Only control characters with a pre-treatment RMSE of at least 1 are considered to exclude overfit specifications.
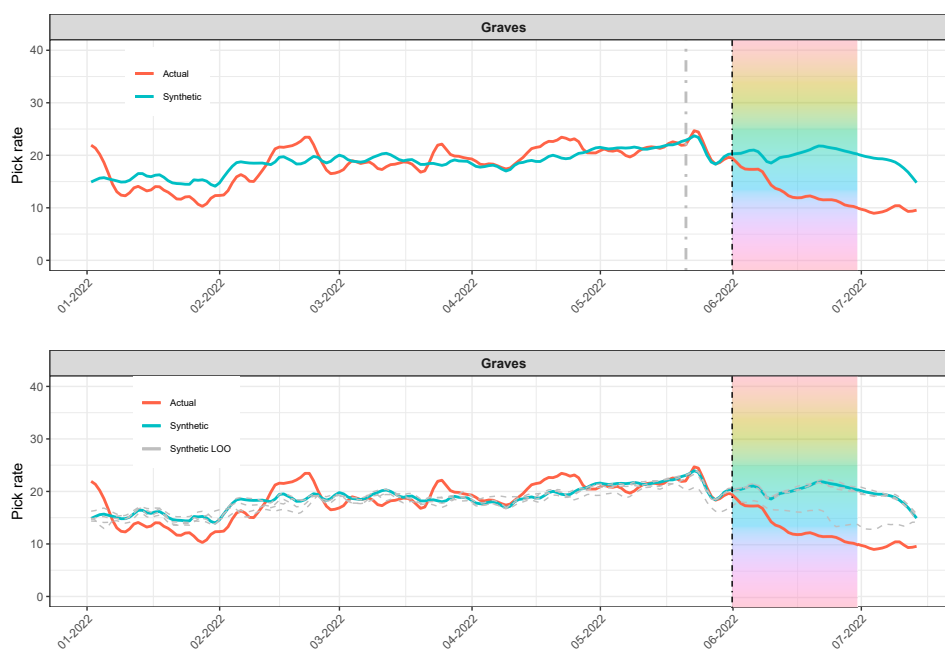

Figure B.2: Robustness checks results. The upper panel shifts the coming-out event ten days earlier, with the new treatment date denoted by the vertical gray dashed line. The lower panel reports leave-one-out estimates of the synthetic control series, obtained by excluding one of the characters of Figure A.1 at a time from the donor pool.

Appendix C Twisted Fate

In the League of Legends universe, Graves, described as a "gruff-looking, broad-shouldered, middle-aged man," forms a criminal partnership with Twisted Fate, who is characterized as "a tall, handsome male with tanned skin, trimmed beard, and long dark hair." Together, they engage in various illicit activities until, in the midst of a heist, Graves finds himself captured. This event leads Graves to perceive a betrayal by Twisted Fate, prompting a pursuit of revenge upon his escape. However, the duo ultimately decides to reconcile their differences and resumes their collaboration.[30]

Notably, one of the initially considered narrative concepts for Graves and Twisted Fate involved them being married or ex-lovers. Although this particular aspect was discarded, the general narrative retained the notion of "palpable sexual tension" between the two characters.

The story unveiling Graves' sexual orientation (see Section 2.2) also subtly hints at Twisted Fate's pansexuality, although this is not explicitly stated. Perhaps, the most notable passage that alludes to this is:

> *No matter the size, shape, make, or model, none can resist the charms of Tobias Felix. I have conned hundreds—nay, thousands—of dew-eyed tourists across the whole of this vast and gullible land.* (Twisted Fate)

We investigate whether this implied revelation has captured the players' attention in Figure C.1, illustrating the Google search interest for the queries *"Twisted Fate gay"* and *"LoL Twisted Fate."* Throughout 2022, we observe approximately no interest in the former query, with a small spike occurring during the week of the coming-out event, amounting to less than half of the spike associated with Graves. In contrast, the search interest for the latter query remains relatively steady over the year and is always lower than that for Graves, suggesting the greater popularity of Graves among players.[31] These results underscore the relatively low attention directed towards Twisted Fate from players, who were primarily focused on Graves and the explicit establishment of his sexual orientation. As a result, we concentrate our analysis on Graves and his disclosure for a more credible identification of the effects of coming out.

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[30] The complete background of Graves and Twisted Fate is available at https://leagueoflegends.fandom.com/wiki/Graves and https://leagueoflegends.fandom.com/wiki/Twisted_Fate.

