The Cost of Coming Out*

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Abstract

This paper expands the growing body of research at the intersection of economics and identity by quantifying social preferences for sexual orientation. Understanding the interplay between identity and individual behavior is crucial yet challenging, particularly for aspects of a person's identity that are not immediately observable. For instance, disclosing one's sexual orientation is a personal choice, complicating data access and introducing endogeneity issues. We address these challenges by using innovative data sources from a popular online video game. We capitalize on an unexpected event during the 2022 LGBT Pride Month: the game developers' announcement that one of their playable characters is gay. This event provides exogenous variation in the character's identity, offering a unique opportunity to study individuals' reactions to sexual minority disclosure. We use detailed daily data to track players' revealed preferences for the character 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 on social preferences for sexual orientation.

Keywords: LGB economics, social stigma, concealable stigma, taste-based discrimination, natural experiment.

JEL Codes: J15, J71

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1 Introduction

Understanding the interplay between identity and individual behavior is of paramount importance (see, e.g., Oh, 2023). Identity represents an individual's multifaceted self-concept, encompassing their membership in different social groups. These groups entail specific prescriptions and behavioral expectations, shaping the thoughts and actions of their members. Deviating from these prescriptions can result in emotional and psychological consequences, highlighting how identity can influence individuals' behavior (Akerlof & Kranton, 2000).

A growing body of literature in economics, along with well-established research in other social sciences, examines how identity shapes preferences, individual behavior, and market outcomes (see, e.g., Charness & Chen, 2020; Shayo, 2020). However, despite the compelling rationale for studying this dynamic and its implications for economic decision-making, measuring preferences for identity remains a challenging task (Atkin et al., 2021). This particularly holds for aspects of a person's identity that are not immediately observable but are fundamental parts of who we are, such as sexual orientation (Stets & Burke, 2000; Luyckx et al., 2011).[1]

This paper expands the growing body of research at the intersection of economics and identity by quantifying social preferences for sexual orientation. Despite significant progress in advancing lesbian, gay, and bisexual (LGB) rights, evidence suggests that discrimination based on sexual orientation remains pervasive in many countries (see, e.g., Badgett, 2020).[2] However, disclosing one's sexual orientation is a personal choice, complicating data access (Badgett et al., 2021) and introducing additional endogeneity issues due to potential correlations with other factors affecting labor market outcomes. This paper overcomes these challenges using innovative data sources and a unique natural experiment.

[1] To further emphasize the importance of studying the economic implications of sexual orientation, one must also consider the substantial size of the LGB community, estimated to be over 18,000,000 individuals in the United States in 2018 (Badgett et al., 2021).

[2] Limited employment opportunities (Bertrand & Duflo, 2017; Neumark, 2018), wage disparities (Badgett, 1995; Klawitter, 2015), and barriers to financial resources (Badgett et al., 2013) are just a few of the challenges that disproportionately affect LGB individuals compared to their heterosexual counterparts.

An ideal experiment to measure social preferences for sexual orientation would involve randomly requesting individuals to disclose their sexual orientation and observing their peer group's reactions over a meaningful period. However, such an approach raises substantial ethical concerns. This paper uses a lab-in-the-field approach that closely approximates the ideal experiment. Utilizing data from the popular online video game *League of Legends*, we credibly identify the effects of sexual minority disclosure on social preferences for sexual orientation by leveraging a natural experiment.

At the start of the 2022 LGBT Pride Month, the developers of League of Legends announced that one of their playable characters is gay. This event provides exogenous variation in the character's identity, offering a unique opportunity to study individuals' reactions to sexual minority disclosure. We use detailed daily data to track players' revealed preferences for the character over time. Utilizing synthetic control methods (e.g., Abadie, 2021; Abadie & Vives-i-Bastida, 2022), we isolate the effect of the disclosure on players' preferences for the character. Our findings reveal a substantial and persistent negative impact, a result consistent across various robustness checks and geographical regions.

To bolster the credibility of identity concerns arising from playing an LGB character as the primary explanation for the estimated effects, it is crucial that players' decisions to switch from the character are not influenced by factors other than these identity concerns. We address and eliminate several alternative channels, thereby enhancing the plausibility of identity concerns 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. We also 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.

We also 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.[3] The results support the interpretation that the estimated effects are driven by the character's disclosure.

Our paper makes a significant contribution to the existing literature by being the first study to investigate the reactions of social preferences for sexual orientation following disclosure. The current body of research primarily focuses on measuring discrimination against LGB individuals either through correspondence designs, where sexual orientation is manipulated in job applications (e.g., Weichselbaumer, 2003; Drydakis, 2009; Tilcsik, 2011; Patacchini et al., 2012; Ahmed et al., 2013; Drydakis, 2014), or by comparing the labor market outcomes of sexual minority individuals with those of non-minority individuals with similar observable characteristics (e.g., Badgett, 1995; Plug et al., 2014; Carpenter & Eppink, 2017; Martell, 2021). These studies consistently reveal that LGB job candidates are less likely to be invited for interviews or offered job opportunities. Additionally, they consistently find a wage penalty for gay and bisexual men and a wage premium for lesbian women, although the latter can be explained by lesbian women working more than their heterosexual counterparts (see e.g., Antecol & Steinberger, 2013).[4] Despite these valuable insights, these approaches do not allow for the investigation of how social preferences for sexual orientation behave after an individual's coming out. Our study addresses this gap and provides an understanding of the social reactions to the disclosure of sexual orientation.