[31] This is also suggested by Graves's *pick rates* (see Section 3.1) being approximately 3 to 4 times higher than those of Twisted Fate, as displayed in Figure C.2.
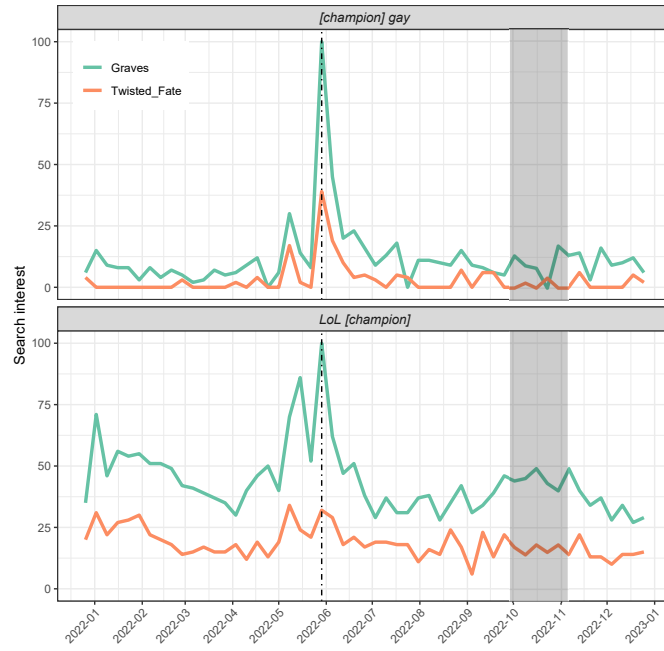
Figure C.1: Google search interest over time for the queries *"Graves gay"* and *"Twisted Fate gay"* (top panel) and the queries *"LoL Graves"* and *"LoL Twisted Fate"* (bottom panel). The dashed vertical line denotes the week of disclosure, and the shaded area highlights the League of Legends World Championship.
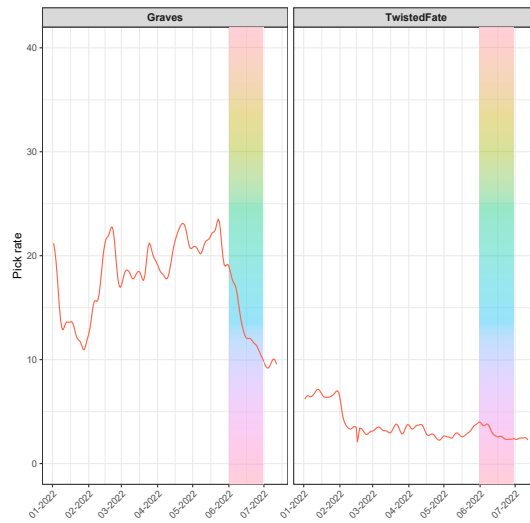

Figure C.2: Graves and Twisted Fate's daily pick rates. The series are smoothed by a Nadaraya-Watson regression. The rainbow area highlights LGBT Pride Month.

Appendix D   Anatomy of the Coming-Out Event

In this section, we discuss how the existence of two treatments - the disclosure of Graves' sexual orientation and the start of LGBT Pride Month - occurring at the same time may affect the interpretation of the main findings of Section 4.1. The notation follows that used in Section 3.2. The results of the analysis are detailed in Section 5.4.

In the next subsection, we introduce the framework that formalizes the existence of two "simultaneous treatments." We then outline sufficient assumptions that enable us to separate the impacts of coming out and LGBT Pride Month on players' preferences for Graves.

D.1   Simultaneous Treatments

As described in Section 2.2, the disclosure of Graves' sexual orientation coincided with the start of LGBT Pride Month. This means that the coming-out event encompasses two treatments occurring at the same time, namely the announcement of Graves' homosexuality and the introduction of visual and expressive elements in League of Legends that support the LGBT community.[32]

We recognize the potential influence of LGBT Pride Month on players' preferences for characters by introducing the binary variable $L_i \in \{0, 1\}$ to represent character i's inclusion in the LGB community no later than $T^{pre} + 1$. Consequently, we observe three distinct groups of units: the first group includes only Graves, with $C_i = L_i = 1$; the second group includes only Diana, Leona, Nami, and Neeko, with $C_i = 0$ and $L_i = 1$; and the third group includes all other characters, with $C_i = L_i = 0$.[33]

To explicitly account for the influence of the two treatments C_i and L_i, we define the potential pick rates as $Y_{i,t}^{c,l}$. Then, for each period $t > T^{pre}$, the effect of the coming-out event on players' preferences for Graves in (3.1) corresponds to:

$$\tau_t = Y_{1,t}^{1,1} - Y_{1,t}^{0,0} \tag{D.1}$$

Equation (D.1) shows why we need to be cautious in interpreting the estimated effects of Section 4.1 as solely stemming from the disclosure of Graves' sexual orientation. Under an extended

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[32] See, e.g., Roller and Steinberg (2023) for a discussion on "simultaneous treatments" and methodologies for disentangling their effects under a Difference-in-Differences identification strategy.