Our paper also emphasizes the relevance of video game data and the unique advantages they offer to economists. First, video games provide a controlled research environment, enabling the observation of behaviors that may be challenging to capture through traditional survey methods.[5] Second, online gaming platforms offer the benefit of anonymity,

[3] 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.

[4] The only study finding a wage premium for gay men is that of Carpenter and Eppink (2017). However, they are not able to control for living in an urban area, which is crucial as those areas typically have higher wages and more gay men than rural areas (Badgett, 2020).

[5] Economists are increasingly acknowledging this potential, although at a gradual pace. To the best

which reduces social desirability bias and facilitates the disclosure of sensitive information. The majority of existing research on LGB individuals relies on survey data where respondents can report their sexual orientation (see e.g, Badgett et al., 2021). However, Coffman et al. (2017) show that a substantial share of LGB respondents is reluctant to answer honestly, which complicates the interpretation of existing results and makes understanding incentives to identity disclosure even more important. Our use of video game data provides an objective measure of behavior and identity, circumventing the limitations of self-reported identity in surveys. Moreover, our setting allows individuals to remain anonymous, minimizing social desirability bias and increasing the likelihood of participants revealing their true attitudes toward sexual minority groups.

Finally, our paper also advances the understanding of consumer behavior in the video game industry. In the context of the contemporary digital era, video games have established themselves as virtual meeting environments where individuals converge and engage with one another. This trend is further amplified by the advent of the Metaverse, a virtual universe where users can engage in various activities and experiences. Given the growing significance of video games as social platforms, it is increasingly crucial for economists to comprehend and analyze these new and evolving markets.[6]

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 on social preferences for sexual orientation. Section 3 introduces the data. Section 4 explains the methodology we use to isolate the effects of coming out and presents the main results. Section 5 examines the underlying mechanisms driving the estimated effects. Section 6 concludes.

of our knowledge, Parshakov et al. (2018), Parshakov et al. (2022), and Dell'Acqua et al. (2023) are the only studies using video game data.

[6] To date, very little is known about consumer behavior in the video game industry. To the best of our knowledge, Parshakov et al. (2022) is the only study focusing on this topic. They examine the impact of marking products with a gay label on consumer demand, finding a significant, albeit short-lived, decrease in consumers' demand following the introduction of the gay label.

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 on social preferences for sexual orientation.

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. In 2022, the game attracted an impressive player base, with an average of over 32 million players joining the game daily and 180 million players overall. 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.

Players have the option to participate in either *draft* or *ranked* matches. In both game modes, the objective remains the same: destroy the opposing team's base. 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. To ensure balanced matches, the matchmaking process in ranked games groups players with similar skill levels.

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.

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* takes place, a dedicated time to honor and celebrate the LGBT community. Originally born out of a series of protests for gay liberation in the United States in 1969, this month-long celebration has gained widespread recognition and evolved into a global movement. Today, LGBT Pride Month stands as an emblem of empowerment, visibility, and equality, fostering inclusivity for individuals of all sexual orientations and gender identities.

Since 2018, Riot Games has actively participated in LGBT Pride Month 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.[7]

At the beginning of the 2022 LGBT Pride Month, Riot Games released a short story featuring two of the League of Legends characters, *Graves* and *Twisted Fate*. The story officially discloses Graves' sexual orientation, revealing him to be a gay character. The following quotes provide two pivotal passages of the narrative:[8]

> *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.[9]

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

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

[9] 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 C.

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."* 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 29^{th} to November 5^{th}), 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.

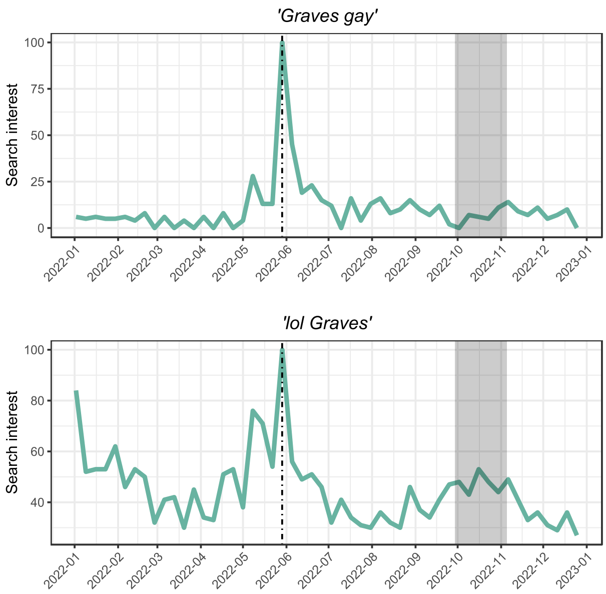

Figure 2.1: Google search interest over time for the queries *"Graves gay"* (top panel) and *"lol Graves"* (bottom panel). The dashed vertical line denotes the week of disclosure, and the shaded area highlights the League of Legends World Championship.

3 Data

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 specifically 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.

For each of these players, we collect all the matches they played during the period January-July 2022. From these data, we construct a balanced daily panel data set that tracks the behavior of each character over time. We filter the data set by removing three League of Legends characters (*K'Sante*, *Nilah*, and *Bel'Veth*), as they were released after the coming-out event. This results in a final data set composed of $129,859$ 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.

4 Methodology and Main Results

In this section, we explain the methodology used to isolate the effects of the coming-out event on players' revealed preferences for Graves and present our main results.

The next subsection provides a formal review of the synthetic control estimator employed in the analysis. We then present our main findings and a series of robustness checks that validate the reliability of our estimates. Finally, we explore the possibility of regional variations in attitudes toward the LGB community by replicating our analysis across different servers.

4.1 Methodology

The red line in Figure 4.1 depicts Graves' pick rate series, which exhibits some upward trend despite daily variations. However, we observe a sharp drop in the series on the day of disclosure which persists over time.

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 effect 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 ($t = 1, \ldots, T$), with $T^{pre} = 150$ days prior to the coming-out event. 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 $T^{pre} + 1$ (i.e., June 1^{st}, 2022). We then posit the existence of two 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 ($Y_{i,t}^{1}$).[10]

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:

$$\tau_t := Y_{1,t}^{1} - Y_{1,t}^{0} \tag{4.1}$$

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

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 (e.g., Imbens & Rubin, 2015) we observe $Y_{1,t} = Y_{1,t}^1$ for all $t > T^{pre}$. Thus, as shown in equation (4.1), 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):

$$\begin{gathered}\hat{\omega} = \arg\min_{\omega \in \Omega} \ell(\omega) \\ \ell(\omega) = \sum_{t=1}^{T^{pre}} \left(\sum_{i=2}^{n} \omega_i Y_{i,t} - Y_{1,t} \right)^2 + \zeta^2 T^{pre} \|\omega\|_2^2, \quad \Omega = \left\{ \omega \in \mathbb{R}_+^{n-1} : \sum_{i=2}^{n} \omega_i = 1 \right\}\end{gathered} \tag{4.2}$$

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. Following Arkhangelsky et al. (2021), we set the regularization parameter $\zeta = (T - T^{pre})^{1/4}\,\hat{\sigma}$, with $\hat{\sigma}$ denoting the standard deviation of first differences of $Y_{i,t}$ for control units over the pre-treatment period. Then, we estimate the counterfactual outcome of Graves as a weighted average of the outcome of the control units:

$$\widehat{Y}_{1,t}^0 = \sum_{i=2}^{n} \hat{\omega}_i Y_{i,t} \tag{4.3}$$

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

$$\hat{\tau}_t = Y_{1,t}^1 - \widehat{Y}_{1,t}^0 \tag{4.4}$$

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:

$$\hat{\tau} = \frac{1}{T - T^{pre}} \sum_{t=T^{pre}+1}^{T} \hat{\tau}_t \tag{4.5}$$

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.[11]

4.2 Main Results

We apply the synthetic control estimator of the previous subsection to estimate the effects of the coming-out event on players' revealed preferences for Graves. To mitigate the potential for spillover effects, we exclude four characters (*Diana*, *Leona*, *Nami*, and *Neeko*) from the donor pool, as they were already members of the LGB community prior to the coming-out event.[12]

Figure 4.1 displays the actual and the synthetic pick rate series, while the third column of Table 4.1 displays point estimates and 95% confidence intervals for the average treatment effect.[13] 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 1^{st}, 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

[11] 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).

[12] Nevertheless, even if included in the donor pool, the estimator assigns them zero weight.

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

5% significance level.

To assess the credibility of the synthetic control estimator, we conduct a robustness check by artificially shifting 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.1 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).

We also 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

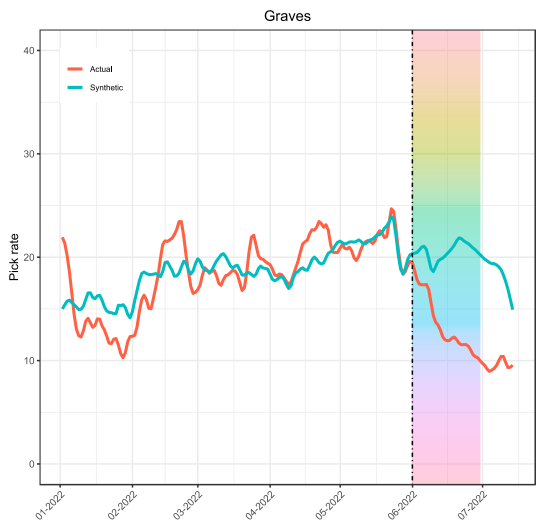

Figure 4.1: Graves' daily pick rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

lower panel of Figure B.1 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.