[33] Neglecting the presence of two simultaneous treatments and treating them as a single treatment does not invalidate the results of Section 4.1. It primarily affects their interpretation, which, without further investigation, could only be attributed to the combined effects of simultaneously receiving both treatments C_i and L_i - referred to as the *coming-out event* in the main body of the paper.

version of the SUTVA assumption (see Section D.2), we observe $Y_{1,t} = Y_{1,t}^{1,1}$ for all $t > T^{pre}$, and the estimator in (3.3) effectively targets the counterfactual series $Y_{1,t}^{0,0}$. Consequently, the estimated effects presented in Section 4.1 encompass the combined impacts of both disclosing Graves' sexual orientation and his affiliation with the LGB community during LGBT Pride Month. This can be formalized as follows:

$$
\begin{aligned}
\tau_t &= Y_{1,t}^{1,1} - Y_{1,t}^{0,0} \\
&= \underbrace{\left[Y_{1,t}^{1,1} - Y_{1,t}^{0,1} \right]}_{:=\tau_t^C} + \underbrace{\left[Y_{1,t}^{0,1} - Y_{1,t}^{0,0} \right]}_{:=\tau_t^L}
\end{aligned}
\tag{D.2}
$$

with τ_t^C representing the effects of the disclosure on players' preferences for Graves, and τ_t^L representing the effects of being part of the LGB community during LGBT Pride Month on players' preferences for Graves.

D.2 Separating Simultaneous Treatment Effects

The decomposition in (D.2) offers a strategy to disentangle the effects of the two treatments C_i and L_i for Graves. If we can successfully estimate the two counterfactual series $Y_{1,t}^{0,1}$ and $Y_{1,t}^{0,0}$, then we would be able to construct estimates $\hat{\tau}_t^C = Y_{1,t}^{1,1} - \hat{Y}_{1,t}^{0,1}$ and $\hat{\tau}_t^L = \hat{Y}_{1,t}^{0,1} - \hat{Y}_{1,t}^{0,0}$ of τ_t^C and τ_t^L, respectively. This would allow us to quantify the extent to which LGBT Pride Month drives the main findings of Section 4.1.

To this end, we assume an extended version of the SUTVA that accommodates the existence of two different treatments.

Assumption D.1. *(SUTVA):* $Y_{i,t} = Y_{i,t}^{1,1} C_i L_i + Y_{i,t}^{0,1} [1 - C_i] L_i + Y_{i,t}^{0,0} [1 - C_i] [1 - L_i]$

Under Assumption D.1, we can estimate the counterfactual series $Y_{1,t}^{0,0}$ by constructing a synthetic control unit that approximates the pick rates of Graves before the coming-out event as in Section 3.2. Thus, as shown in (D.2), the challenge in disentangling our causal effects of interest is to estimate $Y_{1,t}^{0,1}$ for $t > T^{pre}$, i.e., how Graves' pick rates would have evolved if Graves were already part of the LGB community prior to the 2022 LGBT Pride Month.

Having a sufficient number of LGB characters other than Graves (that is, sufficient units such as $C_i = 0$ and $L_i = 1$) would enable us to estimate the counterfactual series $Y_{1,t}^{0,1}$ through standard synthetic control methods. However, since we only have four such characters in our data set, this approach is infeasible.

One way out is to estimate the impact of LGBT Pride Month on players' preferences for LGB characters and compare the results with those obtained for Graves. If the influence of LGBT Pride Month is uniform across all LGB characters, this strategy provides insight into the role of LGBT Pride Month in driving the main findings of Section 4.1.

To achieve this, we create a composite LGB unit by averaging the pick rates of all characters such as $C_i = 0$ and $L_i = 1$ (namely, Diana, Leona, Nami, and Neeko), denoting this unit as character j without loss of generality. Then, for each period $t > T^{pre}$, we define the effect of LGBT Pride Month on players' preferences for LGB characters as the difference in character j's potential pick rates at time t:

$$\gamma_t^L := Y_{j,t}^{0,1} - Y_{j,t}^{0,0} \tag{D.3}$$

Under Assumption (D.1), we observe $Y_{j,t} = Y_{j,t}^{0,1}$ for all $t > T^{pre}$, and we can estimate the counterfactual series $Y_{j,t}^{0,0}$ by constructing a synthetic control unit that approximates the pick rates of character j before the beginning of the 2022 LGBT Pride Month. We can then estimate γ_t^L by computing the differences between character j's observed pick rates and the synthetic counterfactual for all $t > T^{pre}$:

$$\hat{\gamma}_t^L = Y_{j,t}^{0,1} - \widehat{Y}_{j,t}^{0,0} \tag{D.4}$$

Finally, we introduce a homogeneity assumption that leverages the estimates $\hat{\gamma}_t^L$ to provide an interpretation for the estimates $\hat{\tau}_t$ presented in Section 4.1:

Assumption D.2. *(Effect Homogeneity):* $\tau_t^L = \gamma_t^L$ *for all* $t > T^{pre}$.

Under Assumption D.2, the relationship $\tau_t^C = \tau_t - \gamma_t^L$ holds. Thus, if the estimated effects of LGBT Pride Month on players' preferences for LGB characters are small relative to the estimated effects of the coming-out event on players' preferences for Graves, this suggests that the findings of Section 4.1 must be primarily attributed to Graves' disclosure.