Finally, we examine the robustness of our results to the choice of the regularization parameter ζ in (4.2) and the composition of units in the donor pool. In particular, we repeat the main part of our analysis using a standard synthetic control estimator that sets

	Synthetic Controls		*Regularized Synthetic Controls*	
	(1) All champions	(2) Only Bottom	(3) All champions	(4) Only Bottom
Panel 1: *All*				
$\hat{\tau}$	-7.156	-7.727	-7.059	-6.369
95% CI	[-12.033, -2.279]	[-19.317, 3.863]	[-11.469, -2.649]	[-16.568, 3.830]
N. Donors	4	3	4	4
RMSE	2.250	2.569	2.267	2.590
Panel 2: *Europe*				
$\hat{\tau}$	-8.961	-10.411	-8.368	-9.535
95% CI	[-14.072, -3.851]	[-23.044, 2.223]	[-12.671, -4.065]	[-21.682, 2.611]
N. Donors	6	5	7	6
RMSE	2.151	2.624	2.189	2.668
Panel 3: *Korea*				
$\hat{\tau}$	-10.158	-10.727	-10.377	-9.095
95% CI	[-16.858, -3.457]	[-25.445, 3.992]	[-17.160, -3.594]	[-27.692, 9.503]
N. Donors	3	2	3	3
RMSE	6.145	9.697	6.178	9.614
Panel 4: *Latin America*				
$\hat{\tau}$	-6.826	-3.853	-5.769	-3.979
95% CI	[-11.140, -2.512]	[-14.163, 6.457]	[-10.604, -0.933]	[-14.032, 6.075]
N. Donors	4	6	7	7
RMSE	2.400	3.162	2.401	3.109
Panel 5: *North America*				
$\hat{\tau}$	0.945	-0.939	0.984	-0.406
95% CI	[-4.035, 5.926]	[-13.523, 11.644]	[-4.264, 6.232]	[-12.191, 11.378]
N. Donors	3	3	4	3
RMSE	4.521	5.535	4.523	5.534

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.

the regularization parameter to zero and we explore different donor pool configurations focusing on champions 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 champions mainly played in these positions, as players transitioning away from Graves are likely to switch to these alternatives. To mitigate this potential for spillover effects, we restrict our donor pool to champions primarily designed for the bottom lane. The first panel of Table 4.1 displays the results.[14] 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, although restricting the donor pool to specific roles leads to confidence intervals that encompass zero. However, these restricted specifications exhibit a lower goodness-of-fit, with their pre-treatment root mean squared errors being around 14% larger than that of the more inclusive specifications. Overall, these results support our main finding of a substantial negative impact of the coming-out event on players' preferences for Graves.

4.3 Regional Heterogeneity

Previous research has demonstrated that attitudes toward the LGB community can substantially vary between countries (see, e.g., Badgett, 2020; Badgett et al., 2021). To explore potential regional differences in players' attitudes towards the LGB community, we divide the matches based on the server on which they were hosted. 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 4.1 to each of these series 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

[14] Table B.1 in Appendix B displays results for donor pools including only champions primarily designed for the remaining roles. We note that these specifications exhibit poorer goodness-of-fit, indicated by their pre-treatment root mean squared error being between 23% and 228% larger than that of our main specification. Consequently, they are less reliable for analysis.

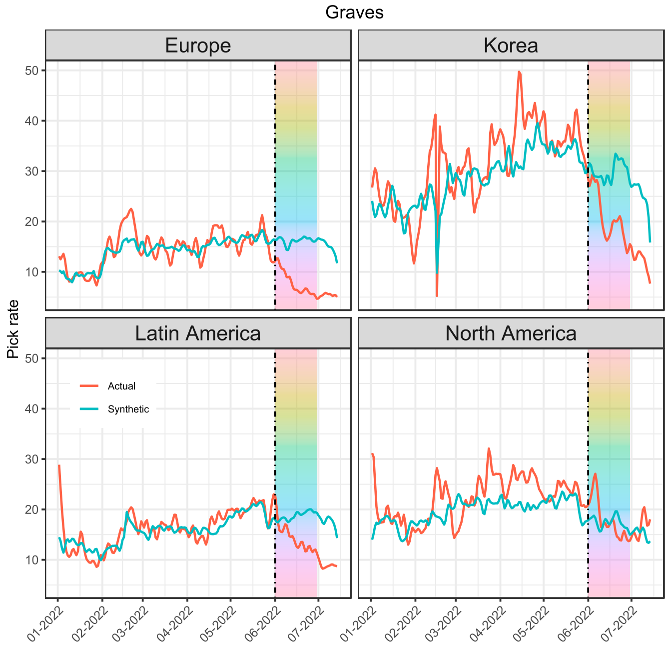

Figure 4.2: Graves' daily pick rates and synthetic control estimation results by region. The actual series are smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

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. This limits our ability to draw conclusions for these regions.

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 confidence intervals include zero when the pre-treatment root mean squared error is higher. The magnitude of the estimated effect varies across regions, with the largest average impact observed in Europe.

However, this regional variation may be influenced by factors other than players' attitudes toward the LGB community. One such factor could be the differential levels of competitiveness on different servers, which may affect the character selection process by introducing different levels of subjectivity. In regions with higher levels of competitiveness, players are more likely to prioritize performance-based choices over personal preferences, potentially attenuating the impact of the coming-out event on their preferences for Graves. Therefore, the regional differences in the estimated effects may reflect a combination of both players' attitudes toward the LGB community and the competitive dynamics specific to each server.

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 identity concerns arising from playing an LGB character. The objective of this section is to eliminate these alternative channels, thereby enhancing the plausibility of identity concerns 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' performance 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 4.2 are solely a consequence of Graves' disclosure or if they are influenced by the broader context of LGBT Pride Month. In Appendix C, we introduce a theoretical framework that formalizes the existence of two "simultaneous treatments" and outline 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 identity concerns arising from playing an LGB character as the primary explanation for the players' observed behavior is the fact that Graves' performance 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 4.1 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' performance. 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

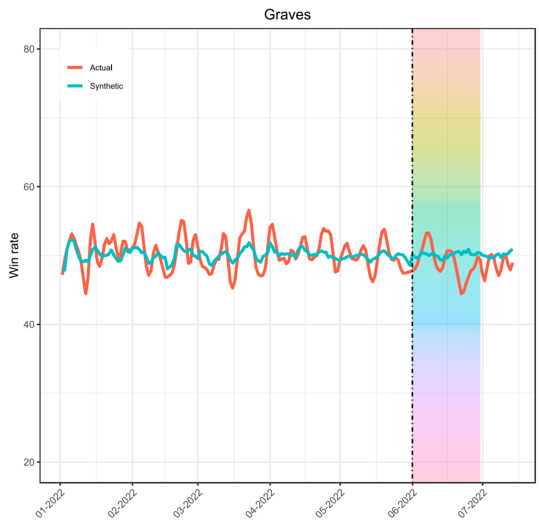

Figure 5.1: Graves' daily win rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride Month.

trend, confirming that the character's performance was unaffected by the disclosure. The average effect is estimated to be −1.136 percentage points (standard error: 2.838), and the conventional 95% confidence intervals encompass zero, indicating a failure to reject the null hypothesis of no effect. These findings demonstrate that Graves' performance remained unchanged during the coming-out event, dismissing the possibility of a shift in his strength as an explanation for the results of Section 4.2.

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.[15] 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 performance remained consistent. These factors suggest that the negative impact of the coming-out event estimated in Section 4.2 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 identity 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

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

yields a sample of 1679 players, with 1090 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 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. Furthermore, we note a minor decrease in matches played post-treatment within both groups, likely attributed to seasonal patterns. This suggests that players are not leaving the game after the coming-out event. Instead, they are shifting their focus to other characters.

Second, the bottom right panel displays the players' average win rates, a metric cap-

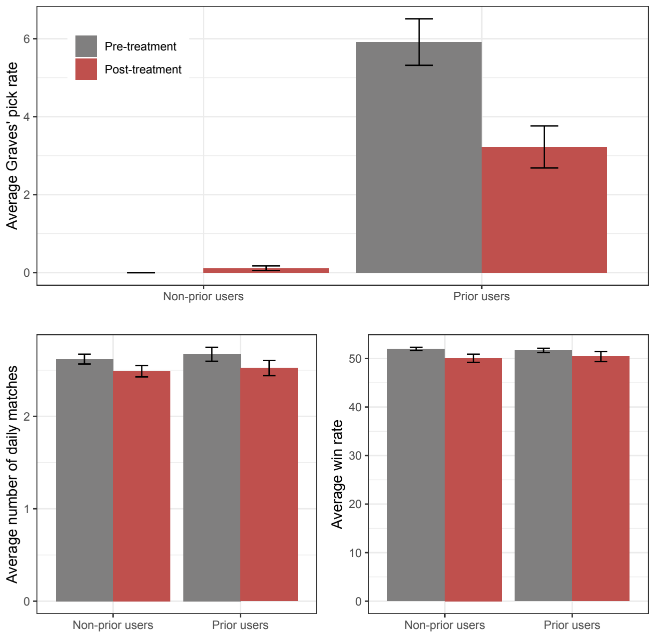

Figure 5.2: Players' average pick rates for Graves and performance measures. Players are divided into two groups based on their preferences for Graves before his disclosure. The panels display the average pick rates for Graves, number of daily matches, and win rate of each group before and after the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

turing 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 4.2, lending additional support to identity concerns arising from playing an LGB character as the mechanism underlying the players' observed behavior.

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 identity concerns.

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 589 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 494). 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 422). 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 351).

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.[16] 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 4.2.

We implement the approach of Callaway and Sant'Anna (2021) to target the ATT at a particular day $t > T^{pre}$:[17]

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

where potential outcomes are defined as in Section 4.1, 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.[18]

The left panels of Figure 5.3 display the point estimates and simultaneous 95% confidence bands for the $ATT\,(t)$. 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

[16] 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).

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

[18] 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.

result in any performance-related consequences. This finding highlights that the decision to move away from Graves is not influenced by performance considerations.

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).[19] 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. Overall, the results are consistent with those obtained under the unconditional parallel trend assumption. For the majority of the estimated

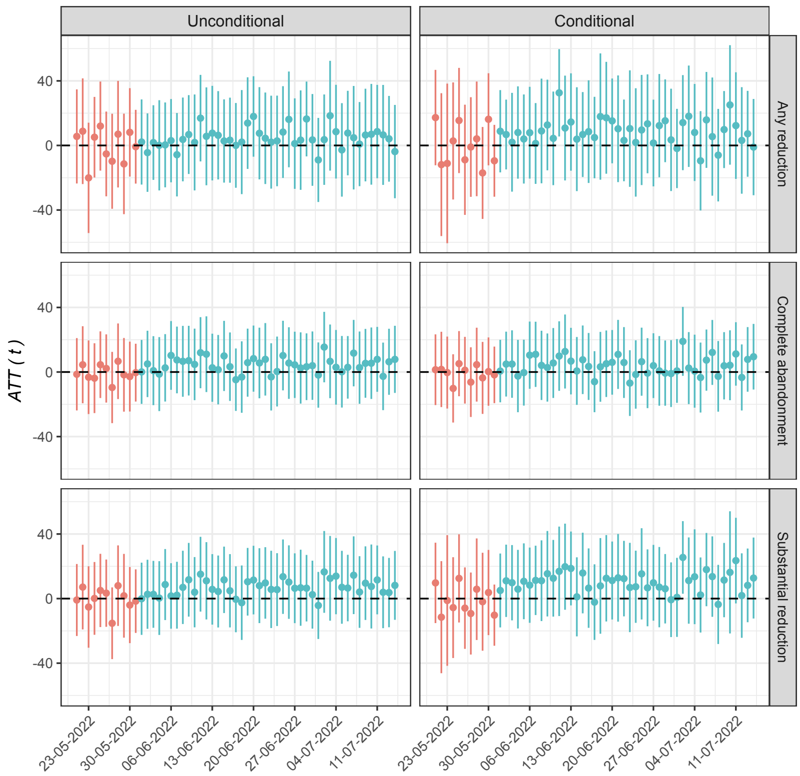

Figure 5.3: Point estimates and simultaneous 95% confidence bands allowing for clustering at the player level for the $ATT(t)$ estimated under an unconditional parallel trend (left panels) and a conditional parallel trend assumption (right panels). Red lines refer to pre-treatment periods, while blue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

[19] 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).

ATT (t), there are no statistically significant effects on performance. Two exceptions emerge in the conditional case, where we observe a statistically significant positive effect on performance.

Finally, Figure 5.3 also displays placebo estimates of the time ATTs for the ten days before the treatment.[20] 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 4.2 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 C, we introduce the 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.

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*,

[20] Figure A.2 in Appendix A displays the remaining estimated placebo *ATT* (t).

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 4.1 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 4.2 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'

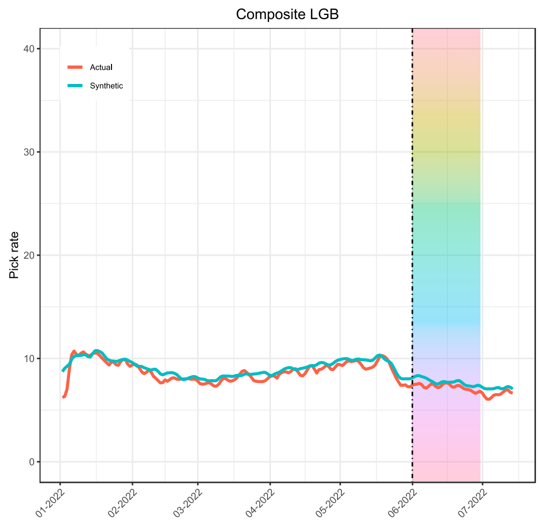

Figure 5.4: Composite LGB unit's daily pick rates and synthetic control estimation results. The actual series is smoothed by a Nadaraya-Watson regression before applying the synthetic control estimator. The dashed vertical line denotes the day of disclosure, and the rainbow area highlights LGBT Pride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

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 series, confirming that the players' preferences for LGB characters were unaffected by LGBT Pride Month. The average effect is estimated to be -0.376 percentage points (standard error: 2.187), and the conventional 95% confidence intervals encompass 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 4.2 are primarily driven by Graves' disclosure rather than being influenced by the broader context of LGBT Pride Month.

6 Conclusion

Understanding the interplay between identity and individual behavior is of paramount importance (see, e.g., Oh, 2023). A growing body of literature in economics, along with well-established research in other social sciences, examines how identity shapes preferences, individual behavior, and market outcomes (see, e.g., Charness & Chen, 2020; Shayo, 2020). However, despite the compelling rationale for studying this dynamic and its implications for economic decision-making, measuring preferences for identity remains a challenging task (Atkin et al., 2021).

This paper expands the growing body of research at the intersection of economics and identity by quantifying social preferences for sexual orientation. We overcome the challenges that traditional methods face using innovative data sources and a unique natural experiment.

We exploit exogenous variation in the identity of a playable character from the online video game *League of Legends* to credibly identify the effects of sexual minority disclosure on social preferences for sexual orientation. Utilizing synthetic control methods (e.g., Abadie, 2021; Abadie & Vives-i-Bastida, 2022), we isolate the effect of the disclosure on players' preferences for the character. Our findings reveal a substantial and persistent negative impact.

To bolster the credibility of identity concerns arising from playing an LGB character 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.

We also 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. The results support the interpretation that the estimated effects are driven by the character's disclosure.

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Appendix A Additional Results

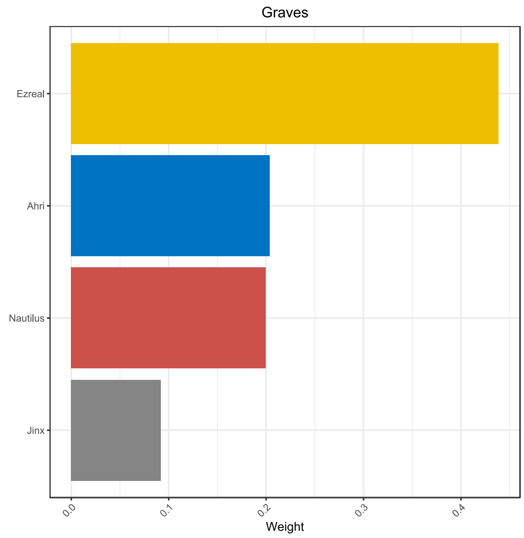

Figure A.1: Identities and contributions of characters in the donor pool for the Graves' synthetic control displayed in Figure 4.1.

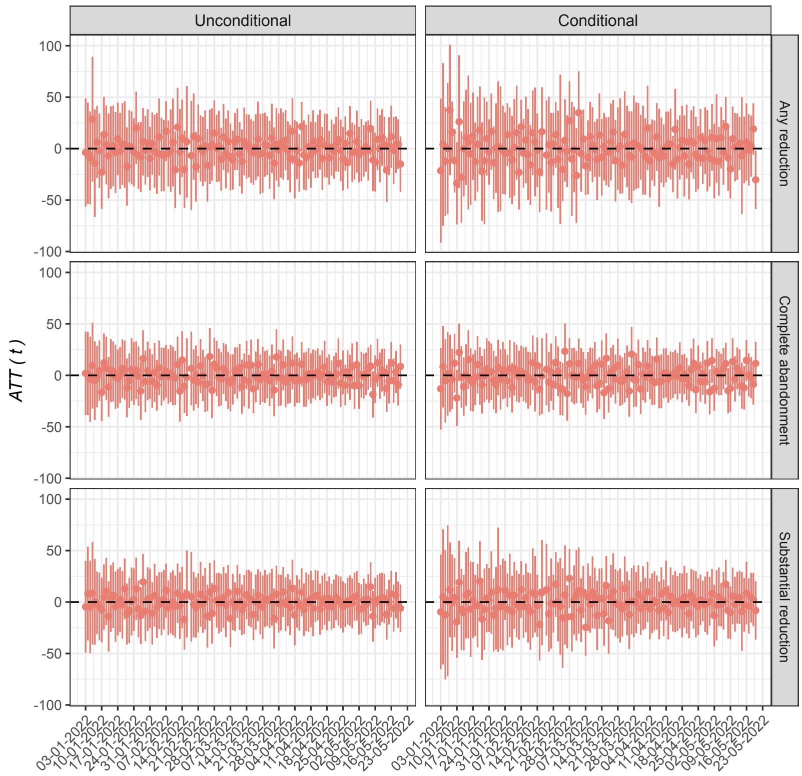

Figure A.2: Point estimates and simultaneous 95% confidence bands allowing for clustering at the player level for the placebo $ATT\,(t)$ estimated under an unconditional parallel trend (left panels) and a conditional parallel trend assumption (right panels). Each row corresponds to a different version of the treatment.

Appendix B Robustness Checks

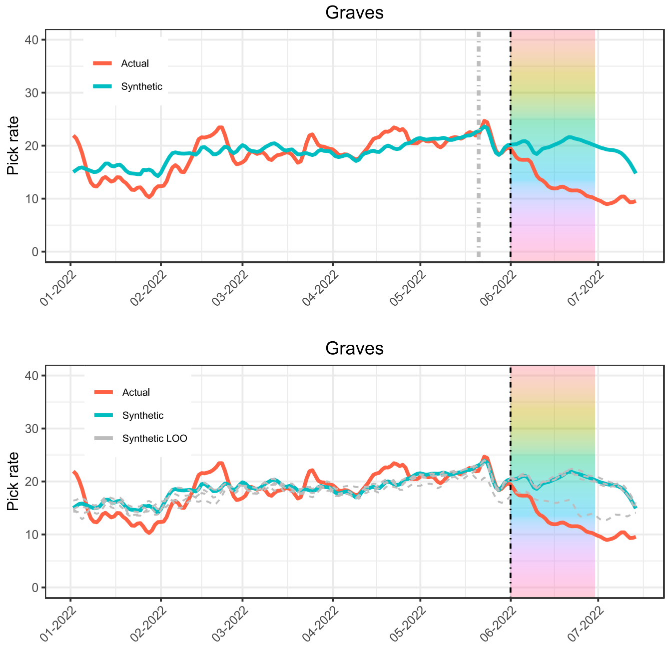

Figure B.1: Robustness checks results. The upper panel shifts the coming-out event ten days earlier, with the new treatment date denoted by the vertical gray dashed line. The lower panel reports leave-one-out estimates of the synthetic control series, obtained by excluding one of the characters of Figure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

	Synthetic Controls				*Regularized Synthetic Controls*			
	(1) Only Top	(2) Only Jungle	(3) Only Mid	(4) Only Support	(5) Only Top	(6) Only Jungle	(7) Only Mid	(8) Only Support
Panel 1: *All*								
$\hat{\tau}$	2.632	-6.842	-2.245	-2.631	2.632	-6.464	-2.285	-2.600
95% CI	[-0.498, 5.762]	[-11.913, -1.770]	[-7.006, 2.515]	[-6.654, 1.391]	[-0.362, 5.626]	[-11.432, -1.495]	[-6.497, 1.928]	[-7.571, 2.366]
N. Donors	1	1	2	2	1	2	2	2
RMSE	7.448	4.496	5.988	2.792	7.448	4.443	5.988	2.792
Panel 2: *Europe*								
$\hat{\tau}$	-3.165	-5.941	-6.218	-6.230	-3.010	-6.041	-5.714	-6.630
95% CI	[-6.149, -0.182]	[-12.152, 0.269]	[-10.790, -1.646]	[-11.975, -0.486]	[-6.082, 0.063]	[-11.142, -0.941]	[-10.598, -0.831]	[-12.431, -0.843]
N. Donors	2	4	3	4	3	4	3	5
RMSE	4.924	3.976	3.454	2.782	4.949	3.980	3.461	2.796
Panel 3: *Korea*								
$\hat{\tau}$	10.413	-8.620	-1.840	-6.525	9.788	-8.371	-0.796	-6.170
95% CI	[3.780, 17.045]	[-16.948, -0.292]	[-10.466, 6.786]	[-13.852, 0.802]	[2.164, 17.412]	[-14.414, -2.328]	[-9.702, 8.109]	[-14.779, 2.424]
N. Donors	1	2	1	2	3	2	2	2
RMSE	19.454	9.735	14.027	6.644	19.540	9.780	14.016	6.673
Panel 4: *Latin America*								
$\hat{\tau}$	3.006	-3.421	-2.220	-1.285	3.006	-3.171	-2.006	-1.320
95% CI	[-0.177, 6.190]	[-9.169, 2.328]	[-6.409, 1.968]	[-4.946, 2.376]	[0.082, 5.930]	[-7.669, 1.327]	[-6.013, 2.002]	[-5.214, 2.567]
N. Donors	1	3	2	3	1	3	2	3
RMSE	5.627	3.984	4.509	3.470	5.627	3.986	4.510	3.483
Panel 5: *North America*								
$\hat{\tau}$	8.643	0.544	8.235	4.071	8.643	0.651	8.273	4.010
95% CI	[5.772, 11.514]	[-4.584, 5.671]	[4.496, 11.974]	[-0.452, 8.593]	[6.043, 11.243]	[-4.416, 5.719]	[3.721, 12.825]	[-0.418, 8.454]
N. Donors	1	1	2	2	1	1	2	2
RMSE	10.761	7.649	10.965	5.194	10.761	7.649	10.965	5.195

Table B.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.

Appendix C 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 4.2. The notation follows that used in Section 4.1. 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.

C.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.[21]

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 $C_i = L_i = 0$.[22]

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 (4.1) corresponds to:

[21] 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.

[22] Neglecting the presence of two simultaneous treatments and treating them as a single treatment does not invalidate the results of Section 4.2. 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.

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

Equation (C.1) shows why we need to be cautious in interpreting the estimated effects of Section 4.2 as solely stemming from the disclosure of Graves' sexual orientation. Under an extended version of the SUTVA assumption (see Section C.2), we observe $Y_{1,t} = Y_{1,t}^{1,1}$ for all $t > T^{pre}$, and the estimator in (4.3) effectively targets the counterfactual series $Y_{1,t}^{0,0}$. Consequently, the estimated effects presented in Section 4.2 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:

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

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.

C.2 Separating Simultaneous Treatment Effects

The decomposition in (C.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 $\hat{\tau}_t^C = Y_{1,t}^{1,1} - \widehat{Y}_{1,t}^{0,1}$ and $\hat{\tau}_t^L = \widehat{Y}_{1,t}^{0,1} - \widehat{Y}_{1,t}^{0,0}$ 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 4.2.

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

Assumption C.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 C.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 4.1. Thus, as shown in (C.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 4.2.

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:

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

Under Assumption (C.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 $t > T^{pre}$:

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

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 4.2:

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

Under Assumption C.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 4.2 must be primarily attributed to Graves' disclosure.